Peer and Family Effects in Work and Program Participation

Gordon B. Dahl

Summary

People don't base decisions about their economic life solely on their own individually formed ideas and preferences. Rather, they're influenced by the experiences of their peers and by social group norms. Gordon Dahl reviews the various ways family and neighborhood peer groups influence decisions to participate in the workforce and in government social assistance programs.

These social spillover effects are hard to estimate because of the problems that economists refer to as *reflection, correlated unobservables,* and *endogenous group membership*. Dahl explains how researchers have overcome these challenges to produce credible estimates of the effects of family and peer groups on work and program participation. He reviews the most rigorous evidence to date and discusses possible mechanisms.

Understanding neighborhood and family group influences is critical to thinking about policy, Dahl writes. The spillover effects on children, siblings, and neighbors can be just as important as the direct impact on parents and directly targeted peers, due to social multiplier effects.

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It's a longstanding question in social science: do families and other peers transmit cultures of work and program participation? In this article, I review the evidence for two settings where these types of peer effects could be especially important: social assistance programs and a selected set of labor market outcomes. My focus is on family and neighborhood peer effects. The effects of other cultural factors, such as ancestry and language, have mostly been studied using an epidemiological approach, and have been reviewed elsewhere.[1] Likewise, research on peer effects for other groups, such as college roommates, and for other outcomes, such as crime, is beyond the scope of this review.[2]

First, I'll address the subject of intergenerational links in welfare use. Academics and policymakers alike have heatedly debated whether such links reflect a culture of welfare. A Nobel Prize winner in Economics, Gary Becker, expressed the belief that "mothers on welfare convey the impression to their children that it is normal to live off government handouts. In such an environment, it is difficult for children to place a high value on doing well at school and preparing for work by seeking out training on jobs and in schools."[3] However, the fact that children with parents on welfare are more likely to be on welfare themselves as adults doesn't mean that the parents' participation is what caused the children to also participate. As the saying goes, "correlation doesn't imply causation."

Still, the question has proven difficult to resolve. Parents' participation in a welfare program isn't randomly assigned. On the one hand, when a child has a parent who isn't working and is on public assistance, that could alter the child's perceptions about the relative costs, benefits, and stigma associated with the two alternatives. Information transmission or differential investment could also occur as a result of having a parent receive government transfers. On the other hand, characteristics like poor health or reduced opportunities could be correlated across generations, creating mechanical intergenerational links that don't reflect a behavioral response on the child's part.

Of course, the United States has many different social programs. Traditional welfare programs include Temporary Assistance to Needy Families and the earlier Aid to Families with Dependent Children. Other means-tested programs include the Supplemental Nutrition Assistance Program (that is, food stamps) and Women, Infants, and Children. Social assistance programs also include the Earned Income Tax Credit, Unemployment Insurance, and Social Security Disability Insurance. In this article, I discuss peer effects for a varied but limited set of social assistance programs, based on the availability of research.

Turning to family effects related to the labor force, we find the rhetorical debate less intense, at least when unemployment is decoupled from welfare participation. But people make similar arguments about whether family members and other peer groups influence how much individuals work and earn. For example, attitudes about traditional gender roles and the desire to fit into one's group might affect a mother's decision to work, especially after the birth of a child. But mothers in the same family or workplace are also likely to share common characteristics, such as similar levels of income, which affect work decisions.

It has proven difficult to estimate causality for these types of peer effects in work and social assistance programs, given the well-known problems of what economists refer to as *reflection, correlated unobservables,* and *endogenous group membership* (I define these terms below in the section "Challenges in Estimating Peer Effects"). It can also be difficult to define the appropriate peer group and to access data that link members of a peer group. But this is changing, both in the United States and even more in other countries, where high-quality administrative data collected by governments is increasingly available.

In this article I review recent advances in the estimation of causal peer effects in the family and neighborhood contexts. A key takeaway is that the statistical methods used to study peer effects aren't equally credible. Recognizing this, I organize my discussion by the statistical method used, rather than by type of question or peer group. Though early studies documented clear correlations in both program participation and labor market outcomes, causality was tenuous. Recent research has identified causal effects using more convincing methods and better data. Taken together, these more empirically rigorous studies generally indicate the presence of intergenerational links and a strong influence of families and neighborhoods.

The emerging evidence is compelling, but we should be cautious about how we interpret the findings. Just because spillovers—where one peer influences another—may occur in certain settings and for certain populations doesn't mean they occur in other settings and populations. Moreover, the existence of peer effects doesn't mean that other contextual factors aren't also important. With these caveats in mind, the best evidence to date supports the idea that family members and neighborhood peers play an important role in decisions about work and program participation.

We know less about the mechanisms behind these peer effects. Several channels have been postulated, most of which can be classified into four categories. The first can be broadly defined as cultural factors, including the transmission of preferences regarding stigma related to program participation, or the desire to conform to a group's social norms. The second is information transmission, such as how to apply for a welfare program or how an employer will react if a mother takes parental leave. The third is direct interactions with other similar individuals; for example, the benefit of staying home could be greater if your friends aren't working and also have free time. The final category is changes to the home environment, such as in family income or parental stress levels. Economists and sociologists have found some suggestive evidence consistent with channels in each of these categories.

Preferences for work and program participation aren't fixed at birth or formed in isolation.

Recent findings on peer effects, regardless of the underlying mechanisms, have important policy implications. What children learn from their parents about employment versus governmental assistance could matter for the financial stability of a number of social insurance and safety net programs. Similarly, peers who serve as important information transmission networks, or are influential in changing social norms, can amplify the effects of policy reforms that affect work and social assistance programs. This is particularly true when information is scarce and perceptions are still being formed. Some of the evidence indicates that these social interactions lead to long-run effects that are substantially larger than otherwise expected.

Possible Mechanisms

Most economists and sociologists would agree that preferences for work and program participation aren't fixed at birth or formed in isolation. The experiences of a person's families and neighbors are key inputs into preference formation. Moreover, families and neighbors could provide valuable information related to both work and program participation. With these ideas in mind, let's take a look at the four main channels that economists have postulated for peer effects in these settings. When discussing specific empirical studies later, I'll highlight what's been learned about these mechanisms. But it's important to note up front that researchers are just beginning to identify peer effects convincingly, and less is known about mechanisms.

The first main channel is a change in preferences, which could happen for several reasons. First, observing a parent on a social assistance program could change a child's perception of the stigma associated with participation. Similarly, children who grow up with a parent on welfare or another program may view that program as the default option for economic support.[4] The same types of forces could also matter for employment, especially if parents serve as role models. Another preference-based reason that peers could matter is social custom or group identity. People may be sanctioned for behaving differently, or may simply increase their happiness by behaving like their peers.

Information is another channel that scholars discuss. These channels include learning from family members and neighbors about how to sign up for a welfare program, what the requirements are, and what it's like to be on the program. Similarly, peers could provide insights about writing a résumé, job interviews, and proper work etiquette. When information is scarce, people can also learn from family members and peers about the costs and benefits of work.[5] Moreover, peers can serve as a network for job referrals.[6]

Peers could also matter if the benefits of work or program participation directly depend on interactions with other similar individuals. That could happen if spending time with others in a peer group produces positive complementarities. For example, a new mother may get more enjoyment from taking leave after the birth of a child if she has other new mothers in her peer group to hang out with.

The final channel is changes in the family environment. Participation in a social program or reduced work hours could lower family income, which could directly affect children's future work and program participation. Related correlational studies document that long-term unemployment is associated with increased rates of depression and stress within the home.

Peer Effect Models

Peer effect models capture the idea that the actions of one individual can have a direct impact on another.[8] It's natural and intuitive to think that parents influence their children's decisions, individuals copy their neighbors, and siblings learn from each other. It's less obvious how large these types of peer effects are, and in what settings they're important, as it's empirically difficult to isolate the impact of peers from other factors.

To start, let's consider a case where a group has just two members—for example, a parent and a child, an older and a younger sibling, or two neighborhood friends. We're interested in how one peer's choices or behavior affects the choices or behavior of the other. Economists create simple models to capture the idea that choices aren't necessarily made in isolation, but can depend on what a peer chooses to do. These models allow for a person's own characteristics, as well as the characteristics of the peer and group, to influence decisions.

Take the example of two siblings and the outcome of participating in a welfare program. A younger sibling's welfare decision could depend on her own characteristics, such as her education level, and also on common sibling characteristics, such as family income while growing up. But the younger sibling's decision about welfare participation could also depend on two types of sibling spillovers: her older sibling's characteristics and her older sibling's welfare status. The first spillover is typically categorized as a contextual effect, while the older sibling's welfare participation is a peer effect. Identifying and estimating these types of peer effects is the focus of this article. A similar set of factors could influence the older sibling's decision to participate in welfare, including spillovers going the other direction (that is, from the younger to the older sibling).

Of course, peer groups often have more than two members. For example, one's peer group might consist of everyone living in a neighborhood. Researchers have generally modeled these larger peer groups by assuming that individuals respond to the average behavior of all the group's other members. This model captures the idea that peers can influence decisions at a more aggregate level. For example, after the birth of her child, a mother living in a neighborhood where many peers work could be influenced to work as well.

For tractability, most researchers assume that peer effects are homogeneous, meaning that each peer in a group has the same effect on an individual. Researchers use this formulation not because they think all peers have identical impacts, but because it's simple and convenient. If the effects are heterogeneous, meaning that the size of the effect differs among peers, then estimates from this homogeneous model can be interpreted as an average effect across peers. Some researchers have moved beyond the homogeneous model by isolating the most relevant peers, while others have calculated the fraction of peers with different-sized effects.

Challenges in Estimating Peer Effects

Estimating peer effect models is difficult due to three problems famously laid out by the Northwestern University economist Charles Manski in the early 1990s.[9] The first is reflection, which arises because peers can affect each other's decisions. This makes it difficult to tell who in a group is affecting whom. Reflection may not be a problem in some settings, such as when an older sibling is assumed to affect a younger sibling, but not the other way around. In other settings reflection is a more serious issue, such as when two peers make simultaneous choices, with no indication in the data of who is influencing whom.

The second problem involves correlated unobservables. Suppose the researcher doesn't observe family income when a person is growing up, but family income plays a role in whether a person participates in a welfare program as an adult. This *omitted variable* will make it appear that a sibling peer effect is in operation, when in fact the correlation in welfare decisions is driven by adolescent family income. More generally, any individual-, peer-, or group-level variable that influences outcomes but isn't observable to the researcher will create a bias in the estimated peer effect. A bias means that the estimated peer effect is either too large or too small compared to the true peer effect. In many settings, it's difficult to eliminate the bias from correlated unobservables, as it's rarely the case that all relevant factors are observed.

The third problem, endogenous group membership, arises when individuals aren't randomly assigned to groups, but rather choose which group to be in. People may choose to be in a group because they share similar preferences—say, two women may choose to live in the same neighborhood because it has good daycare options. In this example, it would be incorrect to conclude that peer effects are driving female labor force participation after the birth of a child. Instead, it could be that both women planned to return to work, which is why they chose to live near daycare centers (and, by coincidence, near each other). In settings where groups are predetermined or randomly assigned, this issue disappears.

In the following sections, I discuss various approaches to contend with these three issues in the context of existing studies. Some empirical designs are more convincing than others at recovering causal effects, and each type of design has its own set of advantages and weaknesses. Because the reliability of the various studies depends so much on the approach taken, the discussion is organized by statistical method rather than by topic. This makes it easier to understand the assumptions required for each approach and the relative strengths of the various designs.

It's hard to interpret observational studies as reflecting a peer effect. That's because with observational data, we generally don't know who's influencing whom, we don't observe all relevant factors, and individuals choose which peer group to be in.

Observational Studies

Observational studies report associations using data where there was no attempt to randomize who was affected by a treatment. In the context of peer effects, the treatment would be whether a person is part of a certain peer group. The most basic observational study is the reporting of a correlation—for example, whether someone's more likely to be on welfare if their neighbor is on welfare. More complex observational studies attempt to control for potentially confounding factors, such as people's education levels. They do this using a statistical approach called *regression analysis*. The primary challenge of this approach is that it can only control for observable factors, and many confounding factors are not observed.

Given the problems of reflection, correlated unobservables, and endogenous group membership, it's hard to interpret observational studies as reflecting a peer effect. That's because with observational data, we generally don't know who's influencing whom, we don't observe all relevant factors, and individuals choose which peer group to be in. Therefore, I discuss observational studies only briefly.

Starting with peer effects in welfare participation, the correlational evidence finds a positive link across siblings and generations.[10] Given the difficulty in interpreting these correlations as causal, the amount of observational research on this topic within economics has waned in recent years. The *Handbook of Labor Economics* effectively summarizes the state of the evidence up to 2010 this way: "while the intergenerational correlations in welfare receipt are clear, there is much less evidence that a causal relationship exists."[11]

Turning to work outcomes, many researchers have studied intergenerational correlations in earnings.[12] The estimates, which suggest a large degree of persistence, are interpreted as measures of intergenerational mobility within a society. Economists have developed theories that rationalize these findings as the result of investments by parents in their children.[13] There's also evidence that sibling earnings are correlated and that unemployment is correlated across generations.[14]

Work in the past two decades has focused on understanding what drives these relationships. For example, research using data from the United Kingdom finds that 80 percent of the rise in intergenerational persistence in earnings over time can be explained by changes in cognitive skills (as measured by test scores), noncognitive traits (such as self-esteem), educational levels, and labor market attachment.[15] More recent evidence from Norway finds that higher parental income in the early and middle childhood years maximizes children's education, an important determinant of future earnings.[16]

Studies of intergenerational persistence in earnings have considered several mediating factors, but only a few have investigated the possibility that preferences could be passed across generations. One study uses US observational data, following parents and children over time to see how labor market outcomes and work preferences are connected intergenerationally.[17] That study finds a positive correlation in hours of work for parents and children and argues that it's most likely due to preferences. Other research using similar US data shows that mothers and their daughters have correlated behaviors and attitudes.[18] That study finds that controls for a family's economic status do little to dampen intergenerational links, which offers suggestive evidence that attitudes themselves are passed from generation to generation separately from any investment channel.

A series of more recent observational studies has documented that the type of attitudes that are likely determinants of economic success are correlated across generations. These studies find a correlation in time preferences, in risk attitudes, and in measures of trust.[19] The transmission of preferences is often found to be gender specific, with mothers' influence on daughters being the strongest relationship in a family.

Considering other peers, there's also evidence that earnings are highly correlated within a neighborhood. But given the large amount of sorting that occurs across neighborhoods by socioeconomic status, most researchers interpret these correlations as the amount of spatial inequality in income, rather than trying to assign causality to the estimates. Several studies also examine the impact of neighborhoods on welfare participation; not surprisingly, they find that poverty and welfare use is concentrated in certain neighborhoods.[20]

Fixed Effect Studies

Early research using observational methods attempted to control for as many group characteristics as possible. Yet most researchers today recognize that while such studies are useful as descriptive tools for documenting associations, they can't be used to determine peer effects. A natural next step is to use *fixed effects* to control for time-invariant determinants, an approach that's been used in many other areas of economic research. The idea of a fixed effect is to eliminate any observable or unobservable factors that are common to a peer group (such as a family) but that don't vary over time (such as family ancestry or shared genetics).

In this section I highlight a few of the more recent and compelling fixed effect studies.[21] First, consider the case of intergenerational peer effects. The fixed effect approach compares siblings, one of whom grew up while a parent was participating in a program and one of whom grew up when the parent wasn't participating. The effect of relative exposure time of the two siblings can also be estimated, allowing the researcher to eliminate any fixed characteristics or trends that are common to a family.

Scandinavian countries maintain high-quality administrative data that can link parents to their children and siblings to each other. Such data are ideally suited for a fixed effect analysis. Researchers studying disability insurance (DI) in Norway, for example, found a positive correlation between a parent's DI use and a child's, based on a regression analysis that uses fixed effects.[22] The study also found that the longer a father is on the program, the greater the probability that his child will also receive benefits as an adult; the effects for mothers were insignificant. Another sibling fixed effect study, on the other hand—this time using administrative data from Sweden—found no support for the idea that a parent's use of welfare affects their children's participation in welfare.[23] This finding contrasts with a regression analysis that didn't include fixed effects; that observational analysis found a large positive intergenerational effect, even after controlling for a variety of background characteristics. One more study using a sibling fixed effect approach to analyze Norwegian data also found no evidence for an intergenerational link in unemployment.[24]

The key identifying assumption in such models is that time-varying factors which can't be controlled don't matter for outcomes. But this assumption could be violated—for example, consider a family where a parent enters the disability insurance program because he or she is hit with a debilitating depression that makes work difficult. In this case, we'd need to assume that the parent's depression doesn't directly affect a child's future chances of participating in DI directly, but does so only through their parent's participation in the DI program itself. But it's likely that having a depressed parent could cause the child to experience depression as well, and to be more likely to participate in DI later in life for this reason. Of course, the problem disappears if we can control for parental depression in the regression, but there's always the concern that the researcher can't observe all relevant time-varying factors.

The previous paragraph makes clear that the problem of correlated unobservables can still arise in fixed effect studies. In contrast, the other two issues that economists usually worry about when studying peer effects are less of a concern. In the intergenerational setting, reflection isn't likely to be a problem; we simply need to assume that parental DI use affects children, but not the other way around. Moreover, there's no concern about endogenous group membership, as long as fertility isn't directly affected by parental DI use.

To study neighborhood effects on intergenerational mobility, Harvard economists Raj Chetty and Nathaniel Hendren used a variant of the fixed effect design.[25] They assembled an impressive data set of over seven million families who move across commuting zones and counties in the United States. Using the fact that children are at different ages when their families move, Chetty and Hendren found that the outcomes of children whose families move become more similar to the outcomes of children already living in a neighborhood as years of exposure to the neighborhood increase. The effects are large, with a 4 percent improvement in earnings for every year spent in a new and better neighborhood. There were similar effects on education, fertility, and marriage.

This type of fixed effect design requires the assumption that the reasons families move when their children are young versus when they're older don't directly impact child outcomes. But biases could be introduced by correlated unobservables. For example, parents might postpone or accelerate a move, or choose which area to move to, based on how disruptive or beneficial they believe the move will be for their child. Similarly, if families move in response to a change in income or wealth, that could directly influence child outcomes. To help establish causality, Chetty and Hendren went beyond a traditional fixed effect approach by examining only moves resulting from unexpected job loss.

The same researchers have looked at the county level to explore the neighborhood characteristics that seem to have the biggest effects on intergenerational mobility.[26] Using the same approach as in their first study, they found that children who grow up in poor families have better outcomes when they live in neighborhoods with less poverty, less income inequality, better schools, more two-parent families, and lower crime.

Studies Using Random Assignment to Peer Groups

Another approach taken by researchers is to use random assignment of individuals to different peer groups.[27] Random assignment means the researcher decides which peer group people are placed in, rather than letting individuals choose for themselves. In some settings it's possible to enforce random assignment to peer groups; for example, children can be randomly assigned to different classrooms. But when that's not possible, researchers use a *randomized encouragement design* instead. This approach randomly gives some people an incentive (often cash) to join a different peer group, while others receive no such incentive. Ultimately, all people in the study are allowed to decide which peer group to join. A good example of a randomized encouragement design is the Moving to Opportunity experiment, which randomly gave some families incentives to move to lower-poverty neighborhoods. Economists have studied a variety of child outcomes related to this experiment, including crime and health.

A randomized encouragement design *gives some people an incentive (often cash) to join a different group, while others receive no such incentive.*

More relevant to our topic, analyses of adults and older children in the Moving to Opportunity experiment found no effect on earnings or employment.[28] A similar study using Canadian data likewise found that neighborhood quality has little effect on a child's later life earnings, unemployment, or welfare use.[29] However, more recent work found large effects from Moving to Opportunity for children who were younger than 13 at the time of the move.[30] This work concludes that better neighborhoods have the potential to reduce the intergenerational persistence of poverty. The results are particularly interesting, as they align with the fixed effect analyses discussed above, which found that more years of exposure to a better neighborhood produces better outcomes for children.

The advantage of randomly assigning people to a different peer group (such as a better neighborhood) is that it solves the problem of endogenous selection into peer groups. And in cases where the number of randomly assigned individuals is small relative to the overall size of the neighborhoods, the reflection problem is minimal. The disadvantage is that it's impossible to separate direct from indirect peer effects. In other words, although we can estimate the effect of being assigned to a new neighborhood, we can't separate out the effect of peers' targeted outcomes and peers' background characteristics. Fortunately, this combined information is often what's most relevant from a policy perspective, even if the direct peer effect can't be isolated. A similar challenge in interpretation is that there could be neighborhood resource effects for young kids, with interaction effects from increasing resources in both early and later childhood.[31]

Thinking about families, it's hard to imagine a case where a sibling, spouse, or parent is randomly assigned, which explains why this approach hasn't been used to study family peer effects. (One exception is adoption studies, which aren't covered here.) But a related set of studies look at shocks to parents that can change children's long-run outcomes. One study using Canadian data found that later in life, the children of a parent who lost a job due to a firm's closure had lower earnings and higher participation in unemployment insurance and social assistance.[32] In contrast, a Norwegian study that looked at worker displacement found no significant effects on earnings for the next generation.[33] A US study found that parents' job losses both worsen adolescent children's mental health and result in lower test scores and educational achievement.[34] A British study that examined major industry contractions during the 1980s recession found that the children of fathers who lost their jobs had no change in their adult earnings many years later.[35] As with the random assignment of individuals to neighborhoods, studies of these shocks can't separate direct and indirect peer effects.

Peers of Peers Studies

Researchers have begun to impose restrictions on network structures to help identify peer effects in a variety of settings. The idea is to take advantage of partially overlapping peer groups.[36] In its simplest form, the approach assumes that while my peers may influence me directly, the peers of my peers affect me only through my peers' outcomes. This restriction allows the use of peers of peers' outcomes as instrumental variables for my peers' outcomes (see the next section for a discussion of instrumental variables). It's a clever idea, but it requires assumptions that may not hold in every setting. Beyond assuming that peers of peers have no direct effect, one also needs to assume that unobserved characteristics of peers of peers aren't correlated with an individual's choices. This second issue arises because of correlated unobservables and the endogenous sorting of peers into groups.

An interesting use of this approach appears in a recent study using Norwegian data.[37] It estimates the causal effect of family networks and of neighbors on mothers' decisions about whether to work. Starting with the family networks, the researchers looked at how siblings (and cousins) affect a mother's decisions about working after the birth of a child. The number of hours worked by a sister's (and cousins') neighbors after the birth of a child were used as an instrumental variable for the sister's work decisions. The assumption is that a sister's neighbors influence whether or not the sister works, but affect the mother's decision to work only through the effect they have on her sister. The necessary restriction is that the mother doesn't directly interact with her sister's neighbors or learn from them.

To solve the reflection problem, the researchers take advantage of the timing of births, using the work behavior of the sister's neighbors who gave birth before the sister. But there's still potential for endogenous peer groups to create a problem. In this case, the researchers must assume there are no unobservable factors that affect the work decisions of both the mother's neighbors and her family's peer neighbors. In an attempt to control for these types of unobservables, the researchers include a control variable for the average hours worked by the mother's neighbors (similar to a neighborhood fixed effect, but excluding the mother). Finally, the authors attempt to control for factors that occur at the level of a geographic area larger than neighborhoods, such as large firms that hire workers from both neighborhoods.

The study found significant family spillover effects on the number of hours worked by mothers of preschool-age children. This included a large social multiplier effect, with each extra hour of work by a woman translating into 30 extra minutes for the other women in her family network. In comparison, the neighborhood spillover effects were smaller. The researchers found suggestive evidence that the family peer effect is driven by time investments in children, with earnings considerations also becoming important when a child reaches five or six years of age.

A recent US study also used peers of peers to study women's work decisions.[38] It examined how a woman's work decisions are affected by the labor market participation of her peers' mothers while she was in high school. The researchers used a regression analysis that relates a woman's labor supply as a young adult to both her own mother's labor force participation and that of her peers' mothers. Peers' mothers' working decisions had a strong impact, above and beyond the work choices made by a woman's own mother. The interpretation is that higher exposure to working mothers in an adolescent's peer group changes perceptions about gender roles regarding the ability to work and have a family at the same time. Both endogenous group membership and correlated unobservables are possible concerns in this setting, though the reflection problem is not.

Instrumental Variable Studies

Instrumental variables is a statistical method to deal with the problem of correlated unobservables. The idea is to find a variable, called an *instrument*, that influences treatment (such as a mother's participation in welfare) but isn't correlated with any unobservable factors common to the mother and child (such as living in an area with few jobs) that might also drive a child's participation decision.

To investigate intergenerational program participation, several studies in the United States have used instruments that vary at the state and year level. For example, an instrument could be the unemployment rate when a mother is in her early 20s. This should influence the mother's probability of being on welfare, but it arguably shouldn't be a factor in whether her daughter takes up welfare years later. The reasoning is that the unemployment rate will have changed by the time the daughter is considering whether to work or be on welfare.

An early study, using state-level welfare benefits and net migration flows, and a method similar to instrumental variables, found evidence for intergenerational links.[39] In contrast, an instrumental variables study from the mid-1990s, using variation in state benefit levels and local labor market conditions, concluded that most of the intergenerational correlation in welfare use isn't causal.[40] This research highlighted the possibility that observed correlations are not causal but could instead be reflecting correlated unobservables.

Perhaps the best example of the instrumental variables approach is a recent study that used a large US data set spanning a long time period for mother-daughter pairs.[41] This study takes advantage of the fact that states implemented welfare reform at different times, so the researchers could use temporal variation in program benefits across the country. The long time period in which these welfare changes occurred allowed the researchers to compare a mother's participation with her daughter's choices both before and after welfare reform. They focused on three programs to create their instruments: Aid to Families with Dependent Children, Temporary Assistance to Needy Families, and the Earned Income Tax Credit. Their key assumption was that the timing of changes in the generosity of these programs at the state level, and of welfare reform in general, is as good as random after a basic set of controls.

The study found large intergenerational effects, with a daughter's chances of using welfare as an adult increasing by 25 to 35 percentage points if her mother also participated. Interestingly, when the researchers considered only traditional welfare programs, these intergenerational effects were cut in half. When food stamps and disability insurance were added to create a broader measure of welfare participation, the intergenerational effects were about the same size both before and after welfare reform.

Another instrumental variables study used data from France to examine how a mother's labor market participation was affected by that of her neighbors.[42] The study first observed that whether a mother works is influenced by the sex composition of her two oldest siblings: mothers of mixed-gender children worked slightly less, on average. It further documents that a mother's labor market participation is affected by the sex composition of the older siblings of mothers living in the same neighborhood. Using the neighbors' older siblings' sex composition as an instrument, the analysis estimates that neighbors' work decisions have a sizable effect on a mother's own labor market participation. This leads to a large social multiplier, where one mother's decision to work can affect the work decisions of many others.

A final example uses Norwegian data to look at peer effects in the disability insurance (DI) program among older workers in that country.[43] As an instrument for neighbors' entry into the DI program, it uses plant downsizing events, which are arguably close to random. These downsizing events should increase DI use among an individual's previously employed neighbors, and at the same time take care of the problem of correlated unobservables. The study found that a 1 percentage point increase in neighbors' DI participation causes a sizable 0.4 percentage point increase in a person's own DI participation over the next four years.

Natural Experiment Studies

A recent set of studies has taken advantage of *natural experiments* to identify family and neighborhood peer effects. Sometimes called *found experiments*, these are situations where an actual experiment wasn't planned or explicitly carried out, but in which variation occurs that's as good as random. Such natural experiments are often paired with instrumental variables estimation.

One example of this approach is a study I helped write on intergenerational peer effects in the setting of disability insurance participation.[44] The key to our research design was the way the DI system in Norway randomly assigns judges to applicants whose cases are initially denied. Some judges are stricter than others, which introduces random variation in the probability that a parent will be allowed on DI during the appeals process. As a measure of a judge's strictness, we used the average allowance rate in all other cases a judge has handled. This measure strongly predicts whether a parent will be allowed on DI, but it isn't correlated with observable case characteristics.

We find that if a parent was allowed on DI because of being assigned to a lenient judge, on average their child's participation rose substantially over the next five to 10 years. In contrast, we found no peer effects related to close neighbors' DI participation. We argue that the mechanism can't be information about how to apply to the program, as all the parents have been through that process. Instead, we see suggestive evidence that children's beliefs change about how best to get onto the DI program; children whose parents received a lenient judge are more likely later in life to report the same type of medical disorder as their parent when applying.

Another article I helped write uses a different natural experiment.[45] We took advantage of a 1993 policy reform in the Netherlands that tightened the criteria for DI eligibility. Current DI recipients who were under age 45 at the time of the reform were re-examined and subjected to the new rules, which often resulted in reduced payments and exit from the program. In contrast, recipients aged 45 and older were grandfathered in under the older, more generous system. The idea behind this natural experiment is that a parent who was one day short of age 45 at the cutoff date should be virtually identical on all observable and unobservable characteristics to a parent who was one day older. The same should be true for their children. The only difference between the two families is whether the parent was subject to the harsher DI eligibility rules. To formally implement this intuition and allow the analysis to use parents who are more than one day away from the cutoff, we used a statistical technique known as *regression discontinuity*.

Prior work has found that the reform had large effects, which was also true for our intergenerational sample.[46] More than 5 percent of parents affected by the reform exited DI and saw their annual benefits drop by 1,300 euros, on average. Looking 21 years later, we found that children of the parents whose DI eligibility had been reduced were 11 percent less likely than the other children to participate in DI themselves. When we searched for other spillovers, we found that as adults these children didn't change their use of other government social assistance programs, and that they earned 2 percent more. The reduced DI payments to children and the increased taxes paid by children account for 40 percent of the fiscal savings from the reform, relative to parents who account for the remaining 60 percent in present discounted value terms (that is, accounting for the fact that money today is worth more than money tomorrow). Moreover, children of parents who were subject to the more stringent DI rules completed more schooling, had a lower probability of serious criminal arrests and incarceration, and took fewer mental health drugs as adults. The weight of this evidence suggests that the reform curtailing parents' DI benefits had positive effects on children.

These positive child outcomes weren't due to increased income or parental supervision; in fact, both income and supervision declined as a result of the reform. Rather, the effects are most consistent with children learning about formal employment, having a better home environment, or experiencing a scarring effect where they infer they can't rely on governmental support.

A final natural experiment study looks at spillovers in social program participation.[47] It analyzes peer effects in a family allowance program in Chile. The background is that participation of eligible poor families in the program was perceived to be low—only 60 percent of eligible families participated. The government introduced home visits from a social worker with the primary goal of connecting the families to the social safety net. Eligibility to receive home visits depended on whether an index of a family's wealth was below a cutoff that varied across municipalities. Much like the Dutch DI work, this study made use of the fact that families just above the wealth cutoff versus those just below should be essentially identical in all dimensions except for receiving home visits. The key assumption was that families weren't able to manipulate whether they were above or below the cutoff.

Eligibility for home visits turned out to have a large impact on participation in the family allowance program. To assess peer spillovers, the study examined whether an individual's geographically close neighbors were eligible for the visits. The idea was to compare participation in the program for families who had a larger fraction of neighbors just below versus just above the cutoff. Both this and the Dutch study use arguably random variation in treatment to identify peer effects.[48] Preliminary results from the Chilean study reveal strong evidence of peer effects on program participation; current iterations of the study are also incorporating the idea of using partially overlapping networks (as discussed in the section on peers of peers studies, above).

Studies Using Bounds

A final approach is the use of *bounds analysis* to study intergenerational peer effects. Bounds analyses impose a set of restrictions that can be used to limit the range of possible effects. A study from almost 20 years ago makes the bounding assumption that for a teenage girl, having her mother on welfare (Aid to Families with Dependent Children) doesn't decrease the time the daughter will later spend on welfare herself.[49] While this somewhat narrows the range of possible intergenerational effects, the resulting bounds are large. Therefore, the study combines the bounding assumption with variation in local unemployment rates as instrumental variables (see the section on instrumental variables above). The result is that growing up in a household that participates in welfare increases the likelihood that a daughter will participate in adulthood.

A more recent study using bounds combines rich administrative data from Norway and imposes weaker assumptions compared to the earlier research.[50] The study assumes that children's mean potential welfare participation is either increasing or unaffected as a function of parental participation. The researchers also added two instrumental variables that help tighten the bounds based on local labor market conditions and parental education. The way they used their instrumental variables required weaker assumptions compared to the typical instrumental variable approach discussed earlier.

For both disability insurance and family assistance programs, the bounds obtained are reasonably tight, meaning that the range of possible effects is narrow. The findings imply that a substantial part of the observed intergenerational correlation in welfare use is due to correlated unobservables, at least when considering the average effect of welfare participation for the entire population.

Conclusions

The best research to date documents that families and neighborhoods have a strong influence on both social program participation and labor markets. Though the recent evidence is compelling, we should be cautious in interpreting the study findings. For example, the lessons on intergenerational spillovers in disability insurance for Europe might not generalize to the Temporary Assistance for Needy Families program in the United States. The same caution applies to peer effects in the labor market, where results may not extrapolate across settings (such as different time periods, genders, or countries). We should also keep in mind that proving the existence of peer effects doesn't disprove the coexistence of other contextual factors on program participation, such as the impact of growing up in a poor neighborhood.

The more policymakers understand about peer effects, the more they can harness the power of peers to increase or discourage the take-up of a social assistance or work program.

With these caveats in mind, however, we can draw some general policy implications. Naively ignoring the roles played by family members and neighborhood peers would result in an incomplete understanding of the factors that influence decisions on work and program participation. The more policymakers understand about peer effects, the more they can harness the power of peers to increase or discourage the take-up of a social assistance or work program. For example, targeting information campaigns toward people with large peer networks can be a cost-effective way to increase knowledge of and participation in a government program. This is particularly true when perceptions about the merits of the program are still in the formative stages.

Another important takeaway is that family and neighborhood peers can amplify the effects of policy reforms. A policymaker who focuses only on those who are directly targeted by a program could grossly underestimate the number of people who will be affected. This matters for cost-benefit analyses. For example, focusing only on how parents are affected by a policy reform, and not including the future effect on their children, could lead to an incorrect conclusion about whether the overall benefits exceed overall costs.

A final related point is that peer effects are large enough to matter for the financial stability of a variety of social insurance and safety net programs. Determining the long-term fiscal impacts of government programs requires a full accounting that includes changes in taxes paid and transfer program receipt for affected peers. The financial costs (or benefits) attributable to peers could be as large as, or larger than, those of the initially targeted individuals. This is particularly true in settings where peer effects can snowball over time—such as in a workplace or a neighborhood—in ways that change the prevailing norms within a society.

Endnotes

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