Peer Effects in Labor Supply

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March 23, 2023

Abstract

This study investigates peer effects in labor supply. Using a representative longitudinal survey of US adolescents which includes data on friendships and combining a difference-in-differences approach and a social interaction model with network structure, I provide a causal estimate of the effect of peer labor supply on individual labor supply. I find a significant social multiplier of approximately 1.07, and provide evidence that peer effects are due to social norm compliance rather than information transmission mechanisms. Further analyses suggest that the behavior of higher socioeconomic status individuals produces larger labor supply externalities.

JEL Classification: J22, D62, D91

Keywords: working hours, endogenous peer effect, social interaction effects, social norms, add health

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1 Introduction

Social interactions are ubiquitous, and individual behavior is likely to be influenced by peers. Understanding how people influence their peers is crucial, both to understand individual choice and to anticipate how changing the behavior of one can potentially change the behavior of others via a social multiplier effect. The question of how peers' labor supply affects individual labor supply is of particular importance because labor supply is one of the most consequential decisions made by individuals, and thus is the target of many programs and policies.[1] If peers' labor supply decisions are strategic complements the aggregate labor supply elasticity is larger than the average of individual labor supply elasticities. The ratio of an aggregate elasticity to the average of individual elasticities is called a social multiplier and shows by how much any intervention will be amplified due to peer effects (see Glaeser et al. 2003). Despite its economic importance, a social multiplier in labor supply has not been yet identified.

This study addresses this gap in the literature by using data from the National Longitudinal Study of Adolescent to Adult Health (Add Health), a representative school-based survey in which US adolescents are interviewed twice during their high-school years. Included in the survey are questions about self-reported friendships and hours worked for pay outside of the home during both school and summer months. I then combine a difference-in-differences estimation strategy with a social interaction model with network structure for identification. I first-difference the data at the individual level to account for any individual specific correlated unobservables that are time constant. Then I difference the data at the school level to eliminate any time-varying shock that is common to each adolescent of a given school such as changes in local labor market conditions.[2] Thus, I investigate the link between changes in individual and peers labor supply that are deviations from the local time trend in labor supply.

By using two time periods and relying only on within-peer variation, this approach is robust to endogeneous peer selection. The difference-in-differences estimation strategy controls for any time-constant unobserved characteristic explaining both labor supply and friendship formation. Therefore, the peer effects estimates are not biased by endogenous network formation, a common concern in the peer effects literature (see Blume et al. 2011, 2015; De Paula 2017, for examples).

One remaining threat to identification of the difference-in-differences estimation strategy is that it is not clear who acts upon whom, i.e. the reflection problem (Manski 1993). To

[1] For an overview on active labor market policies see Crépon and Berg (2016), for recent meta analysis of active labor market policies see Card et al. (2017) or Vooren et al. (2019).

[2] School and network are used interchangeable as each school is an independent network by design.

solve this problem, I follow Bramoullé et al. (2009) and exploit the network structure. The idea is that changes in the characteristics of higher-order peers create exogenous variation in the labor supply of a focal individual's peers. To be precise, I look at individuals who are friends of the focal individual's peers, but not directly friends with the individual herself. The characteristics of the higher-order peers is data on whether these individuals' parents change their employment status and whether one parent moves in or out of the household. The choice of these variables is motivated by the argument that changes in these characteristics are likely an exogenous income shock to adolescents' labor supply and that the direction of the income shock is unambiguous. For example, a job loss can be a negative income shock or no shock to income at all but it cannot be a positive income shock.

Importantly, I go beyond the identification strategy of Bramoullé et al. (2009). Specifically, I solely rely on within-peer variation and exploit changes in the characteristics of higher-order peers as source of exogenous variation as opposed to level differences in peer group characteristics. Therefore, the remaining identifying assumption is much weaker, i.e. strict exogeneity of changes in individual characteristics conditional on time-varying effects on the level of schools *and* time-invariant individual heterogeneity. This assumption requires that the focal individual's labor supply changes are not directly affected by changes in the behavior of higher-order peers. I assess the plausibility of this assumption by showing that peers only respond to one another when they have nominated each other multiple times making it highly unlikely that individuals respond directly to their peers' peers. Strict exogeneity also requires that changes in individual labor supply and changes in the behavior of higher-order peers' parents are not caused by the same unobserved and time-varying shock not captured by the difference-in-differences estimation strategy. To test the validity of this assumption I do several placebo test in which individuals with similar observable characteristics are matched and peer effects are estimated. As I detect no peer effects unobserved and time-varying shocks correlated with observable characteristics cannot be the source of peer effects.

To estimate peer effects in labor supply, I use an extended version of a linear-in-means model, where individual behavior depends on peers' labor supply, as well as on own and peers' characteristics. The estimation is performed using the quasi-maximum likelihood (QML) procedure of Lee et al. (2010). I find that the social multiplier is significantly larger than 1, and varies between 1.05 and 1.07, depending on the specification. Further, even though adolescents have more time available during the summer as their budget constraints are relaxed, there is no statistically significant difference between the social multiplier in labor supply for school and summer weeks, supporting the notion of a generalizable behavioral pattern. Additional tests reveal that the social multiplier is driven by adjustments at the intensive margin, but not by adjustments at the extensive margin. A pattern emerges when investigating how social multipliers vary at the individual level: individuals with a higher socioeconomic status have a higher social multiplier, implying that a change in their labor supply will have the greatest effect on aggregate labor supply.

I then explore alternative mechanisms underlying peer effects in labor supply. I find that individuals for whom the average labor supply level of their peers converges to (diverges from) their own level report an increase (decrease) in well-being. This evidence is consistent with individuals feeling pressured to conform to the average behavior of their peers. Hence, the social multiplier most likely emerges from social norms set by peers through their behavior. This adds in two ways to the literature on the importance of social work norms for labor supply at the extensive margin (e.g. Clark 2003; Eugster et al. 2017; Hetschko et al. 2014; Stutzer and Lalive 2004). First, I show that the same mechanism exists for labor supply at the intensive margin. Second, I show that the peer group for these norms can be very small relative to the peer groups considered in this literature. An alternative explanation for the emergence of the social multiplier in labor supply is information transmission. However, I find no evidence supporting this mechanism. Furthermore, weak ties as opposed to strong ties have no effect on individual labor supply, which is in line with the underlying mechanism being social norm compliance rather than information transmission (see e.g. Gee et al. 2017; Granovetter 1973; Marmaros and Sacerdote 2002).

Finally, I show that individual labor supply increases (decreases) when peers experience a positive (negative) income shock. To the best of my knowledge, this is the first evidence indicating that individuals adjust their labor supply in a "keeping-up-with-the-Joneses" fashion. This interpretation is supported by the fact that changes in individuals' well-being varies negatively with changes in peers' income.

While clean evidence on social multipliers in labor supply is scant, there exists evidence of social interaction effects in the labor market in general. For example, prior studies have shown the importance of peer effects in effort provision (Amodio and Martinez-Carrasco 2018; Arcidiacono et al. 2017; Bandiera et al. 2010; Cornelissen et al. 2017; Falk and Ichino 2006; Mas and Moretti 2009) and that neighborhood employment rate increases individual labor supply at the extensive (Klaauw and Ours 2003; Rege et al. 2012) and intensive margins (Weinberg et al. 2004).[3] One limitation of the identification strategies employed in these

[3]Moreover, two papers show theoretically the importance of social interaction effects in labor supply when income taxes or wages change (Blomquist 1993; Grodner and Kniesner 2006). Others have shown that labor supply is correlated between peers at the intensive margin (Aronsson et al. 1999; Collewet et al. 2017; Woittiez and Kapteyn 1998) and that social interaction effects as young adult are important for maternal labor supply (Olivetti et al. 2018). Furthermore, Rege et al. (2012) provide evidence of social interaction effects in disability pension participation and Brown and Laschever (2012) show that retirement timing is affected by coworkers' retirement.

studies is that they do not allow individuals to affect the behavior of their peers, which generates the peer effect. As a result, they cannot identify a social multiplier. Topa (2001) provides evidence for the existence of social interactions in labor supply across neighborhoods but imposes strong assumptions that preclude the social multiplier being driven by plausible alternative mechanisms. Maurin and Moschion (2009) and Nicoletti et al. (2018) investigate how the labor supply of mothers after childbirth depends on the labor supply of mothers in their neighborhood and family. Both use richer specifications that do allow for other social effects, but a causal interpretation of their estimates hinges on the assumption that neighborhood selection is exogenous conditional on observable characteristics. Goux et al. (2014) do not need to make such an assumption as they use difference-in-differences research design and identify a social multiplier in labor supply for the case of spouses.

Understanding the determinants of adolescent labor supply is critical because of the myriad outcomes affected by labor market conditions during these formative years. The conditions young adults are exposed to when they enter the labor market have lasting effects on their labor supply (Gregg 2001), wages (Altonji et al. 2016; Neumark 2002; Oreopoulos et al. 2012; Wachter and Bender 2006), research output (Oyer 2006), and on their criminal behavior (Bell et al. 2018; Fougère et al. 2009). Even short summer jobs in adolescence can produce medium-term reductions in criminal behavior (Davis and Heller 2020; Gelber et al. 2016; Heller 2014; Modestino 2019), and affect their academic performance (Schwartz et al. 2021; Stinebrickner and Stinebrickner 2003). Accordingly, there are many governmental programs targeting adolescents' labor supply (e.g. Aizer et al. 2020; Attanasio et al. 2011; Card et al. 2011; Schochet et al. 2008), as well as ongoing field experiments to test interventions aimed at tackling youth unemployment (Alfonsi et al. 2020). Further, there is an increasing interest in understanding the labor supply of young adults (Fradkin et al. 2019; Kaplan 2012) and especially the declining labor supply of young men (Aguiar et al. 2017; Autor et al. 2019; Beaudry et al. 2014).

But how informative are these results beyond adolescents' labor supply? On the one hand, adolescents are a relatively homogeneous group with similar low labor market skills and time constraints due to schooling. Moreover, adolescents can make incremental labor supply adjustments compared to adults who might face hours restrictions. This facilitates the identification of peer effects, but makes it unlikely that peer effects estimates of adolescents are informative for adult labor supply at least in the short run. On the other hand, adolescents in the Add Health data are a representative sample of US adolescents engaging in the same activity as adults, that is, working for pay. Further, the social multiplier in labor supply is identified for self-selected peers as opposed to artificially or randomly selected peers who are likely to be not relevant (Carrell et al. 2013). In addition, the Add Health data provide a relatively complete picture of the relevant social networks. Finally, the same underlying mechanism social norm compliance has been shown to exist for adults. Hence, these results could be informative for the long run social multiplier in adult labor supply and contribute to the debate on why labor supply elasticity estimates based on micro data are smaller than when based on macro data (see Alesina et al. 2006; Chetty et al. 2011; Keane and Rogerson 2012).

The remainder of this paper is structured as follows. Section 2 describes the structural model, along with its identification and estimation challenges. Section 3 provides an overview of the data, and Section 4 presents the results and the mechanisms underlying the peer effects. Section 5 shows additional tests to assess threats to identification. In Section 6, I decompose the social multiplier. Lastly, Section 7 concludes the paper.

2 Linear-In-Means Model

Most of the work on the identification of social interactions has been done on linear-in-means models; see De Paula (2017) for a recent overview of this body of work. In this approach, individual behavior depends linearly on individual characteristics, the mean behavior, and the characteristics of the respective peer group. To describe the proposed linear-in-means model, I use the following notation, borrowed from Bramoullé et al. (2009). In this model, a set of individuals are separated in networks denoted by l. Individual i has a peer group P_{il} of size n_{il} and she is *not* connected to everyone in a network. Individuals are not members of their own peer groups. Let Δy_{il} be the change in labor supply between two years, and $\Delta \mathbf{x}_{il}$ be a vector of changes in characteristics. Furthermore, $\Delta\alpha_l$ allows for unobserved factors that are network invariant, but that may change over time, such as local labor market conditions. Then, the structural model can be expressed formally for individual i in network l, as follows:

$$\Delta y_{il} = \Delta\alpha_l + \beta \frac{\sum_{j\in P_{il}} \Delta y_{jl}}{n_{il}} + \boldsymbol{\gamma}\Delta \mathbf{x}_{il} + \boldsymbol{\delta}\frac{\sum_{j\in P_{il}} \Delta \mathbf{x}_{jl}}{n_{il}} + \Delta\varepsilon_{il}. \tag{1}$$

The parameter β denotes the endogenous peer effect and describes how an individual's labor supply responses to a change in peers' mean labor supply. The parameter vector $\boldsymbol{\delta}$ is the contextual peer effect, and it describes the reaction of an individual to a change in the mean characteristics of her peer group. The effect of a change in individual characteristics is given by the parameter vector $\boldsymbol{\gamma}$. As shown by Blume et al. (2015), the reduced form of (1) can be derived as a Bayes–Nash equilibrium of a game with interacting agents and incomplete information. In their model the endogenous peer effect β emerges from individuals experiencing pressure to conform to the average behavior of their peers, or from individual preferences for conformity.[4] The linear-in-means model in (1) can be rewritten in matrix notation for network l, as follows:

$$\Delta \mathbf{y}_l = \Delta \boldsymbol{\alpha}_l \boldsymbol{\iota}_l + \beta \mathbf{G}_l \Delta \mathbf{y}_l + \boldsymbol{\gamma} \Delta \mathbf{X}_l + \boldsymbol{\delta} \mathbf{G}_l \Delta \mathbf{X}_l + \Delta \boldsymbol{\varepsilon}_l, \tag{2}$$

where $\boldsymbol{\iota}_l$ is a vector of ones. The matrix $\mathbf{G}_l$ contains information about peer groups. Element g_{ijl} takes the value $1/n_{il}$ if individual j is a peer of individual i, and zero otherwise. $\mathbf{G}_l$ is constant over the two time periods to limit confounds due to endogenous network formation. The remaining derivation is presented in the appendix.

One obvious difference between the proposed linear-in-means modeling approach and more traditional models of labor supply, is that this approach omits both a wage rate and an explicit budget constraint. However, by using a difference-in-differences approach, the implicit assumption is that wages may differ between individuals, but that the wage differences are constant over time. If wages change from one year to the next, they are assumed to change similarly for everyone in a given network. Because the sample consists of adolescents with similarly low levels of education and labor market experience likely to earn relatively homogeneous wages close to the minimum wage, these assumptions seem reasonable. Furthermore, as long as the residual wage changes are orthogonal to changes in peers' labor supply, they pose no threat to identification. The same reasoning and assumptions apply to the budget constraint. To verify the applicability of the proposed model, it is estimated for two budget constraints, where the total time available to each individual varies.

2.1 Identification

There exist three fundamental problems when identifying a social multiplier, even when peers are identifiable. The first is termed the reflection problem by Manski (1993). To illustrate the problem, imagine two individuals i and j, where i works and is poor, and j does not work and is rich. When only cross-sectional data is available, we cannot tell whether individual i works because of her peer's labor supply decisions, or because of her peer's wealth, because labor supply and wealth adjust simultaneously. Thus, the reflection problem is essentially one of identifying a system of simultaneous equations. Identification can be achieved using the results of Bramoullé et al. (2009), who exploit the network structure. Continuing the previous example, suppose that j has a peer k, who is not a peer of i. Then, the wealth of individual k affects the labor supply decision of j but does not affect i's labor supply decision directly. Hence, the wealth of the peer's peer can be used as an exogenous shock to identify

[4] Blume et al. (2015) indicate that this model is observationally equivalent to one in which the endogenous peer effect stems from strategic complementarities in production.

the effect of the peer's labor supply on an individual's labor supply.

Two conditions must be met to achieve identification. First, the endogenous and contextual peer effects must not cancel each other out. That is, $\beta\boldsymbol{\gamma} + \boldsymbol{\delta} \neq 0$ must hold. Second, we require partially overlapping peer groups. Formally, the condition of partially overlapping peer groups requires $\mathbf{I}, \mathbf{G}$, and $\mathbf{G}^2$ to be linearly independent, where $\mathbf{G}^2 = \mathbf{G} \times \mathbf{G}$ and contains information on peers' peers. A sufficient condition is when there exist at least two individuals who are not peers, but who have a peer in common. In such a network, one can think of $\mathbf{G}^2\Delta\mathbf{X}$ as the identifying instrument for $\mathbf{G}\Delta\mathbf{y}$.

The second problem encountered when identifying a social multiplier is that of correlated effects. Peers share a common environment and, thus, are exposed to the same conditions and shocks. Therefore, unobserved features of the environment could explain similar behavior. For example, peers may work or not work as a result of a local labor market shock, and not as a result of peer effects. To control for such confounds, only within-network variation is used, which means omitted variables that influence everyone similarly in a given network pose no threat to identification. However, to do so, additional information is used and a degree of freedom is lost. Therefore, $\mathbf{I}, \mathbf{G}$, $\mathbf{G}^2$, and $\mathbf{G}^3$ must be linearly independent in order to achieve identification.

A sufficient condition for this requirement can be illustrated in terms of the diameter of a network, which is the largest distance between any two individuals. In the previous example, individuals i and k are the farthest apart, with a distance of two. Suppose k gets an additional peer l, who is only connected to k. Then, the distance between i and l is three, and the diameter of this network increases accordingly. In such a network, where the diameter is greater than or equal to three, $\mathbf{I}, \mathbf{G}$, $\mathbf{G}^2$, and $\mathbf{G}^3$ are linearly independent.

The third problem when identifying a social multiplier is that of endogenous network formation. The most prominent example is homophily; that is, individuals select their peers based on similar characteristics. This can cause a problem if these characteristics (on which peer selection is based) are unobserved and affect the outcome of interest. There are two layers to this problem. Consider an example in which we have two individuals who like to play tennis. Neither can do so alone, and thus decide to work instead. Then, both join the same network and become friends. Subsequently, they play tennis together, and work less often. This labor supply reduction reflects a selection effect, not a peer effect.

The first layer to this problem is this nonrandom network selection. Continuing the previous example, suppose both individuals join the same network (e.g., a tennis club), because they know that other network members will have preferences similar to their own in terms of leisure activities. Additionally, after joining the network, these individuals become peers for reasons unrelated to unobserved characteristics that determine their labor supply.

This nonrandom selection into networks is not a concern, as long as we use only within-network variation for identification.[5]

The second layer to this problem is nonrandom peer selection within a network. Continuing the previous example further, suppose that after joining the network, both individuals look for friends who like to play tennis. They get to know each other, start playing tennis together, and work less. Then, unobserved preferences over leisure activities determine friendship formation and labor supply. Thus, this confound is not fully accounted for when relying on within-network variation for identification.

The data set I use provides two periods; thus, a first-difference approach is possible to control for a potential bias emerging from nonrandom peer selection. To illustrate the advantage of this approach consider again the example of the tennis players. Suppose that after they become friends, one starts working more often for reasons unrelated to the other. Then, this increase in labor supply is related to the change in labor supply of the predetermined friend. Hence, endogenous friendship formation is of no concern, because the friends have been selected already. Therefore $\mathbf{G}$ needs to be constant over the two time periods. By using first differences of individual-level variables any unobserved time-invariant network and individual characteristics are eliminated. Hence, $\mathbf{G}$ is conditioned on any time-constant preferences and traits that affect link formation and labor supply. This results in the following question: given that individuals selected their own peer groups, how does a labor supply change in the peer group affect an individual's labor supply? In this case, endogenous peer selection is no longer a confound, because peer effects are identified using only within-peer variation.

By using this approach, the reflection problem becomes harder to solve. Traditionally, the linear-in-means model used in this paper has been applied to cross-sectional data only. Therefore, time-invariant characteristics, such as gender, race, or parental education, can be used to identify the endogenous peer effect. However, by relying on within-individual variation, individual characteristics need to vary over time.

To summarize my identification strategy: it identifies the social multiplier in labor supply by relating changes in individual labor supply to changes in peer labor supply that are induced by changes in the characteristics of higher-order peers. As a result, unobserved time-constant confounds pose no threat to identification. I make three implicit assumptions by using this identification strategy. First, there are no direct effects of higher-order peers' on individual labor supply. These effects need to be mediated solely by peers' labor supply. Second, there are no systematic time-varying shocks to individual labor supply and to peers'

[5] Many studies have adopted this approach, and assume that peer selection is random once individuals join a network (e.g. Bramoullé et al. 2009; Lin 2010).

peers' characteristics. If such time-varying shocks exist, they need to affect everyone in a given network in a similar way. Third, there are no systematic time-varying shocks to individual labor supply and friendship formation. All three assumptions are assessed in section five.

2.2 QML Estimation

The estimation of the linear-in-means model is performed using the QML procedure proposed by Lee et al. (2010).[6] This approach is for cross-sectional data but can be applied here as the data contains only two time periods and first differencing reduces it to one time period. The advantage of the QML procedure is that additional nonlinearities are used by exploiting peer group sizes. Intuitively, the marginal effect of an individual on a peer depends on the size of the respective peer's peer group. Furthermore, this estimation method imposes several regularity conditions (see Lee et al. 2010, p.152) and, therefore, is efficient relative to a two-stage least squares approach. This efficiency is needed, because the number of observations is low and the data is differenced twice. Details on the QML estimation are laid out in the appendix.

3 Data

The Add Health study is a longitudinal survey study of a nationally representative sample of US adolescents.[7] In Wave 1, during the school year 1994/95 more than 90,000 individuals in Grades 7 through 12 participated in the school-based survey. Then, in the year 1995, a random subsample of these participants of approximately 20,000 individuals was selected for an in-home interview. These interviews contain extensive information on employment experience, peer networks, family composition and dynamics, and educational aspirations and expectations. In 16 schools, all enrolled adolescents were asked to participate in the in-home interview. This saturated subsample of approximately 3,700 individuals was created to enable an analysis of social networks. The 16 schools consist of two large schools and 14 small schools. These schools are independent networks by design. In 1996 the same individuals were interviewed again for Wave 2, except for those who were in Grade 12 during Wave 1. This reduced the saturated sample to approximately 2,800 individuals. I use the

[6] I deviated slightly from Lee et al. (2010) by not allowing autocorrelated errors as it would require to have have two different **G**. Having one **G** for the endogeneous peer effect and a different **G** for autocorrelated errors is not plausible for the case of friendship networks. See Fortin and Yazbeck (2015) and Lin (2010) for applications of Lee et al. (2010).

[7] More information on the study design is available from Harris et al. (2009).

latter saturated sample after excluding individuals with no peers and those with missing values on variables required for the analysis. The smallest school is also excluded because the diameter of its graph $\mathbf{G}_l$ is too small.

3.1 The Social Matrix

The adjacency matrix $\mathbf{G}$ should capture frequent interactions between individuals. However, as in most related studies, no information on these interactions exists. Nevertheless, Kiessling et al. (2019) show that friendship is the most important determinant of peer comparison for individuals aged 12 to 16. Therefore, as in many such studies, friendship nominations are used as a proxy for frequent interactions. In each interview, individuals could nominate an equal number of different male and female friends. In Wave 1, for the in-school questionnaire, this was set to five. When interviewed again during the year 1995 at home, this value was one or five.[8] In the subsequent year, when everyone was interviewed again for Wave 2, individuals could again nominate five different friends of each gender. Thus, anyone could nominate a given friend at most three times, i.e. during the in-school questionnaire, the in-home interview in Wave 1 and in Wave 2. Likewise a participant could reciprocate her nominations up to three times.

To construct friendship networks I pool the nominations of all three surveys. Hence, for a given pair of friends, the maximum number of friendship nominations is six. Even then the friendship networks are sparse. Of all possible friendships, only 0.45% have at least one nomination; and of these, only 46.4% have two or more nominations. Two individuals are said to have frequent interaction if at least two friendship nominations exist. Then, the assigned link is undirected; formally, we have $g_{ij} = g_{ji} = 1$. In this case, each individual is in the other's peer group, and each peer has an equal weight. Finally, the graph $\mathbf{G}$ is row-normalized, because we are interested in the average rather than the aggregate peer effect.

This choice of peer definition has tradeoffs. First, the threshold for identifying a peer is two nominations. Multiple nominations help reassure that the constructed peer groups include only those with whom students have frequent interactions. A threshold of three nominations was not used because it increases the number of isolated individuals and thereby reduces the sample size considerably. Second, the use of undirected graphs means there are individuals who have peers whom they have never nominated as a friend. This may seem

[8] Initially, those who completed the in-school questionnaire could only nominate one male and one female friend. An exception was made for those who did not complete the in-school questionnaire. These individuals could nominate up to five male and five female friends. During Wave 1, the protocol was changed such that everyone who had not yet been interviewed, regardless of the completion of the in-school questionnaire, could nominate up to five male and five female friends during the in-home interview.

counterintuitive. However, this can occur when the peer has nominated the individual at least twice as a friend. Hence, it is likely that some social interaction between both has occurred. Furthermore, 66.5% of all individuals nominated at least one person as a friend who attended the same school, but whose name they could not find on the school roster. Such a friend is likely someone who nominated them twice as a friend. Hence, the use of undirected graphs could account for some of the missing friendship nominations. The same argument for using undirected graphs is used by Banerjee et al. (2012), who show that individuals even fail to name their relatives as close ties on similar surveys.

The alternative of directed graphs poses different problems. When the graph is directed, some individuals have an empty peer group and, consequently, the peer effects for these individuals are zero. Because only one individual reports having no friends, no truly isolated individuals exist. Therefore, a better proxy for the true peer effect should not be 0 but the peer effect of someone who nominated the person at least twice as a friend. For individuals who have others in their peer group, the effect of an additional individual in their peer group diminishes with the size of the peer group because the average behavior of the peer group is used. The use of undirected graphs increases the average peer group size by 0.54, which leads to peer group averages closer to the network average. Therefore, the peer effect estimates with undirected graphs should provide a lower bound of the true effect.

After assigning these peer groups, some individuals are isolated. This occurs for two reasons. Either these individuals only nominated friends whose names they could not find on the school roster, or there exists at most one nomination between them and someone else. In both instances, the school is likely not their primary social network. Hence, these individuals are excluded.

3.2 Descriptive Statistics

Questions about labor supply are asked twice: during the in-home interview in Wave 1, and in the following year, during Wave 2. As shown in Table 1, the average labor supply in school weeks is 8.9 hours, with a high variance and a right-skewed distribution. Furthermore, 26.4% of all individuals report that they do not work for pay in either of the two Waves, 40.5% state that they work in both Waves, and the remaining third work in only one of the two Waves. When individuals adjust their labor supply in school weeks between Wave 1 and 2, then 27% of all individuals do so by at most five hours per week.[9] Hence, adolescents can, and do, adjust their labor supply incrementally. The labor supply during summer weeks refers to those weeks in which individuals do not attend school. The main difference between the

[9] As measurement error can be amplified when taking first differences labor supply and allowance changes are winsorized at 0.5% and 99.5%.

two is that individuals' budget constraints are relaxed by the increase in total time available. This is likely why individuals work on average nearly twice as much during summer weeks, on average.

Table 1: Summary Statistics

	Level		1st Difference	
	Mean	Std. Dev.	Mean	Std. Dev.
Labor supply in school weeks	8.899	11.988	4.099	12.037
Labor supply in summer weeks	16.329	17.737	4.378	16.999
Both parents present	0.590	0.492	-0.020	0.218
Both parents working	0.556	0.497	0.018	0.363
Weekly allowance in $	7.326	10.453	1.162	11.217
Unpaid housework	2.076	0.849	-0.014	0.961
Likely to go to college	4.073	1.184	-0.007	1.036
Want to go to college	4.337	1.088	-0.097	1.005
# of peers	3.703	2.505		
Adolescents per school	135.467	217.287		

Notes: Number of observations for levels is 4,064 from 2032 individuals. The average # of peers is constant for every individual. There are 15 schools and each has a constant number of individuals.

Two individual characteristics are used throughout the analysis. The first, "both parents present", is a dummy variable that takes the value one if both parents live in the same household, and zero otherwise. Similarly, "both parents work", is a dummy that takes the value one if both parents work, and zero otherwise. For some individuals, these characteristics change between Waves.[10] These changes are used to identify the effects of changes in peer labor supply. While such changes may seem like rare events the average size of the peer group is 3.7; hence, when a change occurs in one household, many individuals are affected. Furthermore, the variation on the level of higher-order peers is used for identification. Thus, a change in one household affects many more individuals indirectly. This is why, for 73.5% of all individuals, at least one of the two characteristics on the level of peers' peers is nonzero.

To support the interpretation that changes in both characteristics are very likely income shocks to households in the Add Health data I rely on the parent survey. During Wave 1, one parent in the household was interviewed about, among other things, household income, welfare dependence, and problems paying bills. In Table A1 regression results are presented confirming that for this sample single-parent households and households in which only one

[10]The work status of a nonresidential parent is not elicited. This is why changes in the two characteristics are constructed such that changes in both are mutually exclusive, i.e. when a parent moves in or out she does not change her work status.

parent works are poorer. As parents were interviewed only once I am only able to show that this relationships holds in levels.

The following variables are used in additional tests. The average weekly allowance of an individual is USD 7.31, which has a high variance and a right-skewed distribution. As a proxy for the amount of time an individual has at her disposal, information on how often they work around the house is included. This measurement is based on a four-point Likert scale, and includes unpaid work, such as cleaning, laundry, and yard work. Individuals were asked how much they want to go to college, and how likely this is to happen. Both questions were answered on a five-point Likert scale, where higher values indicate a greater willingness to go to college, and a higher likelihood that this will occur. Finally, the last two rows of Table 1 show the sizes of the peer groups and schools measured in number of individuals.

4 Results

To provide a benchmark, the linear-in-means model is estimated using ordinary least squares (OLS) estimation, and then using the QML estimation method. Both specifications use only the main characteristics, *both parents present* and *both parents work*. The results for school weeks are presented in Table 2, columns (1) and (2). In columns (4) and (5), the same specifications are estimated using the labor supply in summer weeks. I first discuss how the various estimates of the different specification are related, as well as the sign, magnitude, and significance of the estimated coefficients, and their implications for individual labor supply. Then, I discuss why peer effects exist and tease out potential mechanism underlying these effects.[11]

The OLS estimate of the endogenous peer effect in column (1) is approximately 8.8%, and is higher than the QML estimate of 6.2% in column (2). Both specifications use a difference-in-differences approach and, therefore, the discrepancy between the estimates is driven by two diverging confounds: the reflection problem, which is likely to cause an upward bias in the OLS estimate, and classical measurement error, which causes a downward bias in the OLS estimate. Both confounds are addressed by QML approach. However, it is not clear, ex ante, which confound dominates.[12] Because the OLS estimate is larger than the QML estimate, classical measurement error seems to play a minor role, relative to the reflection problem.

The endogenous peer effect of approximately 6.2% implies that a one-hour increase in

[11] The results for the non-winsorized sample are presented in Table A2.

[12] For example, in De Giorgi et al. (2019), the IV estimates of the peer effects are larger than the OLS estimates.

Table 2: Peer Effects in Labor Supply

	School weeks			Summer weeks		
	(1) OLS	(2) QML	(3) QML	(4) OLS	(5) QML	(6) QML
Endogenous Peer Effect: $\beta\mathbf{G}\Delta\mathbf{y}$						
Labor supply	0.0881***	0.0619**	0.0670***	0.0709**	0.0510**	0.0598**
	(0.0325)	(0.0250)	(0.0250)	(0.0334)	(0.0254)	(0.0254)
Contextual Peer Effects: $\boldsymbol{\delta}\mathbf{G}\Delta\mathbf{X}$						
Both parents present	3.783*	3.735*	3.732*	7.177**	7.174**	7.176**
	(1.995)	(1.993)	(1.985)	(2.835)	(2.832)	(2.819)
Both parents working	3.368***	3.389***	3.357***	1.057	1.043	0.774
	(1.129)	(1.128)	(1.128)	(1.605)	(1.603)	(1.602)
Allowance			0.0133			0.0898*
			(0.0336)			(0.0477)
Housework			0.868**			1.367**
			(0.414)			(0.589)
Likely college			-0.0514			0.634
			(0.473)			(0.671)
Want college			0.594			0.734
			(0.506)			(0.719)
Effect of Individual Characteristics: $\boldsymbol{\gamma}\Delta\mathbf{X}$						
Both parents present	0.219	0.246	0.0864	1.667	1.712	1.497
	(1.224)	(1.223)	(1.217)	(1.741)	(1.738)	(1.729)
Both parents work	-0.665	-0.632	-0.584	0.360	0.377	0.436
	(0.731)	(0.730)	(0.727)	(1.038)	(1.037)	(1.032)
Allowance			-0.0737***			-0.0558*
			(0.0236)			(0.0336)
Housework			-0.555**			-1.030***
			(0.276)			(0.393)
Likely college			-0.0514			-0.0114
			(0.310)			(0.440)
Want college			-0.360			-0.642
			(0.318)			(0.452)

Notes: Dependent variable in column (1) - (3) is labor supply in school weeks and in column (4) - (6) labor supply in summer weeks. The regressor labor supply of peers is the labor supply in the same weeks as the dependent variable. All models are estimated in first-differences and are differenced a second time at the school level. The first-differences of labor supply and allowance are winsorized at 0.5% and 99.5%. Models in column (1) and (4) are estimated by OLS and the remaining models by QML. The number of observations is 2,032. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

the average labor supply of peers causes an individual's labor supply to increase by about 4 minutes. The corresponding social multiplier is 1.066, indicating that an increase in an individual's labor supply by one unit leads to an aggregate labor supply increase by 1.066 units. To further illustrate the relevance of this effect, consider the average increase in labor supply of four hours between Wave 1 and 2. A back of the envelope calculation suggests that approximately 16 minutes of this increase is driven by the social multiplier in labor supply.

To put this value into perspective, Goux et al. (2014) find a social multiplier of 1.115 between spouses. It is reassuring that the social multiplier between spouses is higher than that between friends, because spouses are likely to have more frequent interactions than friends. Furthermore, in a meta study by Herbst and Mas (2015) on peer effects in worker output, the average social effect in field studies is estimated to be 0.107. These studies do not identify a social multiplier, but the size of this average social effect is quite similar to the social multiplier estimates. Lastly, Cornelissen et al. (2017) show that the social effect in wages for occupations with potentially high peer pressure is approximately 0.064, which is also in line with the endogenous peer effect estimates presented here.

Next, I discuss the results of estimating the same specification for summer weeks. The endogenous peer effect estimated using QML (column (5)) is 5.1%. The point estimates in columns (2) and (5) are not significantly different from each other. This result is not self-evident. Labor demand may differ between summer weeks and school weeks, and adolescents face a relaxed budget constraint during summer weeks because they do not need to attend school. Thus, the majority of individuals work different amounts of time (in hours) during school and summer weeks. Only 2.7% of all individuals decided to work during both Waves, and work the same number of hours during school and summer weeks.[13] Hence, even under distinct circumstances, and when individuals make different decisions, the endogenous peer effect in labor supply is not different. This result provides evidence in favor of peer effects in labor supply as a stable behavioral pattern.

Next, I examine the effect of peers' characteristics on labor supply. The point estimate of having peers' parents present (column (2)) is positive, large, and significantly different from zero. This implies that individuals decrease their weekly labor supply when one of their peers' parents moves out of home. To interpret the magnitude of the coefficient on the parental presence indicator in column (2), suppose that one has only one peer. Then, if a parent of this peer moves out, weekly labor supply decreases by 3 hours and 44 minutes. This effect seems large, especially given that it is the direct effect, and omits the social

[13] Note that the labor supply of these individuals can differ between Wave 1 and 2. E.g. someone could work four hours during school and summer weeks in Wave 1 and seven hours during school and summer weeks in Wave 2.

multiplier effect. However, recall that the average peer group size is 3.7. For such a peer group, the individual and direct labor supply response when one parent moves in or out of home is approximately one hour. The effect of having peers' parents start or stop working is similar. The point estimate is approximately 3.4 and is highly significant. This result can be interpreted in the same way as that for *both parents present*. For the labor supply in summer weeks, the point estimate of *both parents present* in column (5) is even larger (7.2), and is significant. However, the effect of both parents working is not significantly different from zero.

Changes on the level of individuals' own parents (i.e., both parents are present and/or both work) are not related to individual labor supply. This is not surprising, because there are potentially many different and conflicting mechanisms at work. Especially for a change in the presence of own parents, which could explain why the point estimate in column (2) is relatively close to zero, and very imprecisely estimated. The point estimate in the same column for *both parents work* is negative and is not estimated as imprecisely. The sign of this point estimation can be interpreted as adolescents increasing their labor supply if one of their two parents stops working.

4.1 Why Does Peer Labor Supply Affect Individual Labor Supply?

There are two competing explanations for why peers' labor supply could affect individual labor supply. The first is that the average peers' labor supply constitutes a norm to which individuals feel pressured to conform. This pressure emerges because individuals experience disutility when they deviate from the average behavior of their peers. The second explanation is that well-connected individuals transmit information about vacancies and/or provide referrals to their employer on behalf of their peers. This transmission of information increases their peers' labor supply.

Information transmission implies that better-connected individuals or those who are more central in a given network should work more, because they receive more information. The identifying variation holds constant the position of each individual in a given network. As a result, the endogenous peer effect cannot be driven by the network position alone. However, when network position interacts with changes in labor supply, then information transmission could be the source of the endogenous peer effect. This would imply that those who have many peers should experience the largest changes in labor supply. A natural way to check for this is to estimate aggregate, rather than average peer effects. Aggregate peer effects sum peers' labor supply and, thus, are aligned precisely with the information transmission mechanism. For peer groups of size one, aggregate and average peer effects coincide. However, 78.5% of all peer groups in the sample have a size of two or more allowing for a test of this information transmission mechanism.

To estimate aggregate peer effects, the graph $\mathbf{G}_{agg}$ is used. This is the same as graph $\mathbf{G}$ but is not row-normalized. However, note that the model can no longer be identified because it lacks power. Therefore, only the following reduced form is estimated:

$$\Delta \mathbf{y}_l = \Delta \boldsymbol{\alpha}_l \boldsymbol{\iota}_l + \boldsymbol{\gamma} \Delta \mathbf{X}_l + \boldsymbol{\delta}_r \mathbf{G}_{agg,l} \Delta \mathbf{X}_l + \Delta \boldsymbol{\varepsilon}_l. \tag{3}$$

The reduced-form coefficient vector $\boldsymbol{\delta}_r$ detects endogenous and contextual peer effects and, therefore, is a compound measure of both social effects. The results of this estimation are presented in Table 3. To be able to compare the average and aggregate social effects, both are estimated. The former are presented in column (1), and the latter in column (2). As expected, the average social effects are significant in the reduced form. In contrast, the aggregate social effects are at most a quarter of the size of the average effects, only significantly different from zero in one instance. However, even in the absence of information transmission, the estimated aggregate social effects are likely not zero, because the average and aggregate social effects coincide for 21.5% of all individuals. To further check the plausibility of information transmission, I estimate the same model using labor supply at the extensive margin, because this is where the mechanism should be strongest. Labor supply is transformed into a dummy variable, taking the value one if the individual supplies labor, and zero otherwise. Hence, this variable measures whether someone starts or stops working. The results for the average and aggregate social effects are presented in columns (4) and (5), respectively, and show clearly that neither effect exists at the extensive margin. All four estimations are repeated using labor supply for summer weeks. The results are presented in columns (5), (7), (9), and (10), and are very similar to those for labor supply for school weeks.

The above results suggest that information transmission is not the underlying mechanism of the endogenous peer effect. First, the network is held constant, which rules out a simple relationship between network position and labor supply. Second, barely any aggregate social effect exists at the intensive margin. Third, when information transmission should be strongest (i.e., at the extensive margin), there is no evidence of either average or aggregate social effects.

The alternative explanation is that of norm compliance, which is modeled such that individuals experience disutility when they deviate from the average behavior of their peers. This mechanism generates three predictions. Suppose individual i has a peer j, and that

Table 3: Reduced Form Estimates of Peer Effects in Labor Supply

	School weeks					Summer weeks				
	Intensive margin			Extensive margin		Intensive margin			Extensive margin	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Average Social Effects of Peers: $\boldsymbol{\delta}_r \mathbf{G} \Delta \mathbf{X}$										
Both parents present	3.612*		3.608*	-0.143		7.032**		7.071**	0.0339	
	(1.969)		(1.968)	(0.0932)		(2.796)		(2.796)	(0.0860)	
Both parents work	3.403***		3.427***	0.0662		0.990		1.025	0.0304	
	(1.124)		(1.124)	(0.0532)		(1.597)		(1.597)	(0.0491)	
Aggregate Social Effects of Peers: $\boldsymbol{\delta}_r \mathbf{G}_{agg} \Delta \mathbf{X}$										
Both parents present		0.508			-0.0527		0.920			-0.0199
		(0.746)			(0.0352)		(1.058)			(0.0325)
Both parents work		0.831**			0.0291		1.146**			0.0227
		(0.385)			(0.0182)		(0.546)			(0.0168)
Average Social Effects of Weak Ties: $\boldsymbol{\delta}_w \mathbf{G}_w \Delta \mathbf{X}$										
Both parents present			-0.784					-2.979		
			(2.081)					(2.956)		
Both parents work			1.206					-0.563		
			(1.399)					(1.988)		
Effect of Individual Characteristics: $\boldsymbol{\gamma} \Delta \mathbf{X}$										
Both parents present	0.313	0.258	0.286	0.0202	0.0180	1.828	1.742	1.869	0.0327	0.0303
	(1.220)	(1.223)	(1.220)	(0.0577)	(0.0577)	(1.733)	(1.734)	(1.733)	(0.0533)	(0.0533)
Both parents work	-0.562	-0.562	-0.570	-0.00269	-0.00355	0.410	0.430	0.445	0.0228	0.0229
	(0.728)	(0.729)	(0.728)	(0.0344)	(0.0344)	(1.034)	(1.034)	(1.034)	(0.0318)	(0.0318)

Notes: Dependent variable in column (1) - (5) is labor supply in school weeks and in column (6) - (10) labor supply in summer weeks. Intensive margin labor measures labor supply in hours. Extensive margin measures labor supply as as dummy which is 1 if one works and 0 otherwise. In column (1), (3), (4), (6), (8), and (9) average social effects are estimated whereas in the remaining columns aggregate social effects. All models are in first-differences, include school-wave dummies and are estimated by maximum likelihood. Number of observations is 2,032. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

both work the same number of hours in Wave 1. When j changes her labor supply in Wave 2, i should experience disutility, regardless of the direction of the change, because any change leads to a gap between the labor supply of i and j. Hence, prediction 1 is as follows: if an individual's labor supply is the same as the average labor supply of her peers in Wave 1, then an absolute change in the peers' labor supply decreases her utility. To explain prediction 2, suppose i works more hours than j does in Wave 1. Then, an increase in j's labor supply leads to a more similar labor supply for both. Consequently, i's utility should increase. In contrast, when j decreases her labor supply, the labor supply gap between i and j widens, and i's utility should decrease. Therefore, prediction 2 is as follows: if an individual's labor supply is *higher* than the average labor supply of her peers in Wave 1, then a change in the peers' labor supply changes her utility in the *same* direction. Prediction 3 follows the same logic as prediction 2, but it refers to cases in which i works fewer hours than j does in Wave 1. Thus, prediction 3 is as follows: if an individual's labor supply is *lower* than the average labor supply of her peers in Wave 1, then a change in the peers' labor supply changes her utility in the *opposite* direction.

These three predictions are tested using a reduced-form approach. As a proxy for utility, I use the answers to 19 questions in which individuals are asked how often they feel, for example, happy, bothered, sad, depressed, hopeful, and so on. From these 19 answers, I extract the first principal component.[14] This component is then normalized to have mean zero and standard deviation one, and loads positively on positive feelings and negatively on negative feelings. This measure seems to capture a general emotional state, because it explains 31.7% of the variation. In contrast, the second principal component accounts for just 8.1% of the variation. The change in the first principal component between Waves 1 and 2 is the dependent variable in the following reduced form:

$$\Delta \mathbf{u}_l = \Delta \boldsymbol{\alpha} + \boldsymbol{\delta}_k \mathbf{G}_l^2 \Delta \mathbf{X}_l + \boldsymbol{\delta}_j \mathbf{G}_l \Delta \mathbf{X}_l + \Delta \boldsymbol{\varepsilon}_l. \tag{4}$$

The regressor is the first difference of peers' peers' average characteristics: *both parents present* and *both parents work*. As shown in the previous section, this causes peer labor supply to change. I use the sum of both variables as the effect for both characteristics has the same direction and to sharpen the conclusion. In addition, I control for peers' average characteristics and discuss the coefficient estimates in the next section. By using this reduced-form approach, I implicitly assume that there is no endogenous peer effect in well-being or alternatively estimate a compound measure of endogenous and contextual peer effects in well-being.

[14] More details are presented in Table A3.

Table 4: Social Effects on Well-being

	(1)	(2)	(3)	(4)	(5)
Social Effects of Peers' Peers $\boldsymbol{\delta}_k \mathbf{G}^2 \Delta\mathbf{X}$					
|Both present + both work|	-0.336				
	(0.276)				
Both present + both work		0.191	-0.471***		
		(0.183)	(0.174)		
Both present + both work				-0.305***	-0.305***
(weighted average)				(0.110)	(0.110)
Social Effects of Peers $\boldsymbol{\delta}_j \mathbf{G} \Delta\mathbf{X}$					
Both present + both work	-0.442**	-0.177	0.0181	-0.161**	-0.161**
	(0.175)	(0.115)	(0.109)	(0.0720)	(0.0722)
Social Effects of Weak Ties $\boldsymbol{\delta}_w \mathbf{G}_{\mathbf{w}} \Delta\mathbf{X}$					
Both present + both work					-0.0189
					(0.0886)
Sample used	$y_{1i} = y_{1j}$	$y_{1i} > y_{1j}$	$y_{1i} < y_{1j}$	all	all
N	300	712	1020	2032	2032

Notes: Dependent variable is the first principal component of 19 answers to questions about feelings. All models are estimated in first-differences, with a constant and by OLS. The regressors are the sum of both parents present and both parents work for different levels of peers. In column (1) the regressor for peers' peers is its absolute value and the sample is restricted to individuals whose labor supply coincides with the average labor supply of their peers in Wave 1. In Panel A column (2) the sample is restricted to individuals whose labor supply is larger than the average labor supply of their peers in Wave 1. In Panel A column (3) the sample is restricted to individuals whose labor supply is smaller than the average labor supply of their peers in Wave 1. In Panel A column (4) and (5) the regressor for peers' peers of column (1) - (3) is combined as follows: $\mathbf{G}^2(|\Delta\mathbf{X}|\mathbf{1}(y_{1i} = y_{1j}) + \Delta\mathbf{X}(\mathbf{1}(y_{1i} < y_{1j}) - \mathbf{1}(y_{1i} > y_{1j})))$. Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The results for equation (4) are shown in Table 4. The first three regressions are done for each subgroup separately. Column (1) shows the results for individuals whose labor supply coincides with the average labor supply of their peers. In this case, the independent variables are the absolute values of the sum of peers' peers' characteristics, because any shock reduces an individual's well-being, regardless of its direction. Columns (2) and (3) show the results for individuals whose labor supply is larger or smaller, respectively, than the average labor supply of their peers. Each of the three point estimates has the right sign, but only the estimate in column (3) is significantly different from zero. However, when estimating a weighted average of the three groups, such that the predictions are the same for each group, the conclusion sharpens. As shown in column (4), a change in the characteristic of peers' peers leads to a significant and sizable change in well-being. Thus, deviating from the average behavior of one's peers seems to have direct utility costs.

In summary, peer labor supply likely affects individual labor supply in one way. There is no evidence that peers provide information to each other and, therefore, affect their labor supply. In contrast, there is direct evidence that individuals experience utility costs when their peers' labor supply deviates from their own labor supply. Given this evidence, the most likely interpretation of why peers' labor supply affects individual labor supply is that individuals feel pressured to conform to the average behavior of their peers.

4.2 Why Do Peers' Parents Affect Individual Labor Supply?

There are two potential explanations for why peers' parents affect an individual's labor supply that are consistent with individuals working more (less) when one of their peers' parents moves in (out), and when one of their peers' parents starts (stops) working. The first explanation is that a change in one of these characteristics represents an income shock. Such a shock could affect an individual if, for example, the peers' income directly enters her utility. There is ample evidence that individuals evaluate their income relative to that of others (see e.g. Card et al. 2012; Clark et al. 2008; Luttmer 2005). Hence, the first explanation states that when peers become richer (poorer), individuals increase (decrease) their labor supply to keep up with that of their peers. That this "keeping-up-with-the-Joneses" mechanism exists between peers has been shown for consumption by De Giorgi et al. (2019).

The "keeping-up-with-the-Joneses" mechanism implies that peers' income directly enters an individual's utility, such that a higher (lower) peer income decreases (increases) the individual's utility. In order to test this conjecture, the change in well-being is regressed on the average change in peers' characteristics which proxy peer income. This is done in (4) and the results are presented in Table 4 column (4). The coefficient is -0.161 and significantly different from zero, implying that an increase (decrease) in peers' income reduces (increases) well-being, which is consistent with the "keeping-up-with-the-Joneses" mechanism.

The second explanation is that individuals redirect time away from work and towards their peers when their peers experience significant events like changes in family status. In this case, the change in characteristics is a leisure shock. A similar approach can be used to assess the emotional support mechanism. Here, individuals report about their leisure activities such as how often they meet their friends, and how often they play team sports. When a change in peers' characteristics is a leisure shock, then a negative change should predict for example an increase in meeting with friends and playing team sports. However, as shown in Table 5, columns (1)–(4), a change in peers' characteristics does not lead to a change in these leisure activities. Hence, the presented evidence is not consistent with an emotional support mechanism.

In summary, peers' parents affect an individual's labor supply most likely via a "keeping-up-with-the-Joneses" mechanism, because a change in peers' characteristics is likely to be an income shock that affects individuals' utility such that an increase (decrease) in peers' income decreases (increases) an individual's well-being. The results do not support an emotional support. However, these two mechanisms are not mutually exclusive. Furthermore, as long as peers' parents induce an exogenous shock to an individual's labor supply, the endogenous peer effect is identified, regardless of the mechanism. In addition, the reason why the endogenous peer effect emerges in the first place is independent of any mechanism explaining why peers' characteristics affect an individual's labor supply.

5 Threats to Identification

5.1 Time-varying Correlated Effects

Correlated effects are unobserved features of the environment in which peers interact that can make peers behave in a similar way. Owing to the difference-in-differences approach, the use of a social interaction model with network structure, and having similar effects for the labor supply at different points in time, a correlated effect that threatens identification must satisfy several properties: 1) it must be time varying; 2) it must increase (or decrease) individual labor supply during school and summer weeks; 3) it should encourage higher-order peers' parents to move in (or out); and 4) it should make higher-order peers' parents start (or stop) working. Furthermore, such a correlated effect cannot affect everyone in the same school equally.

Table 5: Effect of Peers on Time Use

	Meet Friends		Team Sport		Meet Friends		Team Sport	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Social Effects of Peers: $\boldsymbol{\delta}_r \mathbf{G} \Delta \mathbf{X}$								
Both parents present	-0.176		0.144		-0.185		0.134	
	(0.183)		(0.203)		(0.184)		(0.204)	
Both parents work	-0.0654		-0.101		-0.0689		-0.105	
	(0.114)		(0.117)		(0.114)		(0.116)	
Both present + both work		-0.0933		-0.0395		-0.0966		-0.0431
		(0.0957)		(0.100)		(0.0958)		(0.1000)
Social Effects of Weak Ties: $\boldsymbol{\delta}_w \mathbf{G}_w \Delta \mathbf{X}$								
Both parents present					0.240		0.276	
					(0.177)		(0.199)	
Both parents work					0.0707		0.0645	
					(0.131)		(0.134)	
Both present + both work						0.123		0.132
						(0.107)		(0.110)

Notes: Dependent variable in column (1), (2), (5), and (6) is how often one meets with one's friends per week; in column (3), (4), (7), and (8) it is how often one does team sports, such as baseball, basketball, soccer or football, per week. All models are estimated in first-differences, with a constant and by OLS. Robust standard errors in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

To evaluate the remaining threat to identification by correlated effects, two methods can be used. One is to add additional control variables to capture such effects. These must be time varying individual characteristics and they need to be strictly exogenous conditional on the difference-in-differences identification strategy. This requirement limits the number of potential candidates. However, four suitable variables exist. Allowance and housework should capture changes in the budget constraint induced by unobserved shocks. I use them because they are at least partly determined by peers' parents and, therefore, are likely to be exogenous to individual labor supply. Furthermore, individuals were asked about both their desire for and the likelihood of their college attendance. The answers to these questions should be affected by economic shocks to which households are exposed. The results are presented in Table 2, columns (3) and (6). The endogenous peer effect increases slightly for the labor supply during school weeks, and is a bit higher for the labor supply during summer weeks. Other than that, the overall results remain unchanged.

The other method used to evaluate whether correlated effects pose a threat to identification are placebo tests, which builds upon the works of Bifulco et al. (2011) and Liu et al. (2017). When unobserved correlated effects are correlated with observable characteristics, a placebo test can detect them. In order to do so, peers are drawn randomly for each individual from a set of similar individuals. If a spurious peer effect for these random peers is observed, then correlated effects are likely to be the source of peer effects.

I draw, for each individual, between one and three random peers from individuals in the same school. These random peers are drawn from those not actually nominated as friends by the focal individual, but who have similar household size, parental education, or school grade as reported by the focal individual in Wave 1. To remain consistent with previous estimations, undirected links are assigned. For these random peers, the reduced form is estimated once for the labor supply during school weeks, and once for the labor supply during summer weeks. This procedure is repeated 1,000 times. The results are presented in Table A4. Overall, the z-values of the estimated coefficients are centered around zero and have a standard deviation of one. Thus, there are no spurious peer effects for similar individuals. Hence, these results confirm that the peer effect estimates are very unlikely to be driven by time-varying correlated effects and, thus, mitigate concerns related to time-varying correlated effects being a threat to identification.

5.2 Endogenous Network Formation

The second threat to identification is a time-varying shock that affects both friendship formation and individual labor supply. To assess this concern I follow the approach by Liu et al.

(2017) and model dyadic friendship based on homophily, which is a common approach used in the literature (see, e.g. Currarini et al. 2009; Girard et al. 2015; Graham 2017; Marmaros and Sacerdote 2006). Following these works, network formation is modeled such that

$$s_{ijl} = \alpha + \phi|\Delta\mathbf{X}_{il} - \Delta\mathbf{X}_{jl}| + \theta|\Delta\boldsymbol{\eta}_{il} - \Delta\boldsymbol{\eta}_{jl}| + \Delta\nu_{il} + \Delta\nu_{jl} + \Delta u_{ijl}, \tag{5}$$

where s_{ijl} is a latent variable that measures the strength of the link between individual i and j. A link is stronger when two individuals experience a similar change in their observable characteristics $\Delta\mathbf{X}_{il}$. Furthermore, the strength of a link also increases in the similarity of the unobserved shock $|\Delta\boldsymbol{\eta}_{il} - \Delta\boldsymbol{\eta}_{jl}|$. In addition, the individual-specific changes $\Delta\nu_{il}$ and $\Delta\nu_{jl}$ are the same for each link of the respective individual. The link-specific error is given by Δu_{ijl}.

Using this model, we can test the threat of endogenous network formation with respect to unobserved shocks that affect the labor supply. To do so, equation (5) is estimated. The latent variable s_{ijl} must be substituted with $d_{ijl} = \mathbf{1}(s_{ijl} > 0)$, where $\mathbf{1}(.)$ is an indicator function. It is set to one for peers with at least two friendship and set to zero for peers with only one friendship nomination. Additionally, $|\Delta\boldsymbol{\eta}_{il} - \Delta\boldsymbol{\eta}_{jl}|$ cannot be observed directly, and has to be substituted with the residuals of (2). To summarize, this model tests whether there is information remaining in the residuals that predicts link formation. In other words, this test answers the question of whether two individuals who experience a similar idiosyncratic shock to their labor supply are more likely to be peers.

The results for the four different models are presented in Table 6. The positive and significant coefficient θ in columns (1), (2), and (4) implies that individuals who have *dissimilar* idiosyncratic shocks to their labor supply are *more* likely to be friends. Thus, for endogenous network formation is properly accounted for. Because θ is positive, the endogenous peer effect estimate gives a lower bound, and the true effect is likely to be higher.

5.3 Network Misspecification

The third threat to identification is a misspecification of the network structure, which implies that higher-order peers have a direct effect on an individual's labor supply. Recall that the group of higher-order peers could consist of two different groups: individuals for whom only one friendship nomination exists, and those for whom none exists. The following test assesses whether peer effects exist between individuals who share only one friendship nomination. If such effects do exist, then a direct effect of higher-order peers cannot be excluded. In contrast, if the hypothesis of no peer effects cannot be rejected, this ensures the validity of the network specification. In order to perform this test, the reduced form is estimated for two

Table 6: Test for Endogenous Network Formation

	School weeks		Summer weeks	
	(1)	(2)	(3)	(4)
Residuals	0.0277*	0.0426***	-0.150***	0.0496***
	(0.0163)	(0.00817)	(0.0148)	(0.00566)
Both parents present	0.165*	0.168*	0.236***	0.149*
	(0.0903)	(0.0912)	(0.0784)	(0.0819)
Both parents work	0.0335	0.0359	0.0627*	0.0338
	(0.0351)	(0.0352)	(0.0346)	(0.0355)
Housework		-0.00285		-0.0206*
		(0.0106)		(0.0106)
Weekly allowance		-0.00196		-0.00115
		(0.00137)		(0.00129)
Likely to go to college		-0.0293**		-0.0307**
		(0.0123)		(0.0123)
Want to go to college		-0.00449		-0.0103
		(0.0122)		(0.0119)
Constant	0.394***	0.402***	0.530***	0.380***
	(0.0168)	(0.0239)	(0.0146)	(0.0229)

Note: Dependent variable is 1 if individuals are peers and 0 when only one friendship between them exists. Number of observations is 7,859. All models are estimated by OLS including individual fixed effects. Robust standard errors two-way clustered on both peers in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

different peer groups. The first peer group is that used throughout this paper, and consists of peers with at least two friendship nominations. The second group consists of weak ties for which only one friendship nomination exists. The results are presented in Table 3, columns (3) and (8), and show no significant social effect estimate for weak ties. Moreover, three of the four coefficient estimates exhibit a negative sign.

To further test whether the network is misspecified, the effect of weak ties is evaluated in two additional dimensions. The first evaluates whether individuals care about weak ties, i.e. test for a "keeping-up-with-the-Joneses" mechanism. Changes in well-being are regressed on changes in the characteristics of weak ties. The results of these regressions are presented in Table 4 column (5), and show that the point estimates for the characteristics of weak ties are close to zero. Hence, individuals' well-being are not affected by weak ties. The second dimension indicates whether other behaviors of individuals are affected by weak ties. To test this, the change in leisure activities is regressed on the changes in the characteristics of peers and those of weak ties. The results are presented in Table 5, columns (5) to (8), and show that individuals do not change their leisure activities in response to changes in the characteristics of weak ties.

To summarize, all three tests establish that individuals neither care about, nor change their behavior in response to weak ties. Because most of higher-order peers are even more distant than weak ties, it is highly unlikely that there exists meaningful network misspecification.

6 Individual Social Multipliers

The social multiplier summarizes the average externality in one parameter. This is a useful measure for evaluating policy changes that either affect everyone or affect a random set of people. However, a policy that changes behavior is most likely costly and, therefore, policymakers may want to maximize efficiency by targeting the most influential people.

The influence of an individual is driven by three properties. One obvious property is the number of peers. The more peers an individual has, the more people she affects. The second property is the number of peers that a given peer has. Suppose individual i has the peer j. When j has many other peers, then a change in i's behavior will not affect j's behavior very much, because the average behavior of j's peer group changes only little. In contrast, when j's only peer is i, then the influence of i on j is high. The third property is the total number of higher-order peers. The effect of i on an individual's higher-order peers is weighted by the endogenous peer effect, such that a larger endogenous peer effect denotes a greater contribution of the higher-order peers to i's influence.

Individual influence can be expressed by the individual social multiplier. This measure shows by how much aggregate labor supply changes when the labor supply of the respective individual changes by one unit. To calculate individual social multipliers, I need to assume that the endogenous peer effect β is the same for everyone. This implies that when one person increases her labor supply by one unit her peer j increases her labor supply by $\frac{\beta}{n_j}$ units, where n_j is the number of peers j has in her peer group. Subsequently, the peer k of peer j increases her labor supply by $\frac{\beta^2}{n_j \times n_k}$ units. As a result, the variation in the individual social multiplier is determined by different network positions.[15] Note that individual social multipliers are likely to vary with different endogenous peer effect estimates, because peers are weighted differently, even if the networks are the same.

The results are presented in Figure A1. The distribution of individual social multipliers is right skewed, where the bottom quarter have an individual social multiplier of at most 1.038, and the top quarter have a multiplier of at least 1.094. Hence, there is considerable

[15] The calculation of individual social multipliers up to third-order peers is considered. This accounts for 99.9983% of the social multiplier.

heterogeneity. Policymakers usually have no information on this heterogeneity. Thus, I investigate whether individual social multipliers vary in an interesting and informative way with observable characteristics.

The individual social multiplier is regressed on various observable characteristics. For ease of interpretation individual social multipliers are normalized such that their average is 0 and their standard deviation (SD) is 1. The results of these regressions are presented in Panel A of Table 7 and demonstrate two things. First, individuals with better grades have a higher social multiplier. For example, individuals with an A grade in mathematics exhibit a social multiplier that is on average 0.064 SD higher than that of individuals with a B grade. Second, individuals with a higher socioeconomic status, measured by whether their parents are present, working, and college educated, have a higher social multiplier, on average. Both results are supported by the fact that individuals who are more likely to go to college also have a higher social multiplier, on average.

To further investigate the role of education and income in predicting individual social multipliers, information from Wave 4 is used. Wave 4 was conducted in 2008, which is 12 years after Wave 2. Similar regressions are performed, but with completed education and own personal and household income. To be informative, these tests do not require that social networks have not changed after 12 years. One only needs to be willing to assume that the way in which individuals build and maintain their social relationships has remained similar over the 12 years relative to others. Then, individuals will have a similar influential position in a network, and one can draw conclusions from the results. The results of these regressions, presented in Panel B of Table 7, confirm previous findings. For example, in column (1), individuals who have a bachelor's degree have a social multiplier that is 0.15 SD higher, on average, than that of people with a high school degree. Furthermore, individuals whose household income is twice as high have a social multiplier that is higher by 0.074 SD, on average.

These results can be summarized as follows. Individuals with a higher socioeconomic status have a higher social multiplier in their labor supply. Hence, an increase in the incentive to work for these individuals may increase aggregate labor supply the most. However, this conclusion neglects that the costs in doing so might vary for people from different socioeconomic status. In contrast, De Giorgi et al. (2019) find the opposite. In their data, individuals at the top of the income distribution exhibit a lower externality. One likely explanation is that De Giorgi et al. (2019) use co-worker networks, which weight peers by similarity in occupation and education. When plants have relatively few highly educated and high-income managers compared with blue- and white-collar workers, then, by design, high-income workers have a smaller influence on their co-workers.

Table 7: Individual Social Multiplier and Individual Characteristics

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Adolescents' characteristics							
Math grade	-0.0644***						
	(0.0201)						
English grade		-0.0479**					
		(0.0219)					
Science grade			-0.00266				
			(0.0201)				
History grade				-0.0843***			
				(0.0210)			
Likely college					0.0971***		
					(0.0265)		
Want college					-0.0259		
					(0.0270)		
Both parents present						0.000984	
						(0.0693)	
Both parents present and working						0.103**	
						(0.0491)	
Parent high school							0.0749
							(0.0621)
Parent college							0.153**
							(0.0714)
N	3504	3858	3367	3251	4064	4064	4064
Panel B: Adult characteristics							
No high school degree	-0.162						
	(0.114)						
Some college	0.150***						
	(0.0625)						
Bachelor degree	0.259***						
	(0.0684)						
Master degree	0.372***						
	(0.114)						
Log household income		0.0735**					
		(0.0320)					
Log personal income			0.0763**				
			(0.0299)				
N	1691	1598	1537				

Notes: Dependent variable is individual social multiplier, which is normalized such that it has mean 1. All regressions include a constant and school-wave dummies. Grades are coded such that grade A is 1, grade B is 2, grade C is 3, and grade D is 4. The omitted category in Panel A column 5 is single parent household. In Panel A column (7) both regressors are dummies that indicate the highest education of both parents. In Panel B column (1) all regressors are dummies indicating the highest completed education. Having a high school degree is the omitted category. All models are estimated by OLS and include a constant. Robust standard errors clustered at the individual in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

7 Conclusion

In this study, I identify the causal effect of peers' labor supply on individual labor supply, overcoming serious identification challenges. I use a data set in which peers are identifiable by reported friendships. Two periods and multiple networks allow for the use of a difference-in-differences estimation strategy, which addresses endogenous network formation and correlated unobservables. A social interaction model with network structure exploiting changes on the level of higher-order peers' parents are used to solve the reflection problem. The estimated social multiplier varies from 1.054 to 1.072, depending on the specification. I argue that these values are remarkably similar to the findings of others on social effects in worker output and wages. Furthermore, I present evidence that peers' labor supply affects individual labor supply because individuals feel pressured to conform to the average behavior of their peers. The alternative explanation, that peers provide information on job offers or referrals, is not supported by the data. When investigating how much each individual affects aggregate labor supply I find that those with a higher socioeconomic background affect aggregate labor supply the most.

The estimated social multiplier may seem small but peer groups are constructed such that this estimate is likely a lower bound. Further, the social multiplier is only identified by labor supply changes happening within a year. Therefore, one could argue that the long run social multiplier in labor supply is likely to be larger. This is relevant to two observations in the literature. First, since 2004, there has been a decline in work hours and increase in leisure time for young men in the US (Aguiar et al. 2017). Peer effects in labor supply may amplify this phenomenon. Second, my results provide evidence in favor of the argument made by Alesina et al. (2006) that a social multiplier in labor supply could have reinforced the decline of hours worked in Western Europe since the 1970s relative to the US.

My results also have important implications for policy interventions that target individual labor supply, but that neglect these peer interdependences. Targeted individuals might react less than expected to a policy change because their peers are not targeted. However, aggregate labor supply might react more than expected, owing to social interactions. Moreover, even nontargeted individuals can be indirectly influenced by a policy change via a program's impact on their peers. These nontrivial policy implications become even more convoluted when we consider that individual labor supply also depends on peers' income. Determining how peers' income and wealth affect individual labor supply could be a fruitful area for future research.

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A Appendix

A.1 Linear-In-Means Model

If we assume $|\beta| < 1$, then $(\mathbf{I}_l - \beta\mathbf{G}_l)$ is invertible, where $\mathbf{I}_l$ is the identity matrix. Hence, the structural equation (2) can be written as reduced form, as follows:

$$\Delta\mathbf{y}_l = \Delta\boldsymbol{\alpha}_l/(1-\beta)\boldsymbol{\iota}_l + (\mathbf{I}_l - \beta\mathbf{G}_l)^{-1}(\boldsymbol{\gamma}\mathbf{I}_l + \boldsymbol{\delta}\mathbf{G}_l)\Delta\mathbf{X}_l + (\mathbf{I}_l - \beta\mathbf{G}_l)^{-1}\Delta\boldsymbol{\varepsilon}_l. \tag{6}$$

Now, we can define the average social multiplier based on (6). To do so, imagine a marginal shock to labor supply by $\Delta\boldsymbol{\alpha}_l$. The effect of this change is given by the partial derivative $\partial\Delta\mathbf{y}_l/\partial\Delta\boldsymbol{\alpha}_l = 1/(1-\beta)$. This is the average social multiplier, which describes the extent to which social interactions reduce or amplify a shock. In the case of norm compliance, individual and peer behaviors are strategic complements. This implies that $\beta > 0$ and, thus, a shock will be amplified.

Next, the following within-network transformation is performed: subtract the average over all individuals in a given network from the individual equations. To do so, equation (6) is multiplied by $(\mathbf{I}_l - \mathbf{H}_l)$, where $\mathbf{H}_l = \frac{1}{\mathbf{n}_l}(\boldsymbol{\iota}_l\boldsymbol{\iota}_l')$. As a result, the effect of the common environment of network l, $\Delta\boldsymbol{\alpha}_l/(1-\beta)\boldsymbol{\iota}_l$, is eliminated. Thus, the new reduced form reads as follows:

$$\begin{aligned}(\mathbf{I}_l - \mathbf{H}_l)\Delta\mathbf{y}_l = {} & (\mathbf{I}_l - \mathbf{H}_l)(\mathbf{I}_l - \beta\mathbf{G}_l)^{-1}(\boldsymbol{\gamma}\mathbf{I}_l + \boldsymbol{\delta}\mathbf{G}_l)\Delta\mathbf{X}_l \\ & + (\mathbf{I}_l - \mathbf{H}_l)(\mathbf{I}_l - \beta\mathbf{G}_l)^{-1}\Delta\boldsymbol{\varepsilon}_l.\end{aligned} \tag{7}$$

A.2 QML Estimation

Before estimating equation (2), the second differencing is applied by performing a within-network transformation, leading to:

$$\mathbf{J}_l\Delta\mathbf{y}_l = \beta\mathbf{J}_l\mathbf{G}_l\Delta\mathbf{y}_l + \mathbf{J}_l\Delta\mathbf{X}_l\boldsymbol{\gamma} + \mathbf{J}_l\mathbf{G}_l\Delta\mathbf{X}_l\boldsymbol{\delta} + \mathbf{J}_l\Delta\boldsymbol{\varepsilon}_l, \tag{8}$$

where $\mathbf{J}_l = (\mathbf{I}_l - \mathbf{H}_l)$. The problem with estimating such a model using a within-transformation is the variance-covariance matrix,

$$Var(\mathbf{J}_l\boldsymbol{\varepsilon}_l) = \mathbf{J}_l\mathbf{J}_l'\sigma^2 = \mathbf{J}_l\sigma^2. \tag{9}$$

The matrix in (9) has rank (n-1) and is therefore singular. The linear dependency is resolved using the orthonormal matrix $[\mathbf{F}_l, \mathbf{C}_l]$ of $\mathbf{J}_l$, where $\mathbf{F}_l$ corresponds to the eigenvalues of one, and $\mathbf{C}_l$ corresponds to the eigenvalues of zero. Next, the following matrices need to be defined: $\mathbf{y}_l^* = \mathbf{F}_l'\mathbf{J}_l\Delta\mathbf{y}_l$, $\mathbf{X}_l^* = \mathbf{F}_l\mathbf{J}_l\Delta\mathbf{X}_l$, $\mathbf{G}_l^* = \mathbf{F}_l'\mathbf{G}_l\mathbf{F}_l$, and $\boldsymbol{\varepsilon}_l^* = \mathbf{F}_l\mathbf{J}_l\Delta\boldsymbol{\varepsilon}_l$. Multiplying equation (8) by $\mathbf{F}_l$ yields the following:

$$\mathbf{y}_l^* = \beta\mathbf{G}_l\mathbf{y}_l^* + \mathbf{X}_l^*\boldsymbol{\gamma} + \mathbf{G}_l^*\mathbf{X}_l^*\boldsymbol{\delta} + \boldsymbol{\varepsilon}_l^*, \tag{10}$$

and the variance-covariance becomes $Var(\boldsymbol{\varepsilon}_l^*) = \sigma^2\mathbf{I}_l$. Hence, the problem of linear dependency is solved. Furthermore, assuming independently and identically distributed errors, the log-likelihood function is given by:

$$\begin{aligned} \ln\mathbb{L} = \frac{n-1}{2}\ln(2\pi\sigma^2) + \sum_{l=1}^{L}\ln|\mathbf{I}_l - \beta\mathbf{G}_l^*| \\ - \frac{1}{2\sigma^2}\sum_{l=1}^{L}(\mathbf{y}_l^* - \beta\mathbf{G}_l^*\mathbf{y}_l^* - \mathbf{X}_l^*\gamma - \mathbf{G}_l^*\mathbf{X}_l^*\delta)' \\ \times(\mathbf{y}_l^* - \beta\mathbf{G}_l^*\mathbf{y}_l^* - \mathbf{X}_l^*\gamma - \mathbf{G}_l^*\mathbf{X}_l^*\delta). \end{aligned} \tag{11}$$

A.3 Figures

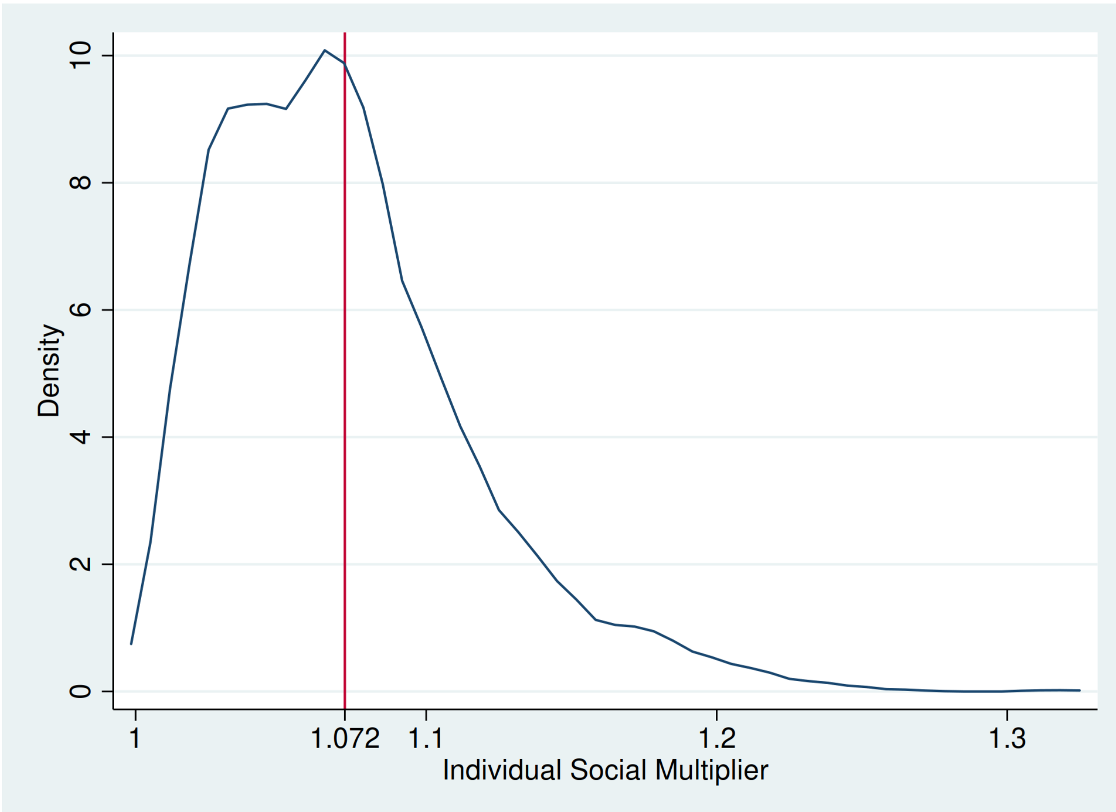

Figure A1: Kernel density estimate of individual social multipliers

Table A1: Household Income and Parental Characteristics

	(1) Log income	(2) Welfare dependence	(3) Problems paying bills
Both parents present	0.107*	-0.0424**	0.00188
	(0.0595)	(0.0203)	(0.0295)
Both parents present and working	0.432***	-0.113***	-0.114***
	(0.0360)	(0.0125)	(0.0189)
Constant	3.392***	0.118***	0.209***
	(0.0305)	(0.0123)	(0.0157)
N	1526	1752	1711

Notes: Dependent variable in column (1) is the log household income, in column (2) a dummy that indicates whether the household receives welfare, in column (3) a dummy that indicates whether the household has problems in paying their bills. The regressors *both parents present* is a dummy indicating that both parents are present in Wave 1 and at most 1 is working. The regressors *both parents present and working* is also a dummy and indicating that in addition to the other dummy both parents are working in Wave 1. The omitted category are single parent households. Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

A.4 Tables

Table A2: Peer Effects in Labor Supply (w/o winsorizing)

	School weeks			Summer weeks		
	(1) OLS	(2) QML	(3) QML	(4) OLS	(5) QML	(6) QML
Endogenous Peer Effect: $\beta \mathbf{G} \Delta \mathbf{y}$						
Labor supply	0.0859***	0.0603**	0.0643**	0.0601*	0.0447*	0.0533**
	(0.0329)	(0.0252)	(0.0251)	(0.0336)	(0.0255)	(0.0255)
Contextual Peer Effects: $\boldsymbol{\delta} \mathbf{G} \Delta \mathbf{X}$						
Both parents present	4.108**	4.066**	4.022*	6.834**	6.821**	6.819**
	(2.071)	(2.068)	(2.062)	(2.941)	(2.938)	(2.925)
Both parents work	3.461***	3.484***	3.473***	1.027	1.014	0.743
	(1.172)	(1.171)	(1.172)	(1.665)	(1.663)	(1.662)
Allowance			0.0103			0.0831*
			(0.0341)			(0.0483)
Housework			0.745*			1.483**
			(0.430)			(0.611)
Likely college			-0.158			0.679
			(0.491)			(0.697)
Want college			0.665			0.679
			(0.525)			(0.746)
Effect of Individual Characteristics: $\boldsymbol{\gamma} \Delta \mathbf{X}$						
Both parents present	0.320	0.350	0.198	1.329	1.360	1.146
	(1.271)	(1.269)	(1.264)	(1.806)	(1.803)	(1.794)
Both parents work	-0.774	-0.740	-0.688	0.213	0.227	0.292
	(0.759)	(0.758)	(0.755)	(1.077)	(1.075)	(1.071)
Allowance			-0.0789***			-0.0472
			(0.0237)			(0.0337)
Housework			-0.515*			-1.117***
			(0.287)			(0.407)
Likely college			-0.0815			-0.0125
			(0.322)			(0.457)
Want college			-0.402			-0.688
			(0.331)			(0.469)

Notes: Dependent variable in column (1) - (3) is labor supply in school weeks and in column (4) - (6) labor supply in summer weeks. The regressor labor supply of peers is the labor supply in the same weeks as the dependent variable. All models are estimated in first-differences and are differenced a second time at the school level. Models in column (1) and (4) are estimated by OLS and the remaining models by QML. Number of observations is 2,032. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A3: First Principal Component Loadings of Well-being

How often was each of the following true during the last week?	Loadings
You were bothered by things that usually do not bother you.	-.2393297
You did not feel like eating, your appetite was poor.	-.2040036
You felt that you could not shake off the blues, ...	-.2894136
You felt that you were just as good as other people.	.1571154
You had trouble keeping your mind on what you were doing.	-.2247738
You felt depressed.	-.3097779
You felt that you were too tired to do things.	-.221877
You felt hopeful about the future.	.1422647
You thought your life had been a failure.	-.2508783
You felt fearful.	-.2171218
You were happy.	.2299433
You talked less than usual.	-.1719104
You felt lonely.	-.2844371
People were unfriendly to you.	-.1541901
You enjoyed life.	.2329618
You felt sad.	-.2995483
You felt that people disliked you.	-.2103528
It was hard to get started doing things.	-.1955501
You felt life was not worth living.	-.230277

Notes: Answer categories are 0 = never or rarely, 1 = sometimes, 2 = a lot of time, 3 = most of the time or all of the time. Of the 77,216 answers, 24 missing values are imputed by the median answer of all individuals.

Table A4: Placebo Tests

Matching criterion:	Parental education (1)	Household size (2)	School grade (3)
Panel A: School weeks			
Both parents present	-0.056	0.088	0.054
	(1.017)	(1.048)	(1.061)
Both parents work	-0.004	0.065	0.000
	(1.006)	(1.046)	(1.001)
Panel B: Summer weeks			
Both parents present	0.041	0.029	0.064
	(1.015)	(0.996)	(1.031)
Both parents work	-0.080	0.117	-0.073
	(0.995)	(1.004)	(0.990)

Note: All columns in each panel show a distribution of 1,000 z-values for two coefficient estimates. The first number is the mean and the standard deviation is in brackets. In column (1) the matching criterion parental education measured as the maximum paternal or maternal education, and has nine ordinal categories. Two individuals are said to be similar if their parental education differs by at most one category. In column (2) the matching criterion is household size. When two individuals have the same number of household members or differ by just one, they are treated as being similar. In column (3) school grade is the matching criterion, where two individuals are similar if their grade is at most one apart. Whenever there are 10 or fewer similar individuals, the set from which peers are drawn consists of all individuals from the same school, except those for which friendship nominations exist.