

# The Role of the Family as an Informal Insurance

## Mechanism

by

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Dissertation submitted in partial fulfillment of the requirements for the degree of  
Doctor of Philosophy in the Department of Economics  
in the Graduate School of Duke University  
2013

ABSTRACT

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# Abstract

This dissertation examines the extent of different forms of informal insurance provided by both co-resident and non-co-resident family members. Primarily relying on the Panel Study of Income Dynamics, a unique, longitudinal survey dataset from the United States, this dissertation provides new insight on the importance and unique motives that may drive interactions between family members. These three essays investigate the different forms of assistance that the family provides in three different contexts: in response to unemployment, declining health, and natural disasters. The results in this dissertation provide new insights into the role that informal interactions can have on decisions and behavior. This research suggests new direction for future economic models dealing with the family, networks, risk, unemployment, health, and location decisions. The overarching theme is that decisions are often made jointly across households, reaching beyond the walls of the individual household.

To mom, dad, sisters, family, friends: Thank you.

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# 1

## Introduction

For many years, papers modeled the decisions of a household as a singular economic unit. In essence, the modelling assumption was that preferences of every unique individual within the household could be represented with an all-encompassing, unitary utility function. Models have since evolved to better represent the preferences of individuals by incorporating both non-cooperative and cooperative interactions between household members. However, interactions are not limited to only the people within one's household. When it comes to potential informal, risk-sharing arrangements, it may actually be beneficial to diversify risks by forming agreements with people outside of the household. The extended family makes for a particularly interesting network to study risk sharing arrangements for a number of reasons. Repeated interactions between family members over time, altruistic preferences for one another, and superior knowledge of each other's behaviors are some reasons why the family may be able to share risk efficiently with one another. Empirically, the family also offers some benefits in dealing with the endogeneity that is often associated with network formation.

There are many canonical studies in the development literature that examine

inter-household risk-sharing. One of the common empirical findings is that households that have some connection, whether geographic or familial, share resources with one another. While theoretical and empirical evidence suggests that risk appears to be shared among households, complete insurance is often rejected. The study of the sharing of risk between households is sometimes dismissed as being something specific to developing countries. The argument being that the citizens of developing countries have lacking infrastructure, and, as a result, have no choice but to turn to each other for necessary support. When sharing of resources across households is examined in developed countries, the focus is often on how government provisions supplant the need for informal resource sharing. The underlying assumption is that government provided benefits are an equal substitute for resource sharing between family members. This approach to studying how individuals interact outside of their own households ignores many of the unique theoretical elements that we believe drive resource sharing, particularly among family members.

The family makes a particularly interesting case study because the people with whom you are genetically related is not a choice. While individuals certainly choose how much to interact with one another, the family network provides an exogenous element in that the potential network is given at the time of birth. Endogenous network formation is one major hurdle in studying networks and risk sharing, but the family inherently side steps some of those concerns. Focusing the study of inter-household risk sharing upon families has both microeconomic and econometric theoretical justification which make the family an informative context for studying risk.

In the second chapter, I examine the role of monetary transfers between family members in dealing with a spell of unemployment. Economic analyses that account for both public and family transfers typically assume that public transfers, such as government-provided unemployment insurance, are a perfect substitute for family transfers. This assumption fails to capture the unique elements of the family that

drive inter vivos transfers (between living persons). I present a model that incorporates asymmetric information, exchange, and altruistic preferences that offers unique predictions regarding the role of family transfers in response to unemployment. Using the Panel Study of Income Dynamics, the empirical analysis includes family fixed effects and measures of local labor market conditions as instruments for unemployment and for family transfers. The results show that respondents receive more family transfers when unemployed but less family transfers when a sibling experiences unemployment. As the model predicts, the empirical results provide evidence that family transfers disproportionately increase human capital investment relative to unemployment insurance. In contrast to research on unemployment insurance, I find that family transfers do not increase the duration of unemployment, but family transfers do have a small, positive increase on average future wages. Lastly, the family's ability to monitor job search effort reduces unemployment duration and increases post-unemployment wages.

In the third chapter, my coauthor, Daniel LaFave, and I examine the extent that monetary transfers and co-residence with family members are used in order to deal with declining health. This study exploits longitudinal and genealogically linked data from the Panel Study of Income Dynamics to examine the relationship between health status, risk-sharing, and mechanisms of informal family insurance. In the context of well-developed theoretical models, we relate deteriorations in health due to specific ailments to losses in expenditure, labor market outcomes, and increased family assistance along a number of channels. These include drawing down wealth, increasing transfers, and taking in ill family members. The relationships are empirically robust to models exploiting the longitudinal structure of the data to look at changes within an individual over time. Our results suggest that family networks fill gaps left by formal insurance coverage. The results are informative for understanding patterns of resource allocation within families and how informal networks operate

while facing adverse events.

In the fourth chapter, I examine the extent and nature of transfers from the extended family in response to hurricanes. This study relies upon the uncertainty of when and where a major hurricane will hit and the difficulty in predicting the path of a hurricane as justification for treating hurricanes as a natural experiment. In order to control for unobserved heterogeneity, I exploit the longitudinal data from the Panel Study of Dynamics. This data also contains a rich set of responses about labor outcomes that allow for an analysis of the effects of hurricanes on earnings and hours worked and how labor market changes may affect family transfers. By combining data directly from FEMA about estimated assistance provided to households, I examine the interplay between private family transfers and the public transfers from FEMA. Lastly, I consider how the relocation decision after a hurricane may be affected by non-co-resident family members.

## Family Transfers in Response to Unemployment

### 2.1 Introduction

Since public unemployment insurance (UI) only provides partial insurance, many unemployed people may depend on informal insurance, such as transfers from the family. Previous research shows that UI has negative impacts on job search effort; however, existing research does not examine the effect of family transfers on job search behavior of the unemployed. Does altruism within the family encourage more shirking? Or is the family better able to monitor search behavior, which leads to better job outcomes post-unemployment? If the family makes transfers, are there expectations on how the transfers should be spent? These questions remain unanswered despite relevance to matters of policy and relevance to understanding the nature of transfers and interactions within in the family.

I motivate my empirical analysis with a theoretical model of asymmetric information between an altruistic parent and an unemployed young adult. Due to altruistic preferences, the parent wishes to make monetary transfers to the unemployed young adult. However, unemployment-contingent transfers distort job search incentives.

Since job search effort is only observable to the unemployed young adult, the parent faces a trade-off between providing insurance and maintaining job search incentives. The parent can limit moral hazard concerns in two ways: 1) reduced asymmetric information because monitoring is less costly for family members, and 2) the parent may condition transfers on a more easily verifiable outcome that improves post-unemployment labor outcomes, such as schooling or human capital investment. I empirically test these predictions using transfer, labor market, and other data from the Panel Study of Income Dynamics (PSID). In order to deal with potential simultaneity and unobserved confounding factors, I include family level fixed effects and instrument using measures of local labor market conditions of both the individual and family.

Compared to somebody not experiencing unemployment, I find that family transfers are approximately 70% more likely and up to \$1200 larger in response to an average spell of unemployment, and family transfers to the respondent are reduced by \$900 in response to a sibling's unemployment. The education expenditures of unemployed respondents increase by about 60% in response to receiving family transfers, suggesting that family transfers may be contingent on human capital investment. Additionally, unemployed individuals receiving family transfers are 40% more likely to enter a training program compared to those not receiving family transfers. In contrast, UI has an insignificant effect on both education expenditures and the likelihood of entering a training program. Lastly, among those receiving transfers, unemployment durations are shorter and post-unemployment wages are higher for those residing in the same county as their parent. This result suggests that proximity to a parent reduces moral hazard within the family through increased monitoring of job search effort.

Research examining both public and private transfers focuses on the extent that public transfers substitute for private transfers. The theoretical and empirical results

in this paper show that unemployment insurance and family transfers play distinctively different roles with respect to unemployment and labor market outcomes. I provide evidence that family transfers are contingent on human capital investment, while UI receipt is closer to a simple shift of the budget constraint of the unemployed. The family gains from increased human capital investment by improving the individual's future labor market outcomes, decreasing the chance the family will have to provide support to the individual in the future, and increasing the ability of that individual to return assistance to the family in the future. I also provide new evidence that the family's ability to monitor helps to induce a higher job search effort level by reducing the asymmetric information between family members. Through the mechanisms of increased human capital and job search effort, labor market outcomes improve significantly for unemployed respondents receiving family transfers. Family transfers lead to increased post-unemployment wages and, in some cases, decreased unemployment duration. I believe that these results have three potential policy implications. First, the results provide evidence that there is benefit to encouraging human capital investment or additional training in conjunction with making transfers. If UI programs encourage entry into training programs, this can improve labor market outcomes post-unemployment. Second, if older individuals face a trade-off between making inter-vivos transfers today or saving for a larger bequest in the future, it is of primary importance to understand the different effects that these types of transfers may have. Since inter-vivos family transfers appear to have positive effects on labor market outcomes, this may justify higher estate taxes since it would give incentives for additional inter-vivos transfers. Lastly, the results provide evidence that monitoring can reduce moral hazard. This implies that there are benefits for state governments to put more resources into programs that monitor job search of the unemployed in conjunction with UI programs.

The results also provide insight into interactions between family members. A

set of influential papers by Chiappori and coauthors examine the efficient sharing of resources within the family. While these papers provide evidence of the household sharing resources in an efficient manner, risk and the possibility of moral hazard induced by asymmetric information may limit the family's ability to maintain efficient sharing of resources across households. I incorporate risk and moral hazard into the model to better understand resource sharing and transfers within the family. I provide empirical evidence of potential shirking which suggests that moral hazard may be a relevant concern in interactions within families. Also, I provide evidence that family transfers are contingent on being spent in human capital improving ways, which also suggests a departure from static Pareto efficient resource sharing. Lastly, I provide further evidence that siblings "compete" for inter-vivos transfers. When one sibling experiences unemployment, it decreases transfers to the other.

## 2.2 Relevance to the Literature

A commonly found result in previous research is that transfers are made unequally across adult children in a multi-child family, where the child with the lowest income receives the most transfers McGarry and Schoeni (1995). However, since parents are likely to have only a noisy measure of income, it is more plausible that transfers respond to events that are easily verifiable. Unemployment is one such observable event that can negatively affect current income. This makes studying family transfers in response to unemployment an interesting question.

This is not the first study to examine family transfers in response to unemployment. Schoeni (2002) and Bentolila and Ichino (2008) analyze the extent that family transfers are displaced by unemployment insurance. Both papers find evidence of the substitutability of family transfers and public assistance. The welfare consequences discussed in these papers are related to the crowding out of private transfers, which results in the true benefits of public assistance moving to the provider of private

transfers. The welfare consequences stop there only if public and private transfers are perfect substitutes. I present a theoretical model that predicts that private transfers will have unique effects on labor market outcomes for the unemployed. These predictions suggest that welfare consequences will be larger than is implied by simple crowding out.

Research on unemployment insurance commonly finds, to varying degrees, increasing unemployment benefits distort the job search incentives for the unemployed (Ehrenberg and Oaxaca (1976); Moffitt (1985); Rothstein (2011)). The analogous impacts for family transfers on job search of the unemployed have never been analyzed. Altruism, ability to monitor, and potential exchange motives are features of the family that may make provided transfers unique in their effects on labor market outcomes for the unemployed. This paper empirically examines the effects that family transfers have on unemployment duration and future wages after the spell of unemployment.

Studies have found evidence of the family providing insurance against a variety of risks (Hayashi et al. (1996); Fafchamps and Lund (2003); Angelucci et al. (2012)). There is evidence in certain contexts of the family protecting investments, particularly in education, when a household experiences a decrease in transitory income (Thomas et al. (2004); Kinnan and Townsend (2012)). This result is confirmed in this paper: family transfers to the unemployed seem to be contingent on human capital investment. Additionally, I extend this result further by finding increased investment in human capital of adults through increased entry into job training programs.

### 2.3 Basic Principal-Agent Model: Parents and Unemployed Young Adults

I present a theoretical model that provides testable implications and intuition for the role of the family in responding to a member's unemployment and how family

transfers affect human capital investment, unemployment, and job search. I setup a basic principal-agent problem in the context of two family members. This model follows Rogerson (1985) and Chami (1998). The parent plays the role of the principal ( $P$ ) with altruistic preferences toward the unemployed, working age child who is the agent ( $A$ ).<sup>1</sup> I treat this as a static model that ends once  $A$  becomes employed. Each period of continued unemployment results in both  $P$  and  $A$  interacting again to form an agreement. The timing of the model is

1. Wage realization of  $w^P(L^P)$  for  $P$ . The wage is a function of exogenous local labor market characteristics faced by  $P$ .  $A$  learns her wage function in the event of finding employment,  $w^A(s; L^A)$ . Wage is a function of schooling ( $s$ ) and the local labor market conditions specific to  $A$ .<sup>2</sup> The wage is assumed to be larger than government benefits and potential family transfers so that I can abstract from the choice of reservation wage.<sup>3</sup> Additionally,  $A$  knows how much in government benefits she will receive in the event of continued unemployment,  $G$ .
2.  $P$  determines the transfer amount to be given to  $A$ .  $P$  sets two transfer schedules:  $T_U$  in the case that  $A$  does not find a job, and  $T_E$  in the case that  $A$  obtains employment.
3. With knowledge of the transfer functions proposed by  $P$ ,  $A$  chooses  $e$ , the job

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<sup>1</sup> I assume that the child enters unemployment through no fault of her own. I make this assumption to focus on unemployment that is due more to exogenous events as opposed to choices such as retirement or actively quitting a job. I discuss this more in the empirical section.

<sup>2</sup> I use schooling as a broad term that encompasses any human capital acquisition or training programs.

<sup>3</sup> I can alter the model so that the wage distribution conditional on schooling and labor market conditions is not degenerate. This would allow the unemployed child to choose a reservation wage each period. By making assumptions about the wage distribution and the effect of effort on the distribution, the content of the results that I present are unaltered. I choose to present the model with no reservation wage to help keep the results more intuitive. In the empirical analysis, I do look at wages post-unemployment as a signal of job match quality.

search effort.  $\phi(e; L^A)$  is the probability of  $A$  not finding employment in this period and is a function of her choice of  $e$  and local labor market conditions.<sup>4</sup>  $P$  cannot observe the choice of job search effort, and, thus, cannot condition transfers on search effort.  $A$  also chooses  $s$ , the amount of schooling to acquire.

4.  $s$  is acquired by  $A$ .  $A$  learns whether she enters employment or not.  $A$  receives transfers according to employment outcome.

While the decision to invest in schooling is perfectly observable to both parties, the effort choice by  $A$  is not.  $P$  only observes whether or not  $A$  exits unemployment. I will discuss the implications of this asymmetric information later in this section.

The agent's problem is

$$\max_{e,s} \phi(e; L^A)u_A(G+T_U-c(s))+(1-\phi(e; L^A))u_A(w^A(s; L^A)+T_E-c(s))-v(e) \quad (2.1)$$

where  $c(s)$  is the price of schooling,  $w^A(s; L^A)$  is the wage draw from the degenerate wage distribution that is a function of schooling and local labor market characteristics, and  $v(e)$  is the utility cost to putting forth effort. I assume that the utility function is increasing in consumption and concave:  $u'_A > 0$ ,  $u''_A < 0$ . Additionally, I assume that the probability of remaining unemployed is decreasing in effort:  $\phi_1(e; L^A) < 0$ . I assume that wage is an increasing function of schooling such that  $\frac{\partial w^A(s; L^A)}{\partial s} > 0$ . Lastly, I assume the two cost functions are increasing and convex:  $c'(s) > 0$ ,  $c''(s) > 0$  and  $v'(e) > 0$ ,  $v''(e) > 0$ .

For the unemployed child, she faces clear trade offs. Schooling has a monetary cost which reduces immediate consumption, but more schooling increases the wage received upon employment. Effort has a utility cost, but more effort increases the probability of employment, which gives a wage that allows for more consumption.

<sup>4</sup> One alteration would be to allow schooling to affect the probability of finding a job, and allow for schooling to increase the probability of obtaining employment. Allowing for this does not change the results presented later in this section. For simplicity, I do not allow schooling to affect the probability of finding a job.

The altruistic parent solves the following problem:

$$\begin{aligned} & \phi [u_P(w^P - T_U) + \gamma u_A(G + T_U - c(s))] \\ \max_{T_U, T_E} & + (1 - \phi) [u_P(w^P - T_E) + \gamma u_A(w^A + T_E - c(s))] + m(s) - \gamma v(e) \end{aligned} \quad (2.2)$$

I abbreviate the probability of unemployment to  $\phi$ . The parent gets consumption utility from the exogenously given wage  $w^P$ , the utility of the child enters directly into the parent's objective function weighted by an altruism parameter  $\gamma$ , and  $m(s)$  is the additional utility that the parent receives from the unemployed child acquiring additional training or education.

The parent may receive direct utility from the child's additional schooling because human capital investment can have long term value. First, it can increase the option value of the child as a source for assistance in future times of need. As the permanent income of the child increases, the potential scope of the child to provide future assistance also increases. While the model presented is admittedly static in nature, the parent receiving additional utility from schooling captures the idea that the nature of the interaction may change in the future when the unemployed child is in a more stable position and the parent may be in need of various forms of support. For example, if the parent faces declining health, financial assistance could be necessary as employment may be difficult to maintain and health care costs may not be covered by insurance. To this extent, transfers may not be made strictly out of altruistic preferences but with some expectation that the parent can rely on the child in the future. Investing in human capital today buys this future security.

Second, there is also the potential to invest in human capital for evolutionary reasons. Cox and Fafchamps (2007) present a model of family transfers being driven by a preference to ensure gene survival. Investing in the human capital of a child increases that child's permanent income, and increases the likelihood that the child can care for herself and her own offspring. To this extent, the parent gets additional

utility from putting his offspring in a better financial position for the future.

Lastly, the parent may simply have paternalistic preferences over the adult child's schooling decisions. Paternalistic preferences suggest that the parent receives utility over somebody else's consumption. If the parent has a general preference for his kids to be more educated or well trained for a job, he receives utility directly from his offspring taking extra classes or training.

The altruistic preferences described are in line with a standard model of the family where the child is selfish, but the parent is altruistic towards the child (Becker (1991)). Altruism is represented by including the utility of the child in the objective function of the parent.

Since schooling enters the parent's objective function in a way that is specific to the parent, he will have preferences for the child to obtain more schooling than the child would otherwise choose for herself. To this point, the model presented only allows  $P$  to condition transfers on the observable employment outcome. Since  $P$  observes schooling, it would be reasonable to model the transfer schedule chosen by  $P$  to be contingent on a specific schooling choice by  $A$ . I will further examine this later in the section.

Due to the asymmetric information between the parent and child with respect to search effort, transfers cannot depend upon a contracted level of effort. Only  $A$  knows her choice of effort. However, due to the timing of the model, the parent can condition transfers on the employment outcome.  $T_U$  is given to the child in the case that her employment search is unsuccessful, and  $T_E$  is given in the case the child obtains a job.

Transfers given by the parent can serve four potential purposes: balancing the marginal utilities between the two individuals, assist with smoothing the child's utility between stochastic outcomes, provide incentives for search, and induce additional human capital investment. By making transfers, the parent faces a tradeoff between

insurance and incentives.

Every dollar given from parent to child in the event of continued unemployment reduces the incentive for the unemployed child to find a job. In the extreme case, if transfers completely made up for the difference between labor earnings during employment and government benefits during unemployment, there would be no incentive for the child to search. The parent chooses the amount of transfers for each employment realization in order to incentivize job search, which leads the child to search more intensely. The tradeoff is that the parent also wants to insure the child. Due to the way that the child's utility enters the parent's objective function, the parent faces a similar aversion to risk that the child faces over the stochastic outcomes. In the absence of concerns about shirking, the parent has the same incentive to smooth the child's consumption as the child has.

In order to illustrate the tradeoffs that  $P$  faces, I use the first order approach suggested by Rogerson (1985) that approximates the incentive compatibility constraint.<sup>5</sup>

This involves replacing the incentive compatibility constraint with the first order condition for the problem faced by  $A$  in eq. 2.1. The Lagrange function of the parent becomes:

The participation constraint for  $A$  is

$$\begin{aligned} \phi u_A(G + T_U - c(s)) + (1 - \phi)u_A(w^A + T_E - c(s)) - v(e) \\ \geq \phi u_A(G - c(s)) + (1 - \phi)u_A(w^A - c(s)) - v(e) \end{aligned} \quad (2.3)$$

---

<sup>5</sup> A quick check shows that the basic assumptions for use of the first order approach are met in this example. Since the stochastic outcome is binary and the probabilities of each outcome respond monotonically to increases in effort, the monotonic likelihood ratio property is met without any additional assumptions to the model.

However, this participation constraint does not need to be included in the parent's Lagrangian. Since  $P$  is altruistic, he will choose to make transfers in both states of unemployment and employment.<sup>6</sup>

Additionally, because there is asymmetric information with regards to the choice of effort by  $A$ ,  $P$  cannot condition transfers on a specific effort level. As the participation constraint shows,  $A$  always prefers to receive family transfers, so the constraint is nonbinding.

The first order conditions for  $P$  with respect to the choice of transfers are:

$$\frac{u'_{PU}}{u'_{AU}} = \gamma + \lambda \frac{\phi_1}{\phi} \quad (2.4)$$

and

$$\frac{u'_{PE}}{u'_{AE}} = \gamma + \lambda \frac{-\phi_1}{1 - \phi} \quad (2.5)$$

In a situation where effort is perfectly observable, the incentive compatibility constraint would be non-binding and  $\lambda = 0$ . When asymmetric information is not affecting decisions, efficient sharing of resources is achieved since the ratios of marginal utilities in each state are equal. However, deviations from efficient resource sharing occur because the parent must incentivize search because effort is not observable. Asymmetric information within the family is one reason why Pareto efficient sharing of resources may fail. The difference from full insurance is determined by the last term in both first order conditions. The Lagrange multiplier is positive since the incentive compatibility constraint is binding. The Lagrange multiplier is multiplied by a ratio that reflects the value of information.

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<sup>6</sup> It should be noted that  $P$  needs to have sufficient income, or available resources, for a non-zero transfer to be made. If income is too low,  $P$  will be at a corner solution for chosen transfers. Zero transfers observed in the data are discussed further in the empirical section.

The first order approach approximation helps to illustrate the tradeoffs between providing insurance and search incentives. In order to solve for the optimal transfer choice of  $P$ , I reframe the optimization problem by removing the first order approximation of the incentive compatibility constraint. I allow  $P$  to directly account for the change in search behavior of  $A$  in response to transfers:

$$\max_{T_U, T_E} L = \phi [u_{PU} + \gamma u_{AU}] + (1 - \phi) [u_{PE} + \gamma u_{AE}] + m(s) - \gamma v(e) \quad (2.6)$$

The first order conditions are then:

$$\phi(-u'_{PU} + \gamma u'_{AU}) + \phi'(u_{PU} - u_{PE}) \frac{\partial e}{\partial T_U} = 0 \quad (2.7)$$

and

$$\phi(-u'_{PE} + \gamma u'_{AE}) + \phi'(u_{PU} - u_{PE}) \frac{\partial e}{\partial T_E} = 0 \quad (2.8)$$

Any increase in transfers that  $A$  receives during unemployment will weaken the incentive to search, thus  $\frac{\partial e}{\partial T_U} < 0$ . Analogously, increasing transfers received during employment improve search incentives:  $\frac{\partial e}{\partial T_E} > 0$ .

Since  $P$  is altruistic towards  $A$ , he ends up providing a transfer scheme that distorts search incentives in order to provide insurance for  $A$ . This is shown in the first testable proposition:

**Proposition 1.**  $T_U > T_E > 0$

*Proof:* Assume a contradiction such that  $T_E > T_U$ . Referring to the second term in eq. 2.7,  $\phi'(u_{PU} - u_{PE}) \frac{\partial e}{\partial T_U} > 0$ . This means  $\phi(-u'_{PU} + \gamma u'_{AU}) < 0$  and, thus,  $u'_{PU} > \gamma u'_{AU}$ . Eq. 2.8 gives  $\gamma u'_{AE} > u'_{PE}$ . The first order condition for  $A$  implies that  $u'_{AU} > u'_{AE}$ . Together, this implies that  $u'_{PU} > \gamma u'_{AU} > \gamma u'_{AE} > u'_{PE}$ . However, since  $u_{PU} > u_{PE}$ , this implies  $u'_{PE} > u'_{PU}$  which is a contradiction.  $\square$

Proposition 1 suggests that the parent will always make a larger transfer in response to continued unemployment relative to the transfer given for finding a job. I test this proposition in the data by examining whether experiencing unemployment leads to larger transfers. Examining this empirically brings up issues of endogeneity that make this test less than straight forward. I will use local labor market conditions faced by the child as instruments for the child's unemployment spell. As seen in the model, the local labor market conditions affect the duration of an unemployment spell by affecting the probability of finding a job. By assuming that the parent does not condition on local labor market conditions faced by the child, local labor market measures are a natural instrument based on the model. I discuss this strategy further in the empirical section.

### *2.3.1 The Role of Monitoring*

One result often found in the literature to varying degrees is that government provided UI has a negative impact on search effort. Specifically, unemployment duration increases as benefits are extended or increased (Moffitt (1985); Meyer (1990); Rothstein (2011)). These results are often cited by critics of UI as evidence of moral hazard due to the government's inability to monitor search effort.

One extension to the previous model is incorporating monitoring of effort. Better monitoring can reduce the asymmetric information between parent and child. For instance, some families may be more capable of monitoring due to proximity. Living closer makes visitation easier, and frequent visits give more concrete knowledge of the behaviors of the child. *Ceteris paribus*, living closer should reduce moral hazard by making asymmetric information less of a concern. In a case where  $e$  is perfectly observable by  $P$ , moral hazard can be completely eliminated and the first best effort is achieved.

Assuming perfect monitoring of  $e$ , allow  $P$  to solve:

$$\begin{aligned}
L = & \phi [u_{PU} + \gamma u_{AU}] + (1 - \phi) [u_{PE} + \gamma u_{AE}] + m(s) - \gamma v(e) \\
\max_{e, T_U, T_E} & + \lambda [\phi u_A(G + T_U - c(s)) + (1 - \phi) u_A(w^A + T_E - c(s)) - v(e) \geq \bar{u}_A]
\end{aligned} \tag{2.9}$$

Where the  $\lambda$  is the Lagrange multiplier on the participation constraint. The constraint is included in this case because  $P$  can now observe  $e$ . Assuming the participation constraint is nonbinding, the first order condition with respect to effort is

$$\frac{\phi' [u_{PU} - u_{PE}]}{\gamma} + \phi' [u_{AU} - u_{AE}] = v'(e) \tag{2.10}$$

Allow  $\hat{e}$  to be the solution to this problem, and  $e^*$  to be the solution to the original problem faced by  $A$  in eq. 2.1, then

**Proposition 2.**  $\hat{e} > e^*$ . *Search effort increases with better monitoring.*

*Proof:* From the first order condition of  $A$ ,  $e^*$  solves  $\phi' [u_{AU} - u_{AE}] = v'(e)$ . Since the first term in eq. 2.10 is positive and  $v''(e) > 0$ , then  $\hat{e} > e^*$ .  $\square$

Proposition 2 states that if families can observe effort, the disincentive effects of transfers will be alleviated because the family can simply condition transfers on a specific effort level. The result is higher level of search effort from unemployed family members that have family members capable of monitoring. I test this in the data by examining whether unemployment duration is significantly shorter for people that live near their parent. If, ceteris paribus, living nearby a parent makes monitoring easier, search effort should be closer to the first best level when the family makes transfers.

### 2.3.2 The Role of Family Transfers on Schooling

So far I have ignored the possibility that  $P$  can condition transfers on schooling. Intuitively,  $P$  would want to make transfers contingent on schooling because  $s$  is

perfectly observable and  $P$  gets positive utility from  $s$  for both altruistic and selfish reasons. Schooling contrasts with the choice of effort because schooling is observable to both decision-makers. With no asymmetric information, the first best level of schooling can potentially be contracted upon.

The first order condition for  $A$  with respect to  $s$  when neither  $G$  nor  $T_U$  are contingent on a specific level of  $s$  is:<sup>7</sup>

$$(1 - \phi)u'_{AE}(w' - c') = \phi u'_{AU}c' \quad (2.11)$$

where  $w'$  is the change in wage of  $A$  with respect to  $s$  and  $c'$  is the change in price of  $s$  as  $s$  increases. When transfers are not contingent on  $s$ ,  $A$  is free to set the marginal cost of extra  $s$  equal to the marginal benefit. However, if  $P$  makes transfers contingent on  $s$ , then  $P$  can now essentially pay for  $A$  to acquire more  $s$  than she would have in autonomy.

Next, I allow  $P$  to make transfers contingent on  $s$  and solve for:

$$\begin{aligned} L = & \phi [u_{PU} + \gamma u_{AU}] + (1 - \phi) [u_{PE} + \gamma u_{AE}] + m(s) - \gamma v(e) \\ \max_{s, T_U, T_E} & + \lambda [\phi u_A(G + T_U - c(s)) + (1 - \phi)u_A(w^A + T_E - c(s)) - v(e) \geq \bar{u}_A] \end{aligned} \quad (2.12)$$

where the  $\lambda$  is the Lagrange multiplier on the participation constraint. The constraint is included in this case because  $P$  can observe  $s$ . Assuming the constraint is nonbinding, the first order condition with respect to  $s$  is:

$$m'(s) + (1 - \phi)u'_{AE}(w' - c') = \phi u'_{AU}c' \quad (2.13)$$

This leads to Proposition 3:

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<sup>7</sup> The first order condition results from taking the derivative with respect to  $s$  in eq. 2.1

**Proposition 3.** *Let  $s_G^*$  be the optimal choice of schooling when  $G = \tau$  and  $T_U = 0$ . Let  $s_T^*$  be the optimal choice of schooling when  $G = 0$  and  $T_U = \tau$ . Then  $s_T^* > s_G^*$ .*

*Proof:* Eq. 2.11 is the first order condition that determines  $s_G^*$  since  $G$  is not contingent on  $s$ . Eq. 2.13 is the first order condition that determines  $s_T^*$  since family transfers can be made contingent on  $s$ . By assumption discussed earlier,  $m'(s) > 0$ . Since  $m'(s)$  is the first term in eq. 2.13, the optimal  $s_T^*$  must be larger in order for the first order condition to hold. Thus, for a given transfer level  $\tau$ ,  $s_T^* > s_G^*$ .  $\square$

Proposition 3 says that for a given level of transfer during unemployment, more schooling will be acquired when the source of the transfer is from the family, as opposed to the government. This is due to the parent's desire to reduce the likelihood of future unemployment, increase the ability of the child to provide support to the parent in the future, and provide a strengthened safety net for future generations.

When  $A$  is choosing  $s$  on her own, she does not account for the “positive externality” of her schooling on  $P$ . By allowing  $P$  to make transfers contingent on  $s$  in the model,  $s$  increases. I test Proposition 3 in the data by using data on education expenditures and job training entrance and examine the differential impacts of family transfers and UI.

## 2.4 Panel Study of Income Dynamics

For the results in this paper, I primarily rely upon the Panel Study of Income Dynamics (PSID). This dataset has a number of elements that I incorporate into this analysis. First, the PSID has a sample replenishment strategy that makes it extremely useful for studying non-co-resident families. The PSID began annually interviewing a nationally representative sample of households in 1968, where each 1968 household member was given the PSID gene. This gene means that the PSID will continue to interview the household of each individual even after separate house-

holds are established. As individuals with the original PSID gene have offspring, their children also receive the gene. Each subsequent new generation continues to receive the gene. This means as of 2009, the most recent interview used in this paper, there are contemporaneous interviews across multiple generations within the same genetically linked, non-co-resident family. This gives the opportunity to focus the study on specific relationships, such as parents and their adult children, siblings, and more. Throughout this paper, I refer to all genetically linked households with the PSID gene as the extended family and all people residing together as a household. A household is determined to experience unemployment if the head of household with the PSID gene is both without a job and searching for a job at any point during the calendar year.

Second, I have access to confidential residence information detailing the county in which each household resides. I match the county of residence with county-specific labor statistics from the Bureau of Economic Analysis (BEA) and Bureau of Labor Statistics (BLS) that I use as instruments for the potentially endogenous variables that are the focus of this research. I will also use this residence information to determine geographic proximity between households in the same family.

Third, the PSID has a long panel history. I use the panel portion of the data in order to incorporate extended family fixed effects to control for unobserved heterogeneity in the regression analysis. Furthermore, I also combine the location information with the panel nature of the data, and create instruments based on local labor market conditions faced in previous years for each head of household.

Fourth, the PSID asks questions about whether the household received monetary transfers from non-co-resident family during the course of the year. The response to this question will be of primary interest throughout this study. There are no questions about the nature or purpose of these transfers, so the goal of this paper is to infer the situations in which these transfers are given and how households use

transfers from the family.

Lastly, the PSID asks a substantial set of labor market experience questions. I use this information to determine unemployment experiences of the PSID gened head of household. Furthermore, by combining labor market outcomes with the panel data, I can use information about labor market history before unemployment and labor market outcomes post-unemployment.

The base sample includes all observations from 1985 and later who have non-missing unemployment and transfers responses. Additionally, I remove observations that report receiving over \$50,000 in transfers from the family as these are extreme outliers from the rest of the sample. The control variables that I include in all regressions are a dummy for whether head of household is married; whether the head is a male; a dummy for whether the head or spouse worked at any point during the year; a set of variables that breakdown by age-gender groups for members of the household and extended family other than the head and spouse; age, age squared, and age cubed of the head and spouse; education, education squared, and education cubed of the head and spouse; number of interviewed extended family members; unemployment insurance received; household income; whether the household moved since the previous interview; and a set of dummies to capture year and state fixed effects.

I provide basic summary statistics of the full base sample in Table A.

## 2.5 Empirical Specifications and Results

### 2.5.1 *Family Transfers in Response to Unemployment*

Proposition *Table1* gives the first and most relevant hypothesis. It predicts that transfers should respond to unemployment duration:

$$\frac{\partial T_{hft}}{\partial U_{hft}} > 0 \tag{2.14}$$

where  $T_{hft}$  are transfers received from the family by the unemployed head of household  $h$  in family  $f$  in year  $t$ , and  $U_{hft}$  is the number of weeks that the head of household spent unemployed during the year. I estimate this relationship in the following equation:

$$T_{hft} = \beta_0 + \beta_1 U_{hft} + \sigma' \mathbf{L}_t^P + \text{controlvars} + \phi_f + \varepsilon_{ht} \quad (2.15)$$

I estimate equations with two different dependent variables: 1) the binary outcome for whether a positive transfer was received from the family and 2) the amount of family transfer received. Unemployment is defined as the PSID-gened head of household not having a job but actively searching for one. The coefficient of interest is  $\beta_1$ , the change in transfer amount or likelihood of receiving a transfer for one additional week of unemployment. I also control for the previously mentioned observed, demographic characteristics of the head of household, the other members of the household, and the extended family members of the head.

All regressions are shown both without and with family fixed effects. Family fixed effects capture both observed and unobserved time-invariant characteristics across family members. Since the PSID interviews multiple genetically linked family members, I can include a family fixed effect to capture confounding, unobserved effects. Some of these common unobserved characteristics may be wealth or permanent income of the extended family, genetic traits, preferences, or similar labor market experiences.

Although the fixed effects control for constant characteristics that persist over time, there may still be concerns of endogeneity between unemployment duration and reported transfers received. For most people, unemployment is a reasonably rare event. If rare unobserved events drive a correlation between unemployment and transfers, then the estimated effects presented may be biased. For instance, if people

expect increases in transfers in the future, this may induce one to quit a job and use the time for leisure while receiving family transfers, thus creating causation in the opposite direction. If I can focus the estimation on unemployment spells that are outside of one's control due to macroeconomic conditions, this can help reduce the endogeneity problem, and allows me to put a causal interpretation on the estimates.

In order to deal with this potential endogeneity, I instrument for unemployment using measures of local labor market conditions. The theoretical model makes predictions about the effects of local labor market conditions. Specifically, the local labor market conditions of the unemployed child affect the difficulty in obtaining a job and the post-unemployment wage. Additionally, the local labor market conditions faced by the parent directly affect income of the parent, thus indirectly affecting the transfer decision of the parent. To the extent that the parent is not directly conditioning transfers on the local labor market conditions of the child and the child is not adjusting his search behavior on the labor market conditions faced by the parent, local labor market conditions can make for important controls and instruments in the empirical equations of interest. In equation *Table2.15*, the labor market conditions of the parent,  $L_t^P$ , are included as controls. Additionally, I can use the local labor market characteristics of the unemployed head of household as instruments for the head's duration of unemployment. Since I am assuming that the family does not take into consideration the local labor market conditions of the unemployed individual in their transfer decision, and the quality of labor market conditions are going to affect the duration of unemployment, labor market conditions meet the primary two assumptions for a valid instrument.

I measure local labor market conditions using changes in employment at the local county level and the national level. Jobs that are lost due to changing idiosyncratic local labor demand conditions are likely to be outside the control of the individual. In order to measure this, I use annual county level labor statistics from the BEA and

BLS. First, I construct a measure of changes in aggregate county level employment levels based upon changes in employment by industry at the national level, weighted according to the industry labor composition of the county in which the household resides (Bartik (1991)). This measure is calculated according to the formula

$$Bartik_{c,t} = \sum_i (Emp_{US,t}^{Industry i} - Emp_{US,t-1}^{Industry i}) \times \frac{Emp_{c,t-1}^{Industry i}}{Emp_{c,t-1}} \quad (2.16)$$

The measure of county  $c$  in year  $t$  is the sum of changes in national industry employment levels from the previous year across all industries  $i$ , weighted by the proportion of employees in that industry in that county in the previous year. This measure makes a good instrument for a respondent's unemployment for a few reasons. First, this measure captures changes in labor demand. Layoffs and job losses resulting from reductions in labor demand are more likely to be outside of one's control. Unemployed people living in areas that are directly affected by labor demand reductions are less likely to be unemployed by their own choice. Second, this measure uses changes in employment in industries at a national level. By using macroeconomic level variation, this gives potentially exogenous variation. There may be concerns related to households relocating across counties in response to labor demand deviations, and by using changes at a national level, endogenous relocation decisions are less of a concern. Third, I can examine different local labor market conditions for households residing in different counties but are within the same family. Location variation of households within families will be an important tool in the monitoring analysis later in this section.

In addition to the county Bartik measure, the set of instruments that I use include the head's previous interview's Bartik county measure; the Bartik measure at the state level this year and the previous year; and the national unemployment rate by age of the household head. Including the contemporaneous national unemployment

rate by age helps to further differentiate the labor market conditions faced by different generations. If some families live close to one another, there is no variation in labor market conditions based solely on geography. Age specific labor market conditions help to differentiate between the parent and the unemployed child.

Table 2.1 presents the limited information maximum likelihood instrumental variables (LIML-IV) and fixed effects IV (FE-IV) results. Coefficients on control variables previously mentioned are not reported in the tables. I treat the number of weeks that the head of household was unemployed as an endogenous regressor, and I instrument for it using the local labor market measures described above. I choose to use a LIML-IV estimation because it is more robust to a weak first stage. Estimates from two stage least squares are similar in magnitude and inference.

Columns 1 and 2 show the effect of an extra week of unemployment on the amount of transfer received. Without fixed effects, column 1 shows a \$117 in extra family transfers for each week of unemployment, and this is statistically significant at the 5% level. When accounting for unobserved family heterogeneity, the effect reduces to \$74 but is no longer statistically significant at conventional levels. Columns 3 and 4 provide evidence that transfers not only increase transfers on the intensive margin but also the extensive margin. An additional week of unemployment makes the respondent 7% more likely to receive a transfer. This result is similar and maintains its statistical significance both with and without fixed effects.

For all regressions, I include the F-statistic from the first stage and the p-value of the Hansen's J-stat. The F-statistic meets the Stock and Yogo (2002) 10% critical values, suggesting that the chosen instruments have strong predictive power of the endogenous regressor, weeks of unemployment. The J-stat is not different from zero for any of the regressions, which provides some evidence that the instruments are not correlated with the error term. While these tests do not prove the success of the identification strategy, they do provide evidence to help validate the choice of

instruments. Additionally, the results are robust to being run as instrumented limited dependent variable models.<sup>8</sup> Lastly, all results include standard errors clustered at the family level. Clustering standard errors at the family level help account for arbitrary correlation between error terms of respondents in the same family. The clustered standard errors are typically larger than both homoscedastic and White standard errors. This choice in reported standard errors makes the statistical inference more conservative with respect to testing null hypotheses.

### 2.5.2 Siblings' Unemployment

Table 2.1 provides support that family transfers do indeed respond to spells of unemployment. An extension to the initial model could make predictions on the effects of unemployment of siblings on the amount of transfers received by the respondent. As a sibling experiences unemployment, this would decrease the available resources of the parent such that:

$$\frac{\partial T_{hft}}{\partial U_{-hft}} < 0 \quad (2.17)$$

Where  $U_{-hft}$  is the unemployment duration for a sibling of the head of household  $h$ . I follow the same instrumenting strategy for the results in Table 2.1 but instrument for a sibling's unemployment with local labor market variables specific to the sibling.

Table 2.2 presents the results for family transfers in response to siblings' unemployment. Panel A limits the sample to only heads of household with one sibling contemporaneously interviewed. The results show that an additional week of sibling's unemployment reduces family transfers received by approximately 60 to 90 dollars, and this is significant at the 10% level. Sibling unemployment does not appear to have a statistically significant impact on the likelihood of receiving a positive transfer. Panel B looks at the unemployment of the youngest and oldest siblings for

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<sup>8</sup> Results available upon request.

heads of household with at least 2 siblings. The youngest sibling has a smaller but statistically significant impact on transfers in both Columns 2 and 4. The oldest sibling has a larger in magnitude impact on amount of transfers, but the standard errors are large relative to the estimated coefficients.

Table 2.2 provides evidence that is consistent with many empirical findings about inter-vivos family transfers. The common finding is that transfers are given disproportionately to children who earn less income. Table 2.2 supports this story since having a sibling experiencing unemployment has a negative impact on the transfers received by the respondent. Since the outcomes of the siblings affect transfers received of the respondent, I will include sibling specific measures as instruments for transfers received in analyses later in the paper.

### 2.5.3 Human Capital Investment

Proposition *Table3* predicts that human capital investment will be larger in response to transfers from the family, compared to UI transfers received:

$$\frac{ds_{hft}}{dT_{hft}} > \frac{ds_{hft}}{dG_{hft}} \quad (2.18)$$

In order to estimate this relationship, I use consumption data from the PSID collected since 1999. Specifically, the PSID asks questions about education expenditures over the course of the year. I use total share of expenditures spent on education as the dependent variable and estimate the effect of both family transfers and unemployment insurance. I limit the sample to the unemployed respondents who have a valid wage in previous interviews and a valid wage in future interviews. I make this sample restriction in order to keep the samples comparable between the analyses presented in this section and the labor market outcome analyses presented in the following section. Also, this sample restriction eliminates unique respondents who

go into retirement directly from unemployment and respondents that have never worked.

Table 2.3 shows the effect of receiving family transfers and UI on the share of education expenditures for the unemployed. Column 1 shows that receiving family transfers increases the share of expenditures by 1.8%, which is approximately 75% of the average education expenditure share. This is statistically significant at the 1% level. Column 2 has a smaller coefficient, although still significant at the 10% level. The Column 1 coefficients on family transfers and unemployment insurance are significantly different at the 10% level when performing a basic F-test of equality. In Column 2, the coefficients are not statistically different, although the coefficient on family transfers is about 8 times the size of the UI coefficient. Family fixed effects may lead to the different results in the two columns if families that are more likely to give transfers also have a preference for more education. Family fixed effects control for unobserved preferences consistent with this story.

While Table 2.3 provides some evidence that unemployed respondents spend more on education when receiving family transfers versus UI, it is unclear for what these expenditures are actually used. I examine this further by looking at the likelihood an unemployed respondent enters a job training program and how this likelihood is correlated with family transfers and UI. This information is asked retroactively by the PSID only once in 2009. I have to reduce the sample to all interviews with respondents who were also interviewed in 2009. Table 2.4 presents these results. Both columns provide further evidence that receiving family transfers has a positive impact on entering a training program. These coefficients are also statistically different from the unemployment insurance coefficients in both columns.

The results in both Table 2.3 and Table 2.4 support the prediction of proposition 3: human capital investment will be positively related to family transfers but not necessarily UI. While the data does not allow me to assess the exact mechanism

that drives the correlation, it is interesting that unemployment insurance does not have the same effect. This suggests that family transfers have some contingency that directs the transfers to be spent in a specific way. If this is the case, and it is assumed additional training and human capital investment have positive externalities for society, then the welfare consequences of crowding out are of greater importance than typically assumed. Crowding out of family transfers with public transfers is often thought to simply shift the benefits of the public transfers from the target of public transfers to the provider of family transfers. If crowding out family transfers result in a decrease in human capital investment, then the welfare consequences may be larger than initially thought.

#### 2.5.4 *Monitoring*

If the family is not capable of monitoring, transfers could have a job search distorting effect, much like UI. As transfers increase, we would expect unobserved effort to decrease since unemployment is more attractive than without the transfers. Thus, if asymmetric information is an issue for the family:

$$\frac{dU_{hft}}{dT_{hft}} > 0 \tag{2.19}$$

As transfers increase, job search effort decreases and unemployment duration increases. Note that this is the inverse of the prediction from Proposition *Table1*. This emphasizes the issue of simultaneity between the decisions that drive transfers and job search behavior. In order to deal with this simultaneity, I revert back to an instrumental variable strategy to estimate a causal impact.

The goal is to see how family transfers affect labor market outcomes of the unemployed. I use two separate measures of labor market outcomes: unemployment duration and reported post-unemployment wage averaged over all future interviews.

Unemployment duration is important because it gives an indication of job search effort. Future wages give an indication of job match. If unemployed respondents are staying unemployed longer in response to receiving family transfers but receive higher wages because of a better job match, then longer unemployment durations are not necessarily a bad thing. This is the motivation to examine both outcomes as dependent variables.

I estimate the following equation using instrumental variables LIML:

$$U_{hft} = \beta_0 + \beta_1 T_{hft} + \alpha_1 w_{hft-} + \alpha_2 w_{hft+} + \sigma' \mathbf{L}_t^h + \text{controlvars} + \phi_f + \varepsilon_{ht} \quad (2.20)$$

Where  $w_{hft-}$  is the average wage in all prior interviews and  $w_{hft+}$  is the average wage in all future interviews with the head of household  $h$ . Now I am controlling directly for local labor market conditions of household  $h$  in the regression, where these were instruments used in equation *Table2.15* for the results in Table 2.1. I instrument for family transfers using information from interviews with the family. I instrument using local labor market measures of the parent of the head of household  $h$ . For parents that have not yet retired, changes in labor market conditions may affect their transitory income, and perhaps affect their expectation of permanent income. In response to a decline in income, the parent will give a smaller transfer, as suggested by the theoretical model. For this reason, I would expect the labor market conditions of the parent to affect transfers but be unrelated to the unemployment of their unemployed child. One caveat to this is that parents and their kids may experience similar local labor markets because they live near one another. This is an additional reason for controlling for the unemployed child's local labor market conditions in the regression. In addition to the local labor market conditions of the parent, I instrument using unemployment duration of siblings and the household income of the parent and siblings.

Table 2.5 presents the results for equation *Table2.20*. The regressor of interest

is in thousands of dollars received from the family. Both dependent variables are in log form. Columns 1 and 2 both show a negative coefficient, suggesting transfers have a negative impact on unemployment duration. Neither coefficient is statistically significant. Column 3 shows that a \$1000 increase in family transfers increases average future wage by about 43%. The coefficients in this table are surprisingly large in magnitude. Part of this could be due to the first stage F-stats that are rather small, which may result in noisy estimates. The first stage with fixed effects is not significant at conventional levels, suggesting that family fixed effects wipe out much of the observed and unobserved variation needed for the instruments to be useful. The regressions without fixed effects meet the first stage critical values of 15%, which is acceptable in these regressions. I still find significance at the 10% level in Column 3. Despite the borderline weak first stage, I am still capable of getting a precise estimate. The coefficients are not significantly different when I run a two-stage least squares as opposed to LIML.

These results have a few potential explanations. First, if family transfers relieve immediate liquidity constraints, then this allows the unemployed respondent to continue search for a better job match. This continued search may lead to higher wages. However, we would expect that unemployment duration would increase if the unemployed respondent is becoming pickier, which is not found in these results. A different explanation says that family is exceptional at monitoring job search effort. When the family provides transfers, they ensure that shirking is not occurring. In this case, for a given duration of unemployment, we would expect wages to be higher since search effort is higher and more interviews, etc. are obtained. This matches with the results presented in Table 2.5. The final potential explanation is if family transfers are contingent on human capital investment, then we should see wages increasing over time in response to better job skills and training. As shown in Table 2.3 and Table 2.4, there is evidence that family transfers are contingent on entering

a job training program. This could be the mechanism that results in family transfers leading to higher post-unemployment wages.

Next, I consider the monitoring hypothesis more in depth. Proposition *Table2* states that if asymmetric information is limited, we would expect that effort should increase. In order to test this, I split respondents by whether they live close to their parents versus farther away. If the respondent lives very close to their parent, then this should make it easier for the parent to observe the search effort of the unemployed child. In response to better monitoring, asymmetric information is reduced, and realized effort approaches the first best level of effort. I define somebody living close to their parent as living in the same county, and compare this to those living outside of the county of their parent.

The key assumption in this part of the analysis is that location is exogenous to the decisions of the unemployed. Papers have discussed the choice of location in relation to labor markets (Kennan and Walker (2011)), moving in response to unemployment (Kaplan (2012)), and moving in relation to the family and labor markets (Coate (2012)). Location decision relative to parents may be a signal of altruism and a desire of wanting to live near parents. It can also be a signal of family wealth, as wealthier families may be more able to live in separate parts of the country. Lastly, close proximity to a parent could also be a sign of similar preferences. Family fixed effects will presumably control for a portion of altruism, family wealth, and preferences. Additionally, in regressions not reported, I include controls for family altruism based on the history of giving and receiving transfers within the family. These measures do not alter the results in a meaningful way. Examining location decision in relation to family and labor markets is left for future work.

The estimated equation is

$$\begin{aligned}
U_{hft} = & \beta_0 + \beta_1 D(\text{Close})T_{hft} + \beta_2 D(\text{Distant})T_{hft} \\
& + \alpha_1 w_{hft-} + \alpha_2 w_{hft+} + \sigma' \mathbf{L}_t^h + \text{controlvars} + \phi_f + \varepsilon_{ht}
\end{aligned} \tag{2.21}$$

where I want to look at how transfers have differing effects on labor market outcomes depending on the parent's proximity to the unemployed household. I instrument for both endogenous regressors using the same instruments as Table 2.5. The dummies for location are also included as separate control variables in the regression.

Table 2.6 presents results supporting the importance of monitoring for the family. Columns 1 and 3 both have economically and statistically significant coefficients for living in the same county as their parent, which are larger in magnitude than living farther away from the parent. If proximity to the parent is a good proxy for monitoring ability, then better monitoring encourages better labor market outcomes for the unemployed. Living in the same county as the parent results in shorter unemployment duration and higher future wages. Although the magnitude is larger in each column, living closer is only statistically different from living in a separate county for Column 1. It is worth noting again that there is a potential issue with a weak first stage. These results suggest that future work on monitoring within the family could be of value.

## 2.6 Conclusions

### *2.6.1 Summary and Implications*

One potential impact of the larger government benefit programs is a decreased reliance on the family for assistance. As shown in previous studies, receiving more government benefits reduces the amount of familial cash assistance. One consequence of this crowd out is that part of the welfare enhancement of public transfers goes to the family member who would have otherwise provided cash transfers. This

shifting of benefits is one inefficiency often associated with public transfers. This paper provides evidence that the crowding out of family transfers may have a larger impact for the unemployed and society than originally expected.

Due to the family's altruistic preferences, the potential for future exchange, and a unique ability to monitor, family transfers have a distinct impact on labor market outcomes compared to unemployment insurance. I present results showing that family transfers appear to be contingent on human capital investment, as receiving family transfers leads to more education expenditures and a more likely entry into job training programs. Additionally, I find evidence that receiving family transfers leads to higher wages post-unemployment compared to those not receiving transfers. One explanation for this could be due to the family encouraging human capital investment, which leads to better wages. If unemployment insurance crowds out family transfers, then there may be a large societal impact as the unemployed will be less likely to actively seek human capital accumulating programs.

I also provide evidence that the family has an ability to monitor job search effort, which can potentially alleviate some of the moral hazard concerns associated with provisions of unemployment insurance. If family members are able to obtain superior knowledge of what is going on with their relatives, then they may be able to offer informal contracts that better incentivize search behavior. Families providing transfers that live closer to one another appear to have better job search outcomes for the unemployed: unemployment durations are shorter and future wages are higher. This provides additional evidence of the potential value of monitoring. As states determine the optimal unemployment insurance program, they should take a closer look at the costs of more intensive monitoring as this can have positive benefits on job finding and reduced unemployment insurance fraud.

The results also have implications for determining optimal estate taxes. If the tradeoff for a parent is to decide whether to make inter vivos transfers today or

hold-off for a lump-sum bequest in the future, the taxing of estates will impact the amount of inter vivos transfers. If inter vivos transfers tend to be contingent on human capital investment, then there is a positive externality to society of these transfers. Further research is necessary to determine whether bequests are spent differently from inter vivos family transfers, but it is an interesting path for future research.

### *2.6.2 Future Work*

This paper presents results that add to the understanding of the role of the family and the nature of interactions between family members. There are a number of additional avenues of research spawned from these results. First, the location decision of the respondents deserves further consideration. While I treat the location relative to parents as an exogenous event, there is likely a a complex process driving this location decision. McElroy (1985) finds evidence of the joint determination of both market work and moving in and out of the household for young males. It would be interesting to examine whether unemployed individuals move to better local labor markets to increase their job opportunities. Likewise, examining the option of co-residence and how this explicitly relates to monitoring is another potentially rewarding research agenda.

Additionally, there are concerns with regards to measurement error in the family transfer data, which should be taken into account in future research. Using one specific wave of data from the PSID that focuses on transfers, Schoeni (2002) finds that nearly 30% of the unemployed report receiving family transfers. This number is significantly larger than what I find when I look across all years using the general question asked every year. Part of the explanation for the discrepancy is due to the detail of the transfer questions asked in the 1988 wave used by Schoeni. The 1988 survey asked a comprehensive series of transfer questions in addition to the typical

annual question about family transfers received. If more detailed questions induce more detailed answers, then we would expect the 1988 transfer questions to produce a higher proportion of respondents reporting receiving a transfer.

Additionally, the PSID annually asks respondents about the amount of money given towards support of family members outside of their household. Combining information on both giving and receiving transfers amongst the family can give a detailed picture of the flow of transfers within the family. This data has two specific issues. First, the questions about giving and receiving transfers use slightly different wording, and, thus, may make it difficult to do any sort of accounting exercise. Even if the respondents' responses are not subject to recall error, the measures may be capturing different concepts between giving and receiving transfers. The wording of the giving question asks about amount of support given to family members outside of household. The wording of the receiving questions asks about help received from family members outside of household. While these are clearly similar concepts, there is the potential for different interpretations. Second, the entire extended family is not followed by the PSID. Again, even with no recall error, there may be family members not interviewed that are the source or destination of transfers reported by current respondents. For example, if a PSID-gened respondent made transfers to the family of a spouse, then it will not be possible to match this transfer to a contemporaneous respondent because of the structure of the PSID described earlier in the paper. Despite these difficulties, combining a household's reported receiving of family transfers with responses from related households about giving transfers can still provide some important information. Finding a way to connect this information will be useful not only for studying the family but for research on networks where different nodes of respondents report separate accounts of the same event.

Another line of research is to consider other events that may induce the family to provide financial assistance. There are many reasons why existing safety nets

or available private insurance markets may be incomplete. The question arises of how family transfers differ depending on the context. Do they tend to fill in the gaps left by incomplete markets? For example, do families provide assistance in response to natural disasters? Home-owners insurance payouts can take a long time to be received, and if there is significant damage as a result of a natural disaster, the household may need more immediate assistance. This suggests value in financial assistance from family members even when the household has a valid formal insurance plan. Another example is that health insurance often has limited or no coverage of certain conditions. For individuals that need uncovered specialists, they may have to pay out-of-pocket a significant portion of the associated expenses. This is potentially another channel that the family can assist in filling in the gaps of formal insurance.

## 2.7 Tables

Table 2.1: Family Transfers in Response to Unemployment: IV-LIML

	<b>Dependent Variable: Received Transfers from Family</b>			
	<b>Amount</b>		<b>Binary; yes=1</b>	
	<b>(1)</b>	<b>(2)</b>	<b>(3)</b>	<b>(4)</b>
Weeks Unemployed by Head of Household	117** (51.0)	74.1 (64.0)	0.068*** (0.017)	0.070*** (0.026)
Mean of Dependent Variable	142	142	6.70%	6.70%
Non-Zero Mean of Dep. Var. (\$)	1628	1628	x	x
Cragg-Donald First Stage F-stat	7.2	5.6	7.2	5.6
Pvalue of Hansen's J-Stat test for Exogeneity	0.6065	0.27	0.58	0.34
Extended Family Fixed Effects?	N	Y	N	Y

Note: All standard errors are clustered at the Family level. Included household controls described in text.

Number of Weeks Unemployed for the head of household is instrumented with local labor market variables described in text.

First stage F-stats are both significant at the 10% criteria of Stock and Yogo

Percent of Heads of Household Experiencing Unemployment: 11.9%

Non-zero mean of weeks of Unemployment of head of household: 17 weeks

147807 individual-year observations; 5208 extended families

Table 2.2: Family Transfers in Response to Sibling's Unemployment: IV-LIML

	Dependent Variable: Received Transfers from Family			
	Amount		Binary- y/n	
	(1)	(2)	(3)	(4)
<b>Panel A. Only 1 Sibling</b>				
Weeks of Unemployment for Only Sibling of Head of Household	-58.6* (33.5)	-91.8* (49.0)	-0.0068 (0.0070)	-0.011 (0.011)
Mean of Dependent Variable	194	194	8.70%	8.70%
Non-Zero Mean of Dep. Var.	1630	1630	x	x
Cragg-Donald First Stage F-stat	8.3	4.9	8.3	4.9
Pvalue of Hansen's J-Stat test for Exogeneity	0.96	0.96	0.67	0.61
<b>Panel B. 2 or more Siblings</b>				
Weeks of Unemployment for <u>Youngest</u> Sibling of Head of Household	-12.4 (8.51)	-33.8** (15.0)	-0.0037 (0.0035)	-0.0091* (0.0048)
Weeks of Unemployment for <u>Oldest</u> Sibling of Head of Household	-30.7 (25.1)	-97.5 (137)	0.0082 (0.010)	0.021 (0.026)
Mean of Dependent Variable	113	113	6.30%	6.30%
Non-Zero Mean of Dep. Var.	1392	1392	x	x
Cragg-Donald First Stage F-stat	19.4	13.6	19.4	13.6
Pvalue of Hansen's J-Stat test for Exogeneity	0.54	0.48	0.26	0.33
Extended Family Fixed Effects?	N	Y	N	Y

Note: All standard errors are clustered at the Family level. Included household controls described in text.

Regressor of interest is the number of weeks of unemployment reported in the household interview of the sibling of the head of household. This is instrumented using local labor market variables specific to the sibling of the head of household.

First stage F-stats are all significant at the 10% criteria of Stock and Yogo

Percent of Heads of Household Experiencing Unemployment: 11.9%; Non-zero mean of weeks of Unemployment of head of household: 17 weeks

Panel A 24520 individual-year observations; Panel B 42870 individual-year observations; Panel A 1597 extended families; Panel B 1035 extended families

Table 2.3: Effect of Transfers on Education Expenditures: OLS

	Dependent Variable: Share of Education Expenditures of Total Expenditures	
	(1)	(2)
Did respondent receive transfer from family?	1.83*** (0.57)	1.08* (0.64)
Did respondent receive unemployment insurance?	-0.080 (0.30)	0.14 (0.38)
Mean of Dependent Variable:	2.51	2.51
Proportion of Households with Zero for Dep Var.	68%	68%
P-value for F-stat for if coefficients are equal	0.004***	0.2
Extended Family Fixed Effects?	N	Y

Note: All standard errors are clustered at the Family level. Included household controls described in text.

Proportion of Respondents Receiving Transfer from Family: 20.3%

Proportion of Respondents Receiving Unemployment Insurance: 26.7%

2326 individual-year observations; 920 extended families. Sample limited to only the Unemployed with valid wages in interviews before and after unemployment. Expenditures data only available since 1999.

Table 2.4: Effect of Transfers on Entering Training Program During Unemployment:  
OLS

	Dependent Variable: Did respondent enter a training program?	
	(1)	(2)
Did respondent receive transfer from family?	0.011** (0.0046)	0.010** (0.0050)
Did respondent receive unemployment insurance?	-0.0029 (0.0028)	0.00033 (0.0032)
Proportion of Unemployed Respondents entering training program:	0.013	0.013
P-value for F-stat for if coefficients are equal	.01***	.08*
Extended Family Fixed Effects?	N	Y

Note: All standard errors are clustered at the Family level. Included household controls described in text.

Proportion of Respondents Receiving Transfer from Family: 15.3%

Proportion of Respondents Receiving Unemployment Insurance: 29%

6241 individual-year observations; 885 extended families. Sample limited to only the Unemployed with valid wage observations prior to and after unemployment. Also, job training question is retrospective and only asked in 2009, so respondents are dropped if there is not a 2009 interview.

Table 2.5: Effect of Transfers on Labor Market Outcomes: IV-LIML

	<b>Dependent Variables: Labor Market Outcomes for the Unemployed</b>			
	<b>Log of Weeks Unemployed</b>		<b>Log of Average Post-Unemployment Wage</b>	
	<b>(1)</b>	<b>(2)</b>	<b>(3)</b>	<b>(4)</b>
Amount of Transfers Received from the Family (in \$1000 increments)	-0.2 (0.25)	-0.93 (1.1)	0.43* (0.25)	0.44 (0.5)
Mean of Dependent Variable	2.27	2.27	2.1	2.1
Cragg-Donaldson F-Stat from First Stage	3	1.65	3.02	1.66
Pvalue of Hansen's J-Stat test for Exogeneity	0.74	0.62	0.39	0.7
Extended Family Fixed Effects?	N	Y	N	Y

Note: All standard errors are clustered at the Extended Family level. Included household controls described in text.

Regressor of interest is the amount of transfers received from the family. This is instrumented using 1) local labor market variables of the parent and siblings and 2) income of the parent and siblings.

First stage F-stat for no fixed effects meets the 15% criteria of Stock & Yogo. First stage F-stats with fixed effects do not meet the 25% criteria of Stock & Yogo.

Non-zero mean of transfers received from family: 1322

6814 individual-year observations; 988 extended families. Sample limited to unemployed with wage observations prior to and after unemployment and have at least 1 sibling.

Table 2.6: Family's Ability to Monitor: IV-LIML

		<b>Dependent Variables: Labor Market Outcomes for the Unemployed</b>			
		<b>Log of Weeks Unemployed</b>	<b>Log of Average Post-Unemployment Wage</b>		
		<b>(1)</b>	<b>(2)</b>	<b>(3)</b>	<b>(4)</b>
Family Transfers Received (in \$1000 increments) when...	Live in same county as parent	-0.58*	-0.47	0.52*	0.54
		(0.33)	(0.77)	(0.32)	(0.49)
	Live in different county from parent	0.049	-0.19	0.35	0.17
		(0.24)	(0.41)	(0.24)	(0.24)
	P-value for F-stat for if coefficient for living in same county is equal to living in a different county	.05**	0.57	0.58	0.27
	Cragg-Donaldson F-Stat from First Stage	2.2	1.5	2.2	1.4
	Pvalue of Hansen's J-Stat test for Exogeneity	0.91	0.48	0.62	0.85
	Extended Family Fixed Effects?	N	Y	N	Y

Note: All standard errors are clustered at the Extended Family level. Included household controls described in text.

Regressor of interest is the amount of transfers received from the family. This is instrumented using 1) local labor market variables of the parent and siblings and 2) income of the parent and siblings.

First stage F-stat for no fixed effects meets the 15% criteria of Stock & Yogo. First stage F-stats with fixed effects do not meet the 25% criteria of Stock & Yogo.

Non-zero mean of transfers received from family: 1322

4957 individual-year observations; 838 extended families. Sample limited to unemployed with wage observations prior to and after unemployment and have at least 1 sibling and parent in the sample.

# Mitigating the Consequences of a Health Condition The Family in the PSID

## 3.1 Introduction

Changes<sup>1</sup> in health as an adult may have serious consequences for short and long-term economic outcomes. These combined impacts necessitate an established safety net for those individuals and families who are most affected. Previous literature has examined the extent that different channels of insurance are relied upon in the presence of shocks. However, while widely acknowledged as important, little is known empirically concerning the relationship between health deteriorations and within family responses. This is particularly true in developed country contexts. Using well-known models from the consumption smoothing and risk-sharing literature, we exploit longitudinal data from the Panel Study of Income Dynamics (PSID) to examine how individuals and families are exposed to health shocks and the mechanisms used to respond to poor health. The results emphasize the connectedness of families across generations while highlighting the exposure to health risk faced by families in

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<sup>1</sup> I would like to acknowledge that this paper is coauthored with Daniel LaFave at Colby College.

a developed setting.

The framework for this study is founded in models of family interaction and informal insurance (e.g. Cochrane (1991); Townsend (1994)), as well as empirical evidence highlighting the role of family transfers in informal networks. We go beyond past work to not only test the existence of risk-sharing and insurance, but to examine particular mechanisms including labor supply responses, informal transfers, and co-residing with family members. Moving beyond examinations of expenditures allows us to illustrate multiple channels families may use to provide informal insurance. Literature in developing settings has documented a relationship between health shocks and non co-resident family transfers (e.g. Fafchamps and Lund (2003); Genoni (2012)), while evidence from developed countries has also highlighted the important role of intergenerational and intrafamily exchange (e.g. Cox (2003); Hotz et al. (2010)).

Our work relies on unique features of the PSID and contributes to the literature in a number of ways. First, by exploiting the split-off following rule of the survey, this paper emphasizes the importance of both coresident and non-coresident family as a main channel of insurance in response to deteriorating health. Second, we combine health and transfer responses with rich labor outcome data to determine how health conditions affect economic outcomes of both the individual and their family. This allows us to examine the extent that family transfers respond directly to health conditions relative to labor market impacts. Third, we incorporate responses regarding health insurance to show how informal forms of insurance and the family help fill in gaps that formal health insurance may miss. Finally, by using the unique genealogical structure of the data, we determine which specific relationships in the family provide informal insurance against changes in health. We are also able to control for the extended family's health history to assess its impact on both the transmission of certain health conditions and a family's likelihood of different insurance responses.

Our results show that households and extended families are exposed to health risk and are unable to fully insure consumption or efficiently share the risk brought on by these shocks. This is true both for young and elderly respondents, as well as whether or not the respondent is employed. In the face of deteriorating health, we show that individuals reduce their labor supply and earn less in the labor market, and respond to these losses by drawing down assets. We then show that the family responds to these events by increasing labor supply, increasing transfers, and taking-in family members. The results paint a picture of partial insurance against health declines that is provided by family networks, findings particularly unique in the developed country setting.

The following section outlines a theoretical framework for studying consumption smoothing, risk allocation, and the responses of family members. We then discuss our empirical implementation and rich data before presenting results.

## 3.2 Theoretical Framework

The theoretical motivation behind this paper lies in models of insurance within households and informal networks. The development of both full insurance and risk sharing models are well known in the literature, including seminal work of Cochrane (1991), Townsend (1994), and Hayashi et al. (1996). We briefly discuss the two models we focus on - full insurance and efficient family risk sharing - below.

### *3.2.1 Full Insurance and Consumption Smoothing*

In models of full insurance, households are able to smooth away risk in order to maintain consumption. Working from a point of expected utility maximization, what matters for determining consumption in a given period  $t$  is only permanent household resources, independent of idiosyncratic fluctuations in income (e.g. Deaton (1992)). While households face a number of states with potential consumption realizations,

they have access to state contingent means of insurance to equate marginal utility across time. Income fluctuations or health shocks should have no effect on the realized change in consumption between periods.

While we begin with the model of full insurance as a starting point, we are particularly interested in examining how negative health events impact well-being along a number of dimensions. As a large literature has tested and rejected the full insurance model, we use it as a baseline for a more detailed analysis of household and family responses to negative shocks.<sup>2</sup> Rather than focusing only on changes in consumption, we look to examine both the extent that households are unable to insure against deteriorating health as well as the mechanisms that they may use to attempt to achieve partial insurance.

This analysis follows in line with literatures examining whether households are able to fully insure consumption against deteriorating health (e.g. Gertler and Gruber (2002)), and the formal and informal mechanisms used as insurance (e.g. Genoni (2012)). The majority of this literature comes from developing countries, where the analysis is framed in terms of missing markets for insurance and health care. Our results show that even households with health insurance in the U.S. are unable to fully insure against this risk.

### *3.2.2 Efficient Risk Sharing*

Another subset of work relaxes the prediction of full insurance that each household can completely insure themselves, and instead looks at insurance within groups. In models of static group risk sharing, there is an aggregate component of risk one's group or network is unable to insure against, but transfers smooth consumption

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<sup>2</sup> For rejections of tests of consumption growth being independent of fluctuations in income, see Cochrane (1991) and Hayashi et al. (1996) among other. The model has also been rejected in developing settings including Cote d'Ivoire (Deaton (1997)), India (Townsend (1994)), Ethiopia (Asfaw and Braun (2004)), Burkina Faso (Kazianga and Udry (2006)), and Thailand (Townsend (1995)).

within the group (e.g. Townsend (1994); Hayashi et al. (1996)). Each member of a group receives a pareto weight on their utility which ensures that the ratio of marginal utilities is constant regardless of the aggregate shock to the group.

Literature from developing contexts often considers the village as the insurance group (e.g. Townsend (1994)), or one's self-reported social network (e.g. Fafchamps and Lund, 2003). These papers often reject the model of efficient risk sharing, and cite a variety of frictions related to asymmetric information and limited commitment.<sup>3</sup>

We choose instead to focus on the genealogically linked family, as there are theoretical reasons why the family may be capable of sharing resources efficiently. In a series of influential papers, Chiappori and coauthors examine the sharing of resources within the household and fail to reject Pareto efficiency (e.g. Chiappori (1988); Chiappori (1992); Bourguignon et al. (1993)). If the family has superior ability to limit asymmetric information, or family members are agents interacting in a repeated game with no determined endpoint, then the extended family can be an efficient network for sharing risk and uncertainty. This is supported by recent work on kinship networks and risk reduction (Kinnan and Townsend (2012)), and extended families and child development (LaFave and Thomas (2013)), yet remains an open question on whether the family is an efficient unit (Coate et al. (2013)).

The subtle difference between the two models motivates an empirical strategy focusing on two different types of variation. We describe these models in the following section.

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<sup>3</sup> A subset of recent papers has highlighted the potential to refine tests of risk-sharing to incorporate heterogeneity in risk preferences, see Schechter and Yuskavage (2011) and Mazzocco and Saini (2012).

### 3.3 Empirical Framework

#### 3.3.1 Full Insurance

As outlined in the previous section, the starting point of our analysis is to examine the extent that deteriorations in health are reflected in consumption patterns. Our primary specification relates our outcomes of interest to health status while controlling for time varying controls and individual fixed effects:

$$Y_{ht} = \beta\theta_{ht} + \delta X_{ht} + \mu_h + \epsilon_{ht} \quad (3.1)$$

where  $Y_{ht}$  is the outcome of interest, beginning with non-health expenditure, for household head  $h$  in time  $t$ . Health status of the household head is measured by  $\theta$ , while time varying variables related to the individual and household are controlled in  $X$ . These include time fixed effects and a variety of demographic characteristics of the head of household, spouse of the head, other members of the household, and non-coresident family. We include polynomials on head and spouse's age and education, household income, household wealth, controls for head and spouse working status, polynomials for household size and composition, and a dummy for whether the head is covered by health insurance.

A primary concern with identification is that individuals that are more prone to experiencing a health condition are permanently different in other unobserved ways than others who may not experience health deteriorations. One example would be if poorer health is related to permanent income, which will affect consumption choices throughout life in a way that is separate from the actual health condition. One way to control for permanent characteristics is to incorporate the panel nature of the data and include individual level fixed effects,  $\mu_h$ , where the individual is the head of household  $h$ . This will control for cases where reporting severe limitations due to a health condition are correlated with permanent, unobserved characteristics of the

individual.

The parameter of interest,  $\beta$ , is then identified by examining how changes in health status are related to changes in our outcomes of interest. In tests of insurance, if households are fully insured, fluctuations in health status should have no relationship to non-medical expenditure, and  $\beta$  will be zero. We will also use the model to examine additional outcomes including the specific channels which families rely upon for insurance, and the responses of non-coresident family members to negative health events.

### *3.3.2 Efficient Risk Sharing within the Family*

As described in the theory section, we distinguish between full insurance of the household, where consumption does not respond to idiosyncratic health events, and efficient risk sharing with a family unit, where consumption may co-move with aggregate family expenditure, but is distributed consistently within the family unit. Even if we see evidence that extended families do share resources with one another, there are many potential reasons why households may fail to fully share risk. Issues of commitment or asymmetric information are two potential reasons why a family may fall short of fully insuring each other's idiosyncratic risks.

Using the PSID, we can test the efficient sharing of risk amongst genetically related households. The intuition behind the test is to control for aggregate resources of the network for the year, and determine whether the idiosyncratic shock specific to a member of the network affects their own consumption. While a health shock can impact both the consumption of the household and extended family, efficient sharing of risk implies that after accounting for the loss of consumption for everyone in the family due to the shock, individual shocks to household  $h$  should have no impact on household  $h$ 's consumption.

The empirical model for household head  $h$ , in family unit  $f$ , and wave  $t$  is the

following:

$$Y_{hft} = \beta\theta_{ht} + \delta X_{hft} + \psi_{ft} + \mu_h + \epsilon_{hft} \quad (3.2)$$

where family-year fixed effects,  $\psi_{ft}$ , are included on top of the controls in the previous model. This allows us to control for family wide consumption in a given year, and to examine the consumption response to a health shock relative to the consumption of other members of the family in the same year. By construction, time varying family fixed effects also control for time-constant characteristics shared across all family members capturing common, additive components of ability, permanent income, genetic background, and preferences.

Identification of  $\beta$  comes from comparisons in expenditure between family members in a given year while continuing to incorporate individual fixed effects specific to the head of household in order to focus on deviations from the average consumption of the household. In this case,  $\beta$  equals zero if the extended family shares risk efficiently.

### 3.4 Data

We use the 6 waves of interviews from 1999-2009 of the Panel Study of Income Dynamics (PSID). The PSID has many unique features including its genealogical construction and recent additions to the question series that make it a useful dataset for our study. Since beginning in 1968 with a nationally representative set of households, the PSID has used a unique following rule that continues to interview individuals from the original households even as they move out and form new households. The study also follows the offspring of any original 1968 PSID household members. This following rule continues with each subsequent generation, leading to a current day sample of approximately 8600 households composed of multiple generations within

numerous genetically linked families. In addition to contemporaneous interviews with multiple households within a family, the longitudinal nature of the PSID allows us to analyze changes in health reported by the same individual over time in order to control for fixed, unobserved individual heterogeneity.

We focus on the 1999-2009 waves of the survey that contain new detailed questions on health, consumption, and a consistent wealth module. Prior to 1999, the only consistent health question in the PSID is general self-reported health status.<sup>4</sup> This question has been found to have a number of issues related to measurement as well as correlation with observed characteristics that lead to concerns about correlations with unobserved characteristics (e.g. Strauss and Thomas (1998), Strauss and Thomas (2007)). In response to the need for a more robust measure of health, researchers developed health status questions anchored in objective events. In 1999, the PSID began including questions about 12 specific acute, chronic, and psychosocial health conditions including a question about the degree of limitation to daily physical activities due to each condition.<sup>5</sup> The respondent can report a lot, somewhat, a little, not at all, or never diagnosed in terms of how much the condition limits daily activities. The survey also began asking the now more common Activities of Daily Living (ADL) questions about whether or not the head of household faces limitations on specific regular activities. This newly available longitudinal health data allows for new contributions to the health and risk sharing literature in the developed country context.<sup>6</sup>

Another new feature of the PSID data is a more complete set of questions related

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<sup>4</sup> The question asks “Would you say your health in general is excellent, very good, good, fair, or poor?”

<sup>5</sup> The 12 conditions asked about are stroke, high blood pressure, diabetes, arthritis, asthma, lung disease, cancer, heart attack, heart disease, emotional distress, memory loss, and learning disabilities.

<sup>6</sup> The PSID health questions we use in this study have been shown to accurately reflect patterns of health in the National Health Interview Survey (Andreski et al. (2009))

to expenditures. Prior to 1999, the survey focused only on food expenditures with some additional consumption questions related to housing. The PSID currently asks a larger set of questions allowing one to separate housing, education, transportation, health and care in addition to the previously asked food questions. With this more complete consumption module, we can perform tests related to consumption smoothing that were either not possible or limited prior to 1999.

Another important feature for our study is that the PSID began asking the wealth module of questions each wave beginning in 1999. These questions allow us to incorporate measures of specific assets and debts in order to determine exactly what means are used to insure against deteriorating health. Combined with data on labor market outcomes and family transfers, we are able to illustrate a detailed picture of informal insurance within the family.

The summary statistics for some of the key variables are presented in Table 3.1. This table shows that there are differences on some observable characteristics between respondents and the degree of physical limitation that they report. Column 1 includes the full sample of individuals, while Columns 2 through 5 limit the sample to only those who have ever reported a health condition. Many of the differences are not surprising: respondents who report “A lot” of limitations are older, more likely to be retired, and slightly less educated. Since there are differences in observed characteristics, this emphasizes the need for an empirical strategy that deals with observed and unobserved differences between respondents. Our results presented below rely on changes across time for a given individual rather than comparisons across the groups in Table 1.

### 3.5 Results

We begin by testing whether households experience changes in consumption due to deteriorations in health status. This then motivates a closer examination of the

effects of deteriorating health, the mechanisms used to insure against this risk, and the role of both intrahousehold and intergenerational family behavior.

### *3.5.1 Do Households Smooth Consumption Against Health Risk?*

Table 3.2 presents the results from equation 3.1 with non-health consumption for a given household in a given year as the dependent variable. Recall that household-head fixed effects are included to focus only on variation within a person over time. We use two different measures of consumption in order to account for the effect that household size may have (Wagstaff (2007)): log of expenditures for all non-health consumption categories (food, housing, education, transportation, and care) and log of per capita expenditures for all non-health consumption categories. The per capita measure allows household size to directly affect the dependent variable.

The regressors of interest are the degree to which the head of household reports having limitations on normal daily activities due to any of the 12 specific conditions. Table 3.2 examines the relationship between each level of limitation and consumption. One issue with this strategy is the concern of non-separability between experiencing a health condition and utility. For instance, if experiencing a health condition leads to drops in consumption related to a change in the utility function, then we may see consumption fall for reasons that are not due to the inability to smooth utility over the event of a negative health condition. By looking across different levels of limitation, we are actually comparing all individuals who experience one of the 12 specific health conditions. If changes in consumption were due only to some sort of state dependence or non-separability, then it is likely that we should see consumption responses be consistent no matter the degree of limitation. However, if consumption smoothing is an integral part of the story, the degree of limitation will matter since more severe limitations can lead to larger bills of health expenditures and larger effects on labor supply. This begins to separate stories of insurance versus state

dependent preferences.

The results in Table 3.2 tell a number of stories. First, the degree of physical limitation does indeed matter for consumption. Using either measure of household consumption, or whether or not individual fixed effects are included, reporting “some-what” or “a lot” of physical limitations has a statistically significant negative effect on consumption. For example, relative to never having experienced any limitations, experiencing “a lot” is related to a 5.5% reduction in expenditures (Column 2). While all coefficients are negative, after accounting for individual fixed effects, having “no” or “little” current limitations due to a health condition does not have a significant impact on consumption. The magnitude of effects follow an intuitive pattern, with “a lot” of limitations being associated with larger reductions in consumption than only some limitations. While we cannot completely rule out non-separability between a health condition and preferences, by looking within the series of respondents’ interviews experiencing a health condition, these results do provide evidence that at least part of the story is about consumption smoothing being more difficult when experiencing a stronger health “shock”. Non-separability could still be an issue if preferences are determined by the degree of limitation, as opposed to only being a function of experiencing a health condition.

Also important to note is that the magnitude of coefficients do change after controlling for individual level fixed effects, leading to a larger than 50% decrease in magnitude for many of the coefficients. Furthermore, the coefficient on “a little” limitations loses its statistical (and economic) significance after controlling for fixed effects. These results suggest that individuals experiencing physical limitations may have permanently different consumption patterns that could bias our coefficient estimates. For this reason, we focus on models including individual fixed effects throughout the rest of the paper. We also focus on instances when individuals report “a lot”

of limitations.<sup>7</sup>

The next step is to better understand what might lead to difficulties insuring against health shocks. We start by examining some of the characteristics of the heads of household in order to see how health shocks may differentially affect subgroups of the sample. First, we split the sample into a group aged 50 or younger and a group 50 or older. The goal is to examine whether insurability of health shocks is only an issue at certain points in the life cycle. Since many health conditions are more likely to occur as one gets older, experiencing a change in health may be more anticipated for the older population. The younger group may have both temporary and permanent earnings negatively affected by a bad health shock, suggesting that it will be more difficult to insure against a health shock for the younger population. On the other hand, the younger group may be more adaptable and capable of dealing with an unforeseen health shock. Panel A of Table 3.3 examines these two groups. The results show that both age groups have consumption significantly impacted by experiencing a health shock, although the younger group has nearly twice as large of an effect.

It may be possible that this age distinction is simply picking up labor supply decisions. Table 3.2 provided suggestive evidence that non-separability of utility and health is not the sole explanation for the dip in expenditures; however, it may be the case of non-separability between labor supply and utility drive the results. If labor supply responds to health shocks, we may be picking up changes in consumption correlated with additional leisure. Panel B examines household heads that worked at all during the previous year compared to household heads that did not work. Interestingly, we see that both groups are significantly affected by the health shock. While the coefficients are statistically indistinguishable, the group that works is more

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<sup>7</sup> Continuing to distinguish between “a lot” and “some” limitations reveals results qualitatively similar to those presented here.

affected by the health shock. The results in Panel B suggest that while health shocks may affect labor supply decisions, health shocks impact even those individuals who are not working.

While rejecting consumption smoothing in and of itself is not particularly novel, we are able to go further than past work and exploit the richness of the PSID to examine the responses to deteriorating health on a number of dimensions. Some reasons we may see non-health consumption drop in response to a health shock is that preferences may change, health expenditures can increase to deal with the health condition, or labor supply may decrease. While Table 3.2 and Table 3.3 provided evidence that preferences are not the only story at play, we look to examine the other two explanations in Table 3.4. In Column 1 of Table 3.4 we see that health expenditures increase by 530 dollars more than average when experiencing a severe physical limitation due to a health condition, with the coefficient significantly different from zero at the 1% level. Also matching with expectations, we see that the head of household reports working approximately 150 fewer hours than average over the year when experiencing severe physical limitations. Relatedly, the head of household earns about \$1500 less in labor income over the year. All of these results provide further evidence that experiencing physical limitations can have a serious impact for an individual and household if not insured properly.

We now shift our focus to examining the way individuals, households, and families may respond to a member experiencing a negative health shock. Panel A of Table 3.5 examines the effect of severe physical limitations on wealth and the likelihood of entering a nursing home. Experiencing severe physical limitations has a very large and statistically significant effect on total wealth of the household. Since wealth also includes total debt obligations of the members of the household, this is likely evidence that respondents who experience these health conditions are turning towards credit or debt in order to deal with the costs associated with major medical bills. This

is consistent with results in developing settings showing depletions of more liquid assets in the face of negative shocks (Frankenberg et al. (2003), Fafchamps and Lund (2003)).

Column 2 shows that a respondent is approximately 2 percentage points more likely to enter a nursing home when having many physical limitations. This is a near doubling of the probability given the mean of 2.2%. On top of potential major medical bills, the respondent may also face new expenses related to assisted living services, which may not be captured in the questions asking about health related expenditures. This is another reason why we may see the respondent's spending down wealth where we see a more modest increase in annual health expenditures.

Panel B further explores the detailed wealth module to examine specific components of wealth. We look at reports from the respondent about the household's money in savings and checking accounts, the amount of debt outside of mortgages, amount in stocks, amount in a retirement account, value of automobiles, and home equity. The results show severe physical limitations have a significant positive impact on debt, and negative impacts on auto value and home equity. These results suggest that some of the ways that people deal with the costs of health conditions is to take on additional home equity debt and to reduce their durable assets. The respondents may be selling off automobiles and either selling off homes or taking additional mortgages on the equity of a home in dealing with a decline in health.

### *3.5.2 What role does the Family Play?*

Having established significant impacts of deteriorating health to the individual and their household, Table 3.6 examines how an individual may rely on their family both within and outside of the household to smooth consumption and utility using equation 3.2. Column 1 shows how the spouse's labor supply increases by approximately 40 hours in the face of partner's health deteriorating. Recall from Table 3.4 that

respondents decreased their own labor supply by about 150 hours in response to a health shock. These results suggest that while the spouse does change labor patterns, only a little more than 25% of the hours lost due to a health condition of the respondent are made up.

Another potential informal insurance mechanism is transfers from non-coresident family members. Column 2 shows the respondent is 4 percentage points more likely than average to receive a transfer from a family member outside of the household upon experiencing severe physical limitations. The value of the received transfers also increases as shown in Column 3. Monetary transfers between households has been studied in a variety of contexts, but this result provides new evidence supporting the idea that transfers are used as a form of informal insurance against negative events. In particular, the family seems to be the source of these transfers.

A different form of insurance from the family can be the option to co-reside. The next column looks at the likelihood that the respondent will move into the household with a family member also interviewed by the PSID. The result suggests that the respondent is about 1 percentage point more likely than average to share residence with a family member after experiencing severe physical limitations. This is about half as large as the effect on entering a nursing or assisted living home (Table 3.5, Column 2). However, this is also statistically significant and large relative to the baseline mean, which suggests this is another way that individuals can cope with a health shock. Moving in with a family member can help in a variety of ways. First, co-residing makes it possible for the family to look after and provide assistance to the respondent with deteriorating health. Second, co-residing can help share costs and reduce some of the financial burden brought on by the health shock. Furthermore, in the context of unemployment, other papers have found the phenomenon of moving back in with parents to be one form of insurance for young adult experiencing unemployment (McElroy (1985); Kaplan (2012)). These results provide new evidence

in a different way in which adult family members may choose to co-reside. Hotz et al. (2010) examine the location decision for parents later in the life cycle, and the results in this paper add to the findings in that research.

### *3.5.3 Do Families Efficiently Share Risk?*

Since there is evidence of non-co-resident, genetically linked households sharing resources, it is a reasonable question to ask whether households that are genetically linked are capable of sharing risk in an efficient manner. As outlined in Section 3, the test of risk sharing examines whether idiosyncratic health shocks to an individual within a family unit impact consumption after controlling for aggregate family resources in that period. If families share risk efficiently, only the aggregate resources will matter.

The results for the test of full risk sharing within the family from equation (2) with both family-year and individual fixed effects appear in Table 3.7. For both measures of consumption, we find evidence that the family does not fully share the risk of declines in health. Since the health decline specific to the head of household is related to approximately a statistically significant 3.5% reduction on household consumption after controlling for family resources, this is evidence that risk is not efficiently shared amongst genetically related family members. Despite the evidence from Table 3.6 on the smoothing responses of non-coresident family through transfers, we still see that families are not able to fully smooth away risk.

The previous specification treats the entire extended family interviewed in the PSID as the primary risk sharing network. However, it may be the case that risk sharing occurs at a more contained level between closely related individuals. For instance, Genicot and Ray (2003) provide evidence that endogenous networks may have bounded size in equilibrium in the case of non-cooperative risk-sharing. Even without bounds on the size of a network, households may only want be connected to

one another when a sharing arrangement is reasonably enforceable. A bond with a parent is likely to be stronger than the bond with distant cousins. A stronger bond may imply reduced asymmetric information and better commitment devices. For this reason, it is an interesting exercise to explore whether a tighter, more contained network may do a better job at sharing risk. This is left for ongoing work.

#### *3.5.4 Comparing Channels of Informal Insurance*

Having established that families are not able to fully insure against risk but do respond to negative health events of their members with partial insurance, the final table examines which of the potential insurance methods does the best at smoothing non-health expenditures in response to a negative health event. In a parsimonious model, we examine how having health insurance, moving in with a family member in the PSID, drawing down wealth assets, receiving a financial transfer from a family member, or having a spouse that works each counter negative effects of health deterioration. The variables of interest are the interactions between each of these possible insurance channels with a dummy for having severe physical limitations. The goal is to see how well each type of insurance mitigates the drop in consumption related to experiencing a negative health event. The models continue to incorporate individual level fixed effects as in equation (1).

Columns 1 and 2 of Table 3.8 present these results. Having a spouse working and moving in with a family member have the largest positive impacts on consumption when faced with a negative health shock. Moving in with a family member comes closest to fully mitigating the consumption loss associated with experiencing the health event. In fact, moving in with a family member actually more than balances the effect of severe limitations for log of per capita expenditures ( $-0.14 + 0.15$  in Column 2). Part of the reason moving in with family may do a good job at smoothing consumption is related to the result in Column 3, where health expenditures is the

dependent variable. Moving in with a family member has a very large and significant negative impact on health expenditures, suggesting that this can reduce some of the costs associated with going to hospitals or receiving treatment. If a family member can provide care for an individual who has severe physical limitations, there is potentially less necessity for a longer hospital stay or other medical services. Having this means of informal insurance seems to be an important element for individuals coping with severe physical limitations.

### 3.6 Robustness and Future Work

There are several potential robustness checks that can strengthen our results. First, along with the health limitations questions used throughout, the PSID also asks a series of questions similar to the typical ADL (Activities of Daily Living) battery. The questions ask about very specific daily activities - dressing oneself, getting in or out of a chair, eating, walking, bathing, getting outside, and using the toilet - and whether these activities cause problems for the head of household. While these questions ask about similar concepts to the physical limitations questions used in the previous results, the ADL questions are not tied to any specific health condition. Additionally, the ADL questions are used in a variety of data sets, with claims that ADLs are a reliable measure of physical functioning that help to distinguish serious health problems. For this reason, it will be a good check that the results are consistent using this different measure for physical limitations.

Second, since many of the outcomes we are looking at either are binary (whether or not household received transfer from the family, whether they moved in with a family member, etc.) or have clustering at zero for continuous variables (health expenditures, hours worked), it makes sense to apply a limited dependent variable model to check if the results hold under alternative specifications. While a limited dependent variable model has some benefits over a basic linear model, there are also

some strong additional assumptions necessary for the models to be valid. However, if the results presented thus far are robust and valid, we would expect to see similar estimates using a logit or tobit model.

Third, a primary concern with our identification strategy would be if the changes in physical limitations we measure were endogenously expected events, where the individual could mitigate the effects of the change beforehand. While this would bias our results towards the null which we clearly reject, the possibility still deserves consideration. One way to focus on more unanticipated health shocks is to look for large jumps in physical limitation status from one interview to the next i.e. restricting our identification to be from transitions from no limitations to a lot. Large jumps may better represent an unanticipated change in health status. Another way to isolate unanticipated changes is to use demographic and consumption decisions at  $t - 1$  to predict health status at wave  $t$ . We then can use the unexplained error term as the unanticipated portion of their health status. The panel dimension of the survey can also be exploited to test whether health in  $t + 1$  effects consumption in wave  $t$ .

Lastly, due to the PSID's sample design, we can use the health information from interviews with family members of the respondent. Since many health conditions have some genetic component, this information is likely a strong predictor for the respondent's health. For instance, if the parents of a respondent have a history of high blood pressure or experience a negative health event themselves, we can use that information as a predictor for whether the respondent has severe physical limitations due to high blood pressure. For the same reasons that physicians rely on family health history, this same information can be used as part of a first stage estimation.

The concern about this strategy is the exogeneity of using family health history as a predictor for personal health; individuals may undertake mitigating behaviors such as taking medication, altering diet, or exercise regimes knowing their own health

history. Health conditions are also not only a function of genetic inheritance, but a complex series of interactions between genetic influences and environmental factors. While asthma can be inherited, perhaps the reason we see both a parent and child experience asthma is due to their location choice where there is significant amount of smog or pollution. These risk factors for health conditions are extremely difficult to parse out as the medical literature has shown. However, it is an interesting starting point and unique application of family health history data as instruments for current health conditions. We will use this estimation strategy as a robustness check for the results we have reported thus far.

Lastly, we also need to take into the account the potential for mortality playing a role in the results. If people without adequate support are more likely to die in response to a negative shock in health, then we may have population estimates that are upward biased. One issue is that the PSID does not report a respondent having passed away in the public use data. We can further examine how health conditions may lead one to attrit from the sample. This is left for future work.

### 3.7 Conclusion

This paper contributes new results to a variety of literatures relating health outcomes, labor market experiences, formal and informal insurance, and family economics. The results are informative for understanding patterns of resource allocation within families, as well as how informal networks operate during adverse events. We present results on how specific health conditions affect labor market outcomes, and shed light on the interplay between formal health insurance and the family's informal transfers.

Our results suggest that households are unable to fully insure against deteriorating health, but undertake a number of partial insurance mechanism in the face of health shocks. These include compensating labor supply changes from family members, monetary transfers, and residency decisions. Yet despite this evidence,

genetically linked families do not efficiently share risk within their networks.

These results offer a number of possible avenues for further examination, and highlight the importance of family networks in a developed country context.

### 3.8 Tables

Table 3.1: Summary Statistics

	<b>Mean of Variables of Interest by Reported Physical Limitation Due to Health Condition</b>				
	<b>Full Sample</b>	<b>Respondents with Health Condition</b>			
		<b>No Current Limitation</b>	<b>Little Limitation</b>	<b>Somewhat Limited</b>	<b>A lot of Limitation</b>
	<b>(1)</b>	<b>(2)</b>	<b>(3)</b>	<b>(4)</b>	<b>(5)</b>
Age	45.71	51.88	53.75	56.98	60.58
Years of Education	13.10	13.09	12.47	12.09	11.51
Married (%)	56.80	55.74	46.33	44.59	36.25
Household Size	2.75	2.58	2.48	2.41	2.31
Male (%)	46.53	46.02	40.84	38.59	40.47
Retired (%)	13.05	20.81	25.46	31.59	35.33
Non-Health Expenditures	28864	29180	24786	22270	17644
Health Expenditures	2401	2866	2889	2773	3272
Received Transfer from Family (%)	9.14	8.37	9.95	9.77	11.72
Value of Family Transfer Received (Non-Zero Average)	2402	2574	2314	2139	2300
Number of Individual-Year Observations	37308	13232	5769	4340	3054

Table 3.2: Changes in Consumption in Response to Physical Limitations Due to Health Condition

Degree of Limitation on Household Head's Daily Physical Activities due to Health Condition:	<i>Dependent Variable: Log of Household [...]</i>			
	<b>Non-Health Expenditures</b>		<b>Per Capita Non-Health Expenditures</b>	
	<b>(1)</b>	<b>(2)</b>	<b>(3)</b>	<b>(4)</b>
A lot	-0.10*** (0.016)	-0.055*** (0.015)	-0.10*** (0.016)	-0.050*** (0.016)
Somewhat	-0.058*** (0.012)	-0.023** (0.011)	-0.052*** (0.012)	-0.022** (0.011)
Little	-0.030*** (0.010)	0.0032 (0.0087)	-0.029*** (0.010)	-0.00080 (0.0086)
No Current Limitations	0.011 (0.0084)	-0.0036 (0.0069)	0.011 (0.0084)	-0.0034 (0.0070)
Never Any Limitations	-	-	-	-
Mean of Dependent Variable	10.00	10.00	9.14	9.14
Individual Fixed Effects	N	Y	N	Y

Note: All standard errors are clustered at the Family level. Included controls described in text.

37308 individual-year observations; 8212 extended families

\*\*\* p<0.01, \*\* p<0.05, \* p<0.1

Table 3.3: Heterogeneity in Consumption Response to Physical Limitation

		<i>Dependent Variable: Log of Household [...]</i>	
		<b>Non-Health Expenditures</b>	<b>Per Capita Non-Health Expenditures</b>
		<b>(1)</b>	<b>(2)</b>
<b>Panel A</b>			
"A lot" of physical limitation for household head interacted with..	Household head Younger than 50	-0.079*** (0.026)	-0.077*** (0.026)
	Household head Older than 50	-0.037** (0.018)	-0.030* (0.018)
<b>Panel B</b>			
"A lot" of physical limitation for household head interacted with..	Household head Works	-0.055** (0.023)	-0.053** (0.023)
	Household head Does not Work	-0.050*** (0.019)	-0.043** (0.019)
	Mean of Dep. Var.	10.00	9.14
	Individual Fixed Effects	Y	Y

Note: All standard errors are clustered at the Family level. Included controls described in text.  
 37308 individual-year observations; 8212 extended families  
 \*\*\* p<0.01, \*\* p<0.05, \* p<0.1

Table 3.4: Difficulties from Physical Limitations

	<i>Dependent Variable:</i>		
	<b>Household Head's [...]</b>		
	<b>Health Expenditure</b>	<b>Labor Income</b>	<b>Hours Worked Past Year</b>
	<b>(1)</b>	<b>(2)</b>	<b>(3)</b>
"A lot" of limitations for household head	530*** (179)	-1,529*** (542)	-145*** (17.2)
Mean of Dep. Var.	2400	28667	1484
Individual Fixed Effects	Y	Y	Y

Note: Standard errors are clustered at the Family level. Included controls described in text.

37308 individual-year observations; 8212 extended families

\*\*\* p<0.01, \*\* p<0.05, \* p<0.1

Table 3.5: Responses for Dealing with Physical Limitations

**Panel A**

	Household Wealth (1)	Live in Nursing Home (2)
"A lot" of limitations for household head	-62,041*** (21,735)	0.018*** (0.0059)
Mean of Dep Var. Individual FE	242404 Y	0.022 Y

**Panel B - Specific Household Assets**

	<i>Dependent Variable - Value of [...]</i>					
	Savings (1)	Debt (2)	Stocks (3)	Automobiles (4)	IRAs (5)	Home Equity (6)
"A lot" of limitations for household head	-3,492 (2,493)	1,179* (708)	-1,442 (11,422)	-697** (328)	1,186 (1,878)	-11,750*** (1,982)
Mean of Dep Var. Individual FE	18847 Y	8447 Y	35859 Y	13132 Y	26947 Y	68528 Y

Note: All standard errors are clustered at the Family level. Included controls described in text.  
37308 individual-year observations; 8212 extended families

\*\*\* p<0.01, \*\* p<0.05, \* p<0.1

Table 3.6: The Family as Insurance Against Physical Limitations

	<i>Dependent Variable</i>			
	<b>Hours Worked by Spouse of Head for the Year</b>	<b>Y/N Did Head Receive Transfer from Family?</b>	<b>Amount of Transfer Received from Family</b>	<b>Y/N Did Respondent Move into House with a Family Member?</b>
	<b>(1)</b>	<b>(2)</b>	<b>(3)</b>	<b>(4)</b>
"A lot" of limitations for household head	42.7*** (12.1)	0.040*** (0.0082)	102** (47.9)	0.0092** (0.0045)
Mean of Dep. Var. Individual Fixed Effects	878 Y	0.091 Y	220 Y	0.037 Y

Note: All standard errors are clustered at the Family level. Included household controls described in text.

37308 individual-year observations; 8212 extended families

\*\*\* p<0.01, \*\* p<0.05, \* p<0.1

Table 3.7: Does the Family Fully Share Risk?

<i>Dependent Variable: Log of Household [...]</i>		
	<b>Non-Health Expenditures</b>	<b>Per Capita Non-Health Expenditures</b>
	<b>(1)</b>	<b>(2)</b>
"A lot" of limitations for household head	-0.033* (0.018)	-0.036** (0.018)
Individual Fixed Effects?	Y	Y
Family-Year Fixed Effects?	Y	Y

Note: All standard errors are clustered at the Family level. Included controls described in text.

37308 individual-year observations; 8212 extended families

\*\*\* p<0.01, \*\* p<0.05, \* p<0.1

Table 3.8: Comparison of Insurance Channels in Smoothing Consumption

<i>Dependent Variable: Annual Household [...]</i>			
	<b>Log Expenditure</b>	<b>Log Per Capita Expenditures</b>	<b>Health Expenditures</b>
	<b>(1)</b>	<b>(2)</b>	<b>(3)</b>
Dummy for "A lot" of physical limitation for head of household	-0.13*** (0.048)	-0.14*** (0.050)	453* (272)
<i>I(Spouse of Head Works)</i>			
Interaction with Physical Limitation	0.080*** (0.027)	0.074*** (0.027)	-176 (271)
Main Effect	-0.022 (0.018)	-0.032* (0.018)	-111 (131)
<i>I(Received Transfer from Family)</i>			
Interaction with Physical Limitation	-0.023 (0.043)	-0.027 (0.044)	-144 (352)
Main Effect	-0.032** (0.014)	-0.036** (0.014)	-118 (73.7)
<i>I(Wealth Drawn Down from Previous Year)</i>			
Interaction with Physical Limitation	-0.016 (0.020)	-0.017 (0.021)	-128 (290)
Main Effect	-0.013*** (0.0051)	-0.016*** (0.0051)	-1.06 (41.5)
<i>I(Moved in with Family)</i>			
Interaction with Physical Limitation	0.11** (0.051)	0.15*** (0.050)	-1,222*** (364)
Main Effect	-0.024 (0.024)	-0.060** (0.023)	14.9 (289)
<i>I(Have Health Insurance)</i>			
Interaction with Physical Limitation	0.066 (0.049)	0.075 (0.051)	318 (280)
Main Effect	0.027** (0.012)	0.026** (0.012)	528*** (67.5)
Individual/Household Fixed Effects?	Y	Y	Y

Note: All standard errors are clustered at the Family level. Included household controls described in text.

37308 individual-year observations; 8212 extended families

\*\*\* p<0.01, \*\* p<0.05, \* p<0.1

## Family Transfers in Response to Hurricanes

### 4.1 Introduction

Hurricanes have the potential to cause widespread, catastrophic damage that can affect personal property, housing markets, and labor markets. For example, the National Hurricane Center gives a preliminary estimate of \$50 billion dollars of damage caused by Hurricane Sandy in the United States in 2012.<sup>1</sup> With the potential for such devastation, it is important to understand what means people rely upon in order to deal with hurricanes and, more generally, natural disasters.

Homeowners' insurance is one way that people can protect themselves against property damage resulting from a hurricane. However, even with formal institutions like homeowners' insurance, there may still be considerable gaps in the overall protection offered by these programs in insuring individuals against catastrophic damage. First, insurance companies may deny claims for a variety of reasons. Particularly in the case of a catastrophic disaster with billions of dollars in insurance claims, insurance companies may not actually be capable of meeting all of the claims. The

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<sup>1</sup> [http://www.nhc.noaa.gov/data/tcr/AL182012\\_Sandy.pdf](http://www.nhc.noaa.gov/data/tcr/AL182012_Sandy.pdf)

results are numerous stories of insurance companies delaying claims payments, only paying out a fraction of the claimed losses, or outright denying claims.<sup>2</sup>

Second, insurance claimants may not have the proper insurance in dealing with a hurricane. This can be due to either misunderstanding of their own insurance policy, or an active choice not to get coverage necessary for dealing with hurricanes. Flood insurance is often the most relevant coverage for dealing with hurricanes. Despite federal regulations requiring flood insurance, many homeowners elect to not purchase flood insurance. Prior to Hurricane Katrina in 2005, it was estimated that about 30% of homes in Louisiana were protected by flood insurance (King (2005)).

Third, hurricane related risks can affect individuals in a multitude of ways beyond property damage. Homeowners' insurance does not protect against changes in labor market conditions resulting from the aftermath of a major disaster. Labor demand can decrease, resulting in reduced hours worked and labor income for people in certain employment sectors (Vigdor (2008), Belasen and Polachek (2009)). Other hurricane related risks include deterioration of health that may have long term impacts (Currie and Rossin-Slater (2013)). Given the wide array of impacts that a catastrophic hurricane can have, it may not be surprising if formal institutions do not fully insure all of the associated risks.

Individuals may turn towards more informal channels in order to further insure themselves against the negative shock of a hurricane. Fafchamps and Lund (2003) find that monetary assistance from the family is one way that people experiencing a shock insure themselves in developing countries. This phenomenon is not limited to just developing countries. Intrafamily transfers are a documented occurrence in the United States, too (Cox and Fafchamps (2007), Hotz et al. (2010)). The family has been shown to assist in contexts other than natural disasters, such as unemployment and negative health changes (Dalton (2013), Dalton and LaFave (2013)). Since the

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<sup>2</sup> <http://www.nytimes.com/2007/09/02/business/worldbusiness/02iht-orleans.4.7353442.html>

family may have superior knowledge of each other's circumstances and behaviors, the reduced asymmetric information may make the family an efficient risk sharing network. Repeated interactions over time and altruistic preferences may also induce more risk sharing between family members than other non-related individuals.

Aside from dealing with financial concerns related to property damage, lost income, or health issues, family transfers may actually make it possible for people to evacuate an area, which helps reduce loss of life and bodily harm. Blendon et al. (2007) surveyed a group of individuals in hurricane prone areas after Hurricane Katrina and found that 23% did not evacuate because they could not afford to leave and 18% did not evacuate because they had no family outside the area with whom they could stay. This brings another potential avenue that family can assist. There is evidence that temporary co-residence with family members occurs in response to spells of unemployment (McElroy (1985), Kaplan (2012)), and that co-residence may also occur as parents age and face health issues (Hotz et al. (2010)). Additionally, Frankenberg et al. (2003) find evidence that households combine after a financial shock. On a short or long-term basis, the ability to move in with a family member could be another important way that people deal with difficulties surrounding a hurricane. The decision of evacuees to return home is an important topic for understanding how the demographics of an area may change after a major disaster (Groen and Polivka (2008b), Groen and Polivka (2010)). By examining the option to move in with family and how this affects the evacuation decision and the decision to return, policymakers can better target individuals who may be at risk for staying instead of evacuating, and we will have a better understanding of how an area returns to a new equilibrium post-disaster.

The goal of this paper is to examine the ways people and households may respond to experiencing a hurricane. I focus on two specific ways that the non-co-resident family may provide help: monetary transfers and the ability to move in with a

family member. I find modest evidence using the Panel Study of Income Dynamics (PSID) that respondents do receive more financial assistance from family members after a hurricane, and I also find evidence that after a parent experiences a hurricane, they are more likely to live with their kids a year after the hurricane. Lastly, I use the PSID to examine some hypotheses from both the hurricanes literature and the family interactions literature that have not been examined with micro-level data in this context before.

## 4.2 Framework

Hurricanes have an unpredictability that can potentially be exploited as part of an identification strategy for understanding ex post responses to experiencing a hurricane. There are three key elements of hurricanes that can make them a good exogenous shock: the location of a hurricane, the timing of a hurricane, and the intensity.

### *4.2.1 What Are Hurricanes?*

A hurricane is a specific type of tropical cyclone that forms in the Northern Atlantic Ocean and has sustained winds of at least 119 kilometers per hour. A hurricane is characterized by having very high wind speeds and low pressure. This can be a very dangerous combination because a low pressure will displace water onto shore as the hurricane makes landfall and the wind will push the water further inland. This phenomenon is known as the “storm surge”. Between powerful winds, large amounts of rain, tornadoes, and the storm surge creating massive flooding, there are many ways that a hurricane can impact an individual, community, or country.

By the nature of a hurricane originating in the Atlantic Ocean, coastal communities from as far southwest as Texas and as far northeast as Maine are at highest risk for catastrophic damages resulting from being in the path of a hurricane. Hurricanes

can take a radius of a couple hundred of kilometers, making the storm system potentially very large. However, the most significant damage typically occurs around the eye, or center of the storm. The eye has the highest winds and heaviest rains. The eye is typically about 100 kilometers in radius. Next, I argue that there is exogeneity on three different dimensions with respect to hurricanes.

#### *4.2.2 Predictability of Hurricanes*

Previous research uses hurricanes as a natural experiment in a variety of contexts.<sup>3</sup> Hurricanes have the potential as a valid negative shock, or “disaster treatment”, because of the difficulty in predicting both the path and timing. A month or longer in advance, hurricanes are essentially impossible to predict.<sup>4</sup> In the shorter term, once a hurricane forms, it is still extremely difficult to predict the path of a hurricane. Hurricanes often are only in existence for a week or two before they make any landfall, and the actual predictive powers of where and when the hurricane will hit face significant forecasting errors.<sup>5</sup> The National Hurricane Center says that 50% of predictions made 120 hours in advance miss the realized path of the hurricane by 200 or more miles. At 24 hours beforehand, predictions are off by 50 or more miles 50% of the time. For predictions made 12 hours in advance, 50% of the hurricane path predictions are off by 30 or more miles.

Even with the notable forecasting error, there is some information to be gleaned from a warning about a forthcoming storm. Is this short term warning enough to undermine the hurricane as a natural experiment? It depends upon what is being

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<sup>3</sup> (Currie and Rossin-Slater (2013), Strobl (2011), Skidmore and Toya (2002), Sastry and Gregory (2013), Noy (2009), Murphy and Strobl (2009), Hallstrom and Smith (2005), Crespo Cuaresma et al. (2008), Belasen and Polachek (2009))

<sup>4</sup> In 2011, hurricane forecast experts William Gray and Phil Klotzbach ended their annual December prediction for the forthcoming hurricane season. They cited lack of predictive value in these predictions.

<sup>5</sup> <http://www.nhc.noaa.gov/verification/verify4.shtml>

studied. For example, one of the reasons hurricanes have minimal fatalities despite often hitting populous coastal areas is because the National Weather Service has typically done an excellent job of issuing evacuation warnings to prepare people who may be in the path of the storm.<sup>6</sup> If the goal is to study mortality resulting from a hurricane, then forecasting may lead to a bias towards zero. For studies that examine natural disasters and mortality, they must use disasters that are completely unanticipated (Frankenberg et al. (2011)). In the context of studying the insuring of financial losses, hurricanes work well as a natural experiment. There is little one can do in terms of limiting financial losses with only three or four days of warning before a hurricane is likely to make an impact. Common actions include boarding windows to reduce glass shattering, and placing sandbags at the doorsteps to impede water flooding into the building. While these actions reduce some damage, it is unlikely to have significant impact on averting major losses.

As part of my identification strategy, I rely upon three different sources of variation related to hurricanes: location, timing, and intensity.

### *Location*

As noted above, the path of a hurricane is difficult to predict even hours in advance. For this reason, one locality could be hit by hurricane, but a nearby locality could have just as easily been hit by the same hurricane, and each locality presumably had the same amount of preparation time. For my primary results, I will make comparisons between areas that were within a certain radius of the eye of the hurricane and areas that were in a slightly larger radius around the eye of the hurricane as a control group.

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<sup>6</sup> Notable recent exceptions are Hurricane Katrina and, to a lesser extent, Hurricane Sandy.

### *Timing*

Similar to the location being difficult to predict, the timing of when to expect a hurricane is even more unpredictable, particularly from a long-term perspective. When the calendar turns to June and the official hurricane season begins, no person, household, business, or community has any idea about whether a hurricane will impact their lives. In that sense, a valid control group for a set of households affected by a hurricane in year  $t$  is the group of households living in that same location in year  $t - 1$  because from their ex ante perspective, the hurricane was just as likely in either year.

### *Intensity*

The intensity with which a hurricane hits a locality is also unpredictable. In the sense that the intensity of a hurricane can be quantified according to measurable characteristics, I can use these measures to test whether more intense hurricanes have a larger impact on the dependent variables of interest.

## 4.3 Data

### *4.3.1 Panel Study of Income Dynamics*

My primary data source is the Panel Study of Income Dynamics (PSID), where my base sample is every annual interview from 1985-1996 and the biennial interviews from 1997-2009. The PSID began in 1968 with a nationally representative set of households, and followed every individual in those households even if they moved out and formed separate households. Additionally, the PSID has a following rule such that they interview any offspring of a PSID respondent. This following rule replenishes the sample over time, and results in numerous contemporaneous interviews within an extended family in any given year. Having contemporaneous interviews with family members helps me identify household composition if the PSID respon-

dents move back in with each other, and it allows me to control for the experiences of family members when they live in separate households.

In addition to the genetic sampling structure, I use a number of the other unique features of the PSID. First, the panel nature of the data allows me to control for time invariant, individual heterogeneity of respondents by controlling for multiple interviews per respondent. I can use this information to see how the dependent variables change over time for a particular respondent. Second, the PSID collects information about monetary transfers received from the family over the course of the previous calendar year. I will use this information as one of my primary dependent variables of interest. Lastly, I also have access to confidential geographic information for each respondent. This allows me to identify their location of residence at the Census tract level. I will use this information to match with hurricane data so that I can assess to what extent any particular respondent may have been affected by a hurricane in any given year.

#### *4.3.2 Hurricane Data*

In order to determine whether a hurricane may have affected an individual respondent in the PSID, I need to have finely detailed location information for many hurricanes over the time for which I have interviews. The National Oceanic Atmospheric Administration (NOAA) provides reports for the longitude, latitude coordinates of the eye of every hurricane, every 6 hours. In addition to the location information, the NOAA also provides measures of maximum recorded wind speed at that time and minimum barometric pressure at the eye of the storm. I can incorporate these measures so that each hurricane has a varying treatment effect based upon exogenous, observable measures. Many papers relying upon hurricanes as an instrument often treat each hurricane as a homogenous treatment. Combining the measurements of wind speed with geographic distance from the eye allows me to get heterogeneous

treatments within a single storm system.

In order to match the hurricane data with the PSID, I determine the longitude and latitude coordinates for each Census tract by the overall population density centroid from the 2000 Census. From this, I can calculate the distance from the coordinates for each 6 hour hurricane observation to every Census tract in the United States.<sup>7</sup> Matching this with the PSID data gives the maximum hurricane wind speed faced by each respondent over the calendar year, and the distance each respondent was from a hurricane. Given the nationally representative nature and long history of the PSID, there are a reasonable number of respondents that can be categorized as being potentially impacted by a number of hurricanes.

## 4.4 Empirical Approach

The goal of the empirical analysis is to determine to what extent monetary transfers from the family respond to experiencing a hurricane. Additionally, I will examine whether there is any evidence of respondents moving in with family members after a hurricane. In the next section, I will describe my empirical strategy for identifying the effect of a hurricane on each of the dependent variables of interest.

### *4.4.1 Treatment and Control Groups by Location*

The path of a storm system is an exogenous event which is outside the control of any individual. Since hurricane forecasting has limitations, it would be reasonable to argue that Census tracts that neighbor Census tracts which were hit by a hurricane are a sensible control group. Both groups of Census tracts are similar in that they are located near each other, the only difference is that one group happened to have an eye of a hurricane passby, whereas the other group did not. In the treatment

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<sup>7</sup> Stata has a user written program called `geodist` that measures the distance between any two coordinates, while also accounting for the curvature of the Earth.

effects literature, this is represented by the following equation:

$$\mathbb{E}(Y_0|d_H = 1) = \mathbb{E}(Y_0|d_H = 0) \quad (4.1)$$

In expectations, the assumption is that the group experiencing a hurricane,  $d_H = 1$ , and the control group,  $d_H = 0$ , would have the same outcome in a state of the world where the hurricane never happened,  $Y_0$ . If this equation holds, then the nearby Census tracts are potentially a valid control group and selection bias may not be an issue.

Empirically, I determine a PSID respondent to be in the treatment group if an eye of a hurricane with winds of at least 119 kilometers per hour comes within 150 kilometers of the respondent during the calendar year. The control group that I use are respondents who are within 300 kilometers (but not 150 kilometers) of the eye of a hurricane. One concern may be that my sample composition by location changes as a result of the hurricane affecting an area. I address this by relying upon the panel aspect of the data and determine a respondent's location as the location in the interview prior to the hurricane. This way my control and treatment groups are composed of individuals in the area before the hurricane had a chance to alter their behavior or location choice.<sup>8</sup>

#### 4.4.2 *Differences-in-Differences*

The data can also be seen as repeated cross-sections for each of the two groups of respondents. In this sense, the treatment identification strategy can incorporate a before group as part of the controls. The control group can then be thought of as the group of respondents in the same Census Tracts in the year prior to a hurricane. Incorporating both the location and timing variation into the treatment identification

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<sup>8</sup> Attrition may still be an issue. I could not find evidence that respondents were more likely to attrit from the sample if they were in a hurricane prone area prior to a hurricane.

strategy means using a differences-in-differences approach. One necessary assumption for this approach to work is that the time trend not explained by experiencing a hurricane is the same for both the group of Census tracts within 150 kilometers and within 300 kilometers of a hurricane.<sup>9</sup> The estimating equation of interest is

$$Y_{jt} = \alpha d_{t=t',j=150} + \mu d_{t=t'} + \phi d_{j=150} + \epsilon_{jt} \quad (4.2)$$

where  $t'$  is the interview after the hurricane, and  $t''$  is the year prior to the hurricane, and  $d_{j=150}$  is a dummy for the respondent being within 150 km of the hurricane eye either in the interview before or after the hurricane. The necessary assumption is that the difference in unobserved time trends between the treatment ( $j = 150$ ) and control ( $j = 300$ ) groups are equal,

$$\mathbb{E}(\epsilon_{j=\bar{150},t'} - \epsilon_{j=\bar{150},t''}) = \mathbb{E}(\epsilon_{j=\bar{300},t'} - \epsilon_{j=\bar{300},t''}) \quad (4.3)$$

Equation 4.2 controls for the time invariant components of both groups of Census tracts. Equation 4.2 may be a preferred strategy if there are concerns about using a wider radius around a hurricane's path as the control group. This could be a problem if the wider radius is likely to include more non-coastal communities that may have different population compositions than those living closer to the coast. If this is the case, then the assumption in equation 4.1 may be invalid. The differences-in-differences strategy helps control for time invariant characteristics of both areas separately, which leads to a potentially weaker identifying assumption in equation 4.3.

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<sup>9</sup> An additional necessary assumption is that time invariant characteristics are not affected by a sample composition change, for instance.

### 4.4.3 Panel Data

Incorporating the panel nature of the data directly into the estimation strategy can further reduce potential bias in identifying the treatment effect. By looking at differences in outcomes across interviews for any single respondent, this controls for time invariant, individual heterogeneity in the PSID sample. The estimating equation now becomes:

$$Y_{ijt} = \beta_0 + \alpha_1 d_{j=150,t=t'} + \alpha_2 d_{j=300,t=t'} + \psi_1 d_{j=150} + \psi_2 d_{j=300} + \gamma_i + X'_{it}\theta + \epsilon_{ijt} \quad (4.4)$$

Each observation is specific to individual  $i$ , who may be located within 150 or 300 ( $j = 150, j = 300$ ) kilometers in the interview before or after a hurricane hits in year  $t$ .  $\alpha_1$  estimates the deviation from the average outcome of respondent  $i$  ( $\gamma_i$ ) resulting from being within 150 kilometers of the hurricane.  $\alpha_2$  estimates a similar effect but for being within 300 kilometers where the impact of the hurricane will be smaller.

The time varying controls include year fixed effects and a variety of demographic characteristics of the head of household, spouse of the head, other members of the household, and non-coresident family. I include polynomials on head and spouse's age and education, household income, controls for head and spouse working status, polynomials for household size and composition, dummies for whether the Census tract is on the coast, and state fixed effects. Additionally, I control for whether the parent, sibling, or kid of the respondent (who themselves are respondents) experienced a hurricane during the year.

## 4.5 Results

Table 4.1 presents the results from equation 4.4 where I look at the effect of a category 1 hurricane with winds of at least 119 kilometers per hour on transfers received

from the family. I consider both the binary outcome of receiving transfers and the amount of transfers received. The results show that a hurricane has a very small and statistically insignificant negative effect on the likelihood of receiving a transfer. This result is consistent when controlling for observed characteristics and individual fixed effects. It is also similar for respondents both 150 and 300 kilometers away from the hurricane eye. Columns 5-8 examine the amount of transfer as the dependent variable. All of the coefficients are significant at the 5% level, but there are different signs for the coefficients within 150 kilometers compared to 300 kilometers. Being exposed to a hurricane within 150 kilometers has an effect of about a 3% increase over the average transfer given. For the 300 km group, there is a negative impact of about \$50, or a 2% decrease in an average transfer. Since there is no effect on the likelihood of receiving a transfer, the results suggest that being in the immediate vicinity of the most devastating portion of a hurricane increases transfers to those who already receive them. Another key result is that individuals in the closer ring to the hurricane eye receive more transfers, whereas respondents in the more distant radius from the eye actually receive less transfers.

One potential explanation for the last result is that if respondents have residence near family members, then there is the potential that multiple family members are negatively affected at the same time, which would put a strain on total family resources. If family resources are limited, then transfers could be limited compared to years when a hurricane does not have a big impact on total family resources. In the results presented, I do control for whether a non-co-resident parent, sibling, or kid of the PSID respondent experienced a hurricane. I find no significant impact on received family transfers when any of the family members experience a hurricane. I discuss towards the end of the paper potential paths for incorporating more information about the family.

Another question is whether these coefficients are economically significant. Al-

though the coefficients for the amount of transfer received are statistically significant, they amount to less than \$100 increase in transfers. This is unlikely to cover a significant portion of damages in the case of catastrophic damages. The transfers could be put towards deductibles for the insurance company in order to make claims on property damage. In this case, the transfers do not have to cover much of the overall damages, just assist with deductibles. A different point is the potential for measurement error with regards to reported transfers. Altonji et al. (1997) finds evidence in the PSID of significant underreporting of transfers from the family, both in the frequency and amount of transfers reported. If there is significant underreporting, then the results should be biased towards zero. So while I may find statistical significance, the estimated coefficients will be smaller than the actual response. Future direction will directly model and try to deal with the potential for inherent measurement error in transfer reports. Lastly, estimating a limited dependent variable model, such as tobit or probit, may affect the estimates since these nonlinear models may better represent transfer reports as a dependent variable. I leave this for future robustness checks.

As a comparison, Table 4.2 looks at reports of transfers received from people who are not family, such as friends. The results show very small and statistically insignificant results across the board. Although the overall incidence is lower than family transfers, these null results are interesting for two reasons. First, these questions are asked in the same series as the family transfers and they have very similar wording. This helps support the idea that there is something unique about the family and their desire to assist compared to non-family members. Second, Fafchamps and Lund (2003) find that both family and friends are actually a significant source of support in response to various shocks in the Philippines. These results suggest that in the United States, family is more likely to be a form of support when facing the shock of a natural disaster such as a hurricane. Since the PSID does not have

interviews with or information about these non-relatives, I cannot examine whether this group is more or less likely to simultaneously experience a hurricane.

#### *4.5.1 Hurricane Intensity*

Table 4.3 examines whether changing the intensity of hurricane has the expected effects. Hurricanes with higher wind speeds are more likely to cause significant damage to those respondents who reside close to the eye. The impact on transfers received should be larger for more intense hurricanes compared to Table 4.1. The results for category 1 hurricanes are carried over from Table 4.1, and I compare these to experiencing a category 2 (winds of at least 150 kph) and category 3 (winds of at least 175 kph). Even for the more severe hurricanes, there is still not a significant impact on the likelihood of receiving transfers. Examining the amount of transfers, the coefficients are somewhat larger and, despite the dwindling number of affected respondents, still as statistically significant as in Table 4.1. Since stronger hurricanes are less common, restricting the definition of a hurricane to category 3 winds or higher yield a fairly small “treated” sample, despite the large overall sample. This can put some strains on the power if there is not enough variation in the treated group due to small sizes.

Table 4.4 revisits the transfers received from non-relatives. Not even intensity of the hurricane seems to have much of an impact on transfers received from sources who are not family members.

#### *4.5.2 Heterogeneity in Response to Hurricanes*

It is very feasible that not everyone will have the same experience when a hurricane impacts their area of residence. On one hand, catastrophic damage could cause property damage and financial loss in various ways. On the other hand, some people may actually benefit from the hurricane. Vigdor (2008) and Belasen and Solomon

(2008) both find evidence with county-aggregated level data that workers in specific industries tend to earn higher wages after a hurricane. In particular, workers in construction and services receive higher wages in counties that were impacted by a hurricane. I examine these previous findings further by using the micro-level data in the PSID. Since the PSID asks questions about industry of work, I can see whether workers in strong hurricane sectors have different experiences to a hurricane.

I create a dummy for if a PSID respondent reports being in construction or services industries and interact this with the main effect for being 150 km from the eye of a hurricane. Table 4.5 examines whether there is a different effect on hours worked and labor income of the respondent when experiencing a hurricane. The coefficients for working in a strong sector are all positive but not statistically significant for working more hours. However, total labor income earned during the year is statistically significant and does increase as the hurricane strength increases. This is consistent with the results in the previous papers where they find evidence that working in construction or services leads to higher wages when looking at aggregated county level. The results in Table 4.5 confirming results in previous papers using individual panel data make for a nice complement to the literature.

The next question is, if some people benefit from a hurricane, then do they receive less assistance from family sources? Table 4.6 examines whether there is a differential effect of a hurricane for working in a strong industry. The results show that respondents who work in a strong industry are less likely to receive a transfers and with statistical significance at the 10% level. Additionally, the magnitude of the coefficients is increasing as the strength of the hurricane increases, with a 4% drop in the likelihood of receiving a transfer if working in a strong sector during a category 3 hurricane. It is also worth noting that when accounting for this heterogeneous effect, now the main effect of a hurricane is now positive for category 2 and 3 hurricanes, with some statistical significance for category 2. This matches with the results in

Table 4.5 because we saw a significant and positive impact on earnings for category 2 and 3 hurricanes but not category 1. This paints a story that when respondents are benefitting from a hurricane, the family actually reduces support. These results match with a model of altruism where the family wants to provide transfers in times of need because they care about the respondent, but if the respondent is doing well financially, they may actually reduce transfers because the money can be better spent in other utility improving ways.

The coefficients for amount of transfers received are negative for hurricanes of category 2 and 3, although the standard errors are large. The coefficients match with a story that families do respond with transfers in the face of a hurricane, but may reduce transfers if the hurricane improved a family member's financial situation.

#### *4.5.3 FEMA Payments*

Another potential mitigating force for people experiencing a hurricane are payments from the Federal Emergency Management Agency (FEMA). The goal of the agency is to provide support for areas experiencing a disaster where the local and state governments do not have the resources available to deal with the disaster. One of the tools that FEMA has available to them is to provide individual assistance (IA). If a county is declared a Major Disaster area by FEMA, then the residents of that county may be eligible for IA payments from FEMA to help deal with severe property damage. These payments can potentially take many months (even more than a year) to be fully paid out.

I incorporate data provided by FEMA that tells how much in IA was paid to each county, each month, for each disaster since 1999. The goal is to determine if respondents in areas that received more assistance were less likely to receive help from other sources, such as the family. If the government provided assistance supplants family transfers, we would expect a negative correlation between IA receipt

and transfers received from family. One issue with this hypothesis is that the amount of IA a county receives is a function of many confounding factors. First, high income areas are potentially more likely to receive larger IA payments compared with a lower income area affected by a similar hurricane. One reason is higher income areas have more expensive property that can be damaged, necessitating more assistance. Another reason is that high income areas may have more political clout that will get the larger assistance immediately after a hurricane. Since there is an application process, there may be a political element as far as how funds are dispersed immediately following a disaster. Some of the characteristics that determine whether one lives in a higher income area may also dictate the propensity to receive transfers from the family. Controlling for household income and individual fixed effects may help with some of these unobserved characteristics.

An additional strategy would be to control for the total amount of IA received by the county for the hurricane disaster declaration and examine how the IA received in any given month affects the likelihood of receiving a transfer, conditional on total amount received. In order to examine this, I use questions from the 1993-2009 waves of the PSID that ask, month by month, whether the respondent received a transfer from a family member or a non-relative. I can match this with the hurricane data and data from FEMA on individual assistance to see how and if FEMA assistance may affect the receipt of family transfers.

The equation that I attempt to estimate is

$$Y_{ijmy} = \alpha_1 d_{j=150,t=t'} + \alpha_2 IA_{jmy} * d_{j=150,t=t'} + \beta_1 d_{j=300,t=t'} + \beta_2 IA_{jmy} * d_{j=300,t=t'} + \theta IA_{j,H} + \psi_1 d_{j=150} + \psi_2 d_{j=300} + \gamma_{iy} + \epsilon_{ijt} \quad (4.5)$$

Since I have observations for each respondent by month and year ( $m,y$ ), I can now control for individual-year fixed effects ( $\gamma_{iy}$ ) so that I am looking at differences

in transfers receipt across the 12 months within the calendar year for each respondent. The coefficients of interest are  $\alpha_1, \alpha_2, \beta_1, \beta_2$ .  $IA_{j,H}$  controls for total individual assistance received by county  $j$  for disaster  $H$ . After controlling for total assistance,  $\alpha_2$  and  $\beta_2$  are now the effect of receiving more IA in any given month conditional on total IA received by the county for the disaster.

The results are reported in Table 4.8. Despite a very large sample size, most of the coefficients fail to achieve any notable statistical significance. If FEMA assistance crowds out or supplants family transfers, we would expect to see a negative coefficient for the amount of FEMA assistance received. The coefficients do not take any consistent sign, although they are consistently of a small magnitude and of minimal statistical significance. These results suggest that the decisions and behaviors motivating family transfers in response to a hurricane do not seem to be affected by FEMA assistance. This is notable as other papers have found evidence of government benefits crowding out family transfers in the context of unemployment (Schoeni (2002), Bentolila and Ichino (2008)).

#### 4.5.4 *Location decision and Family Co-Residence*

There have been a few papers which have examined many aspects of the relocation decision in response to a hurricane. <sup>10</sup>While the family can assist with monetary transfers, they can also share their residences as a way of helping each other after a hurricane. I can use information about residents in a household in order to determine whether respondents are more likely to still live with particular family members a year after the hurricane. First, I examine the likelihood that somebody lives in a different a year after the hurricane. Table 4.9 provides some evidence that being within 150 km of a hurricane eye makes the respondent about 3% more likely to live

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<sup>10</sup> (Landry et al. (2007), Groen and Polivka (2008b), Groen and Polivka (2010), Paxson and Rouse (2008), Strobl (2011))

in a different Census tract. However, there is no evidence suggesting they make a distant move out of county or state.

If respondents are moving after a hurricane, it may be the case that they are moving in with family members. McElroy (1985) and Kaplan (2012) examine the prevalence of young adults moving in with family members as a form insurance against unemployment. Frankenberg et al. (2003) find evidence that doubling up, or separate households forming a single unit, were more likely to occur after the financial crisis. Table 4.10 examines the likelihood that the respondent lives with a financially independent family member a year after the hurricane. I examine 3 specific relationships: parent, sibling, and kid of respondent. I find that the respondent is 6% more likely to live with a kid who is also a respondent in the PSID a year after experiencing a hurricane. This suggests that there is some evidence that non-co-resident parents are likely to move in with their adult children after a hurricane. This could be due to significant damage to a property that they cannot return to, or a temporary residence until they are able to return. Without more detailed information about the damages any individual directly faced, untangling the exact explanation is difficult with the data. This is left for future work.

## 4.6 Robustness and Future Work

The first check to see if the results are robust is to examine different distances from the eye to see how dependent the results are on the chosen distances. The distances were chosen as 150km is a reasonable radius for the eye of a typical hurricane, and 300 km is often on the outskirts of a typical hurricane storm system. At the expense of loss of brevity, I can simultaneously include more than 2 distance markers to better compare the effects as distance from the eye of a hurricane increases.

Another goal for future extensions of this work is to find a good source for localized damages estimates due to each hurricane. A good measure of localized damage

will give me another metric to see how transfers and residence decisions respond to the extent of damages. Furthermore, I can instrument the damage estimates using location-specific hurricane measures in order to use the exogenous variation of the intensity of the hurricane as an instrument for local damages. This exogenous variation may help with concerns of endogeneity of transfers and location decisions.

Further additions to this work include giving a closer examination of the effect of a family member experiencing a hurricane on transfer and co-residence behavior. This would entail looking more closely at family members that live near one another and how multiple family members in a network experiencing a hurricane may affect interactions with one another.

## 4.7 Conclusion

In this paper, I combine unique micro-data from the Panel Study of Income Dynamics with location specific hurricane data from the NOAA and disaster assistance data from FEMA. I examine two particular ways that the family may assist a relative when the relative experiences a hurricane: monetary transfers and co-residence. The family has been shown in other contexts to play an important role as a provider of informal insurance, which matches with theory regarding the family and interactions between family members.

The empirical results provide modest evidence of the family responding with assistance after a hurricane. Similarly, Currie and Rossin-Slater (2013) also find modest evidence of the effect of hurricanes on birth outcomes. Part of the reason why evidence is difficult to find at the micro level is that, in reality, what is being estimated is akin to an “intent to treat” effect. Since a typical micro dataset does not ask questions about how a hurricane directly affected the respondent, behavioral responses are inferred from an exposure to the “treatment” of the hurricane. There is rarely direct evidence of whether the hurricane actually had a meaningful, direct

impact on the respondent's behavior. If enough people are not directly affected by the hurricane, then coefficients will be smaller relative to a treatment effect for respondents who are directly impacted. Dealing with this more formally is another avenue for future research.

Another reaction to the empirical results may be that the modest statistical significance is even less meaningful when taking in to consideration the large overall sample size. The Schwarz criterion adjusts the typical test of the null hypothesis so that a larger t-stat is required as sample sizes increase. This criterion emphasizes the trade-off between Type 1 and Type 2 errors in any statistical analysis. Given that the baseline sample is approximately 130,000, there is reason to consider the less standard Schwarz criterion in assessing statistical significance. However, it should also be noted that there is a small portion of the sample that is in the hurricane impact zone (around 1-2%), and potentially an even smaller group that may have been directly impacted. This is also left for future work on this paper.

I also provide evidence of heterogeneous effects of a hurricane for the population. In particular, workers in construction and some types of services seem to have a positive effect on their labor markets due to a hurricane. They receive higher labor earnings and some evidence for more hours worked. This translates into supplanting some of the monetary transfers from the family, which is a unique result that brings together literature on family interactions, labor market responses to natural disasters, and insurance in the face of natural disasters. I do not find the same "crowd out" effect using data from FEMA about the amount of assistance paid to individuals in response to a disaster.

Lastly, I provide evidence that relocating a year after a hurricane is something that happens, although the effect seems to be limited to moving outside the Census tract but staying within the county. The family seems to assist with this process. The results show that parents are more likely to live their kids after experiencing a

hurricane. This result will be examined further in future editions to the paper.

## 4.8 Tables

Table 4.1: Family Transfers in Response to a Hurricane

	Dependent Variable- Calendar Year							
	Y/N Did Head Receive Transfer from Family?				Amount of Transfer Received from Family			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Within 150 km of hurricane eye	-0.0051 (0.0062)	-0.0054 (0.0060)	-0.0038 (0.0065)	-0.0046 (0.0063)	60.7*** (23.0)	56.5** (26.6)	64.6** (26.2)	72.0** (28.2)
Within 300 km of hurricane eye	-0.0012 (0.0035)	-0.00080 (0.0034)	-0.0044 (0.0036)	-0.0039 (0.0035)	-36.9** (18.7)	-44.8** (21.9)	-38.8** (19.7)	-51.5** (23.2)
Mean (Non-Zero Mean) of Dependent Variable	0.058	0.058	0.058	0.058	2346	2346	2346	2346
Strength of hurricane	Cat. 1	Cat. 1	Cat. 1	Cat. 1	Cat. 1	Cat. 1	Cat. 1	Cat. 1
Control Variables?	N	N	Y	Y	N	N	Y	Y
Individual Fixed Effects	N	Y	N	Y	N	Y	N	Y

Note: All standard errors are clustered at the Individual level. Included household controls described in text.

132366 individual-year observations; 14,963 individual fixed effects

\*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$

Number of respondents within 150km of hurricane: 3961

Number of respondents within 300km of hurricane: 8920

Table 4.2: Non-Family Transfers in Response to a Hurricane

	Dependent Variable- Calendar Year							
	Y/N Did Head Receive Transfer from Non-family Sources?				Amount of Transfer Received from Non-family Sources			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Within 150 km of hurricane eye	-0.0031 (0.0032)	-0.0020 (0.0033)	-0.0066* (0.0036)	-0.0046 (0.0037)	0.65 (8.5)	1.70 (12.6)	-3.65 (15.7)	1.76 (15.7)
Within 300 km of hurricane eye	0.0012 (0.0020)	0.0027 (0.0020)	0.0033 (0.0021)	0.0041* (0.0021)	2.3 (6.4)	4.87 (6.10)	4.87 (5.64)	10.4 (7.75)
Mean (Non-Zero Mean) of Dependent Variable	0.019	0.019	0.019	0.019	1938	1938	1938	1938
Strength of hurricane	Cat. 1	Cat. 1	Cat. 1	Cat. 1	Cat. 1	Cat. 1	Cat. 1	Cat. 1
Control Variables?	N	N	Y	Y	N	N	Y	Y
Individual Fixed Effects	N	Y	N	Y	N	Y	N	Y

Note: All standard errors are clustered at the Individual level. Included household controls described in text.  
132366 individual-year observations; 14,963 individual fixed effects

\*\*\* p<0.01, \*\* p<0.05, \* p<0.1

Number of respondents within 150km of hurricane: 3961

Number of respondents within 300km of hurricane: 8920

Table 4.3: Intensity Effects of Hurricanes on Family Transfers

	Dependent Variable- Calendar Year					
	Y/N Did Head Receive Transfer from Family?			Amount of Transfer Received from Family		
	(1)	(2)	(3)	(4)	(5)	(6)
Within 150 km of hurricane eye	-0.0046 (0.0063)	0.0085 (0.0086)	0.0018 (0.012)	72.0** (28.2)	97.5*** (36.2)	88.3** (43.1)
Within 300 km of hurricane eye	-0.0039 (0.0035)	-0.0097** (0.0044)	-0.0063 (0.0053)	-51.5** (23.2)	-40.3** (18.3)	-25.6 (22.9)
Mean (Non-Zero Mean) of Dependent Variable	0.058	0.058	0.058	2346	2346	2346
Strength of hurricane	Cat. 1	Cat. 2	Cat. 3	Cat. 1	Cat. 2	Cat. 3
Individual Fixed Effects	Y	Y	Y	Y	Y	Y

Note: All standard errors are clustered at the Individual level. Included household controls described 132366 individual-year observations; 14,963 individual fixed effects

\*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$

Number of respondents within 150km of Cat1: 3961, Cat2: 2121, Cat3: 1213

Number of respondents within 300km of Cat1: 8920, Cat2: 6501, Cat3: 4199

Table 4.4: Intensity Effects of Hurricanes on Non-Family Transfers

	Dependent Variable- Calendar Year					
	Y/N Did Head Receive Transfer from Non-family Sources?			Amount of Transfer Received from Non-family Sources		
	(1)	(2)	(3)	(4)	(5)	(6)
Within 150 km of hurricane eye	-0.0046 (0.0037)	-0.0076 (0.0050)	0.0036 (0.0072)	1.76 (15.7)	14.1 (28.4)	36.6 (45.7)
Within 300 km of hurricane eye	0.0041* (0.0021)	0.0046* (0.0026)	0.000011 (0.0031)	10.4 (7.75)	11.6 (11.1)	9.17 (13.6)
Mean (Non-Zero Mean) of Dependent Variable	0.019	0.019	0.019	1938	1938	1938
Strength of hurricane	Cat. 1	Cat. 2	Cat. 3	Cat. 1	Cat. 2	Cat. 3
Individual Fixed Effects	Y	Y	Y	Y	Y	Y

Note: All standard errors are clustered at the Individual level. Included household controls described 132366 individual-year observations; 14,963 individual fixed effects

\*\*\* p<0.01, \*\* p<0.05, \* p<0.1

Number of respondents within 150km of Cat1: 3961, Cat2: 2121, Cat3: 1213

Number of respondents within 300km of Cat1: 8920, Cat2: 6501, Cat3: 4199

Table 4.5: Labor Market Effects of a Hurricane

		Dependent Variable- Calendar Year					
		Number of Hours Respondent Worked During the Year			Respondent's Earned Labor Income		
		(1)	(2)	(3)	(4)	(5)	(6)
Within 150 km of hurricane eye interacted with...	Job in sector that performs well <sup>^</sup>	13.1 (39.2)	42.5 (52.7)	39.3 (73.5)	734 (542)	2,325* (1,440)	3,487** (1,705)
	Main Effect	0.16 (17.0)	-21.8 (23.2)	-33.6 (32.8)	-232 (321)	-462 (488)	-437 (661)
	Mean of Dependent Variable	1425	1425	1425	20357	20357	20357
Strength of hurricane		Cat. 1	Cat. 2	Cat. 3	Cat. 1	Cat. 2	Cat. 3
Individual Fixed Effects		Y	Y	Y	Y	Y	Y

Note: All standard errors are clustered at the Individual level. Included household controls described in 132366 individual-year observations; 14,963 individual fixed effects

\*\*\* p<0.01, \*\* p<0.05, \* p<0.1

<sup>^</sup> Construction and Services Sectors

Table 4.6: Heterogenous Effects of Hurricanes on Family Transfers

		Dependent Variable- Calendar Year					
		Y/N Did Head Receive Transfer from Family?			Amount of Transfer Received from Family		
		(1)	(2)	(3)	(4)	(5)	(6)
Within 150 km of hurricane eye interacted with...	Job in sector that performs well	-0.0040 (0.013)	-0.028* (.016)	-0.039* (0.024)	35.9 (55.2)	-40.8 (79.5)	-82.3 (107)
	Main Effect	-0.0034 (0.0078)	0.018* (0.010)	0.015 (0.015)	58.8** (28.6)	110** (45.5)	87.5* (50.3)
	Mean (Non-Zero Mean) of Dep. Var.	0.058	0.058	0.058	2346	2346	2346
Strength of hurricane		Cat. 1	Cat. 2	Cat. 3	Cat. 1	Cat. 2	Cat. 3
Individual Fixed Effects		Y	Y	Y	Y	Y	Y

Note: All standard errors are clustered at the Individual level. Included household controls described 132366 individual-year observations; 14,963 individual fixed effects

\*\*\* p<0.01, \*\* p<0.05, \* p<0.1

Table 4.7: Heterogenous Effects of Hurricanes on Family Transfers

		Dependent Variable- Calendar Year					
		Y/N Did Head Receive Transfer from Non-family Sources?			Amount of Transfer Received from Non-Family Sources		
		(1)	(2)	(3)	(4)	(5)	(6)
Within 150 km of hurricane eye	Job in sector that performs well post-hurricane	-0.018** (0.0071)	-0.010 (0.0092)	-0.0076 (0.014)	-49.3** (24.4)	-71.3 (45.0)	-119* (70.9)
	Main Effect	0.0015 (0.0041)	-0.0040 (0.0059)	0.0064 (0.0087)	18.2 (20.6)	38.3 (38.3)	77.2 (63.4)
	Mean of Dep. Var.	0.019	0.019	0.019	1938	1938	1938
	Strength of hurricane	Cat. 1	Cat. 2	Cat. 3	Cat. 1	Cat. 2	Cat. 3
	Individual Fixed Effects	Y	Y	Y	Y	Y	Y

Note: All standard errors are clustered at the Individual level. Included household controls described in 132366 individual-year observations; 14,963 individual fixed effects

\*\*\* p<0.01, \*\* p<0.05, \* p<0.1

Table 4.8: FEMA Payments and Transfers

		Dependent Variable- Monthly					
		Y/N Did Head Receive Transfer from Non-family Sources?			Y/N Did Head Receive Transfer from Non-family Sources?		
		(1)	(2)	(3)	(4)	(5)	(6)
Within 150 km of hurricane eye interacted with...	Main Effect	0.0064*	0.0076	0.0095	0.0010	0.0017	0.0053*
		(0.0034)	(0.0060)	(0.0084)	(0.0016)	(0.0013)	(0.0027)
	Amount of FEMA Individual Assistance per resident in County (\$1000)	0.005	-0.004	-0.005	-0.004	0.003	0.002
		(.009)	(.004)	(.004)	(.005)	(.005)	(.005)
Within 300 km of hurricane eye interacted with...	Main Effect	-0.0023*	-0.0017	-0.00079	0.00012	0.00018	-0.00036
		(0.0014)	(0.0018)	(0.0025)	(0.00082)	(0.0011)	(0.00096)
	Amount of FEMA Individual Assistance per resident in County (\$1000)	-0.006	.002	.002	.004	-.0002	.0004
		(.009)	(.003)	(.003)	(.003)	(.004)	(.004)
Mean of Dep. Var.		0.042	0.042	0.042	0.012	0.012	0.012
Strength of hurricane		Cat. 1	Cat. 2	Cat. 3	Cat. 1	Cat. 2	Cat. 3
Individual Fixed Effects		Y	Y	Y	Y	Y	Y

Note: All standard errors are clustered at the Individual level.

680,112 individual-month observations; 56676 individual-year fixed

\*\*\* p<0.01, \*\* p<0.05, \* p<0.1

Mean of FEMA assistance per thousand county inhabitants: \$10561

Table 4.9: Change in Residence After a Hurricane

	<b>Dependent Variable: 1 year after hurricane, respondent lives in a different...</b>		
	<b>Census Tract</b>	<b>County</b>	<b>State</b>
	<b>(1)</b>	<b>(2)</b>	<b>(3)</b>
Within 150 km of hurricane eye	0.030* (0.016)	-0.012 (0.013)	0.00036 (0.0091)
Within 300 km of hurricane eye	0.00071 (0.0091)	-0.0034 (0.0060)	-0.011*** (0.0039)
Mean of Dep. Var.	0.198	0.075	0.032
Strength of hurricane	Cat. 3	Cat. 3	Cat. 3
Individual Fixed Effects	Y	Y	Y

Note: All standard errors are clustered at the Individual level.

132366 individual-year observations; 14,963 individual fixed effects

\*\*\* p<0.01, \*\* p<0.05, \* p<0.1

Table 4.10: Family Co-Residence After a Hurricane

<b>Dependent Variable: 1 year after hurricane, respondent shares residence with...</b>			
	<b>Parent<sup>^</sup></b>	<b>Sibling<sup>^</sup></b>	<b>Kid<sup>^</sup></b>
	<b>(1)</b>	<b>(2)</b>	<b>(3)</b>
Within 150 km of hurricane eye	-0.0035 (0.014)	0.011 (0.011)	0.058*** (0.019)
Within 300 km of hurricane eye	-0.0085 (0.0064)	-0.0062 (0.0048)	-0.012 (0.0100)
Mean of Dep. Var.	0.066	0.033	0.108
Strength of hurricane	Cat. 3	Cat. 3	Cat. 3
Individual Fixed Effects	Y	Y	Y

Note: All standard errors are clustered at the Individual level.

132366 individual-year observations; 14,963 individual fixed effects

\*\*\* p<0.01, \*\* p<0.05, \* p<0.1

<sup>^</sup>This refers to a family member who is also a respondent in the PSID. More details in text.

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# Biography

Michael Robert Dalton was born on December 8th, 1984 in Virginia Beach, Virginia, and conceived approximately 9 months before that in Washington DC. In December 2006, he earned a B.S. in Economics and minor in Mathematics from Virginia Tech, where he graduated Summa Cum Laude, which is Latin and translates to “with greatest Laude”. In 2008, he defied all odds and earned an M.A. in Economics from Duke University. An uncountable number of years later, he earned his Ph.D. from Duke University in Economics in May of 2013. His graduate studies were supported with the emotional and psychological assistance of many family members, friends, fellow students, and advisors. But more meaningfully, his graduate studies were financially supported by the Sutherland Summer Fellowship and the Duke University Population Research Institute (DuPRI) with the T32 Matching Grant. He will begin a position as a Research Economist at the Bureau of Labor Statistics in July 2013 in Washington DC, proving that life does come full circle.