Bailing out the Kids: New Evidence on Informal Insurance from one Billion Bank Transfers *

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Abstract

We combine transaction-level data from the largest retail bank in Denmark and individual-level data from government registers to study informal insurance within social networks. Accounting for transfers in cash (money transfers) and in kind (cohabitation), we estimate that family and friends jointly replace around 7 cents of the marginal dollar lost within the bottom income decile, but much less at higher income levels. We document that informal insurance covers other adverse events than income losses: expenditure shocks, family ruptures and financial distress. Parents appear to be the key providers of informal insurance with a small amount of insurance coming from siblings and virtually none from grandparents and friends. Replacement rates vary monotonically with parent economic resources.

keywords: informal insurance, altruism, private transfers, risk sharing

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1 Introduction

Insurance against income losses and other adverse shocks is highly important for welfare and a key objective for public policy. A vast literature highlights how self-insurance through precautionary savings and social insurance through government transfers allow households to sustain consumption in difficult times. Empirical analysis of informal insurance within families and other social networks is much less advanced, partly because researchers rarely observe inter-personal transfers directly. Faced with this challenge, one strand of literature makes inference from income and consumption data for individuals belonging to the same network (e.g. Townsend, 1994), while another strand relies on scarce surveys with direct questions about transfers (e.g. McGarry, 2016). While the literature is far from conclusive, most existing evidence seems to suggest that family, friends and neighbors constitute an important source of insurance in developing countries, but play a smaller role in advanced economies where, arguably, government transfer programs and private credit markets reduce the scope for altruism (Roberts, 1984) and private risk sharing (Cutler and Gruber, 1996).[1]

This paper provides new empirical evidence on informal insurance in the context of a developed economy. Our ultimate goal is to quantify the *replacement rate* implied by informal insurance: what fraction of a dollar shock to the budget is replaced by resource transfers from the social network? The replacement rate is a key statistic to summarize the economic importance of insurance and is widely used to describe the generosity of social insurance programs, but we are not aware of existing estimates of replacement rates in the context of informal insurance. While studies of informal insurance often focus on financial support provided by parents, we aim to estimate replacement rates that are as comprehensive as possible and thus account for resource transfers from the broad social network (e.g. parents, siblings, grandparents and friends) made in the form of money and – whenever possible – in kind. Finally, motivated by

[1]Consistent with extensive informal insurance in developing economies, Townsend (1994) finds that household consumption in Indian villages covaries strongly with average consumption in the village but is not much influenced by idiosyncratic income shocks. Moreover, Fafchamps and Lund (2003) provide direct evidence that gifts and loans within social networks in the Philippines respond strongly to income and expenditure shocks. Conversely, based on consumption and income data for the U.S., Altonji et al. (1992) and Hayashi et al. (1996) strongly reject that parents and adult children fully share risk and Attanasio et al. (2015) conclude that *no* detectable risk sharing takes place within the family even though most income risk is potentially insurable. McGarry (2016) uses survey information on money transfers to show that income losses are associated with small increases in money transfers from parents. She also finds evidence that money transfers from parents are higher in years with life events such as college graduation, marriage, home purchase, child birth and divorce. Using annual information from government registers in Denmark, Kolodziejczyk and Leth-Petersen (2013) find no evidence that parents draw down liquid assets when adult children become unemployed. Kaplan (2012) uses survey information on cohabitation with parents to show that job losses for young adults in the U.S. are associated with a sizeable increase in the probability to move back to the parents.

theories of altruism predicting that individuals should receive more support when the marginal value of resources is high for themselves and low for people in their network (e.g. Becker, 1981), we allow marginal replacement rates to vary with the position in the income distribution and with the economic resources of the social network.

The key methodological advance of our paper is a data innovation that goes to the heart of the measurement challenge in the existing literature: by combining bank customer records and government registers we are able to measure inter-personal transfers directly, at a high frequency and at a much larger scale than earlier studies. Through a collaboration with Danske Bank, the largest retail bank in Denmark, we have access to detailed records for each of its 1 million customers, a largely representative sample of the Danish population, including transaction-level data on money transfers across personal accounts. Adding information from government registers on family relations, we are able to identify money transfers to and from members of the extended family: parents, siblings and grandparents. Further, adding information from government registers on education and employment, we identify transfers to and from others in the social network: individuals who have been enrolled at the same school or study program in the same cohort ("school friends") or who have been employed at the same workplace in the same year ("work friends"). Finally, we extract detailed information on spending from the bank customer records, which serves, among other things, to identify expenditure shocks.

There are several advantages of measuring inter-personal transfers with bank data: the large sample makes it possible to zoom in on relatively rare circumstances where insurance is particularly important; the high frequency allows us to exploit sharp variation in income and expenditures for empirical identification; and the use of objective bank records effectively overcomes the recall bias inherent to survey measurement. Yet, our approach has at least one important limitation: when resource transfers take other forms than bank transfers (e.g. cash in envelopes, dinner invitations, sleeping in a guest room), they are not directly observable in the bank records. While cash use is exceptionally low in Denmark and therefore a smaller problem for measurement than in most other contexts (Danmarks Nationalbank, 2017), we nevertheless take this limitation seriously and address it in two ways. First, as physical proximity may lead to more reliance on unobservable transfers in cash and kind, we generally exclude individuals living in the same municipality as their parents when we study money transfers. Second, we present a separate analysis of perhaps the most important type of in-kind transfers: cohabitation with parents (Kaplan, 2012).

In the first part of the empirical analysis, we regress outcomes capturing transfers from family and friends on dummies indicating the position in the income distribution, individual fixed effects and age-specific time effects. With this specification, we estimate how much transfers from the social network change as the individual's annual income changes while controlling exhaustively for the fixed characteristics of both the individual (e.g. ability) and the social network (e.g. parent generosity) as well as age dynamics. Our sample consists of young adults (age 20-39) who are customers at the Bank and hold no accounts at other banks, ensuring that we have a complete overview of incoming and outgoing money transfers;[2] however, we exclude students for whom low income may reflect investments in human capital rather than adverse circumstances.

The results indicate that income changes in the bottom half of the income distribution induce much larger changes in money transfers from parents than in the upper half. For instance, going from the median income level to the bottom vigintile of the income distribution increases monthly transfers from parents by around \$100.[3] By contrast, going from the median income level to the top vigintile reduces parent transfers by around \$30. Insurance responses by other social connections are generally less significant: transfers from siblings respond to income losses, but less than transfers from parents by an order of magnitude, and transfers from grandparents and friends do not respond at all. We find evidence that insurance provided by parents extends beyond money transfers: going from the median income level to the bottom vigintile increases cohabitation with parents by almost four percentage points. The results are not confounded by life events and correlated income shocks: individuals receive significantly more transfers from parents in years where they have a baby or buy a home and less in years where parents suffer adverse income shocks, but controlling for these factors barely changes the effect of own income on transfers received.

In the second part of the empirical analysis, we study a broader range of adverse circumstances in an event framework: the rupture of stable employment relationships ("job losses"); large and plausibly unexpected bills from dentists and auto repair shops ("expenditure shocks"); the breaking up of cohabiting couples ("divorce"); and notices from the bank about arrears ("financial distress"). We first characterize each of the events in terms of income and spending dynamics to understand their economic nature and magnitude and then estimate responses in

[2] We exploit the comprehensive account-level reporting from banks to the tax authorities at the end of each year to exclude individuals with multiple banks. The combination of bank and government data thus helps us addressing one of the key concerns in the emerging literature using transaction data from banks or financial aggregators: completeness (Baker, 2018).

[3] We observe all amounts in Danish Kroner (DKK) but convert them to US Dollars (USD) throughout the paper at the fixed rate 5.6 DKK / USD, which is the average market exchange rate for the sample period 2010-2014.

the form of resource transfers from the social network. Specifically, we estimate the change in resource transfers around adverse events relative to the pre-event baseline over and above the change observed for a reference group not exposed to the event.

Consistent with the first set of results, we find clear responses to job losses: money transfers from parents, other family and friends as well as the propensity to move back to the parents all increase significantly around job losses and then slowly revert to the baseline level in subsequent months. The event study approach allows us to document that informal insurance goes beyond income losses. Expenditure shocks in the form of dental and auto repair bills raise total spending significantly above the baseline level in a single month, which is mirrored by spikes in money transfers from parents of around \$90 and, to a lesser extent, money transfers from other family members. Divorces also manifest themselves as expenditure shocks: spending surges around the month where couples move apart and remains above the baseline level in subsequent months, whereas income is unchanged. At the time of such household ruptures, monthly transfers from parents increase to a level around \$100 above the baseline for a few months and the likelihood of moving to the parents surges. Financial distress in the form of arrears notices occurs after a period of decreasing income and increasing spending and is followed by a sharp reversal in both outcomes. While arrears notices thus appear to induce immediate adjustments to both spending and income, they also trigger transfers from the network: monthly money transfers from parents increase sharply by around \$20 and money transfers from other family members and friends increase too.

In the final part of the paper, we express informal insurance in terms of replacement rates that are comparable across contexts, sources and transfer types. We first estimate the rate at which parents replace marginal income losses through money transfers at different income levels of the child. We find that the marginal replacement rate is above 4% in the bottom income decile and declining through the income distribution. Intuitively, parents replace income losses at a higher rate when child income is lower and marginal utility of consumption therefore higher. We find qualitatively similar patterns for money transfers from other family members, but the implied replacement rates are much smaller. To make comparable estimates for in-kind transfers, we estimate the drop in living costs (rent, utilities, groceries and fuel) around the time individuals move to their parents and let the estimate approximate the implicit resource transfer associated with cohabitation. Combining all channels - money transfers from family and friends as well as cohabitation with parents - we estimate that income losses are replaced at the marginal rate of 7% in the bottom income decile, 4% in the second decile, 1.5% in the third decile and an insignificant 1% at higher income levels. The strong negative income gradient in marginal replacement rates is a key result suggesting that, consistent with the fundamental principles of altruism, the social network provides most insurance when it is most needed. It follows that marginal replacement rates averaged over all income levels may severely understate the value of informal insurance in utility terms. Finally, we find that the generosity of the informal insurance increases systematically with the economic resources of the social network: marginal replacement rates in the bottom income decile are four times larger when parents are high-income rather than low-income.

Some of our findings are more difficult to reconcile with the simplest theory of altruism where transfers from the network only depend on marginal utilities of economic resources. Specifically, our analysis of high-frequency transfer dynamics uncovers that resource transfers from the social network appear to increase at the time of the adverse shock and then revert to the baseline level even in the cases where the shock is persistent. For instance, money transfers from parents increase sharply around job losses and divorce, but only remain high for a few months although the decrease in income following job losses and the increase in expenditure following divorces persist much longer. These patterns highlight the importance of salient *changes* to income and expenditure in determining the supply of transfers within the network. Consistent with this interpretation, we estimate a higher replacement rate for expenditure shocks, where the adverse effect on the budget is concentrated in a single month, than for job losses, where the effect is spread out over many months.

The paper contributes to the broader literature on insurance against income shocks (e.g. Blundell et al., 2008; Ganong and Noel, 2019) and more specifically to the empirical literature on insurance through informal channels (see references above). The unique combination of micro-data from bank and government sources allows us to push the research frontier by identifying replacement rates for different income groups (by position in the income distribution) while accounting for resource transfers in different forms (money transfers and cohabitation) and from different parts of the social network (parents, siblings, grandparents and friends); distinguishing between families with different economic resources (by parent position in the income distribution); and studying a range of different adverse circumstances (income losses, expenditure shocks, household ruptures, financial distress) in a coherent empirical framework. Our finding that parents are key providers of informal insurance and that replacement rates correlate strongly with parent lifetime income relates our study to the literatures on inequality and social mobility (e.g. Chetty, 2014). Finally, our analysis relates to various theoretical literatures predicting that family and friends provide support in response to adverse circumstances because of altruism (e.g. Cox, 1987; Bourles et al., 2017) or incentives for risk pooling (e.g. Kocherlakota, 1996; Ligon et al., 2002).

Although our Danish laboratory is unusual in certain dimensions that have a bearing on inter-personal transfers – e.g. social insurance is relatively generous and college education is free – we believe our results are relevant for economies with less government intervention for the following reasons. First, while a given loss of earnings almost certainly induces different responses by family and friends depending on how the loss is compensated by the government (DiTella and MacCulloch, 2002), our estimates of replacement rates generally relate changes in inter-personal transfers to the size of the adverse shock *after* government intervention. Second, we go beyond income losses and study a range of adverse circumstances that are generally not covered by social insurance. Finally, excluding students allows us to abstract from questions about parent financing of higher education that interact directly with government policy.

The paper proceeds in the following way. Section 2 describes the data. Section 3 lays out the empirical strategy. Section 4 presents results on transfer responses to adverse circumstances. Section 5 expresses the transfer responses in terms of replacement rates. Section 6 concludes.

2 Data

Our analysis uses a unique combination of customer data from the biggest retail bank in Denmark, Danske Bank ("DB"), and administrative data from various government registers. The bank records contain, amongst other things, transaction-level data on money transfers and spending. The government registers include information about family relations and residence ("population register"), income and balance sheet items ("tax register"), education ("education register") and workplace ("employment register"). All data sources identify individuals by their unique personal identification number and can therefore be linked.

To study informal insurance, we need to measure three components: the adverse circumstances triggering an individual's need for assistance ("adverse shocks"), the groups of individuals who may potentially provide assistance ("social networks") and the amount of support actually provided ("inter-personal transfers"). The linked bank records and government registers help us capture all three components.

In this section, we first describe how the samples used in the various empirical analyses are selected and how observable characteristics change as we impose more restrictions. Next, we describe in more detail how adverse shocks, social networks and inter-personal transfers are measured. Finally, we provide some descriptive statistics of key variables.

2.1 Sample selection

Starting from the full population of adults in their 20s and 30s, we restrict the sample in various ways.

First, we exclude individuals for whom we cannot identify at least one parent. This criterion reflects that we cannot identify resource transfers to and from parents unless we know who the parents are. Since 1960, the parents of all individuals born in Denmark have been recorded in the population register, although fathers are unknown in a non-trivial number of cases. We can rarely identify the parents of individuals born outside of Denmark, so most immigrants fall out of our sample.

Second, we restrict the sample to exclusive DB customers. By excluding individuals who conduct some of their banking business through other banks than DB, we address the concern, often raised in the emerging literature using transaction data from banks and financial apps, that a lack of completeness may introduce a bias (e.g. Baker, 2018). For instance, if parents provide financial support in response to an income shock and the transfers flow into both DB and non-DB accounts, an analysis of the DB customer records would systematically underestimate the extent of informal insurance. While existing studies typically address this concern by restricting the sample to active customers based on spending activity, we exploit the unique link to government registers: all banks in Denmark report the balance of all deposit and loan accounts to the tax authorities at the end of each year (Jensen and Johannesen, 2017; Iyer et al., 2019). By restricting the sample to individuals who do not hold non-DB accounts neither at the end of the year nor at the end of the previous year, we identify individuals who most likely conducted all their banking business through DB accounts during the year.

Third, in estimations where the outcome is money transfers from parents, we also exclude individuals living in the same municipality as their parents. With greater spatial proximity, parents and children are likely to interact more physically and transfers between them are therefore more likely to take the form of cash, goods and services. We attempt to reduce measurement error due to such unobservable transfers by restricting attention to individuals who live further away from their parents and are therefore more likely to rely on observable electronic money transfers.[4]

Table 1 shows how the selection criteria affect the sample size and sample characteristics

[4]Consistent with our intuition, money transfers from parents respond less to changes in income when we include individuals who live in close proximity to their parents, as detailed below.

starting from the full population between 20 and 39 years (pooled over the sample period 2010-2014). First, starting with the gross sample of 6.9 million individual-year observations (Column 1), requiring that at least one parent is known leaves 6.1 million observations (Column 2); further requiring that individuals hold a DB account leaves 1.8 million observations (Column 3); further requiring that individuals hold no non-DB accounts leaves 1.1 million observations (Column 4); and further requiring that individuals do not live in the same municipality as their parents leaves 0.5 million observations (Column 5). The most restricted sample is very similar to the full sample with at least one known parent on most observable dimensions including annual income ($51,800 vs $52,800) and liquidity ($11,500 vs $11,700).

Finally, because of the importance of parents as a source of informal insurance, we only include individuals with at least one living parent. It follows from Table 1 that more than 95% of individuals with at least one known parent also have at least one living parent so this restriction only reduces the sample marginally. To focus the analysis on *inter vivo* transfers, we also generally exclude observations around years where parents die and where money transfers from parents are therefore likely to represent the inheritance.[5]

2.2 Adverse shocks

In the first part of the empirical analysis, we study how resource transfers from family and friends respond to changes in income. Drawing on information from the tax register, we measure annual income in a given year as taxable income including government transfers averaged across cohabiting partners.[6] In each year, we rank the annual income of individuals in the gross sample and estimate how transfers change in response to changes in the income rank.

In the second part of the empirical analysis, we study resource transfers around a broader range of adverse events. Drawing on monthly information from the tax register, we define a *job loss* as a month where an individual receives almost no earnings (less than $200) after having received a normal salary (more than $2,000) for at least 12 consecutive months.[7] Drawing on DB transaction data, we define an *expenditure shock* as a month where an individual pays a

[5]As shown in an event framework in Figure A7 in the Appendix, money transfers from parents increase sharply in years where a parent dies, remain elevated in the following year and then return to the pre-death level (Panel A). This pattern is consistent with inheritance settlements occurring predominantly in the year where parents die and the following year. In the regression analysis, we therefore exclude each year in which a parent dies as well as the following year.

[6]The income information on tax returns is generally highly accurate as the vast majority of income is reported by third parties such as employers and financial institutions (Kleven et al., 2011) and tax evasion is limited except among the very wealthiest (Alstadsæter, et al., 2019).

[7]In practice, we use thresholds that are salient in local currency: we require monthly earnings above DKK 10,000 ($\approx$ $ 1,800) for at least 12 consecutive months followed by monthly earnings below DKK 1,000 ($\approx$ $ 180).

significant amount (more than \$1,000) to either a car repair shop or a dental clinic.[8] Drawing on the population register, we define a *divorce* as a month where one of two cohabiting partners move away from the joint address. Drawing on the DB customer data, we define a *financial distress* as a month where a customer receives the first notice about arrears.

We characterize each of the events in terms of income and spending dynamics to understand their economic nature and magnitude. We draw monthly income information directly from the tax register and construct a monthly spending measure from DB transaction data. Starting from the universe of transactions, we categorize three types of account outflows as spending: payments by credit and debit card, bill payments and cash withdrawals. We define monthly spending as the sum of these outflows with a few exceptions: using the bank's s internal classification, we identify and exclude payments related to tax and debt service, which we do not consider spending, as well as rent and other housing-related payments.[9]

2.3 Social networks

We draw on the population register to identify family members. As described above, we have direct information about at least one *parent* for around 90% of the individuals in the full population. We define the set of *siblings* as everyone in the population with whom the individual shares at least one parent and the set of *grandparents* as all the known parents of the known parents. Coverage is generally somewhat lower for siblings and grandparents than for parents as the parent-child link is key to establishing other family links.

We use information about education history from the education register to delineate a set of *school friends* for each individual. For each individual and each year since 1987, we observe current enrolment in educational institutions (including primary, secondary and higher education) as well as information about the highest degree completed. Since we have no information on actual social interactions, we define school friends as individuals who have had opportunity to form friendships through continued interactions at educational institutions. To avoid excessive numbers of school friends, we operationalize this notion in a conservative manner. In the context of primary and secondary education, we consider two individuals as school friends if they attended the same grade at the same school in the same year, but not if they attended different grades. In the context of higher education, we consider two individuals as school friends if they

[8] In practice, we use a threshold that is salient in local currency: we require expenditure above DKK 5,000 ($\approx$ \$ 900).

[9] Several recent papers have used transaction-level information from banks and web-based financial aggregators to measure spending in a similar way (e.g. Gelman et al, 2014; Baker, 2018).

started the same degree program at the same institution in the same year, but not if they started different degree programs in the same year or the same degree programs in different years.[10]

We use the information about employment history in the employment register to construct the set of *work friends*. For each individual and each year since 1987, the registers contain information about employers and workplaces. Analogous to school friends, we define work friends as individuals who have had opportunity to form friendships through continued interactions at work. Following De Giorgi et al. (2020), we thus consider two individuals as work friends if they worked for the same employer at the same workplace in the same year, but not if they worked for the same employer at different workplaces.[11]

2.4 Inter-personal transfers

Individuals can make money transfers in two distinct ways: *wire transfers*, typically initiated by the customer through the onling banking system and *mobile transfers* conducted through an application for mobile phones ("MobilePay").[12] For wire transfers to and from DB accounts, we observe the amount transferred and the unique account number of the counterpart. When the counterpart account is also at DB, we obtain the unique personal identification number of the account owner through DB's customer lists; hence, we can precisely identify the individual who is the counterpart to the transfer. When the counterpart account is at another bank, we cannot obtain the personal identification number of the account owner; however, we can infer the unique branch number of the counterpart from the account number. For mobile transfers, a mobile phone number rather than an account number specifies the counterpart. Because the Bank manages the application and maintains a complete customer list, we can retrieve the personal identification number of counterparts to mobile transfers regardless of where they are banking.

Our goal is to identify money transfers flowing to and from family and friends for the DB customers in our sample. For each money transfer where we have retrieved the personal identification number of the counterpart, we check whether it matches parents, siblings, grandparents, school friends or work friends.[13] Summing the flagged transactions, we obtain monthly measures

[10] We provide more details on these definitions map to the raw data sources in the Appendix.

[11] For each individual-year, we only consider at most three workplaces. In the rare cases where an individual worked at more than three distinct workplaces during a year, we only consider the three workplaces where the individual earned most income.

[12] The mobile application was introduced in 2013 and quickly adopted by customers in all Danish banks (Sheridan, 2020).

[13] We generally consider all transactions between an individual's parents and members of the individual's household (e.g. spouse) as transfers between the parents and the individual. We disregard transactions where

of money transfers to and from each part of the social network.

We improve on the measurement of money transfers to and from parents in one important way. From the tax register, we retrieve the unique identification numbers of the bank branches in which parents hold accounts. For each money transfer where we have no information about the personal identification number of the counterpart account, we check whether the branch identification number matches a bank branch used by the parents. We sum the flagged transactions and add them to our measure of money transfers to and from parents. While this procedure introduces some error by assuming that all transactions with branches where parents hold accounts are transactions with parents, the sheer number of branches in the Danish banking system, around 3,000 in 2014, suggests that the error is small.[14] Since individuals may potentially have thousands of friends with accounts at hundreds of branches, we do not correct our measures of money transfers to and from other parts of the social network in the same way.

In addition to money transfers, we also consider a form of in-kind resource transfer from parents: cohabitation.[15]. In the population register, we observe a unique address identification number for each individual at the end of each year and the month of moving for individuals who have changed address in the course of the year. We define *cohabitation with parents* as sharing an address with at least one parent and *moving to parents* as moving the address to an address already used by at least one parent. We do not consider cohabitation with other family members or friends.

2.5 Heterogeneity

We study heterogeneity in replacement rates in one important dimension: the economic resources of the parents. Theories of altruism predict that parents with more resources, who are likely to have a lower marginal utility of own consumption, should respond more strongly to an adverse shock that raises the marginal utility of consumption for their children.

We capture parents' economic resources with a measure of earnings capacity that is used ex-

the counterpart is a business account to the largest extent possible to avoid picking up salary payments. In most cases, business accounts are associated with a corporate identification number rather than a personal identification number and therefore do not lead to matches with the personal identification number of family and friends.

[14] If parents and other counterparties are clustered in geographical areas, the error could potentially be significant. We address this concern by exploiting the subsample of individuals whose parents are themselves exclusive DB customers such that all transactions with parents are identified based on unique personal identification numbers. We verify that the distribution of money transfers from parents in this subsample is similar to the full sample (see Figure 1C) and that the main results are robust to using this subsample (see Figure A4 in the Appendix).

[15] Previous research has shown that moving back to the parents is a common response to job losses among young adults in the U.S. (Kaplan, 2012)

tensively in the literature on inter-generational mobility (e.g. Chetty, 2014). For each individual in the sample, we aggregate parental income over a 5-year period in childhood, i.e. when they were 11-15 years old.[16] When children are this age, most parents have returned to the labor market, even if they engaged in full-time care after child birth, and are still far from retirement. Hence, at this time in the life-cycle, income is a good approximation for the earnings capacity and thus for life-time economic resources. Within each birth year-cohort, we rank individuals according to this measure of parental economic resources and introduce the notation that individuals above the 90th percentile have "high-income parents"; individuals between the median and the 90th percentile have "middle-income parents"; and individuals below the median have "low-income parents".

Our measure of parent economic resources has one major conceptual advantage: unlike other possible measures, such as current income and current wealth, it is exogenous to the adverse shocks we are studying. While parents may endogenously increase labor supply when their adult children face adverse shocks and accumulate more wealth if they anticipate that their adult children are likely to face adverse shocks in the future (Boar, 2019), our measure of economic resources is pre-determined at the beginning of the estimation period.

2.6 Descriptives

Table 2 provides basic descriptives of our measures of resource transfers within the social network. Net money transfers from parents average just below \$65 per month for the individuals in our sample, which reflects gross transfers from parents of around \$140 and gross transfers to parents of around \$75 per month.[17] Money transfers to and from other parts of the social network are much smaller in magnitude: combined gross transfers from siblings, grandparents, school friends and work friends average less than \$20 per month. Transactions with siblings and friends are almost balanced whereas transactions with grandparents, though small in absolute numbers, are mostly in the form of incoming transfers. Finally, around 5 percent of the sample cohabit with their parents.

The monthly transfer averages conceal large heterogeneity across individuals and months. As shown in Figure 1A, for around half of the individual-year observations in our sample, there

[16]To be precise, our parental income measure is household income averaged over the two parents. In the most common case where the two parents remain partners at the time of measurement, this is simply household income divided by two. In the rarer case when parents are separated, we first compute household income per adult in their respective households and take the average across the two parents. When only one parent is known, our measure is simply household income per adult for that parents.

[17]The mean corresponds roughly to survey data from the U.S. where mean transfers from parents amount to around \$900 annually (McGarry, 2016).

are no money transfers from parents whereas observations with money transfers from parents in every month of the year account for around 2% of the sample. As shown in Figure 1B, for individual-year observations with some parent transactions (in either direction), net money transfers from parents average $100 per month, but there is a significant tail at both ends of the distribution with around 2% giving and around 4% receiving net amounts of more than $1,000 per month. As shown in Figure 1C, money transfers from parents also vary systematically with income: the income gradient in net transfers is negative through most of the distribution except at the bottom where it is strongly negative.[18] We do not interpret these patterns causally, but note that large money transfers from parents at the lowest income levels are consistent with informal insurance by parents. The figure also corroborates our approach to identifying parent transfers through branch identification numbers (explained above) by showing that the relationship between income and net money transfers from parents is virtually identical in the main sample and in the subsample where parents are exclusive DB customers so that parent transfers are identified only through unique personal identification numbers. Finally, Figure 1D describes the distribution of our income and spending measures: average net income (i.e. net of income taxes) and spending are around $3,300 and $2,400 respectively suggesting an average propensity to consume of around 0.75.[19]

3 Empirical strategy

Our goal is to estimate how net resource transfers from family and friends respond to adverse circumstances, both losses of annual income and events such as job losses, expenditure shocks, family ruptures and arrears notices.

[18] The overall positive correlation between income and transfers from parents in the cross-section is consistent with early survey evidence from the U.S. (e.g. Cox, 1987).

[19] As low-income individuals are of particular interest for our analysis, we provide additional descriptive statistics for the bottom decile of the income distribution in Figure A1 in the Online Appendix. For around 50% of these individuals government transfers is the only source of income whereas around 35% supplement government transfers with some wage income and less than 1% only have self-employment income (Panel A). Within the group whose only income source over a given year is government transfers, individuals in the bottom decile tend to receive less government transfers in months with non-zero government transfers than others (Panel B) and are more likely to experience months with zero income (Panel C). The former finding reflects that government transfers are highly differentiated with monthly pre-tax transfer amounts ranging from around $1,000 (i.e. social benefits for immigrants and youth) to around $2,500 (i.e. unemployment benefits and disability pensions). The latter finding reflects that the social safety net in Denmark has holes: individuals with zero market income are not always eligible for government transfers and do not always take up government transfers even when they are eligible. Finally, we document that within the group whose only income source is government transfers, the bottom decile has a higher fraction of young, single, childless, male individuals (Panel D), which partly reflects that having children and reaching age thresholds mechanically increase the applicable rates. The graph also shows that low-income is persistent across generations and over time and that individuals with low income have a larger propensity to move out of the country.

3.1 Losses of annual income

Our first empirical approach exploits all the within-individual variation in annual income to estimate how inter-personal transfers change as individuals move around the income distribution. Specifically, we take averages of income over cohabiting partners within each year and construct a vector of binary indicators of the vigintiles of the income distribution inc_{it}^{G}. To illustrate, the indicator inc_{it}^{25-30} takes the value one for individuals whose income is between the 25th and the 30th percentile and zero for everyone else. We then proceed to estimate the following equation:

$$y_{it} = \alpha_i + \gamma_{age,t} + \sum \beta^G inc_{it}^G + \varepsilon_{it} \tag{1}$$

where y_{it} captures some dimension of resource transfers in the network. A vector of individual fixed effects (α_i) absorbs permanent characteristics of the individual (e.g. innate ability and diligence) and permanent characteristics of the network (e.g. parents' lifetime resources and preferences for giving). A full set of interactions between time dummies and age dummies ($\gamma_{age,t}$) flexibly absorbs age-specific trends in resource transfers (e.g. due to business cycle fluctuations).

The coefficients on the income indicators are identified exclusively from moves up and down the income distribution. The omitted category is incomes between the 50th and the 55th percentile so the coefficients on the other income ranges are measured relative to this range. To illustrate, the coefficient on inc_{it}^{25-30} expresses the estimated change in transfers associated with a move down the income distribution from the 50-55th percentile to the 25-30th percentile.[20]

We address potential endogeneity problems in a series of robustness tests. First, correlated income shocks within networks represent a challenge for identification. For instance, if parents tend to suffer income losses in the same periods as their adult children, our baseline estimates do not capture the partial effect of adverse shocks to children, but the joint effect of adverse shocks to children and parents. Second, important life choices such as child births, home purchases and emigration may confound the estimates to the extent that they correlate with income and at the same time have an independent effect on resource transfers from family and friends. We address these two concerns by controlling for contemporaneous parent income, home purchases and child births and by restricting the sample to individuals who do not migrate.

Further, one may be concerned about reverse causality: individuals may respond to large

[20] To be precise about the identifying variation, note that not only individuals moving precisely between the 50-55th percentile and the 25-30th percentile contribute to identification of inc_{it}^{25-30}. In principle, individuals moving between, say, the 50-55th percentile and the 40-45th percentile and other individuals moving between, say, the 40-45th percentile and the 25-30th percentile could jointly identify inc_{it}^{25-30} and inc_{it}^{40-45}.

transfers from, say, their parents by lowering their labor supply and thus their earnings.[21] The problem arises because the model uses all time variation in income, both the part that is due to exogenous shocks such as unemployment and the part that is due to individual choices. The most obvious solution is to isolate variation that is plausibly exogenous. This is precisely what we do in the event framework (see next subsection) where we study how resource transfers change around drops in income following job losses and hikes in expenditures due to car repairs, dental work and divorce.

3.2 Adverse events

Our second empirical approach uses data at the monthly frequency to estimate how interpersonal transfers respond to a broader range of adverse events: job losses, expenditure shocks, family ruptures and arrears notices. For each event, we construct a vector of event time dummies (D_{it}^m) indicating the month m relative to the time of the event. To illustrate, D_{it}^1 takes the value one for individuals who experienced the event in the previous month and zero otherwise. For individuals who did not experience the event during the sample period, all the event time dummies are coded zero. We estimate the following equation:

$$y_{it} = \alpha_i + \gamma_{age,t} + \sum \beta^m D_{it}^m + \varepsilon_{it} \tag{2}$$

As before, y_{it} is some dimension of resource transfers and the model includes individual fixed effects (α_i) and interactions between time dummies and age dummies ($\gamma_{age,t}$). We are interested in the coefficients on the event time dummies, which express the dynamics in transfers relative to a counterfactual trajectory identified by the reference group of individuals who did not experience the event. Specifically, the coefficient on D_{it}^m captures the change in transfers since the baseline period (6 months before the event) measured relative to the change in transfers over the same calendar months in the reference group of individuals at the same age.[22]

The endogeneity concerns discussed above are attenuated in the event specification. First, at the monthly frequency, it is less likely that confounding shocks coincide with the events we are studying. Second, we can corroborate the counterfactual used to identify transfer responses by comparing trends in the pre-event period to the reference group.

[21] This relates to the "Carnegie effect" whereby large inheritances may discourage heirs from exerting effort and developing productive skills (Holtz-Eakin et al., 1993; Bø, 2019).

[22] The reference group ensures statistical identification of all calendar time dummies except one and all event time dummies except one (Borusyak and Jaravel, 2017).

4 Transfer responses to adverse circumstances

In this section, we document how resource transfers from the social network change when individuals move around the income distribution and when they experience adverse events such as job loss, expenditure shocks, family ruptures and financial distress.

4.1 Losses of annual income

By estimating equation (1) for various outcomes, we show how resource transfers from the social network vary with the position in the income distribution while controlling for individual fixed factors (e.g. ability and diligence), network fixed factors (e.g. parent preferences and life-time income) and time-varying age dynamics in transfers. The estimates are reported in Figures 2-3.[23]

Parents

We first present results on the informal insurance provided by parents. Figure 2A illustrates the size of the changes in net income (blue line) and spending (red line) associated with moves around the income distribution. For instance, moving from the median income level to the bottom vigintile represents a net income loss of around \$2,900 per month and induces a reduction in spending of around \$700 per month. The finding that spending adjusts much less than net income is consistent with canonical theories of consumption smoothing and with recent evidence on behavioral responses to income loss (e.g. Ganong and Noel 2019; Andersen et al., 2020).

We illustrate how money transfers to and from parents respond to income changes in Figure 2B. Gross transfers from parents (green line) are almost unaffected by income changes in the upper part of the income distribution but respond strongly in the lower part: moving from the median income level to the bottom vigintile induces an increase in transfers from parents of around \$90 per month. Gross transfers to parents (red line) are increasing in net income throughout the income distribution but the gradient is relatively flat. Net transfers from parents (blue line) combine money transfers to and from parents and represent a key insurance outcome. The responses are sizeable in the bottom part of the income distribution but smaller in the upper part: moving from the median income level to the bottom vigintile increases net money transfers from parents by more than \$100 per month while moving to the top vigintile reduces them by around \$30.[24]

[23]For comparison, we show *unconditional* correlations between the outcomes and the position in the income distribution in Figures A2-A3 in the Appendix.

[24]By comparison, when we include individuals who live in the same municipality as their parents in the sample,

The qualitative patterns in Figure 2B remain when using the number of months with positive money transfers as the outcome rather than average monthly transfers. As shown in Figure 2C, moving from the median income level to the bottom vigintile raises the number of months with transfers *from* parents by around 0.5 (green line) and lowers the number of months with transfers *to* parents by roughly the same amount (red line). Consistent with the notion that parent transfers respond less to income changes at high income levels, the gradient is less steep in the upper part of the income distribution.

Finally, in Figure 2D, we show that the probability of cohabitation with parents changes with income in a non-linear fashion. There is a negative gradient in the lower part of the income distribution: moving from the median income level to the bottom vigintile increases the propensity to live with the parents by around 4 percentage points. The gradient is particularly steep within the bottom deciles suggesting that cohabitation primarily works as insurance against the worst outcomes. The slightly positive gradient in the upper part of the distribution may reflect, and evidence presented below corroborates this interpretation, that individuals have better housing conditions, and therefore are more likely to host parents, in periods with higher income.

Other family and friends

Next, we provide results on informal insurance by other family members and friends. Income changes have small but significant effects on net money transfers from siblings (Figure 3A - red line): moving from the median income level to the bottom vigintile increases net transfers from siblings by around \$5 per month. We detect no significant effects on money transfers from grandparents (Figure 3A - green line), work friends (Figure 3B - red line) and school friends (Figure 3B - green line).

The results are suggestive that parents are a much more important source of informal insurance than other family and friends: the increase in money transfers from parents as individuals move from the middle to the bottom of the income distribution (\$100) dwarfs the increase in transfers from others (\$5). There are several reasons why these results may somewhat understate the importance of non-parents relative to parents. First, we do not capture all parts of the social network and cannot exclude that there is significant informal insurance through friends from other places than school and work (e.g. neighborhoods, sports clubs, distant relatives). Second, the coverage of transactions with non-parents is less complete than with parents. Specifically, when the money transfer data does not include the personal identifier of the counterpart, we do

we estimate that moving from the median income level to the bottom vigintile increases net money transfers from parents by around \$70 per month.

not attempt to link transactions to other family and friends through the bank branch identifier (as explained above) in the same way as for parents. It is unlikely, however, that these two sources of error are large enough to overturn the qualitative finding that parents are the main source of informal insurance. To illustrate, we make the estimate for parent transfers more comparable to the estimates for non-parents by using a measure of money transfers that only uses links through personal identifiers and report the results in Figure A4 in the Online Appendix (Panel D). With this approach, the increase in net transfers from parents as individuals move from the middle to the bottom of the income distribution is around \$75. This is somewhat less than our baseline estimates but many times larger than the estimates for non-parents.

Heterogeneity

We also explore heterogeneity in informal insurance across individuals whose social networks have different economic resources. Given that parents appear to be key insurers, we split the sample by our proxy for the economic resources of parents and estimate the model for each subsample separately. As shown in Figure 3C, parent insurance in the form of money transfers vary monotonically with parent resources: moving from the middle to the bottom of the income distribution increases net transfers from parents by around \$230 when parents are high-income (p90-p100); around \$130 when parents are middle-income (p50-p90) and by less than \$50 when parents are low-income (p0-p50). As shown in Figure 3D, parent insurance in the form of cohabitation is more homogeneous across parental groups: moving from the middle to the bottom of the income distribution increases the probability of cohabitation by around 5 percentage points when parents are high-income or mid-income and by around 2.5 percentage points when parents are low-income. The positive gradient at the top of the income distribution is most pronounced for individuals with low-income parents whereas there is virtually no gradient for high-income parents. This may reflect that parents with limited economic resources move in with their adult children in periods when the latter have high incomes.

Robustness

We present the results of a number of robustness tests in Figure A4 in the Online Appendix. First, we absorb potentially correlated income shocks to parents by adding non-parametric controls for the vigintiles of the distribution of current parent income. Second, we account for potentially confounding life events by adding controls for child births and home purchases. Third, we address the concern that some individuals may appear to have low incomes because they emigrate in the course of the year by restricting the sample to those who remain registered residents in Denmark throughout the year. None of these modifications have a material impact on our estimates of how resource transfers from parents vary with the position in the income distribution (Panels A-B).[25] Finally, we check the sensitivity of the results to our preferred approach to identifying transactions with parents, which partly relies on links through bank branch identifiers. The results remain almost unchanged when we restrict the sample to individuals whose parents are exclusive DB customers, in which case money transfers to and from parents are identified exclusively from unique personal identifiers (Panel C).

4.2 Adverse events

By estimating equation (2) for various outcomes and various adverse events, we characterize the economic nature of the events and document how resource transfers from the social network evolve over a period of 24 months centered at the event.

Job losses

As shown in Figure 4A, a job loss amounts to a persistent and sizeable loss of net income, which induces an equally persistent but much smaller loss of spending.[26] Specifically, net income is roughly \$2,300 lower in the month of the job loss than in the baseline period.[27] More than half of the income loss is recovered already in month +1, reflecting that our definition of job losses includes many almost immediate transitions into new jobs and that disbursements of unemployment benefits begin, and income continues to increase slowly for the rest of the event period.[28] Spending drops by around \$170 in month +1 and remains close to that level, with a slightly increasing trend that mirrors the slow increase in income, for the rest of the event period.[29]

[25] The additional controls all have a strongly significant effect on money transfers: individuals receive more money from their parents in years where they purchase a house or have a baby and in years where parents have higher income. However, the figures indicate that the controls do not change the estimated effect of the individual's own income.

[26] Net income at the monthly frequency is not fully equivalent to the annual net income: it captures payments by private employers (e.g. salary) and government agencies (e.g. unemployment benefits) net of income taxes withheld by the paying agent. It does not include interest and dividends paid by financial institutions and does not account for the final settlement of annual taxes at the end of the fiscal year.

[27] The effect on income is visible already in month -1 reflecting that we cannot determine the timing of the job loss within a month. Consider, for instance, an individual with a monthly salary of \$3,000. If the individual is laid off on 20 August, recorded earnings are \$3,000 in July, \$2,000 in August and \$0 in September. While there is a \$1,000 income loss in August, we will code this as a job loss in September when income falls to zero.

[28] This is consistent with a large literature on earnings dynamics around unemployment (e.g. Jacobson, 1993).

[29] The finding that spending drops much less than income suggests that consumption is to a large extent insured against income shocks through a combination of self-insurance and informal insurance, which is qualitatively consistent with the literature measuring partial insurance with income and consumption data (Blundell et al., 2006).

Job losses are associated with pronounced increases in resource transfers from family and friends. First, net money transfers from parents are \$30 above the baseline level in month -1 (the onset of the income loss), peak at \$40 above the baseline level in $+1$ and then decrease while remaining slightly above the baseline level for the rest of the post-event period (Figure 4B). Second, net money transfers from other family and friends follow a similar qualitative pattern, but the point estimates are generally much smaller with a combined peak of less than \$5 in month 0 (Figure 4C). Third, there is a clear spike in the propensity to move to the parents around the job loss suggesting that some individuals losing jobs respond by returning to their parents' home (Figure 4D).

Expenditure shocks

As shown in Figure 5A, spending surges to around \$2,000 above the baseline level in the month of the payment while there is no detectable change in income. Both spending and income remain close to the baseline level in the rest of the event period.

Expenditure shocks induce financial assistance from parents: net money transfers from parents are around \$90 above the baseline level in the month of the shock and then return to the baseline level (Figure 5B). There are also some signs of weak transfer responses by other family and friends with a combined peak in the event month of less than \$10 (Figure 5C) whereas there are no signs that expenditure shocks increase the propensity to move to parents (Figure 5D).

Divorces

Since the economic impact of divorces is not *a priori* obvious, the illustration of income and spending dynamics is particularly useful in this case. Figure 6A shows that, from a purely financial perspective, divorces can meaningfully be considered as persistent expenditure shocks: spending is around \$300 above the baseline level in the month of the divorce and subsequently converges to a new level around \$60 above the baseline level at the end of the event period. While the spike in spending around the split-up may reflect relocation costs, the long-run shift in spending is consistent with descrution of consumption economies of scale (e.g. Browning et al., 2013).[30] There is a small and temporary increase in net income in the months after the divorce.

Parents play a particularly important role in insuring the financial costs associated with divorces. Net money transfers from parents are \$100 above the baseline level in months -1 and

[30]Our estimates may very well understate the shock to total expenditures since the spending measure does not include housing expenses, which are particularly likely to be associated with scale economies.

0, suggesting that parents insure a significant share of the relocation costs, and then quickly return to the baseline level (Figure 6B). Moreover, the propensity to move back to the parents increases sharply by around 2 percentage points in period 0 and stays slightly above the baseline level for the rest of the event period (Figure 6D).[31]. By contrast, there are no clear signs that money transfers from other family and friends change around divorces (Figure 6C).

Financial distress

In the case of financial distress, we do not expect the event to affect the budget mechanically so the analysis of income and spending dynamics serves mostly to describe the circumstances triggering the arrears notice. Figure 7A suggests that arrears notices are caused by income shocks that are not accompanied by appropriate spending adjustments: net income decreases quickly through the pre-event period while spending increases slightly. The arrears notice appears to induce behavioral responses on both margins: in just two months net income roughly reverts to the pre-event level and monthly spending drops by almost $200. Throughout the post-event period, the balance between income inflows and spending outflows is improved by around $250 relative to the month immediately prior to the arrears notice.

Notably parents but also other family and friends provide some financial support around instances of financial distress. Net money transfers from parents are $10-20 above the baseline level in months 0 and +1 and then quickly return to the baseline level (Figure 7B). Unlike for the other events, there is a slight indication that transfers from parents fall *below* the baseline level toward the end of the post-event period suggesting that part of the unusually high transfers around the arrears notice is in the form of loans. Net money transfers from other family as well as friends also rise slightly above the baseline level in the event month, but the amounts involved are small (Figure 7C). There is no spike in the propensity to move back to the parents at the event, but a slightly higher level, statistically indistinguishable from the baseline level, throughout the post-event period (Figure 7D).

Heterogeneity

For all four types of events, we study resource transfers from parents with different economic resources separately in Table 3. For compactness, we only report the estimates for month 0 and month +6; the full dynamics is illustrated in Figures A5-A6 in the Online Appendix.

As shown in Table 3A, there is a clear monotonicity in parents' responses to adverse events in terms of their financial support: across all four events, net money transfers from parents with

[31] The sharpness of the increase at least partly reflects that divorces are identified based on changes of residence

more economic resources increase more in the event month and remain at a higher level after six months.[32] Around job losses, the increase in money transfers from high-income parents relative to the baseline level is around $70 in month 0 and around $40 in month +6 whereas there is virtually no increase in transfers from low-income parents. Around expenditure shocks, the increase in money transfers is concentrated in month 0 and is significant for all three groups; however, it is around $200 for high-income parents and $75 and $55 for middle-income and low-income parents respectively. Around divorces, money transfers are around $230 above the baseline level in month 0 for from high-income parents as compared to $110 for middle-income parents and $40 for low-income parents. The ranking remains in month +6 although the amounts are considerably smaller. Around financial distress, high-income parents increase net money transfers by around $25 in month 0 (and more than $60 in the following month) while the responses from parents in lower income groups are in the range $5-15.

Cohabitation responses to adverse events are much more uniform across parent groups as shown in Table 3B. There are significant increases in the propensity to move back to the parents around job losses and divorces and the magnitudes of the estimates are similar for the three groups. Around divorce, our estimate is slightly lower for individuals with high-income parents suggesting some substitution between the two modes of assistance, money transfers and cohabitation. None of the three groups exhibit pronounced increases in the propensity to move back to the parents around expenditure shocks and financial distress.

5 Implied replacement rates

In the final step of the empirical analysis, we quantify the importance of informal insurance by expressing private transfer responses to adverse circumstances as marginal replacement rates.

5.1 Losses of annual income

To derive marginal replacement rates of annual income, we rewrite equation (1) slightly: rather than dummies indicating the position in the income distribution, our main explanatory variables now capture the dollar amount of net income. In the simplest possible specification, there would be a single income variable capturing total net income. The resulting point estimate would capture the marginal replacement averaged over all income levels.[33] To allow the marginal effect

[32] It should be noted that standard errors are often too large to statistically distinguish point estimates across income groups and sometimes even to distinguish them from zero.

[33] McGarry (2016) estimates a specification similar to this one and reports a coefficient of around 0.004 on the income term corresponding to a replacement rate of around 0.4 cents on the dollar.

of net income on transfers to vary over the income distribution, we instead estimate a piece-wise linear relation between net income and transfers with five income ranges corresponding to the following ranges of the income distribution: p0-10, p10-20, p20-30, p30-50 and p50-100.[34] The resulting specification writes:

$$y_{it} = \alpha_i + \gamma_{age,t} + \sum \beta^R inc_{it}^R + \varepsilon_{it} \tag{3}$$

where inc_{it}^R expresses income in income range R. The estimated marginal replacement rate in range R is given by β^R.

We estimate equation (3) for three money transfer outcomes separately – net money transfers from parents, from other family (siblings and grandparents combined) and from friends (school friends and work friends combined) – and report the estimated marginal replacement rates in Figure 8A. Marginal replacement by parents (blue bars) is monotonically decreasing in the income level: an income loss of one dollar within the lowest decile induces an increase in net money transfers of more than 4 cents; in the second decile around 3 cents; in the next three deciles around 1 cent; and at incomes above the median around 0.5 cents. Declining marginal replacement rates may reflect decreasing marginal utility of income or increasing ability to self-insure. Replacement by other family members (green bars) is generally much lower than by parents; the rate also tends to decrease in income but is slightly higher in the second decile than in the first decile. Replacement by friends (brown bars) is economically and statistically insignificant in all income ranges.

To produce comparable replacement rates for resource transfers in the form of cohabitation, we first estimate the monetary value of living with the parents. Specifically, we aggregate four expenditure categories – rent, utilities, groceries and fuel – into a single measure of *living costs* and estimate equation (2) using this variable as an outcome and the month where an individual moves back to the parents as the event. As shown in Figure 8B, there is a clear downward shift in living costs when young individuals move back to their parents (blue line).[35]. Figure A7 in the Online Appendix shows that the overall decrease in living costs primarily reflects a large drop in

[34]To understand the mechanics, assume that p10 corresponds to the income level 100, p20 to the income level 200 and p30 to the income level 300. For an individual with income 50, we assign 50 to the income range p0-p10 and zero to the other income ranges. For an individual with income 120, we assign 100 to the income range p0-p10, 20 to the income range p10-p20 and zero to the other income ranges. For an individual with income 240, we assign 100 to the income range p0-p10, 100 to the income range p10-p20, 40 to the income range p20-30 and zero to the other income ranges. Income in each of the five ranges enter the model as separate variables. We fix the income thresholds across years to prevent changes in the thresholds from moving income across ranges.

[35]The fact that the estimated line starts trending prior to month 0 may reflect that individuals in some cases move to the parents one or two months before reporting the change of address to the population register

rent payments (Panel C), but also smaller decreases in spending on utilities and groceries (Panel B).[36] To summarize the monthly savings associated with cohabitation in a single number, we estimate a compact version of the equation where the 12 post-event dummies, $D^0, D^1, ..., D^{11}$, are replaced with a single dummy, D^{post} taking the value one in all 12 post-event months and zero otherwise. The resulting estimates suggest that the average monthly cost savings associated with cohabitation amount to \$645 (black line in Figure 8B).[37]

We are now able to estimate the replacement rate for transfers in the form of cohabitation with parents. Specifically, we estimate equation (3) using the estimated monthly value of such resource transfers as the outcome: \$645 for observations with cohabitation and \$0 for observations with no cohabitation. As shown in Figure 8A, replacement from parents in the form of cohabitation (red bars) is lower than in the form of money transfers, but economically and statistically significant at low income levels: around 1.7 cent on the dollar in the first income decile and 0.7 cent in the second.

Finally, aggregating transfers in all forms and from all sources, we arrive at our estimates of the key statistic expressing the overall importance of informal insurance: comprehensive marginal replacement rates (black bars in Figure 8C). The estimates imply that an income loss of one dollar within the lowest decile induces an increase in total transfers from the social network of more than 7 cents; in the second decile around 4 cents; in the third decile around 1.5 cents; and in the next rest of the income distribution less than 1 cent.

The replacement rate increases systematically with parents' economic resources: an income loss of one dollar within the bottom decile is associated with an overall increase in resource transfers of 3 cents for individuals with low-income parents (blue bar in Figure 8C), almost 8 cents for those with middle-income parents (red bar) and 12 cents for those with high-income parents (green bar). Table 4 provides details on heterogeneity in the underlying insurance components: resource transfers from parents dominate in all three groups with other family and friends making economically and statistically insignificant contributions. The insurance value of cohabitation is roughly similar across income groups whereas parent responses in the form of money transfers are highly heterogeneous and account for almost the entire difference in comprehensive replacement rates.

[36] We observe a small increase in spending on fuel when individuals move back to their parents, presumably because moving creates a need to cover longer distances going to work and visiting friends

[37] Figure A7 in the Online Appendix also shows that money transfers *to* parents increase substantially after individuals move back to their parents (Panel D), perhaps to cover some of the extra costs. This is another rationale for studying money transfers and cohabitation jointly: if adverse circumstances induce individuals to move to their parents and to transfer money to their parents to partly cover the costs, one would overestimate replacement by studying cohabitation alone and underestimate it by focusing exclusively on money transfers.

5.2 Adverse events

To derive replacement rates in the context of adverse events, we rewrite equation (2) in two ways. First, drawing on the analysis of income and spending dynamics in the previous section, we replace the event time dummies with an explanatory variable capturing the budget component mechanically affected by the event. Hence, the explanatory variable is net income when the event is job loss and spending when the event is expenditure shocks.[38] Second, as we want to identify replacement rates exclusively from the variation in the budget that derives from the event, we construct a dummy variable Z_{it} taking the value one in event months -1, 0, ...+10 and use it as an instrument. The estimating equation thus writes:

$$y_{it} = \alpha_i + \gamma_{age,t} + \beta X_{it} + \varepsilon_{it} \tag{4}$$

where X_{it} is either net income or spending depending on the event and X_{it} is instrumented with Z_{it}. The estimated coefficient on X_{it} expresses what fraction of the adverse shock to the budget caused by the event over a period of 12 months is offset by increased resource transfers from the network.

As shown in Figure 8A, job losses induce resource transfers from parents of around 2 cents (blue bars) in the form of money transfers and 1 cent in the form of cohabitation (red bars) for each dollar of income lost. By comparison, expenditure shocks induce resource transfers from parents of around 7 cents in the form of money transfers and less than 0.5 cent in the form of cohabitation for each dollar of additional expenditures. In both cases, the estimated transfer responses by other family (green bars)and friends (brown bars) are economically insignificant.

As shown in Figure 8D, the resulting estimates for comprehensive replacement rates, including transfers in all forms and from all sources, are around 3 cents for job losses and 8 cents for expenditure shocks (black bars). Comprehensive replacement rates vary systematically with parent resources: they range from 2 cents for individuals with low-income parents (blue bars) to 5 cents for those with high-income parents (green bars) in the context of job losses and from 5 cents to 15 cents for the same two groups in the context of expenditure shocks. As shown in Table 4, money transfers from parents account for most of the heterogeneity in comprehensive replacement rates for both types of adverse events; cohabitation with parents makes strikingly similar contributions to replacement rates across groups.

[38] We do not compute replacement rates for divorces and financial distress where the budget is only indirectly affected by the event.

6 Conclusion

In this paper, we set out to provide new evidence on informal insurance. We are ultimately interested in quantifying replacement rates: how much of a one dollar shock to the household budget is replaced by increases in resource transfers from the social network? We estimate comprehensive replacement rates accounting for resource transfers from parents, siblings, grandparents and friends made in cash as well as in kind. Motivated by theories of altruism, we allow our estimates of the marginal replacement rates to vary with the position in the income distribution and with the economic resources of the social network.

At the heart of our contribution is a data innovation: by combining transaction-level customer records from a large retail bank and individual-level information from government registers, we are able to identify a range of *adverse circumstances* (e.g. income shocks and financial distress), various types of *resource transfers* (e.g. money transfers and cohabitation) and different parts of the *social network* (e.g. parents, siblings and school friends). These three components are generally hard to capture empirically in large samples; yet, they are all necessary to study how resource transfers from the social network responds to adverse shocks.

We show that resource transfers from the social network increase when individuals are in adverse circumstances and express these responses as replacement rates, the key statistic used to capture the generosity of social insurance. We estimate that, aggregating across all forms of transfers from all parts of the social network, income losses are replaced at the marginal rate of 7% in the bottom income decile, 4% in the second decile, 1.5% in the third decile and an insignificant 1% at higher income levels. The negative income gradient shows that, consistent with the fundamental principles of altruism, the social network provides most insurance when it is most needed. Parents are the key providers of insurance and marginal replacement rates correlate strongly with parent income levels. This implies that access to informal insurance is highly unequal and thus points to an important motivation for social insurance schemes.

While our key results are consistent with theories of altruism where marginal utilities of economic resources determine inter-personal transfers, we find some patterns that cannot be explained by altruism in its simplest form. Specifically, resource transfers from the social network appear to increase sharply at the time of adverse shocks and then revert to the baseline level even when the shocks are persistent. These patterns suggest that salient *changes* to income and expenditure may play a role in shaping transfers within social networks.

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Table 1: sample selection. The table shows how the observable characteristics of the sample changes as we start from the full sample of individuals aged 20-39 (Column 1) and condition on at least one parent being known (Column 2), the individual being a DB customer (Column 3), the individual being an DB exclusive customer (Column 4) and the individual being an exclusive DB customer who does not live in the same municipality as the parents (Column 5).

	All	At least one parent known	Customers in the Bank	Exclusive customers in the Bank	Exclusive customers in the Bank and live in different municipality than parents
Observations (max)	6,911,043	6,135,105	1,797,922	1,080,010	538,532
Demographics					
age	29.71	29.67	29.52	29.26	30.13
male	50%	51%	51%	50%	48%
cohabitation with parents	9%	10%	11%	13%	0%
student	19%	21%	22%	24%	25%
Income					
gross income	49,786	51,796	51,340	48,477	52,816
- salary	39,487	41,178	40,251	37,346	41,765
- business income	1,199	1,264	1,158	987	1,096
- government transfers	8,114	8,307	8,790	9,194	8,840
net income	34,626	35,966	35,519	33,800	36,424
unemployment rate	3.3%	3.3%	3.3%	3.5%	3.3%
Assets and liabilities					
value of real estate	73,241	78,980	72,177	64,358	70,194
owns real estate	39%	41%	36%	33%	38%
bank deposits	11,039	11,486	12,116	10,526	11,659
securities	2,095	2,259	2,711	2,277	2,799
liabilities	92,357	99,757	88,766	77,496	85,322
Parents					
at least one parent known	89%	100%	100%	100%	100%
at least one parent alive	87%	97%	97%	97%	94%
parent past rank in income	50%	50%	51%	50%	54%
parent current income	59,072	59,072	60,172	59,234	62,626

Table 2: resource transfers within the social network. The table provides summary statistics on resource transfers within the social network: gross monthly money transfers from others (Column 1), gross monthly money transfers to others (Column 2), net monthly money from others (Column 3) and the probability of cohabitation (Column 4) where others refer to parents (Row 1), siblings (Row 2), grandparents (Row 3), individuals who have been enrolled at the same school or study program in the same cohort (Row 4) or who have been employed at the same workplace in the same year (Row 5).

	Gross monthly money transfers (ingoing)	Gross monthly money transfers (outgoing)	Net monthly money transfers (ingoing)	Probability of cohabitation
parents	138.7	75.1	63.4	5.3%
siblings	8.6	8.8	-0.2	-
grandparents	1.7	0.3	1.4	-
school friends	2.4	2.8	-0.4	-
work friends	6.8	6.7	0.1	-

Table 3: informal insurance by the economic resources of parents. The table shows the estimated effect of adverse events on resource transfers from parents in the form of net money transfers (Panel A) and cohabitation (Panel B). We estimate equation (1) and report the estimates for month 0 (Columns 1-4) and month 6 (Columns 1-4). We report separate results for the full estimating sample (Columns 1 and 5) and for subsamples of individuals whose parents have earnings capacity below the median (Columns 2 and 6); between the median and the 90th percentile (Columns 3 and 7) and above the 90th percentile (Columns 4 and 8). Standard errors are clustered at the individual-level.

	Month 0				Month 6			
	All	low-income parents	mid-income parents	high-income parents	All	low-income parents	mid-income parents	high-income parents
Panel A: net money transfers from parents								
Job loss	20.7	-6.7	28.3	70.9	8.0	-6.3	10.7	39.0
	(9.8)	(12)	(15)	(37)	(10)	(12.6)	(15.3)	(37.6)
Expenditure shock	89.9	56.0	74.6	200.3	8.4	17.6	-7.0	26.0
	(17.1)	(18.6)	(23.9)	(66.2)	(15.3)	(17.9)	(19.8)	(61.3)
Divorce	95.7	39.3	112.0	228.0	8.3	-6.0	13.4	34.1
	(11.6)	(13.6)	(18.8)	(45.6)	(9.1)	(10.2)	(15.1)	(36.5)
Financial distress	10.0	3.6	12.2	24.5	-1.2	-0.7	-5.3	13.7
	(4.4)	(4.8)	(7.3)	(19.2)	(4.7)	(5.3)	(7.6)	(20.4)
Panel B: moving to parents								
Job loss	0.00091	0.00072	0.00102	0.00148	0.00008	0.00003	0.00031	-0.00002
	(0.00021)	(0.00032)	(0.00032)	(0.00066)	(0.00015)	(0.00024)	(0.00024)	(0.0001)
Expenditure shock	0.00010	-0.00006	0.00028	0.00009	-0.00023	-0.00062	-0.00014	0.00059
	(0.00027)	(0.00048)	(0.00043)	(0.00007)	(0.00022)	(0.00036)	(0.00034)	(0.00062)
Divorce	0.02127	0.02150	0.02215	0.01838	0.00058	0.00056	0.00050	0.00047
	(0.00091)	(0.00133)	(0.00152)	(0.0026)	(0.00018)	(0.00026)	(0.0003)	(0.00039)
Financial distress	0.00013	0.00013	0.00006	0.00027	0.00004	-0.00004	0.00004	0.00034
	(0.00009)	(0.00014)	(0.00016)	(0.00022)	(0.00009)	(0.00013)	(0.00016)	(0.00025)

Table 4: Replacement rates by source, form and income of parents. The table shows estimated marginal replacement rates for annual income variation (left panel) and replacement rates for job losses (middle panel) and expenditure shocks (right panel). There are comprehensive replacement rates, aggregating transfers across all sources and forms, as well as contributions from different sources (parents, other family, friends) and forms (money transfers, cohabitation). There are replacement rates for the full estimating sample as well as for individuals with high-income, middle-income and low-income parents separately.

	Marginal replacement rate within bottom income decile				**Replacement rate at job loss**				**Replacement rate at expenditure shocks**			
	All	low-income parents	mid-income parents	high-income parents	All	low-income parents	mid-income parents	high-income parents	All	low-income parents	mid-income parents	high-income parents
Comprehensive replacement rate	0.066	0.033	0.082	0.122	0.033	0.020	0.040	0.048	0.075	0.056	0.055	0.144
	(0.0074)	(0.008)	(0.013)	(0.0314)	(0.0026)	(0.0037)	(0.0042)	(0.008)	(0.0153)	(0.018)	(0.0246)	(0.0676)
- money transfers from parents	0.044	0.017	0.058	0.084	0.022	0.010	0.028	0.039	0.069	0.048	0.061	0.133
	(0.0067)	(0.0067)	(0.012)	(0.0287)	(0.0024)	(0.0032)	(0.0038)	(0.0072)	(0.0137)	(0.0157)	(0.0223)	(0.0612)
- cohabitation with parents	0.017	0.013	0.022	0.014	0.010	0.009	0.011	0.008	0.004	0.003	0.008	-0.010
	(0.0019)	(0.0028)	(0.0036)	(0.0047)	(0.0003)	(0.0005)	(0.0005)	(0.0006)	(0.0017)	(0.0026)	(0.0028)	(0.005)
- money transfers from other family	0.002	0.001	0.003	0.002	0.001	0.000	0.000	0.002	0.002	0.004	-0.005	0.014
	(0.001)	(0.0016)	(0.0018)	(0.003)	(0.0003)	(0.0006)	(0.0005)	(0.0008)	(0.0019)	(0.0029)	(0.0028)	(0.0065)
- money transfers from friends	0.000	0.000	-0.001	0.003	0.001	0.000	0.001	0.001	-0.001	0.000	-0.001	0.002
	(0.0008)	(0.0009)	(0.0015)	(0.0024)	(0.0003)	(0.0005)	(0.0005)	(0.0007)	(0.0018)	(0.0024)	(0.003)	(0.0064)

Figure 1: Descriptive statistics. The figure describes the data on money transfers to and from parents. Panel A shows the distribution of individual-year observations by the number of months with money transfers from parents. Panel B shows the distribution of individual-year observations by net monthly transfers from parents excluding observations with zero incoming and zero outgoing gross transfers. The vertical dotted line indicates the mean. Amounts below $-1,000 and above $1,000 are recoded to $-1,000 and $1,000 respectively. Panel C shows average net money transfers from parents by the position in the income distribution for the baseline sample (round markers) and for the subsample whose parents are exclusive DB customers (quadratic markers). Panel D shows the distribution of individual-year observations by monthly net income and monthly spending.

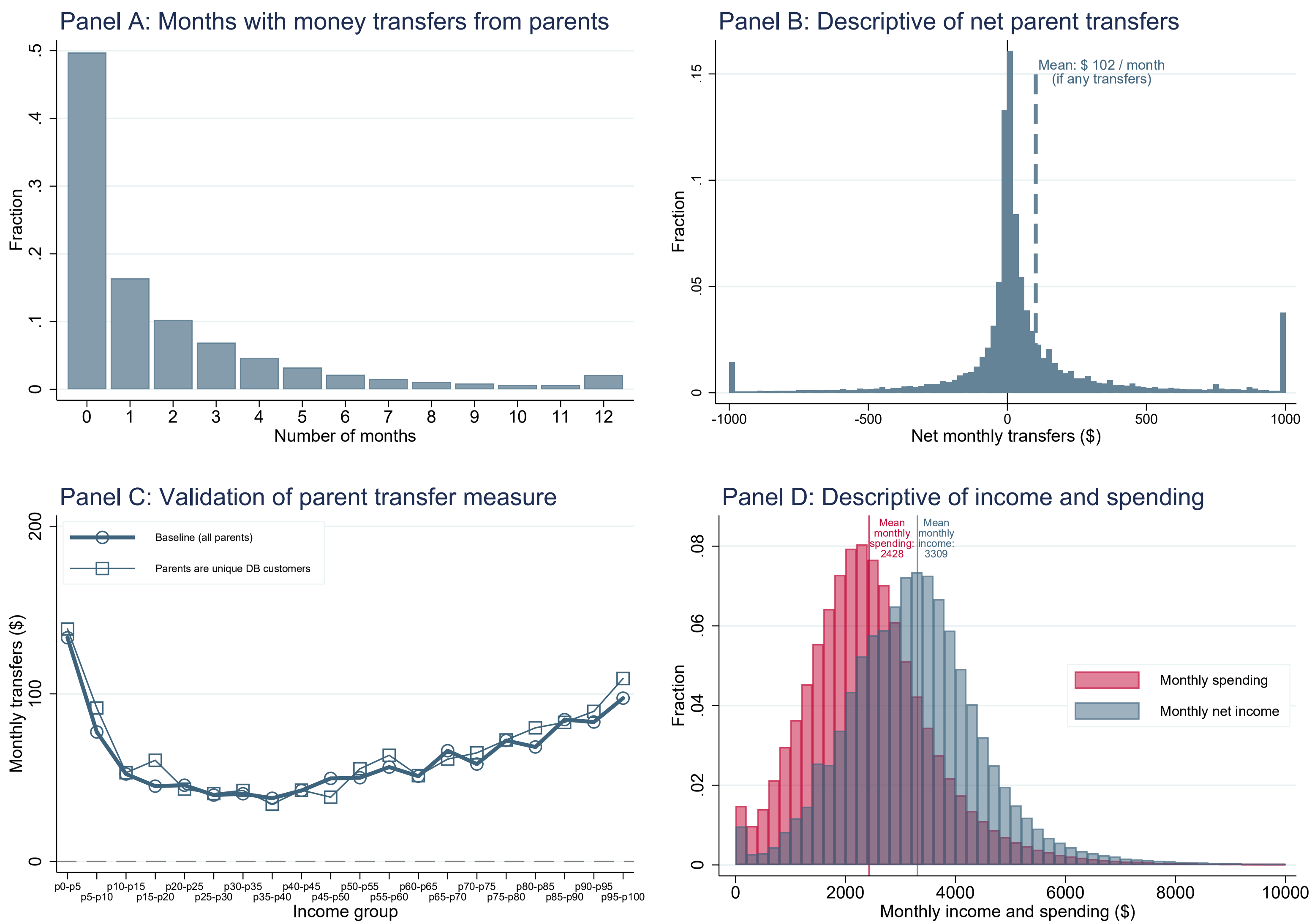


Figure 2: Parent responses to variation in annual income. The figure shows results from estimating equation (1) using various outcomes: net income and spending (Panel A), money transfers to and from parents (Panel B), the number of months with money transfers to and from parents (Panel C) and the probability of cohabiting with parents (Panel D). Besides dummies indicating the position in the income distribution (depicted in the graph), the equation includes individual fixed effects and interactions between age indicators and calendar year indicators. The horizontal lines indicate 95% confidence intervals based on standard errors with clustering at the individual level. The regression coefficients are in Table A1 in the Online Appendix. Analogous graphs plotting the unconditional mean of the same outcomes by position in the income distribution are in Figure A2 in the Online Appendix.

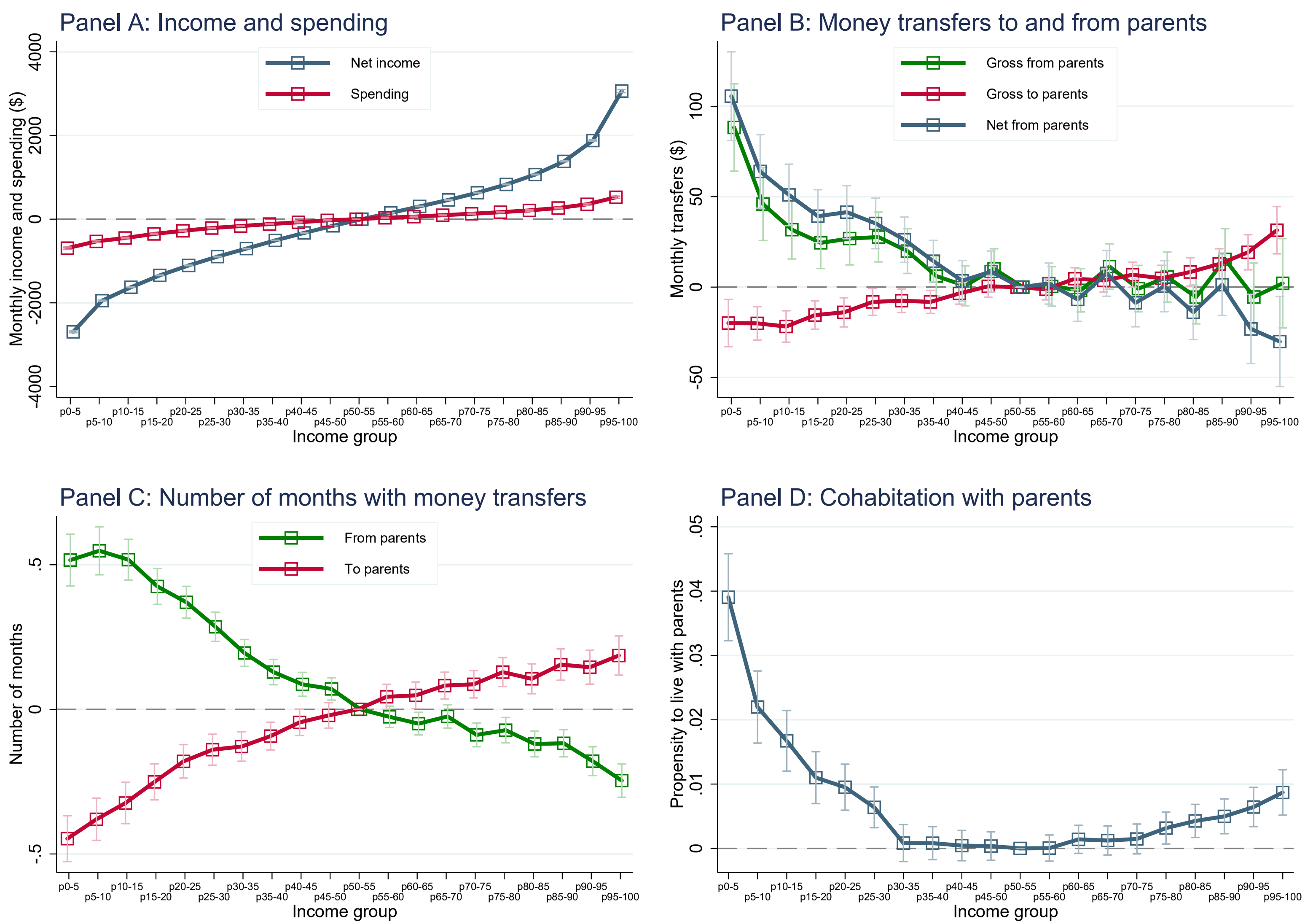


Figure 3: Non-parent transfers and parent heterogeneity. The figure shows results from estimating equation (1) using various outcomes: net money transfers from grandparents and siblings (Panel A), net money transfers from school friends and work friends (Panel B), net money transfers to and from parents (Panel C) and the probability of cohabiting with parents (Panel D). Besides dummies indicating the position in the income distribution (depicted in the graph), the equation includes individual fixed effects and interactions between age indicators and calendar year indicators. Panels C-D show separate results for samples of individuals with high-income parents (green bars), middle-income parents (red bars) and low-income parents (blue bars). The horizontal lines indicate 95% confidence intervals based on standard errors with clustering at the individual level. The regression coefficients are in Table A2 in the Online Appendix. Analogous graphs plotting the unconditional mean of the same outcomes by position in the income distribution are in Figure A3 in the Online Appendix

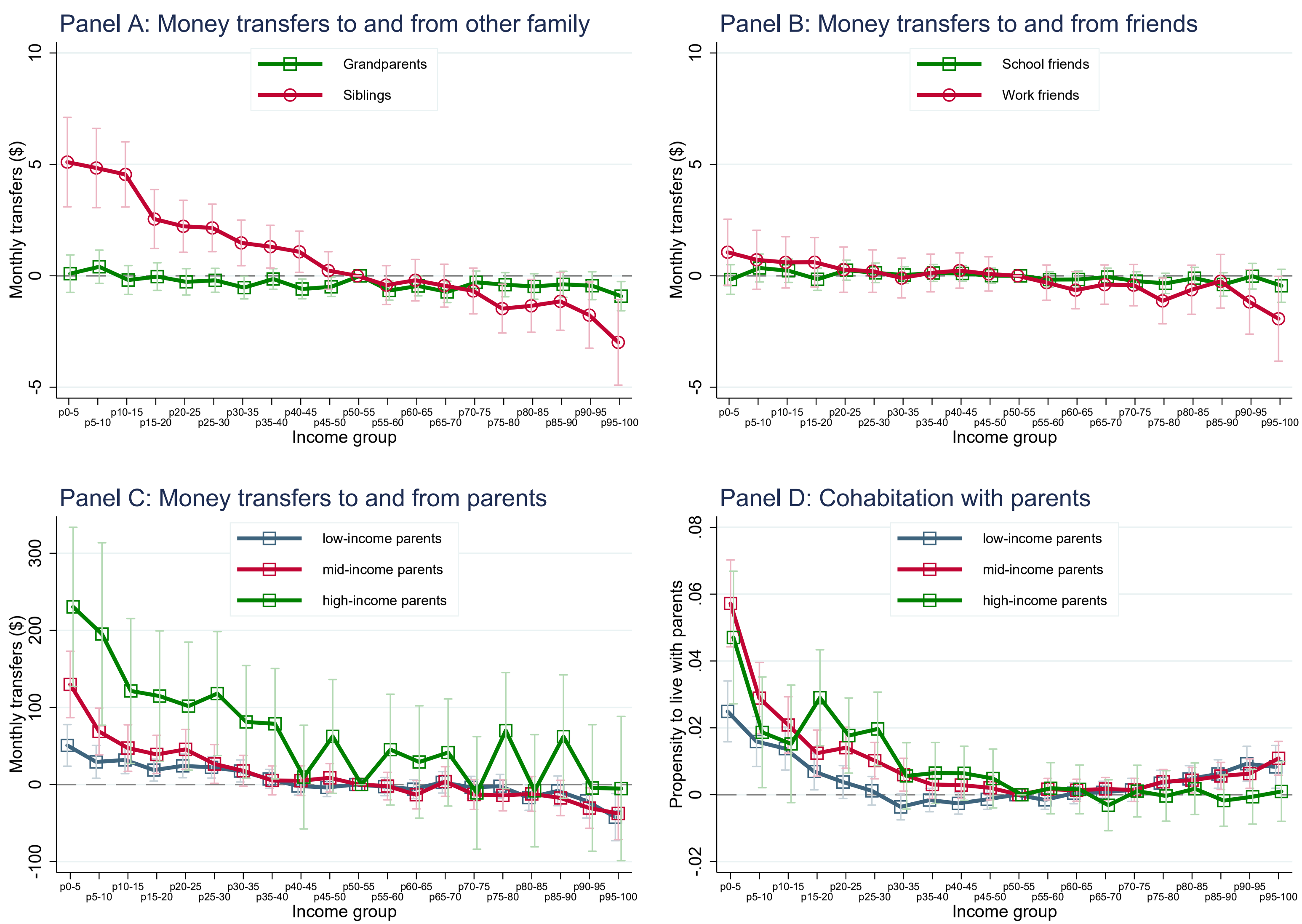


Figure 4: Job loss. The figure shows the results from estimating equation (2) where the event is a job loss defined as a month with earnings below \$200 after 12 consecutive months with earnings above \$2,000. The outcomes are net income and spending (Panel A), net money transfers from parents (Panel B), net money transfers from other family and friends (Panel C) and the probability of moving to parents (Panel D). Besides dummies indicating the month relative to the event (depicted in the graph), the equation includes individual fixed effects and interactions between age indicators and calendar month indicators. The horizontal lines indicate 95% confidence intervals based on standard errors with clustering at the individual level. The regression coefficients are in Table A3 in the Online Appendix.

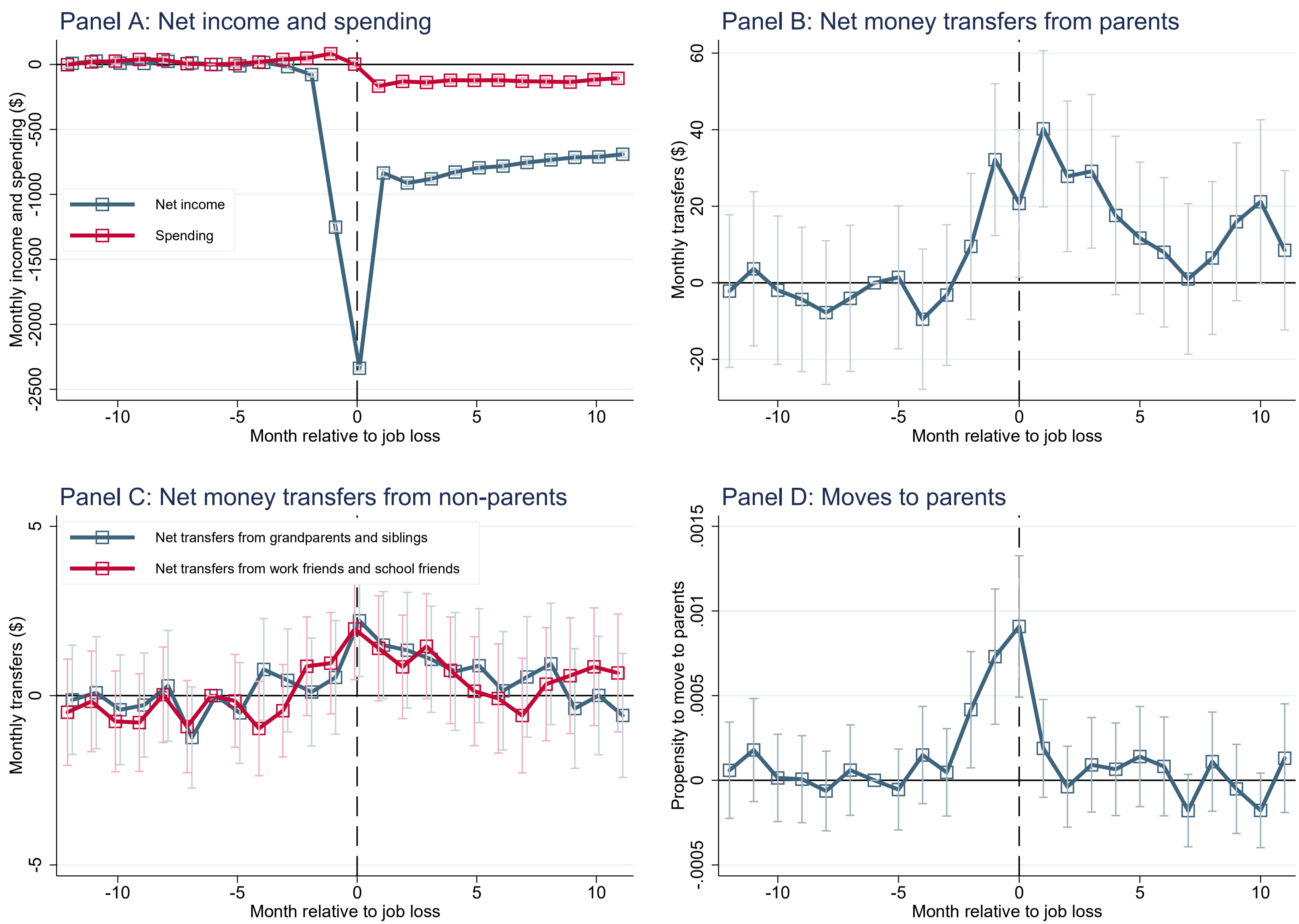


Figure 5: Expenditure shock. The figure shows the results from estimating equation (2) where the event is an expenditure shock defined as a month where spending at car repair shops or dental clinics exceeds $2,000. The outcomes are net income and spending (Panel A), net money transfers from parents (Panel B), net money transfers from other family and friends (Panel C) and the probability of moving to parents (Panel D). Besides dummies indicating the month relative to the event (depicted in the graph), the equation includes individual fixed effects and interactions between age indicators and calendar month indicators. The horizontal lines indicate 95% confidence intervals based on standard errors with clustering at the individual level. The regression coefficients are in Table A4 in the Online Appendix.

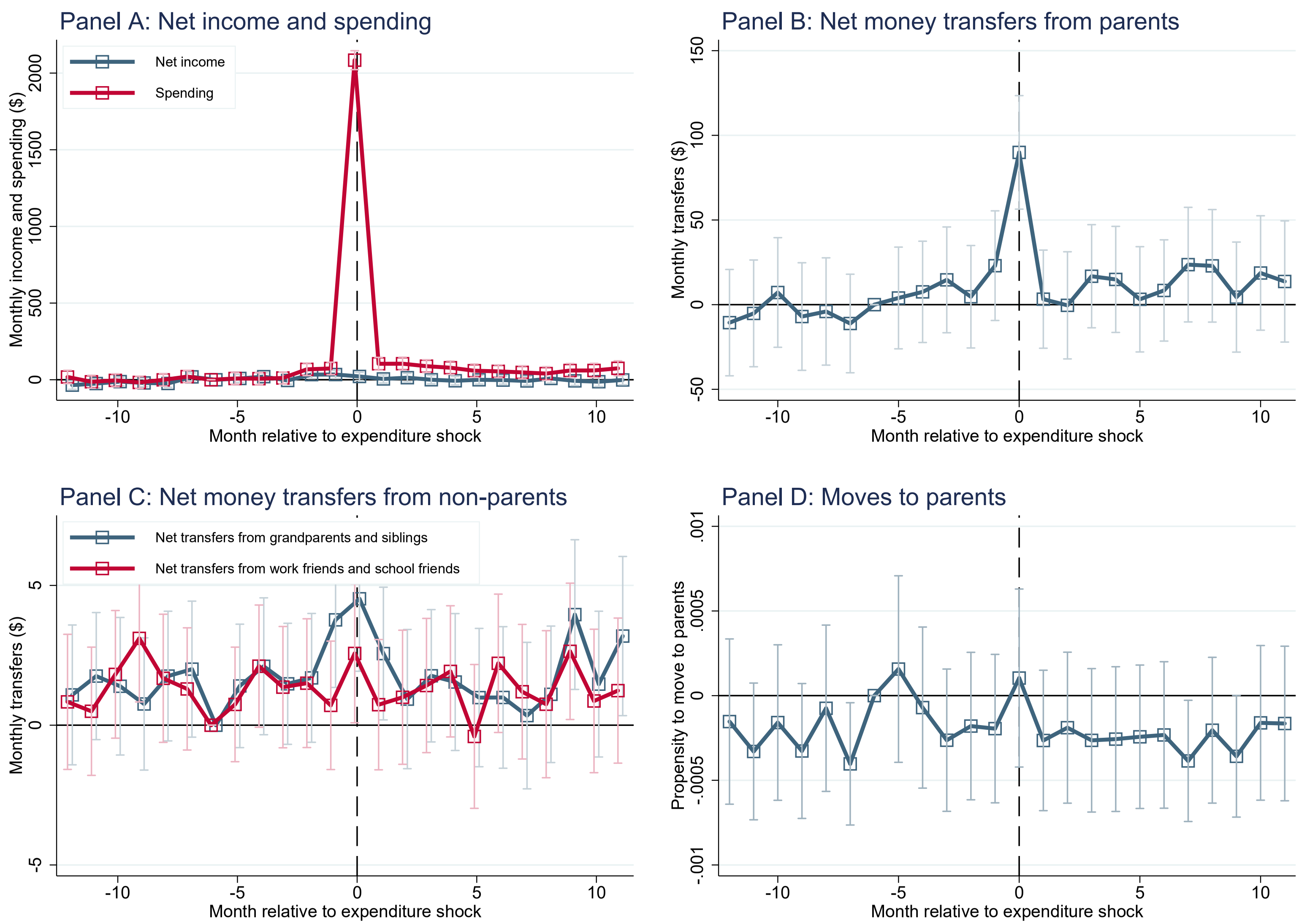


Figure 6: Divorce. The figure shows the results from estimating equation (2) where the event is a divorce defined as a month where . The outcomes are net income and spending (Panel A), net money transfers from parents (Panel B), net money transfers from other family and friends (Panel C) and the probability of moving to parents (Panel D). Besides dummies indicating the month relative to the event (depicted in the graph), the equation includes individual fixed effects and interactions between age indicators and calendar month indicators. The horizontal lines indicate 95% confidence intervals based on standard errors with clustering at the individual level. The regression coefficients are in Table A5 in the Online Appendix.

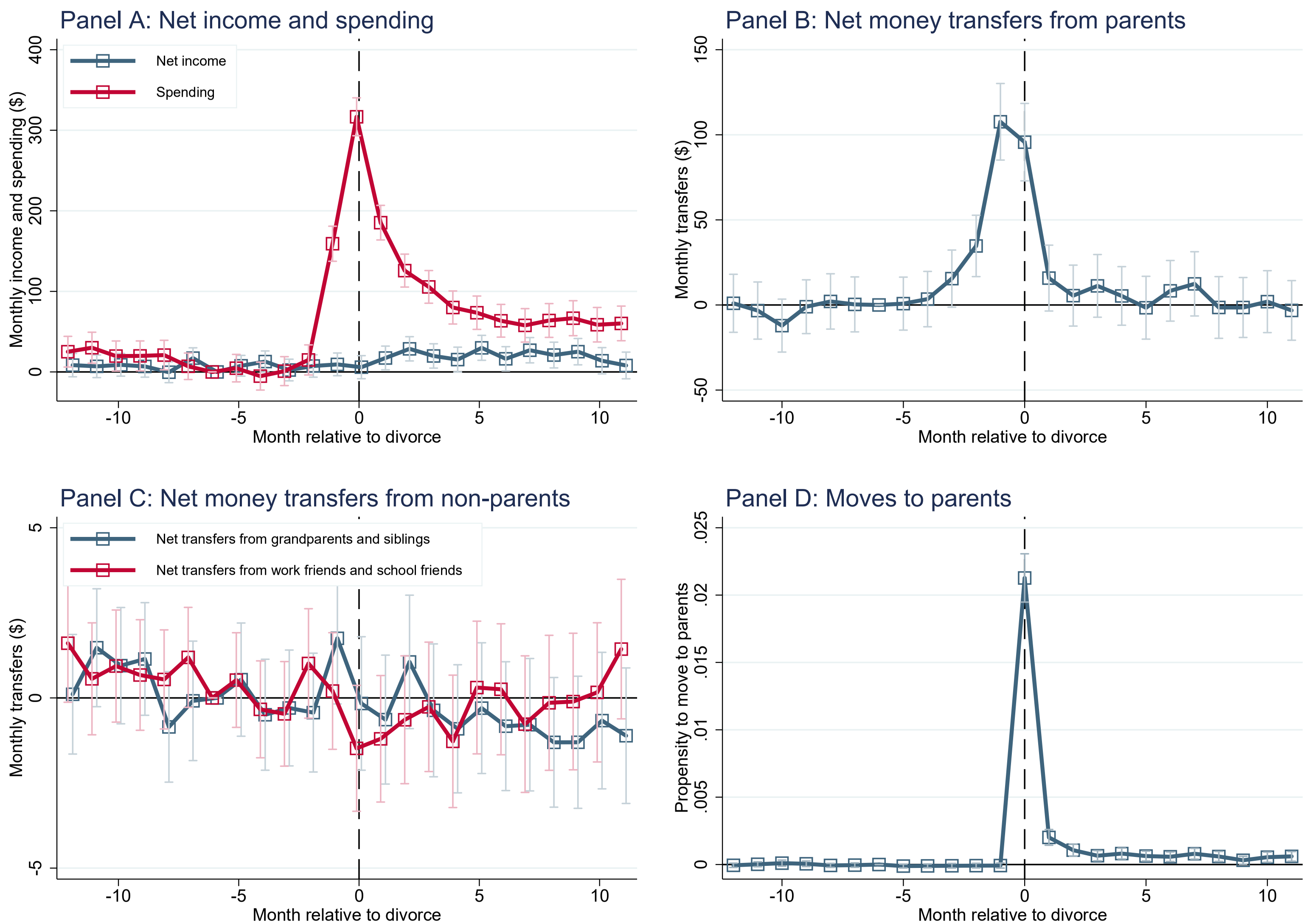


Figure 7: Financial distress. The figure shows the results from estimating equation (2) where the event is financial distress defined as a month where an individual receives the first notice about arrears from the bank. The outcomes are net income and spending (Panel A), net money transfers from parents (Panel B), net money transfers from other family and friends (Panel C) and the probability of moving to parents (Panel D). Besides dummies indicating the month relative to the event (depicted in the graph), the equation includes individual fixed effects and interactions between age indicators and calendar month indicators. The horizontal lines indicate 95% confidence intervals based on standard errors with clustering at the individual level. The regression coefficients are in Table A6 in the Online Appendix.

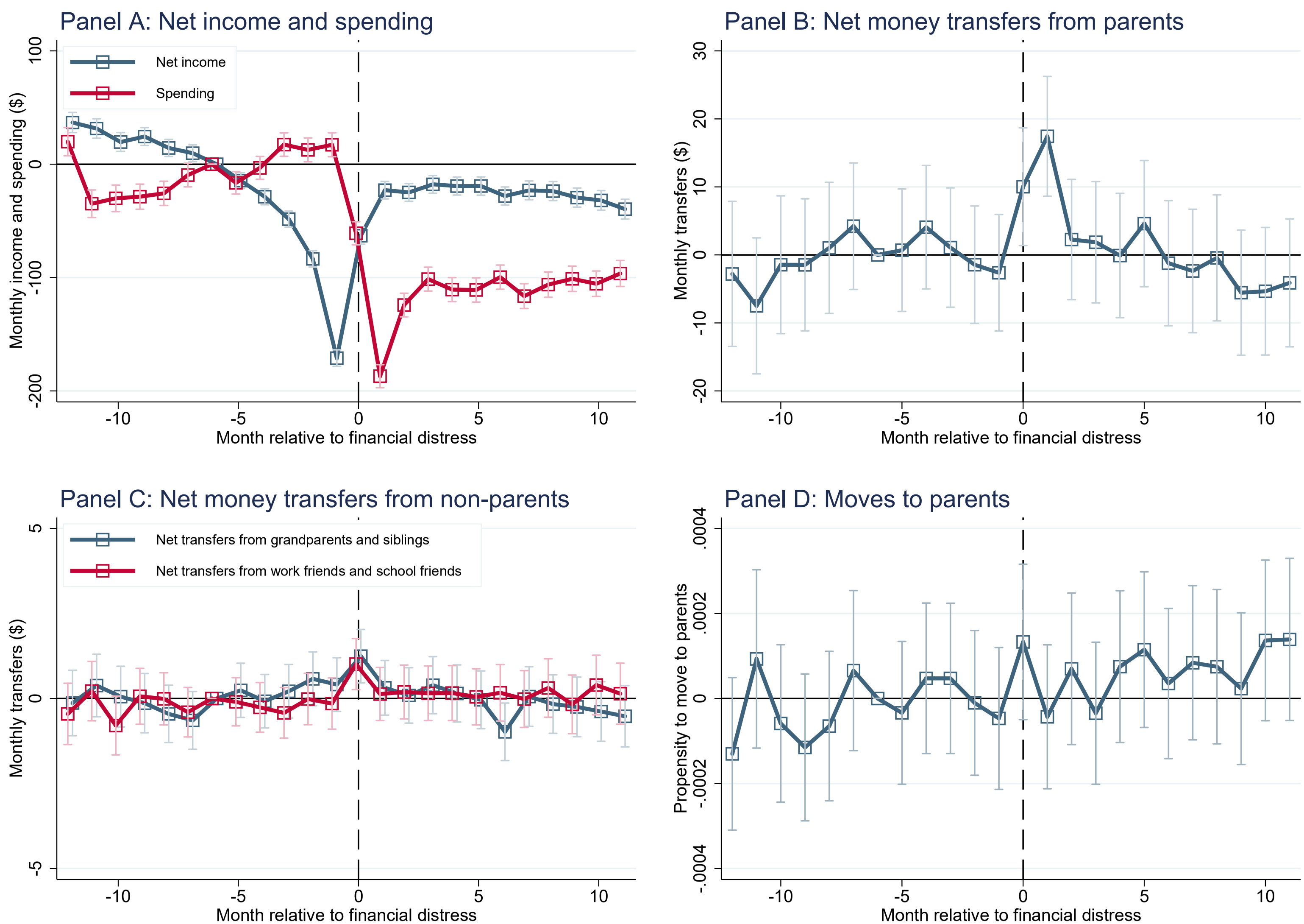
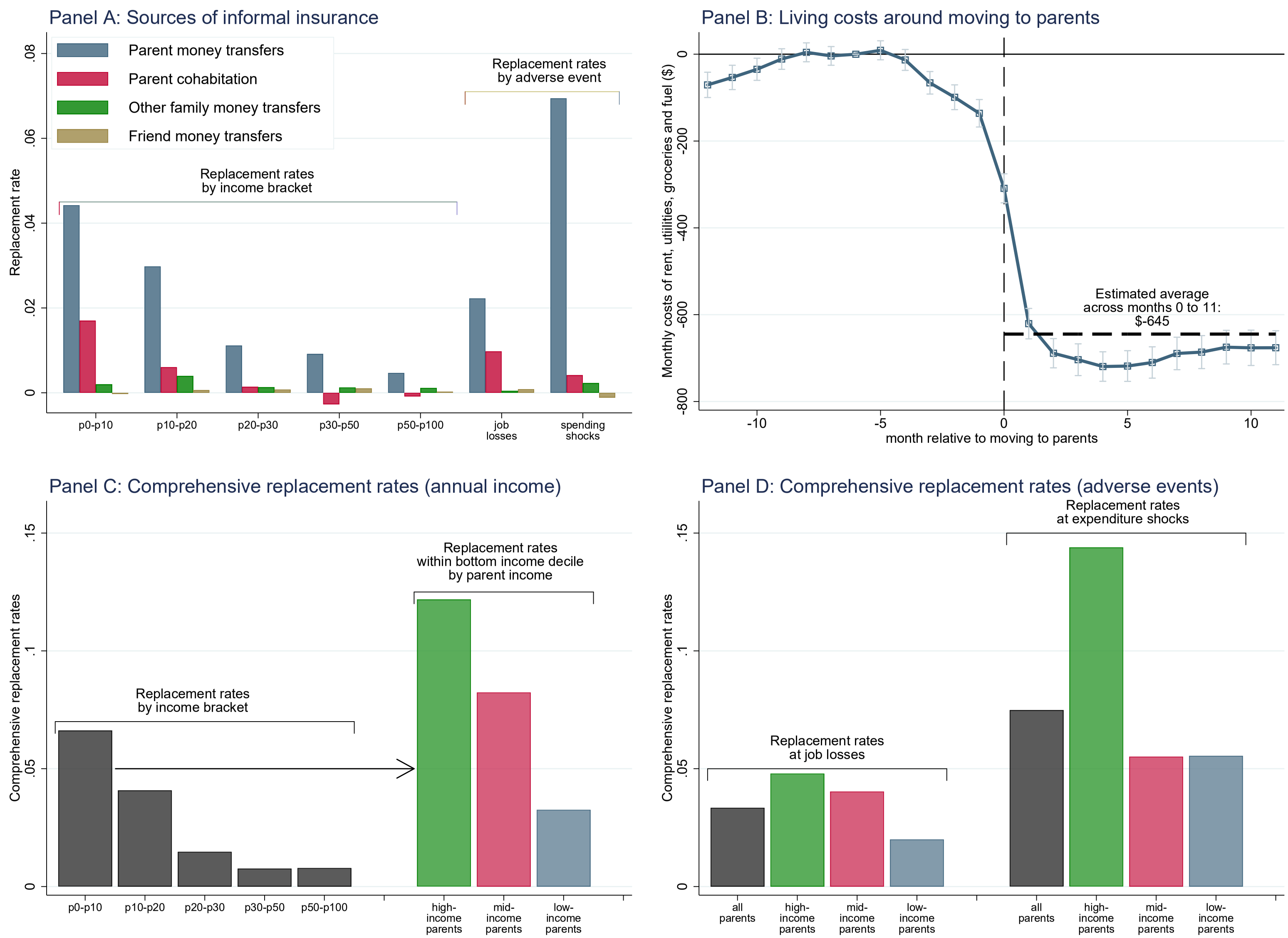


Figure 8: Replacement rates. Panel A shows marginal replacement rates by position in the income distribution estimated with equation (3) and replacement rates by event estimated with equation (4) - by source. Panel B shows the results from estimating equation (2) where the event is moving back to the parents and the outcome is combined spending on rent, utilities, groceries and fuel. The panel reports results from the full model (blue line) and a compact version with a single post-event dummy (black line). Panel C shows comprehensive replacement rates estimated with equation (3) by position in the income distribution for all individuals (black bars) and, within the bottom decile, for individuals with high-income parents (green bars), middle-income parents (red bars) and low-income parents (blue bars) separately. Panel D shows comprehensive replacement rates estimated with equation (4) for all individuals (black bars) and for individuals with high-income parents (green bars), middle-income parents (red bars) and low-income parents (blue bars) separately.



ONLINE APPENDIX

Table A1: Raw coefficients. The Table shows the raw point estimates and standard errors underlying the four panels in Figure 2.

	Net income	Spending	Gross transfers from parents	Gross transfers to parents	Net transfers from parents	Cobitation	Gross transfers from parents	Gross transfers to parents
p0-5	-2692.4	-692.5	88.3	-19.9	105.6	0.039	0.516	-0.447
	(10.5)	(12.9)	(12.3)	(6.7)	(12.5)	(0.003)	(0.046)	(0.04)
p5-10	-1946.8	-530.3	45.9	-20.0	64.0	0.022	0.548	-0.380
	(5.5)	(10)	(10.3)	(4.7)	(10.4)	(0.003)	(0.042)	(0.037)
p10-15	-1626.9	-448.9	31.8	-21.8	51.0	0.017	0.518	-0.324
	(4.1)	(8.5)	(8.3)	(4.4)	(8.7)	(0.002)	(0.036)	(0.037)
p15-20	-1342.1	-352.1	24.5	-15.5	39.2	0.011	0.425	-0.251
	(3.4)	(7.5)	(7.3)	(4)	(7.5)	(0.002)	(0.032)	(0.032)
p20-25	-1105.6	-277.9	26.9	-13.9	41.4	0.010	0.370	-0.180
	(3.1)	(6.9)	(7.4)	(4.1)	(7.5)	(0.002)	(0.028)	(0.03)
p25-30	-894.3	-211.4	27.7	-8.2	35.2	0.006	0.286	-0.139
	(2.7)	(6.3)	(7)	(3.8)	(7.1)	(0.002)	(0.026)	(0.027)
p30-35	-702.6	-164.3	19.9	-7.5	26.2	0.001	0.195	-0.128
	(2.2)	(6.1)	(6.3)	(3.3)	(6.4)	(0.001)	(0.024)	(0.026)
p35-40	-506.9	-116.4	6.1	-8.2	14.3	0.001	0.129	-0.092
	(1.8)	(5.7)	(5.7)	(3.3)	(5.9)	(0.001)	(0.022)	(0.025)
p40-45	-327.8	-74.4	0.7	-3.5	3.5	0.000	0.086	-0.045
	(1.7)	(5.4)	(5.6)	(3)	(5.7)	(0.0012)	(0.021)	(0.023)
p45-50	-158.5	-27.5	10.1	0.5	8.6	0.000	0.071	-0.021
	(1.4)	(5.1)	(5.6)	(3.1)	(5.8)	(0.0011)	(0.02)	(0.023)
p55-60	151.1	34.0	0.4	-1.2	1.9	0.000	-0.026	0.044
	(1.5)	(5.2)	(5.6)	(3)	(5.8)	(0.001)	(0.019)	(0.022)
p60-65	305.9	60.6	-1.8	4.6	-6.8	0.001	-0.049	0.049
	(1.7)	(5.5)	(6.1)	(3.1)	(6.2)	(0.0011)	(0.02)	(0.023)
p65-70	461.6	95.5	11.4	3.7	7.6	0.001	-0.024	0.082
	(2)	(6)	(6.4)	(3.3)	(6.5)	(0.0011)	(0.021)	(0.024)
p70-75	632.3	129.9	-0.8	6.8	-8.7	0.001	-0.088	0.087
	(2.4)	(6.4)	(6.6)	(3.5)	(6.8)	(0.0012)	(0.021)	(0.024)
p75-80	830.5	166.8	5.6	4.9	0.5	0.003	-0.072	0.129
	(3)	(6.9)	(7.1)	(3.6)	(7.2)	(0.0013)	(0.022)	(0.025)
p80-85	1066.8	209.9	-5.5	8.4	-13.9	0.004	-0.120	0.106
	(3.7)	(7.4)	(7.5)	(4)	(7.7)	(0.0013)	(0.023)	(0.026)
p85-90	1381.7	267.2	15.4	12.8	1.3	0.005	-0.117	0.155
	(5)	(8.5)	(8.6)	(4.3)	(8.7)	(0.0014)	(0.024)	(0.028)
p90-95	1879.3	356.1	-5.4	19.3	-23.1	0.006	-0.179	0.146
	(7.7)	(9.8)	(9.6)	(5)	(9.7)	(0.0016)	(0.025)	(0.03)
p95-100	3061.1	524.0	2.1	31.5	-30.1	0.009	-0.246	0.186
	(18.5)	(13.5)	(12.6)	(6.7)	(12.7)	(0.0018)	(0.029)	(0.035)
Observations	732,675	732,675	371,245	371,245	371,245	732,675	371,245	371,245

Table A2: Raw coefficients. The Table shows the raw point estimates and standard errors underlying the four panels in Figure 3.

	Net transfers from grandpar.	Net transfers from siblings	Net transfers from work friends	Net transfers from school friends	Net transfers, Low-income parents	Net transfers, Middle-income parents	Net transfers, High-income parents	Cohabitation, Low-income parents	Cohabitation, Middle-income parents	Cohabitation, High-income parents
p0-5	0.1	5.1	-0.2	1.1	50.7	129.9	230.5	0.025	0.057	0.047
	(0.43)	(1.02)	(0.34)	(0.76)	(13.76)	(21.98)	(52.67)	(0.0046)	(0.0066)	(0.0101)
p5-10	0.4	4.8	0.4	0.7	29.4	68.8	195.3	0.016	0.029	0.019
	(0.38)	(0.91)	(0.32)	(0.68)	(10.87)	(15.49)	(60.4)	(0.0038)	(0.0054)	(0.0085)
p10-15	-0.2	4.6	0.2	0.6	31.8	47.3	121.4	0.014	0.021	0.015
	(0.33)	(0.74)	(0.27)	(0.59)	(9.04)	(15.38)	(47.96)	(0.0033)	(0.0043)	(0.009)
p15-20	0.0	2.5	-0.2	0.6	18.8	39.1	114.7	0.007	0.012	0.029
	(0.32)	(0.68)	(0.25)	(0.57)	(7.32)	(12.6)	(43.16)	(0.0028)	(0.0035)	(0.0073)
p20-25	-0.3	2.2	0.3	0.3	24.2	45.6	101.7	0.004	0.014	0.018
	(0.3)	(0.6)	(0.23)	(0.52)	(7.87)	(13.15)	(42.37)	(0.0025)	(0.0031)	(0.0057)
p25-30	-0.2	2.2	0.1	0.2	22.3	26.7	118.0	0.001	0.010	0.020
	(0.27)	(0.54)	(0.22)	(0.49)	(7.09)	(12.85)	(41.03)	(0.0022)	(0.0028)	(0.0056)
p30-35	-0.5	1.5	0.0	-0.1	17.5	17.8	81.2	-0.004	0.006	0.006
	(0.26)	(0.52)	(0.19)	(0.45)	(7.3)	(10.23)	(37.3)	(0.002)	(0.0025)	(0.0051)
p35-40	-0.1	1.3	0.1	0.1	7.2	5.3	78.8	-0.002	0.003	0.007
	(0.24)	(0.49)	(0.2)	(0.43)	(6.29)	(9.55)	(36.55)	(0.0018)	(0.0022)	(0.0046)
p40-45	-0.6	1.1	0.1	0.2	-1.9	4.9	9.6	-0.003	0.003	0.006
	(0.23)	(0.47)	(0.18)	(0.4)	(6)	(9.8)	(34.31)	(0.0016)	(0.002)	(0.0041)
p45-50	-0.5	0.2	0.0	0.1	-3.8	8.7	62.4	-0.001	0.002	0.005
	(0.22)	(0.43)	(0.17)	(0.39)	(6.03)	(9.39)	(37.66)	(0.0015)	(0.0019)	(0.0045)
p55-60	-0.7	-0.4	-0.2	-0.3	-2.8	-2.0	45.3	-0.002	0.002	0.002
	(0.22)	(0.45)	(0.18)	(0.4)	(6.01)	(9.09)	(36.68)	(0.0014)	(0.0016)	(0.0039)
p60-65	-0.5	-0.2	-0.2	-0.6	-6.0	-13.3	29.2	0.000	0.001	0.002
	(0.23)	(0.47)	(0.19)	(0.43)	(6.31)	(9.41)	(37.19)	(0.0016)	(0.0017)	(0.0037)
p65-70	-0.7	-0.4	-0.1	-0.4	2.8	3.9	41.5	0.001	0.002	-0.003
	(0.24)	(0.49)	(0.2)	(0.45)	(7.09)	(9.79)	(35.44)	(0.0017)	(0.0017)	(0.0039)
p70-75	-0.3	-0.7	-0.2	-0.4	-3.7	-12.9	-10.9	0.001	0.001	0.001
	(0.26)	(0.52)	(0.21)	(0.47)	(7.25)	(9.96)	(37.26)	(0.0018)	(0.0018)	(0.0039)
p75-80	-0.4	-1.5	-0.3	-1.1	-2.2	-14.1	69.9	0.003	0.004	0.000
	(0.28)	(0.56)	(0.23)	(0.52)	(7.84)	(10.24)	(38.46)	(0.002)	(0.0019)	(0.0039)
p80-85	-0.5	-1.3	-0.1	-0.6	-17.0	-12.2	-8.1	0.005	0.004	0.002
	(0.29)	(0.6)	(0.25)	(0.56)	(8.45)	(11.53)	(37.14)	(0.002)	(0.002)	(0.0039)
p85-90	-0.4	-1.1	-0.4	-0.2	-8.3	-17.4	62.2	0.006	0.006	-0.002
	(0.3)	(0.66)	(0.27)	(0.61)	(9.84)	(11.69)	(40.81)	(0.0022)	(0.0021)	(0.0039)
p90-95	-0.4	-1.8	0.0	-1.2	-21.3	-30.6	-4.5	0.009	0.006	-0.001
	(0.32)	(0.76)	(0.29)	(0.74)	(11.3)	(13.39)	(41.88)	(0.0027)	(0.0022)	(0.0042)
p95-100	-0.9	-3.0	-0.4	-1.9	-42.3	-37.6	-5.3	0.008	0.011	0.001
	(0.33)	(0.98)	(0.38)	(0.97)	(15.59)	(17.31)	(47.73)	(0.0033)	(0.0026)	(0.0046)
Obs	732,675	732,675	732,675	732,675	158,975	150,983	47,589	355,988	271,631	71,509

Table A3: Raw coefficients. The Table shows the raw point estimates and standard errors underlying the four panels in Figure 4 (job loss).

Dependent variable	net income	spending	net money transfers from parents	net money transfers from friends	net money transfers from other family	propensity to move to parents		net money transfers from parents			propensity to move to parents	
Sample	All parents	All parents	All parents	All parents	All parents	All parents	low-income parents	mid-income parents	high-income parents	low-income parents	mid-income parents	high-income parents
month -12	8.75	-1.61	-2.16	-0.12	-0.49	0.000059	-19.01	15.95	-4.22	-0.000023	0.000162	0.000027
	(7.8071)	(11.8476)	(10.1625)	(0.8228)	(0.8012)	(0.000145)	(11.4268)	(16.3189)	(38.4067)	(0.000226)	(0.000217)	(0.000081)
month -11	26.29	19.70	3.66	0.09	-0.17	0.000179	-12.31	7.02	36.39	0.000055	0.000265	0.000838
	(7.5596)	(11.9911)	(10.2773)	(0.8444)	(0.757)	(0.000155)	(11.8945)	(15.3396)	(40.8157)	(0.000242)	(0.000215)	(0.000533)
month -10	10.23	26.01	-1.94	-0.42	-0.76	0.000014	-13.38	6.79	0.35	0.000057	-0.000048	0.000055
	(7.55)	(12.028)	(9.8956)	(0.827)	(0.759)	(0.000132)	(12.7999)	(14.6887)	(36.7466)	(0.000239)	(0.000128)	(0.000079)
month -9	7.74	38.86	-4.34	-0.28	-0.79	0.000007	-15.40	7.59	-5.43	-0.000034	-0.000056	0.000100
	(7.2416)	(11.388)	(9.6186)	(0.7836)	(0.7363)	(0.000131)	(12.2316)	(15.1488)	(34.6723)	(0.000221)	(0.00013)	(0.000076)
month -8	23.85	36.73	-7.78	0.29	0.03	-0.000063	-25.30	10.15	-15.41	-0.000217	0.000076	0.000086
	(7.211)	(11.4032)	(9.5673)	(0.8346)	(0.7184)	(0.00012)	(11.5444)	(14.8951)	(34.3545)	(0.000185)	(0.00017)	(0.000068)
month -7	12.62	5.73	-4.06	-1.24	-0.92	0.000060	-4.10	3.98	-31.81	0.000030	0.000115	0.000047
	(7.2041)	(10.7792)	(9.7366)	(0.7622)	(0.6939)	(0.000136)	(12.4117)	(14.3871)	(37.724)	(0.000234)	(0.000168)	(0.000057)
month -5	-10.67	6.30	1.45	-0.51	-0.16	-0.000054	6.57	-4.15	18.79	-0.000171	-0.000104	0.000660
	(7.2911)	(10.7201)	(9.5256)	(0.7587)	(0.7)	(0.000122)	(12.8691)	(13.4579)	(36.777)	(0.0002)	(0.000097)	(0.000464)
month -4	15.53	19.18	-9.51	0.77	-0.97	0.000149	1.42	-7.82	-30.05	0.000175	0.000188	0.000353
	(7.3778)	(11.2135)	(9.3408)	(0.7665)	(0.7103)	(0.000146)	(12.3846)	(13.788)	(34.4772)	(0.000255)	(0.000186)	(0.000323)
month -3	-16.76	39.12	-3.20	0.45	-0.45	0.000047	2.90	-9.47	6.18	0.000022	0.000112	0.000052
	(7.5339)	(11.1622)	(9.3714)	(0.776)	(0.6972)	(0.000132)	(12.7953)	(13.2826)	(35.5168)	(0.000228)	(0.000161)	(0.000054)
month -2	-78.01	48.69	9.51	0.11	0.87	0.000417	-2.04	16.68	29.24	0.000475	0.000642	0.000037
	(8.6052)	(11.5992)	(9.7217)	(0.8143)	(0.7442)	(0.000175)	(12.4981)	(14.9325)	(35.3997)	(0.000295)	(0.000269)	(0.000056)
month -1	-1252.18	83.01	32.17	0.54	0.96	0.000730	17.16	40.73	57.53	0.000378	0.000955	0.001807
	(16.0922)	(11.8527)	(10.1196)	(0.8553)	(0.7641)	(0.000204)	(13.4013)	(15.579)	(35.2205)	(0.000281)	(0.000318)	(0.000744)
month -0	-2337.54	2.49	20.73	2.21	1.97	0.000908	-6.65	28.29	70.93	0.000724	0.001019	0.001483
	(11.7023)	(11.9086)	(9.8374)	(0.8383)	(0.7642)	(0.000213)	(12.0452)	(14.9852)	(37.0327)	(0.000317)	(0.000317)	(0.000658)
month 1	-835.11	-166.41	40.24	1.49	1.40	0.000188	-7.76	55.49	137.68	0.000279	0.000173	0.000336
	(14.1435)	(11.9539)	(10.4136)	(0.8061)	(0.7918)	(0.000147)	(12.1938)	(16.0872)	(40.3654)	(0.000265)	(0.000173)	(0.000313)
month 2	-912.27	-130.04	27.82	1.34	0.85	-0.000038	3.04	46.93	57.64	-0.000266	0.000266	0.000283
	(12.8778)	(12.4602)	(10.0325)	(0.8723)	(0.7788)	(0.000122)	(12.9339)	(15.6787)	(35.7512)	(0.000169)	(0.000203)	(0.000319)
month 3	-880.21	-138.45	29.13	1.07	1.46	0.000091	-1.66	41.59	74.05	-0.000044	0.000158	0.000648
	(12.2835)	(12.2019)	(10.2492)	(0.8002)	(0.7921)	(0.000142)	(13.0362)	(14.9257)	(40.6536)	(0.000216)	(0.000187)	(0.000458)
month 4	-827.96	-120.97	17.59	0.71	0.75	0.000065	-10.34	24.00	84.02	0.000040	0.000158	0.000276
	(12.0944)	(12.6899)	(10.5471)	(0.8862)	(0.8034)	(0.00014)	(13.5787)	(15.5011)	(41.7559)	(0.00023)	(0.000191)	(0.000339)
month 5	-795.03	-121.68	11.70	0.88	0.13	0.000140	4.19	3.52	70.45	0.000201	0.000211	0.000050
	(12.0489)	(12.4145)	(10.1121)	(0.8569)	(0.8215)	(0.000151)	(12.964)	(14.6103)	(40.5098)	(0.00026)	(0.000215)	(0.000084)
month 6	-782.16	-120.81	7.98	0.14	-0.08	0.000082	-6.29	10.72	39.03	0.000029	0.000308	-0.000019
	(11.5464)	(12.603)	(9.9626)	(0.8919)	(0.8237)	(0.000149)	(12.6055)	(15.2851)	(37.6033)	(0.000236)	(0.000242)	(0.000105)
month 7	-754.25	-128.68	1.01	0.55	-0.59	-0.000179	-18.18	-2.01	55.52	-0.000219	-0.000077	-0.000046
	(11.6154)	(12.7629)	(10.0242)	(0.9082)	(0.8634)	(0.000109)	(11.7522)	(14.5798)	(41.9935)	(0.000188)	(0.000139)	(0.000106)
month 8	-734.15	-131.63	6.49	0.94	0.34	0.000110	-11.95	22.49	26.68	-0.000015	0.000120	0.000715
	(11.7104)	(12.6253)	(10.1863)	(0.9142)	(0.8529)	(0.000149)	(12.1496)	(15.4832)	(40.5018)	(0.000228)	(0.000194)	(0.000469)
month 9	-714.71	-135.47	15.94	-0.38	0.59	-0.000051	4.62	26.85	21.74	-0.000116	0.000146	-0.000063
	(11.6342)	(12.6841)	(10.5137)	(0.9007)	(0.8724)	(0.000134)	(14.0459)	(16.3213)	(36.6359)	(0.000213)	(0.000213)	(0.000111)
month 10	-710.95	-116.83	21.18	0.01	0.85	-0.000178	-12.75	35.64	69.38	-0.000126	-0.000175	-0.000089
	(11.6237)	(13.2932)	(10.9292)	(0.8916)	(0.888)	(0.000112)	(12.4796)	(16.6618)	(44.929)	(0.000211)	(0.000106)	(0.000115)
month 11	-690.83	-106.57	8.51	-0.59	0.67	0.000130	-15.87	24.07	35.91	-0.000018	0.000400	0.000325
	(12.0541)	(13.2834)	(10.6166)	(0.9337)	(0.8866)	(0.000164)	(12.6699)	(16.1636)	(43.0298)	(0.000238)	(0.000272)	(0.000435)
obervations	12,599,008	12,599,008	6,115,156	12,599,008	12,599,008	12,599,008	2,516,350	2,509,304	858,510	5,969,516	4,706,444	1,345,335

Table A4: Raw coefficients. The Table shows the raw point estimates and standard errors underlying the four panels in Figure 5 (expenditure shock).

Dependent variable	net income	spending	net money transfers from parents	net money transfers from friends	net money transfers from other family	propensity to move to parents		net money transfers from parents			propensity to move to parents	
Sample	All parents	All parents	All parents	All parents	All parents	All parents	low-income parents	mid-income parents	high-income parents	low-income parents	mid-income parents	high-income parents
month -12	-34.97	18.11	-10.63	1.08	0.83	-0.000153	17.18	-5.55	-80.66	-0.000124	-0.000481	0.000774
	(14.0117)	(22.1882)	(16.0196)	(1.2759)	(1.233)	(0.000249)	(18.0347)	(23.7094)	(58.704)	(0.000488)	(0.000281)	(0.000688)
month -11	-24.65	-13.21	-5.16	1.76	0.50	-0.000330	14.08	-26.98	6.42	-0.000366	-0.000460	0.000046
	(13.8166)	(21.612)	(16.0809)	(1.1595)	(1.1702)	(0.000206)	(18.1999)	(20.9445)	(62.509)	(0.000419)	(0.00028)	(0.000074)
month -10	-12.11	-3.86	7.19	1.39	1.82	-0.000159	23.93	2.48	-6.86	-0.000170	-0.000217	0.000056
	(13.5573)	(21.7383)	(16.5208)	(1.2552)	(1.1651)	(0.000234)	(20.1395)	(23.4997)	(60.8596)	(0.000473)	(0.000324)	(0.00007)
month -9	-20.67	-17.23	-7.02	0.76	3.11	-0.000327	17.03	-15.15	-35.11	-0.000384	-0.000430	0.000105
	(13.1101)	(20.6623)	(16.2056)	(1.207)	(1.16)	(0.000203)	(20.7162)	(21.6015)	(59.9255)	(0.000412)	(0.000278)	(0.000065)
month -8	-24.03	-0.67	-4.03	1.76	1.68	-0.000074	-12.31	-6.01	17.57	-0.000181	-0.000026	0.000076
	(12.9341)	(20.8733)	(16.1656)	(1.1837)	(1.1692)	(0.000251)	(18.411)	(22.4213)	(61.8525)	(0.000461)	(0.000398)	(0.000067)
month -7	18.93	20.65	-11.13	2.00	1.30	-0.000403	5.31	-14.78	-30.41	-0.000597	-0.000378	0.000074
	(13.2129)	(20.3129)	(14.8489)	(1.2412)	(1.1151)	(0.000184)	(18.117)	(20.2818)	(56.1005)	(0.000357)	(0.000273)	(0.000066)
month -5	8.62	8.20	3.95	1.40	0.74	0.000157	23.19	-6.72	-8.04	0.000390	-0.000011	0.000024
	(13.1797)	(19.3491)	(15.3276)	(1.1264)	(1.0453)	(0.000281)	(18.0717)	(20.8766)	(59.582)	(0.000574)	(0.00038)	(0.000069)
month -4	20.15	7.04	7.56	2.11	2.11	-0.000071	10.57	5.95	-11.17	-0.000198	0.000002	0.000059
	(12.8744)	(19.565)	(15.2584)	(1.2491)	(1.1156)	(0.000243)	(19.1431)	(20.9126)	(58.1002)	(0.000453)	(0.000377)	(0.000067)
month -3	-4.45	11.61	14.64	1.48	1.36	-0.000263	3.86	11.30	53.60	-0.000414	-0.000408	0.000602
	(12.5105)	(20.0062)	(15.936)	(1.1045)	(1.1068)	(0.000214)	(17.7332)	(22.2565)	(61.6404)	(0.000406)	(0.000273)	(0.000552)
month -2	33.67	68.10	4.68	1.69	1.50	-0.000180	-2.21	21.22	-28.95	-0.000218	-0.000202	0.000021
	(13.3464)	(21.0036)	(15.4361)	(1.1755)	(1.1747)	(0.000222)	(15.4876)	(22.68)	(58.6367)	(0.000448)	(0.000308)	(0.000071)
month -1	34.34	73.73	23.02	3.77	0.71	-0.000195	19.05	6.72	60.03	-0.000249	-0.000415	0.000029
	(13.4116)	(20.8887)	(16.5141)	(1.2334)	(1.1722)	(0.000224)	(18.5015)	(22.4749)	(64.1718)	(0.000447)	(0.000261)	(0.000069)
month -0	21.58	2084.48	89.93	4.52	2.57	0.000104	56.00	74.65	200.28	-0.000059	0.000279	0.000086
	(13.5951)	(31.5841)	(17.1)	(1.323)	(1.2672)	(0.000268)	(18.635)	(23.8677)	(66.1749)	(0.000482)	(0.000435)	(0.000067)
month 1	5.44	104.31	3.25	2.56	0.73	-0.000265	-12.09	7.72	31.97	-0.000424	-0.000216	0.000071
	(13.6558)	(21.1755)	(14.7842)	(1.2111)	(1.1889)	(0.000211)	(15.8255)	(21.393)	(56.5156)	(0.000406)	(0.000317)	(0.000067)
month 2	13.62	104.72	-0.40	0.93	1.00	-0.000189	28.62	-4.11	-42.68	-0.000028	-0.000402	0.000039
	(14.077)	(21.5569)	(16.1436)	(1.2704)	(1.2234)	(0.000227)	(20.9376)	(22.7592)	(58.4242)	(0.000495)	(0.000263)	(0.000073)
month 3	0.33	88.54	16.79	1.77	1.42	-0.000264	32.41	11.28	-2.90	-0.000234	-0.000388	0.000056
	(13.9826)	(21.4413)	(15.5415)	(1.2077)	(1.2251)	(0.000216)	(19.4389)	(22.5493)	(54.6876)	(0.000462)	(0.000265)	(0.000069)
month 4	-6.41	78.63	14.91	1.54	1.93	-0.000257	-0.61	31.66	-23.00	-0.000431	-0.000181	-0.000047
	(14.0026)	(22.3953)	(15.9818)	(1.2498)	(1.197)	(0.000218)	(16.1775)	(24.0975)	(57.8055)	(0.000419)	(0.000327)	(0.000081)
month 5	-0.03	59.14	3.16	0.99	-0.40	-0.000243	-2.59	2.36	9.68	-0.000613	0.000026	-0.000056
	(14.4034)	(22.1504)	(15.8543)	(1.2622)	(1.3125)	(0.000216)	(16.5156)	(22.2306)	(62.38)	(0.000355)	(0.00038)	(0.000081)
month 6	-1.95	54.97	8.39	0.99	2.21	-0.000232	17.59	-7.01	26.00	-0.000616	-0.000142	0.000586
	(13.763)	(21.5359)	(15.2527)	(1.292)	(1.2626)	(0.000221)	(17.9232)	(19.8037)	(61.2801)	(0.000356)	(0.000337)	(0.000622)
month 7	-7.49	48.15	23.64	0.34	1.20	-0.000386	33.85	-3.51	54.52	-0.000574	-0.000349	0.000021
	(14.5161)	(21.9925)	(17.2616)	(1.3365)	(1.2284)	(0.000183)	(21.0415)	(22.9249)	(66.0737)	(0.000357)	(0.000267)	(0.000075)
month 8	8.47	40.43	22.92	1.11	0.75	-0.000204	12.84	13.70	35.72	-0.000580	0.000089	0.000069
	(15.4559)	(22.7776)	(16.9518)	(1.2455)	(1.3416)	(0.00022)	(18.8052)	(23.6092)	(65.1929)	(0.000357)	(0.00039)	(0.000069)
month 9	-7.05	60.34	4.47	3.96	2.64	-0.000358	-5.30	18.97	-10.82	-0.000569	-0.000302	0.000024
	(15.4797)	(23.1795)	(16.5823)	(1.3658)	(1.2439)	(0.000183)	(17.7974)	(23.8385)	(63.6996)	(0.000358)	(0.000268)	(0.000078)
month 10	-12.71	60.60	18.70	1.47	0.87	-0.000161	40.92	20.35	-34.16	-0.000309	-0.000100	0.000031
	(15.8192)	(23.6057)	(17.2379)	(1.3299)	(1.3091)	(0.000233)	(22.8518)	(23.797)	(61.8675)	(0.00044)	(0.000357)	(0.000078)
month 11	-1.16	74.72	13.70	3.19	1.24	-0.000165	41.41	-29.24	44.48	-0.000560	-0.000086	-0.000061
	(16.0556)	(24.8345)	(18.2601)	(1.4526)	(1.3236)	(0.000233)	(21.9089)	(22.5299)	(74.3163)	(0.000359)	(0.000362)	(0.000084)
obervations	12,599,008	12,599,008	6,115,156	12,599,008	12,599,008	12,599,008	2,516,350	2,509,304	858,510	5,969,516	4,706,444	1,345,335

Table A5: Raw coefficients. The Table shows the raw point estimates and standard errors underlying the four panels in Figure 6 (divorce).

Dependent variable	net income	spending	net money transfers from parents	net money transfers from friends	net money transfers from other family	propensity to move to parents		net money transfers from parents			propensity to move to parents	
Sample	All parents	All parents	All parents	All parents	All parents	All parents	low-income parents	mid-income parents	high-income parents	low-income parents	mid-income parents	high-income parents
month -12	8.48	25.13	0.99	0.11	1.61	-0.000057	-15.23	0.18	62.98	-0.000125	0.000021	0.000022
	(7.3892)	(9.7228)	(8.6934)	(0.8963)	(0.8857)	(0.00008)	(9.4325)	(14.5073)	(36.4553)	(0.000135)	(0.000126)	(0.000122)
month -11	7.00	30.09	-3.29	1.47	0.56	0.000021	-4.34	-6.82	33.73	0.000046	0.000000	0.000010
	(7.1558)	(9.812)	(8.5667)	(0.8839)	(0.8392)	(0.000093)	(10.7794)	(13.3817)	(34.8978)	(0.000169)	(0.000125)	(0.000117)
month -10	8.87	19.75	-12.13	0.95	0.94	0.000102	-18.08	-18.72	21.72	0.000092	0.000117	0.000030
	(7.1849)	(9.5364)	(7.9349)	(0.8716)	(0.8404)	(0.000116)	(10.5687)	(12.0806)	(31.8562)	(0.000203)	(0.000167)	(0.000105)
month -9	6.90	19.92	-1.02	1.14	0.67	0.000056	-10.49	-10.25	58.05	-0.000057	0.000114	0.000343
	(6.8387)	(9.4782)	(8.0576)	(0.8442)	(0.8287)	(0.000105)	(9.3589)	(12.8994)	(33.7106)	(0.000154)	(0.000164)	(0.000402)
month -8	-0.33	20.97	2.07	-0.85	0.54	-0.000065	-4.77	-7.42	66.53	-0.000134	-0.000005	-0.000041
	(6.6132)	(9.3492)	(8.2887)	(0.8282)	(0.7423)	(0.000075)	(9.4038)	(13.557)	(34.1868)	(0.000125)	(0.000119)	(0.000103)
month -7	17.16	7.01	0.33	-0.09	1.19	-0.000043	-5.52	-4.41	34.58	-0.000026	-0.000060	-0.000128
	(6.529)	(8.3729)	(8.2371)	(0.8954)	(0.7489)	(0.000084)	(9.632)	(12.9917)	(34.6862)	(0.00015)	(0.000115)	(0.000106)
month -5	7.69	4.69	0.80	0.54	0.52	-0.000115	-4.23	-7.55	54.31	-0.000136	-0.000121	0.000001
	(6.5689)	(8.7091)	(7.9464)	(0.8483)	(0.7091)	(0.000072)	(10.4727)	(12.2931)	(31.228)	(0.000124)	(0.000114)	(0.000091)
month -4	12.91	-5.16	3.46	-0.49	-0.34	-0.000100	5.14	6.81	-8.80	-0.000095	-0.000144	0.000072
	(6.6948)	(8.8427)	(8.2973)	(0.8316)	(0.726)	(0.000074)	(10.7266)	(13.9947)	(28.4538)	(0.000126)	(0.000116)	(0.00009)
month -3	2.39	1.00	15.48	-0.30	-0.47	-0.000091	-2.45	18.97	87.29	-0.000035	-0.000188	0.000095
	(6.8388)	(9.1614)	(8.5719)	(0.8685)	(0.7838)	(0.000085)	(10.2578)	(13.8069)	(35.0654)	(0.000152)	(0.000119)	(0.000098)
month -2	7.42	14.91	34.68	-0.43	1.01	-0.000083	21.87	25.87	110.01	-0.000096	-0.000103	0.000123
	(7.0929)	(9.5225)	(9.1983)	(0.8905)	(0.8203)	(0.000087)	(11.3206)	(14.1179)	(39.6981)	(0.000129)	(0.000164)	(0.000103)
month -1	9.40	159.16	107.64	1.75	0.20	-0.000076	65.80	131.15	170.54	-0.000109	-0.000118	-0.000002
	(7.1854)	(11.1077)	(11.4833)	(0.9835)	(0.8741)	(0.000097)	(14.169)	(18.3727)	(44.2181)	(0.000131)	(0.000164)	(0.000115)
month -0	5.93	316.72	95.67	-0.16	-1.48	0.021272	39.31	112.04	227.96	0.021497	0.022151	0.018382
	(7.3075)	(11.9966)	(11.6068)	(1.0004)	(0.9438)	(0.000914)	(13.5772)	(18.7808)	(45.5832)	(0.001328)	(0.001521)	(0.002601)
month 1	17.35	185.29	15.81	-0.64	-1.20	0.002015	8.58	19.72	54.90	0.002060	0.002168	0.001351
	(7.5112)	(10.9469)	(9.8749)	(0.9664)	(0.9485)	(0.000298)	(12.655)	(16.2584)	(36.4949)	(0.000438)	(0.000501)	(0.000776)
month 2	28.71	125.78	5.50	1.06	-0.64	0.001066	-8.56	11.16	27.97	0.001107	0.001122	0.000047
	(7.6771)	(10.4233)	(9.1332)	(1.0004)	(0.9583)	(0.000227)	(10.5461)	(15.4998)	(35.3344)	(0.000334)	(0.000386)	(0.000166)
month 3	19.84	105.57	11.22	-0.36	-0.26	0.000654	3.98	4.92	73.44	0.000521	0.000653	0.001586
	(7.7032)	(10.3358)	(9.4001)	(0.9959)	(0.9695)	(0.000193)	(11.4473)	(15.4512)	(37.2675)	(0.000262)	(0.00033)	(0.000752)
month 4	15.35	80.03	5.31	-0.91	-1.28	0.000813	-1.56	5.03	23.42	0.000926	0.000784	0.000465
	(7.8523)	(10.4634)	(8.7761)	(0.9603)	(0.9923)	(0.000207)	(10.4876)	(14.6629)	(33.7177)	(0.000318)	(0.000342)	(0.000421)
month 5	29.94	73.52	-1.62	-0.30	0.30	0.000630	-16.98	-9.42	64.37	0.000794	0.000385	0.000822
	(7.8923)	(10.5663)	(9.4155)	(0.9799)	(0.9946)	(0.000187)	(11.0281)	(14.1804)	(41.4576)	(0.00029)	(0.000278)	(0.000543)
month 6	16.31	63.53	8.32	-0.83	0.25	0.000577	-6.03	13.35	34.15	0.000559	0.000505	0.000472
	(7.6883)	(10.3624)	(9.0896)	(0.9655)	(0.9818)	(0.000181)	(10.2416)	(15.0657)	(36.4872)	(0.000262)	(0.000297)	(0.000392)
month 7	26.97	57.80	12.41	-0.79	-0.77	0.000801	1.47	10.41	41.53	0.000723	0.001056	0.000400
	(7.995)	(10.6039)	(9.6321)	(0.9923)	(1.0237)	(0.000204)	(11.5236)	(15.47)	(38.1037)	(0.000287)	(0.000373)	(0.000436)
month 8	20.96	63.89	-1.46	-1.31	-0.14	0.000599	-13.22	6.41	-5.73	0.000857	0.000320	0.000831
	(8.1545)	(10.6953)	(9.2471)	(0.9715)	(1.0119)	(0.000189)	(10.2216)	(15.4586)	(35.6717)	(0.000313)	(0.00027)	(0.000507)
month 9	25.19	66.71	-1.47	-1.30	-0.11	0.000315	-11.30	-0.95	43.29	0.000338	0.000342	0.000082
	(8.3455)	(11.0795)	(8.9842)	(0.99)	(1.0234)	(0.000151)	(10.3872)	(14.7644)	(36.0729)	(0.000221)	(0.000259)	(0.000215)
month 10	13.90	58.63	1.95	-0.67	0.16	0.000545	-7.73	8.54	21.66	0.000456	0.000820	0.000459
	(8.3131)	(10.9301)	(9.2825)	(1.0234)	(1.0432)	(0.000192)	(11.2612)	(15.5321)	(34.5223)	(0.000272)	(0.000355)	(0.000449)
month 11	8.04	60.22	-3.19	-1.11	1.43	0.000606	-9.83	-6.43	29.59	0.000800	0.000544	0.000323
	(8.4531)	(10.9712)	(8.9332)	(1.0158)	(1.046)	(0.000182)	(10.1466)	(14.4158)	(37.0807)	(0.000292)	(0.000292)	(0.000365)
obervations	12,599,008	12,599,008	6,115,156	12,599,008	12,599,008	12,599,008	2,516,350	2,509,304	858,510	5,969,516	4,706,444	1,345,335

Table A6: Raw coefficients. The Table shows the raw point estimates and standard errors underlying the four panels in Figure 7 (distress).

Dependent variable	net income	spending	net money transfers from parents	net money transfers from friends	net money transfers from other family	propensity to move to parents		net money transfers from parents			propensity to move to parents	
Sample	All parents	All parents	All parents	All parents	All parents	All parents	low-income parents	mid-income parents	high-income parents	low-income parents	mid-income parents	high-income parents
month -12	36.78	19.90	-2.80	-0.13	-0.45	-0.000130	-1.55	-6.39	5.35	-0.000228	-0.000185	0.000451
	(4.5344)	(6.3618)	(5.4436)	(0.4911)	(0.4599)	(0.000092)	(5.5036)	(9.1299)	(24.1448)	(0.000127)	(0.000163)	(0.000313)
month -11	31.50	-34.81	-7.49	0.38	0.22	0.000093	-2.36	-18.11	1.77	-0.000030	0.000013	0.000254
	(4.3785)	(6.1859)	(5.1025)	(0.4687)	(0.4459)	(0.000107)	(6.0817)	(7.796)	(23.0228)	(0.000146)	(0.000183)	(0.000259)
month -10	19.61	-30.08	-1.45	0.06	-0.79	-0.000059	1.14	0.92	-25.65	-0.000106	-0.000149	0.000345
	(4.2238)	(5.9796)	(5.1659)	(0.4552)	(0.4406)	(0.000094)	(5.7956)	(8.5356)	(22.3285)	(0.000136)	(0.000161)	(0.000284)
month -9	24.43	-28.64	-1.46	-0.14	0.06	-0.000115	-3.46	-4.14	12.81	-0.000113	-0.000243	0.000201
	(4.0395)	(5.6552)	(4.9556)	(0.4444)	(0.4194)	(0.000088)	(5.4934)	(8.1331)	(21.6142)	(0.000133)	(0.000146)	(0.000227)
month -8	14.35	-25.67	1.03	-0.45	-0.01	-0.000065	2.55	0.68	-2.69	0.000021	-0.000284	0.000201
	(3.8852)	(5.4685)	(4.9173)	(0.4308)	(0.3918)	(0.00009)	(5.3734)	(8.3738)	(20.9674)	(0.000143)	(0.000137)	(0.000218)
month -7	9.74	-9.59	4.23	-0.64	-0.40	0.000066	7.69	3.85	-13.76	-0.000140	0.000257	0.000508
	(3.7464)	(5.3279)	(4.7454)	(0.4337)	(0.3708)	(0.000096)	(5.2994)	(7.9734)	(19.8866)	(0.000123)	(0.000188)	(0.000293)
month -5	-14.47	-16.42	0.69	0.24	-0.10	-0.000034	3.34	0.53	-8.81	-0.000109	0.000012	0.000084
	(3.6012)	(5.0397)	(4.5925)	(0.4071)	(0.3615)	(0.000086)	(5.2501)	(7.5627)	(19.7913)	(0.000121)	(0.000159)	(0.000181)
month -4	-28.68	-3.19	4.07	-0.08	-0.26	0.000047	2.71	-3.36	27.19	-0.000040	0.000082	0.000169
	(3.5891)	(5.1519)	(4.6314)	(0.4013)	(0.3728)	(0.00009)	(5.2041)	(7.4325)	(20.5691)	(0.000127)	(0.000166)	(0.000198)
month -3	-48.45	17.37	1.08	0.21	-0.42	0.000047	1.96	-0.78	4.71	0.000012	0.000009	0.000239
	(3.6094)	(5.2668)	(4.4759)	(0.4023)	(0.3793)	(0.00009)	(4.9766)	(7.2466)	(19.7782)	(0.00013)	(0.000159)	(0.000216)
month -2	-83.47	12.68	-1.44	0.58	-0.02	-0.000010	-6.55	6.05	-11.29	-0.000010	-0.000064	-0.000080
	(3.6953)	(5.3681)	(4.4024)	(0.4046)	(0.3854)	(0.000087)	(4.7464)	(7.4883)	(18.6722)	(0.000129)	(0.000153)	(0.000148)
month -1	-171.07	17.17	-2.63	0.41	-0.15	-0.000047	0.20	-4.31	-4.07	0.000001	-0.000153	0.000104
	(3.7529)	(5.3801)	(4.3752)	(0.4025)	(0.3842)	(0.000085)	(4.9929)	(7.0158)	(19.2104)	(0.000129)	(0.000145)	(0.000187)
month -0	-63.07	-60.91	10.03	1.24	1.01	0.000133	3.61	12.18	24.54	0.000126	0.000059	0.000265
	(3.8332)	(5.1937)	(4.4148)	(0.4006)	(0.3836)	(0.000093)	(4.7594)	(7.347)	(19.1738)	(0.000137)	(0.000161)	(0.000222)
month 1	-22.89	-187.00	17.44	0.31	0.13	-0.000043	6.80	14.15	62.78	0.000033	-0.000222	0.000048
	(3.942)	(5.2021)	(4.491)	(0.4102)	(0.3983)	(0.000086)	(4.9702)	(7.3088)	(19.7539)	(0.000132)	(0.000144)	(0.000183)
month 2	-24.86	-124.21	2.26	0.09	0.19	0.000070	2.36	2.13	5.08	0.000098	-0.000078	0.000039
	(3.9795)	(5.3185)	(4.51)	(0.4157)	(0.404)	(0.000091)	(5.0279)	(7.3853)	(19.6493)	(0.000134)	(0.000154)	(0.000192)
month 3	-17.73	-101.35	1.86	0.39	0.15	-0.000035	2.59	3.72	-5.35	-0.000008	-0.000070	-0.000130
	(4.0013)	(5.3684)	(4.5466)	(0.428)	(0.41)	(0.000085)	(4.9656)	(7.6476)	(19.259)	(0.000126)	(0.000153)	(0.000123)
month 4	-19.28	-110.61	-0.09	0.15	0.16	0.000075	5.48	-2.98	-10.29	0.000062	0.000084	0.000006
	(4.0411)	(5.4035)	(4.6619)	(0.4288)	(0.4122)	(0.000091)	(5.3233)	(7.4963)	(20.2851)	(0.000133)	(0.000164)	(0.000177)
month 5	-19.25	-110.90	4.60	-0.04	0.05	0.000115	2.94	10.13	-10.96	0.000056	0.000175	0.000003
	(4.111)	(5.447)	(4.7352)	(0.434)	(0.4217)	(0.000093)	(5.3498)	(7.8635)	(19.8019)	(0.000133)	(0.000169)	(0.00017)
month 6	-28.04	-99.61	-1.22	-0.98	0.17	0.000035	-0.73	-5.27	13.71	-0.000042	0.000036	0.000337
	(4.0574)	(5.4376)	(4.6952)	(0.4312)	(0.424)	(0.00009)	(5.3207)	(7.563)	(20.3598)	(0.000126)	(0.000162)	(0.000248)
month 7	-23.05	-116.34	-2.36	0.06	-0.02	0.000084	-0.57	-1.10	-5.82	0.000142	-0.000146	0.000186
	(4.2204)	(5.5877)	(4.6319)	(0.4475)	(0.4262)	(0.000092)	(5.1433)	(7.5284)	(20.21)	(0.00014)	(0.00015)	(0.000206)
month 8	-23.70	-106.17	-0.44	-0.16	0.31	0.000075	-4.54	3.03	5.21	0.000083	-0.000011	0.000471
	(4.2734)	(5.7014)	(4.7289)	(0.4388)	(0.4379)	(0.000093)	(5.1242)	(7.7182)	(20.7785)	(0.000134)	(0.000161)	(0.00027)
month 9	-29.41	-101.06	-5.55	-0.25	-0.17	0.000023	-1.59	-5.49	-19.37	0.000063	-0.000090	0.000250
	(4.3011)	(5.6979)	(4.6907)	(0.4479)	(0.4397)	(0.000091)	(5.3755)	(7.5158)	(20.2429)	(0.000135)	(0.000156)	(0.000237)
month 10	-31.91	-105.43	-5.34	-0.38	0.40	0.000137	2.38	-2.74	-33.83	0.000323	-0.000032	0.000057
	(4.4059)	(5.7355)	(4.7835)	(0.4469)	(0.4475)	(0.000096)	(5.3801)	(7.9592)	(19.9884)	(0.000152)	(0.00016)	(0.000183)
month 11	-39.66	-96.39	-4.11	-0.52	0.14	0.000139	-5.03	-1.53	-7.93	0.000270	-0.000091	0.000388
	(4.4544)	(5.8423)	(4.7981)	(0.4599)	(0.458)	(0.000097)	(5.1359)	(7.9066)	(20.995)	(0.00015)	(0.000157)	(0.000272)
obervations	12,599,008	12,599,008	6,115,156	12,599,008	12,599,008	12,599,008	2,516,350	2,509,304	858,510	5,969,516	4,706,444	1,345,335

Figure A1: The bottom decile of the income distribution The figure describes the bottom decile of the distribution of annual income in various ways. Panel A shows the fraction of individuals within the bottom decile with business income, wage income, government transfers and combinations thereof. Panel B shows the distribution of monthly government transfers for individuals with no other income in the month for the bottom decile (blue bars) and other income deciles (red bars) separately. Panel C shows the distribution of the number of months with non-zero government transfers for individuals with no other income in the year for the bottom decile (blue bars) and other income deciles (red bars) separately. Panel D shows key characteristics for the bottom decile (blue bars) and other income deciles (red bars) separately: the fraction who is female ("female"), who has children ("has children"), who is under 30 years old ("under thirty"), whose parents are in the bottom income decile ("parents in bottom dec."), who is in the bottom decile in teh following year ("next year in bottom dec."), who has no cohabiting partner ("single") and who emigrates from Denmark in the course of the year ("leaves Denmark").

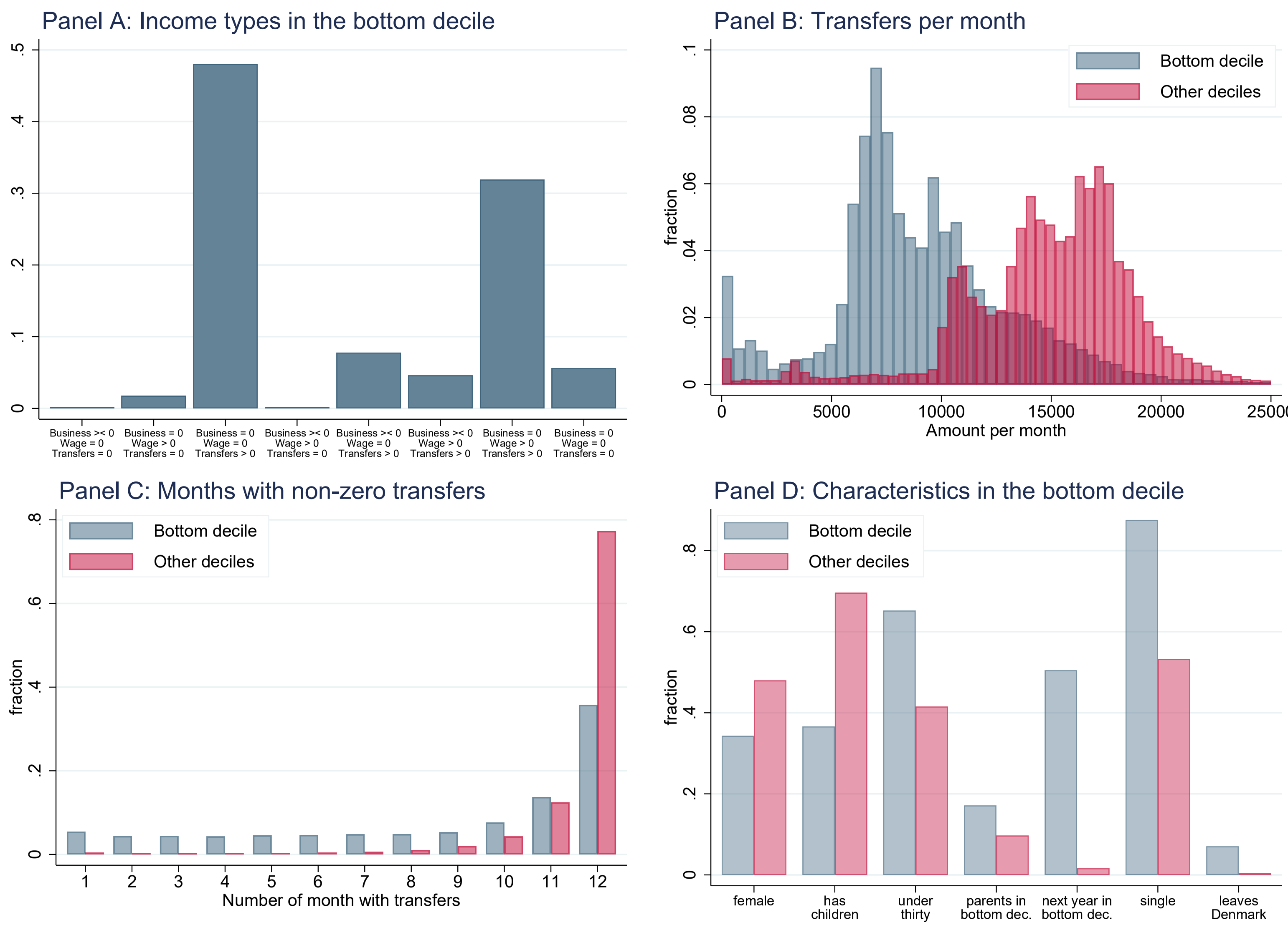


Figure A2: Informal insurance outcomes by position in the income distribution. The figure shows the simple of the outcomes used in Figure 2 by position in the income distribution: net income and spending (Panel A), money transfers to and from parents (Panel B), the probability of cohabiting with parents (Panel C) and the number of months with money transfers to and from parents (Panel D). The horizontal lines indicate 95% confidence intervals based on standard errors with clustering at the individual level.

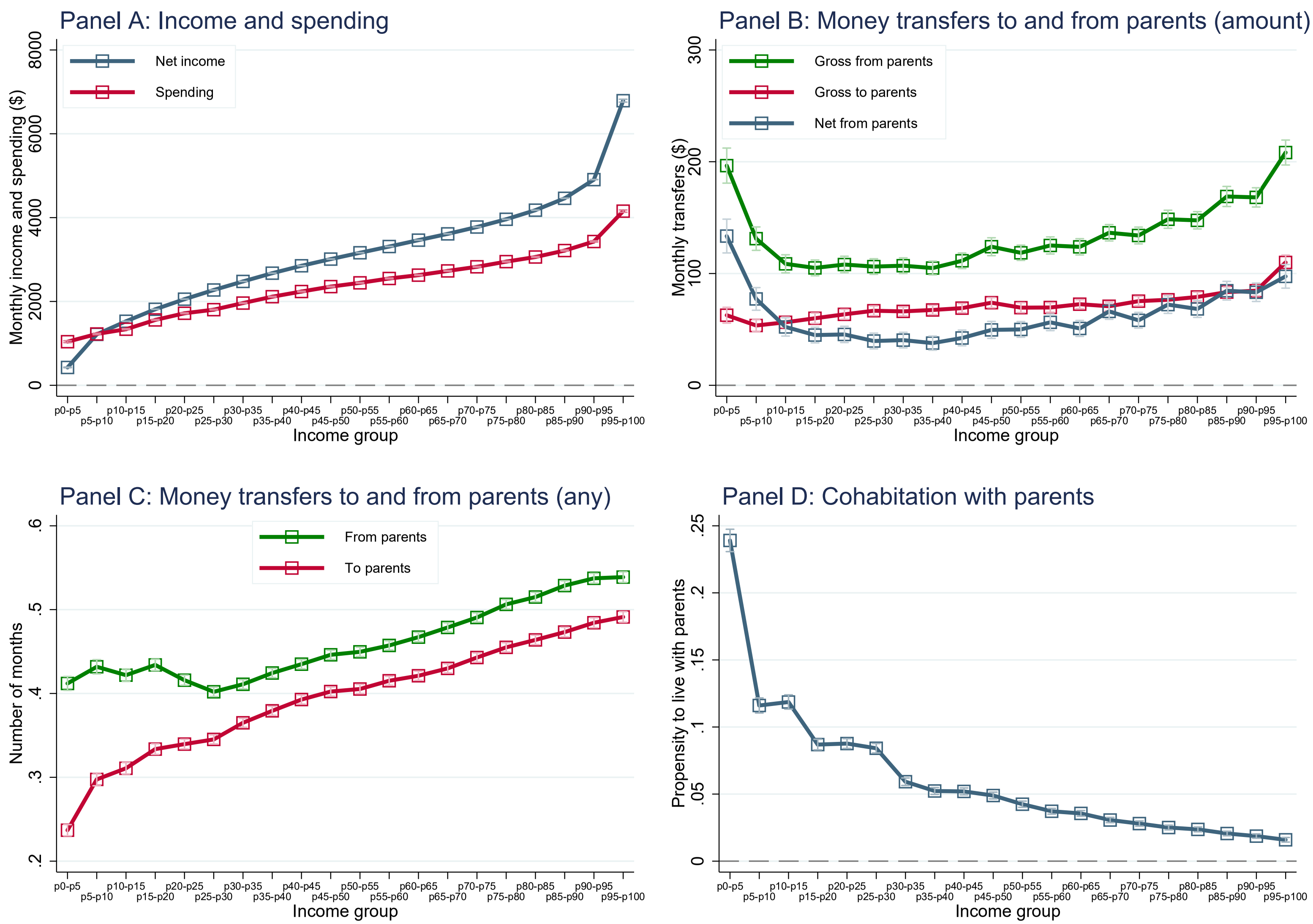


Figure A3: Informal insurance outcomes by position in the income distribution. The figure shows the simple of the outcomes used in Figure 3 by position in the income distribution: money transfers to and from grandparents and siblings (Panel A), money transfers to and from school friends and work friends (Panel B), net money transfers to and from parents by parent income (Panel C) and the probability of cohabiting with parents by parent income (Panel D).

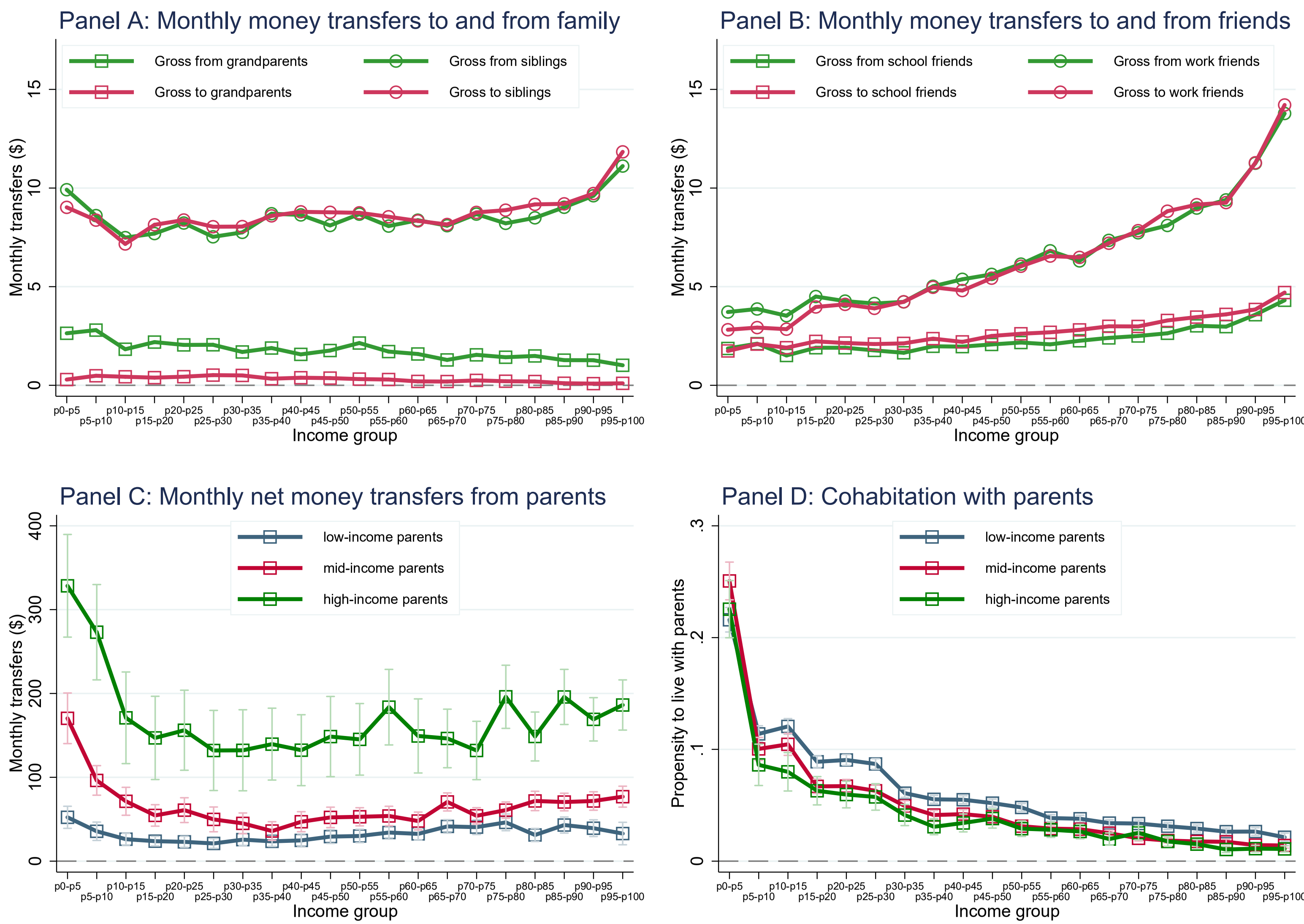


Figure A4: Robustness. The figure shows results from estimating equation (1) using as outcome net money transfers from parents (Panels A and C) and the probability of cohabiting with parents (Panels B and D). Panels A and B test the robustness of the baseline results (blue line) to variations: including indicators of first child birth and first home purchase in the model (green line), including indicators of the parents' position in the income distribution in the current year in the model (red line) and excluding individuals who emigrate during the year (brown line). Panels C and D test the robustness of the baseline results (blue line) to restricting the sample to individuals whose parents are exclusive DB customers (green line).

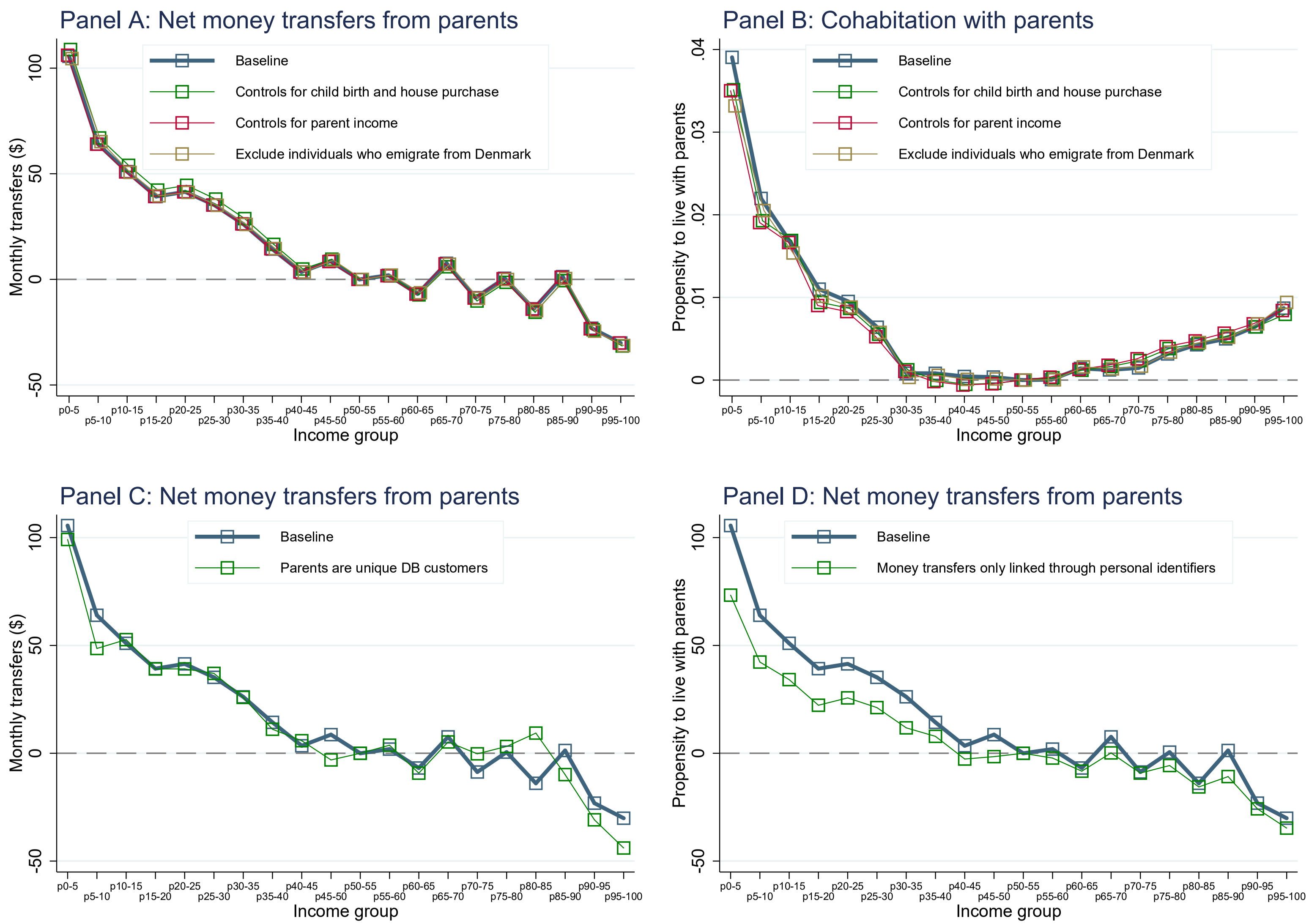


Figure A5: Heterogeneity in parent response to adverse events. The figure shows the results from estimating equation (2) where the event is job loss (Panel A), expenditure shock (Panel B), divorce (Panel C) and financial distress (D) defined as above and the outcome is net money transfers from parents. Besides dummies indicating the month relative to the event (depicted in the graph), the equation includes individual fixed effects and interactions between age indicators and calendar month indicators. The sample is delimited in the same way as in the main analysis, however, we split the sample according to parent ecomomic resources and estimate the model for individuals with low-income parents (blue line), middle-income parents (red line) and high-income parents (green line) separately. The horizontal lines indicate 95% confidence intervals based on standard errors with clustering at the individual level.

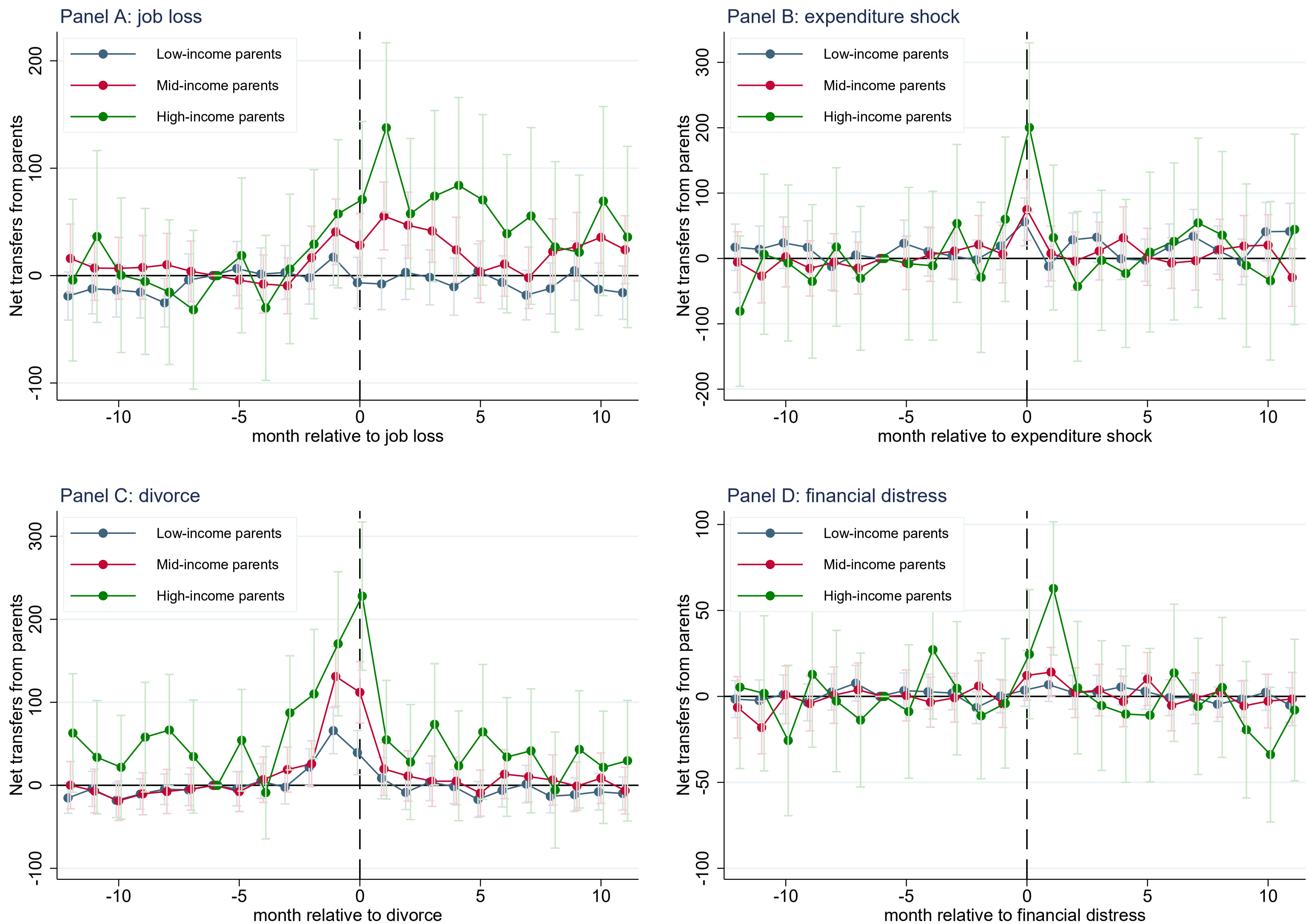


Figure A6: Heterogeneity in parent response to adverse events. The figure shows the results from estimating equation (2) where the event is job loss (Panel A), expenditure shock (Panel B), divorce (Panel C) and financial distress (D) defined as above and the outcome is cohabitation with parents. Besides dummies indicating the month relative to the event (depicted in the graph), the equation includes individual fixed effects and interactions between age indicators and calendar month indicators. The sample is delimited in the same way as in the main analysis, however, we split the sample according to parent economic resources and estimate the model for individuals with low-income parents (blue line), middle-income parents (red line) and high-income parents (green line) separately. The horizontal lines indicate 95% confidence intervals based on standard errors with clustering at the individual level .

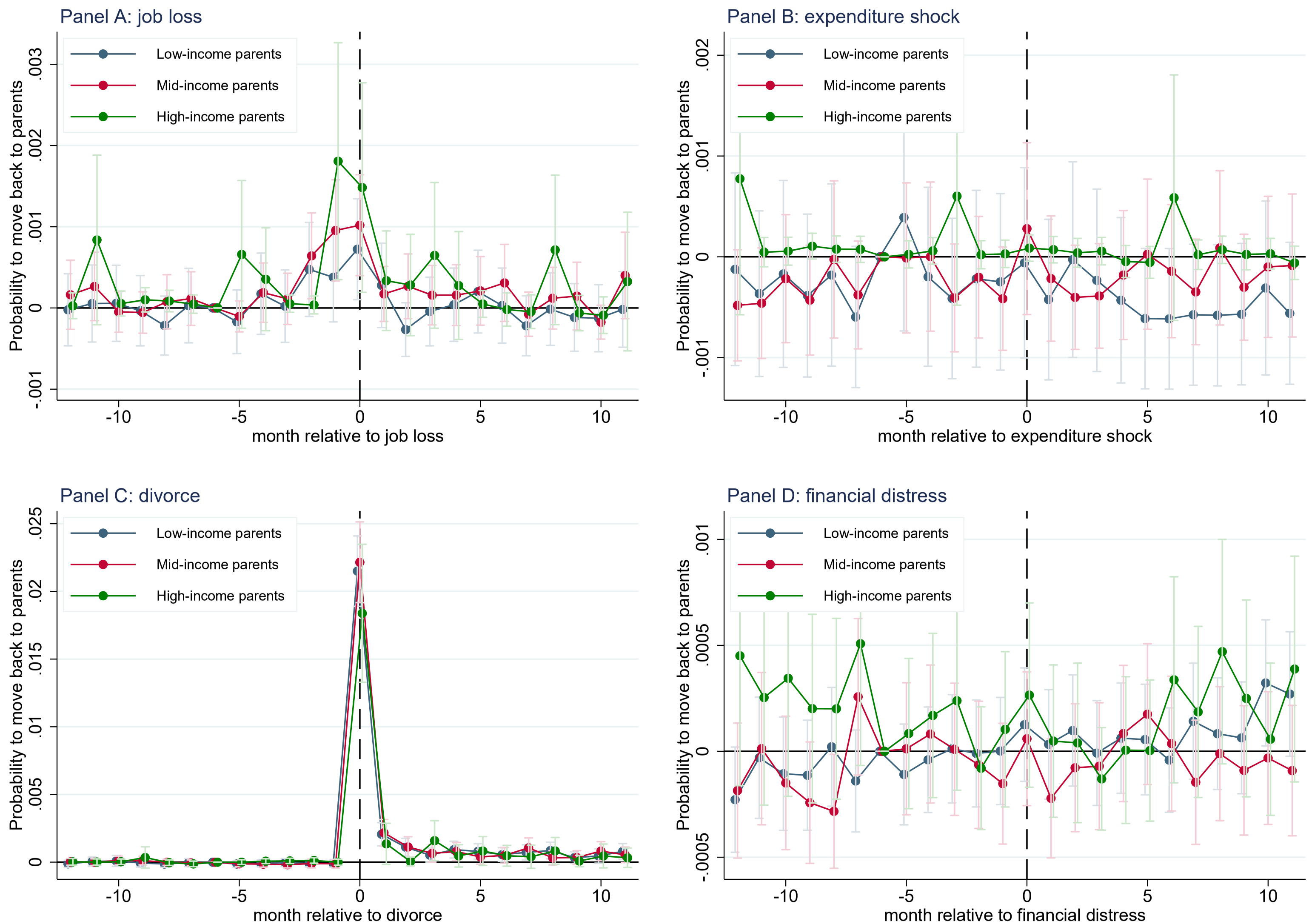
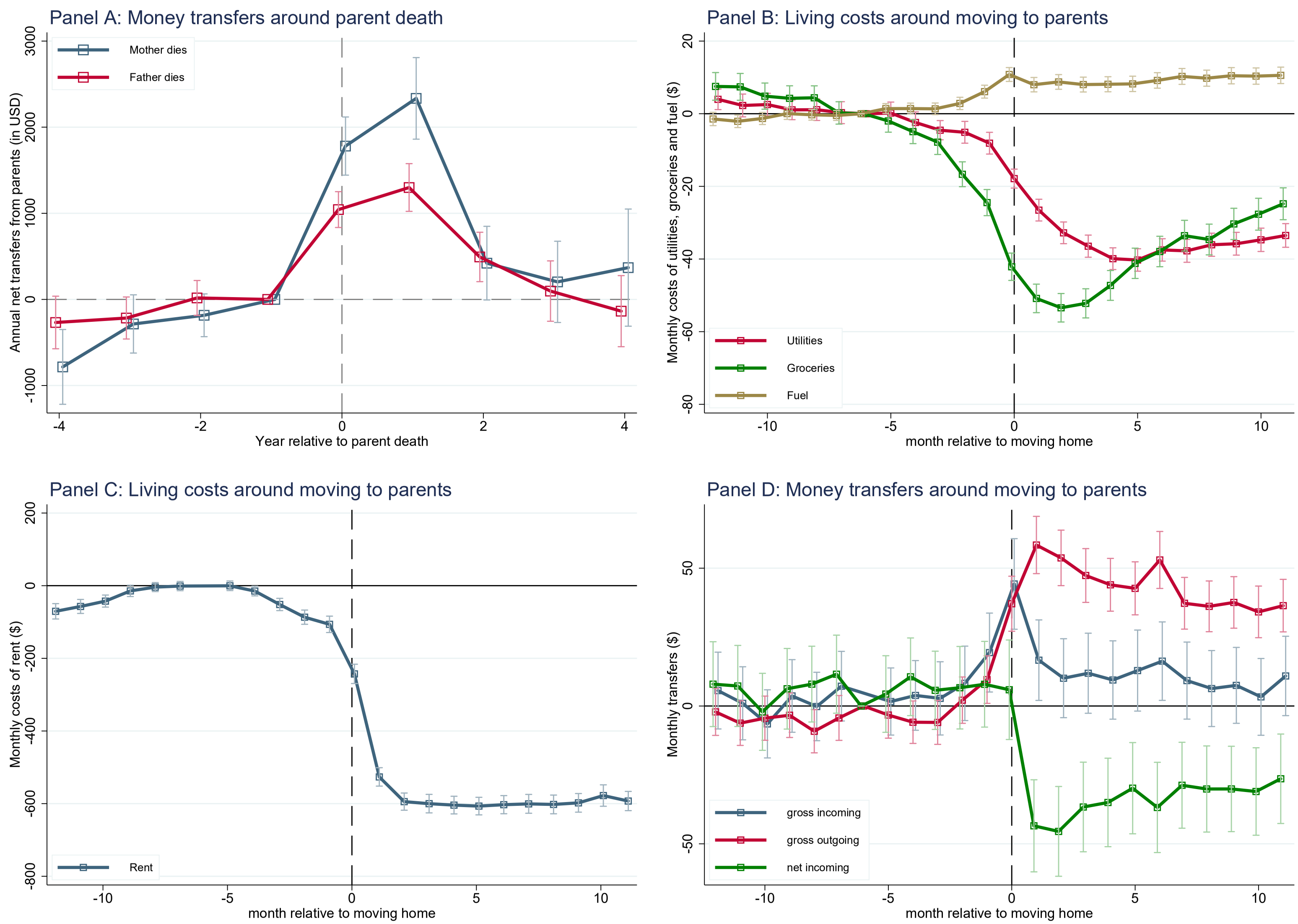


Figure A7: event studies of parent death and moving to parents. The figure shows the results from estimating equation (2) where the event is the year where a parent dies (Panel A) or the month an individual moves back to the parents (Panel B). The is outcome is net money transfers from parents (Panel A), spending on utilities, groceries and fuel (Panel B), spending on rent (Panel C) and money transfers to and from parents (Panel B). Besides dummies indicating the month relative to the event (depicted in the graph), the equation includes individual fixed effects and interactions between age indicators and calendar month indicators. The sample is generally defined in the same way as in the main analysis; however, to address that rent payments are often not captured well in the data, regressions with this outcome exclude individuals with monthly rent payments below \$500 (where extremely low rent payments likely reflect data issues) except if the observation is after period -4 in event time (where very low rent payments likely reflect moving home).



Empirical identification of "school friends"

Given the available information in the Danish education register, the best approximation of the criteria set out in the main text is to consider two individuals as "school friends" if they satisfy one of the following: (i) belong to the same age cohort and were, at some point, enrolled in the same primary school in the same calendar year; (ii) were admitted to the same secondary school in the same year; (iii) were admitted to the same degree program at the same university or other institution for higher education in the same year; (iv) completed the same degree from the same institution in a year before 1987. In primary school (10 years), grades follow age cohorts closely, so (i) is likely to include all class mates while excluding children in higher and lower grades at the same school. In secondary school (around 3 years) and higher education (2-8 years), students often enter at different ages, so (ii) and (iii) represent our best attempt at identifying individuals in the same class or study cohort. Before 1987, we have no information on current enrolment, so (iv) is the best possible attempt to capture school friends from the pre-1987 period.