FINANCIAL TROUBLE ACROSS GENERATIONS:
EVIDENCE FROM THE UNIVERSE OF PERSONAL LOANS IN DENMARK*

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Abstract

This paper uses administrative data with longitudinal information about defaults for the universe of personal loans in Denmark to analyse the driving forces behind financial problems. Non-parametric evidence shows that the default propensity is more than four times higher for individuals with parents who are in default compared to individuals with parents not in default. This intergenerational relationship is apparent soon after children move into adulthood and become legally able to borrow, and is remarkably stable across parental income levels, childhood school performances, levels of loan balances and time periods. Basic theory points to three possible explanations for the intergenerational correlation in financial trouble: (*i*) children and parents face common shocks; (*ii*) children and parents insure each other against adverse shocks; (*iii*) financial behavior differs across individuals and is transmitted across generations. Our evidence indicates that inherited differences in financial behavior is most important. The interest rates on loans do not incorporate the full risk of default related to the differences in financial behavior, which points to the existence of an interest rate externality in the credit market for personal loans.

Keywords: Household borrowing decisions, default, intergenerational dependency
JEL: D12, D91, G20

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1 Introduction

It is important to know why some people end up in financial trouble while others do not. A non-trivial share of individuals in modern societies do not meet their debt obligations. This has adverse effects on individual welfare and macroeconomic consequences because downturns may be amplified by spending cuts of people in financial difficulties or at risk of entering financial difficulties (Carroll et al. 2017).[1] Disentangling the driving forces behind financial problems can also carry important implications for the design of debt relief policies and bankrupcy laws (White 2007).

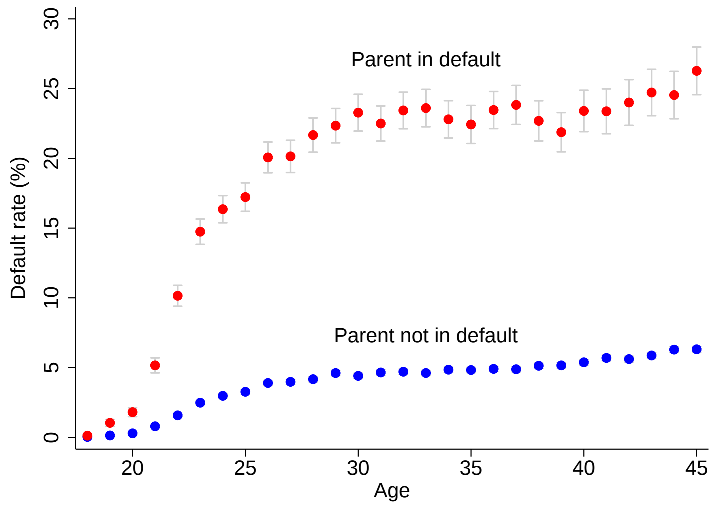
The objective of this paper is to study the intergenerational persistency in financial trouble, its underlying mechanisms and the economic implications. For this purpose, we use a unique administrative data set with longitudinal information about loan defaults for the universe of personal loans in Danish financial institutions. We document a strong correlation in financial trouble across generations and provide several pieces of evidence indicating that the intergenerational correlation is driven mainly by persistent differences in people's financial behavior passed on from generation to generation. Finally, we show that interest rates on loans do not fully incorporate the underlying variation in people's financial behavior, which points to the existence of an interest rate externality in the credit market for personal loans.

Our main data is gathered for tax purposes by the Danish tax authorities. The data contains personal identifiers for all borrowers, making it possible to see all accounts held by all individuals in the Danish population and enabling us to link the information to a number of other registers. Our primary indicator of financial trouble is whether an individual has defaulted on a loan, defined as being more than 60 days behind with payments on the loan at the end of the year. According to this definition, about five percent of the adult population are in financial trouble in any given year.

We contribute with three sets of results. The first result, and the starting point for the remaining analysis, is the basic intergenerational relationship in financial trouble displayed in Figure 1. The figure shows the share of individuals in financial trouble in 2011 plotted by age and stratified by whether the parents are in financial trouble or not. For example, the default propensity is 23 percent for 30 year olds with parents in default, while it is only 5 percent for those with parents not recorded as being in default.

[1] Financial trouble is associated with distress and viewed as a determinant of suicide (Appleby et al. 2017). In January 2017, Theresa May launched an updated national suicide prevention strategy in England recognising financial difficulties as a risk factor that needs to be considered (HM Government 2017).

Figure 1: Default propensity by age and by parental default status



Notes: The figure shows the mean default rate surrounded by 95% CIs for each age group in 2011. Standard errors are clustered at the child level. Each age group is categorized into two groups according to parental default in 2011. An individual is defined as being in default if having at least one delinquent loan at the end of the year. Obs: 2,533,969
Sources: Loan register from the Danish Tax Agency (SKAT) and population register from Statistics Denmark.

The nonparametric relationship reveals that the intergenerational correlation is apparent soon after children turn 18 years old and become legally eligible to establish debt. The default rates for both groups increase until the late twenties and are then almost constant at 22-23 percent for individuals with parents in default and at 4-5 percent for individuals with parents not in default. Thus, the probability of being in financial trouble is more than 4 times higher for individuals with parents in financial trouble. This intergenerational relationship is stable across different levels of loan balances, time periods and different measures of financial trouble. Additionally, it exists conditional on middle school grade point average and parental income, suggesting a relationship beyond the well-known correlation in earnings capacity (Solon 1999 and Black and Devereux 2011).

The second set of findings concern factors able to explain the intergenerational persistence in financial trouble. Using basic theory, we establish three mechanisms: persistent differences in financial behavior transmitted across generations (*financial behavior*); correlation in shocks faced by children and parents (*common shocks*); risk-sharing against adverse shocks through resource pooling of children and parents (*resource pooling*). Disentangling these mechanisms is difficult. We can use quasi-experimental techniques to assess the impact of shocks, for example by exploiting randomness in the timing of unemployment. However, identifying the causal impact of differences in behavior and preferences is a challenge because of the impossibility of randomly assigning type characteristics to people. Our empirical strategy is to compile different types of evidence, which piece together an overall understanding of the relative importance of the different mechanisms.

As a first simple test of the common shock hypothesis, we reproduce the intergenerational correlation in Figure 1, but measure parental default seven years earlier than child default. The graph is almost identical to Figure 1. If contemporaneous arrival of temporary shocks to both parents and children is important then the intergenerational correlation should be attenuated when introducing a long time span between measuring defaults of parents and children. The analysis is not able to rule out the possibility of long-lasting shocks, say health shocks, that lead to permanent reductions in income and are correlated across generations, but the result indicates that common shocks at the business cycle frequency are unlikely to be the main reason for the intergenerational correlation. This conclusion is supported by results from an unemployment event study. Unemployment shocks appear frequently in the population and often have serious consequences for the household economy. As expected, an unemployment event causes a large drop in disposable income and a rise in the default propensity of the individual. However, the unemployment event is not associated with any change in the income or default propensity of the parents in the surrounding years, which would be the case if contemporaneous unemployment shocks were important. Furthermore, the sharp increase in the intergenerational correlation soon after children become legally eligible to borrow, observed in Figure 1, and also when following cohorts over time, seems difficult to reconcile with common shocks to children and parents.

The resource pooling hypothesis implies that parents transfer resources to their children when a child is hit by an adverse shock. In our unemployment event study, we observe a drop in financial wealth of the individuals who become unemployed, but we do not detect any significant change in the financial wealth of their parents. We do not find any evidence either that children transfer resources to parents hit by an unemployment shock. The strong intergenerational persistence in financial trouble is also robust to controlling for other major life events, such as family instability and health events. These findings jointly indicate that resource pooling is unlikely to be the main driver of the intergenerational dependency in financial trouble. This is in line with other studies finding little evidence in favour of resource pooling in other contexts (Altonji et al. 1992, Attanasio et al. 2015, Kolodziejczyk and Leth-Petersen 2013).

In order to learn about the importance of heterogeneity in behavior and its transmission across generations we pursue two strategies. The first strategy is inspired by standard consumption-savings theory (Deaton 1991, Carroll 1997), which predicts that impatient and risk-willing individuals tend to persistently hold low levels of precautionary savings relative to their permanent income. Based on this insight, we exploit information about historical holdings of financial assets relative to disposable income of parents observed over a ten-year period almost two decades earlier (1987-1996). The idea/assumption is that the historical variation in asset-income ratios of the parents are informative about differences in their financial behavior, but are orthogonal to current shocks that can drive parents and children into default. The historical asset-income ratios turn out to be strong predictors of parental default in 2011, and when used as instruments for parental default in 2011, the estimates of the intergenerational correlation in financial trouble double. The method cannot distinguish between fixed differences in behavioral types and very persistent or permanent shocks, which occur before 1997 and affect default propensities in 2011, but it filters out the impact of shocks at the business cycle frequency occuring after 1997. Using the method, we find that about 50 percent of the variation in defaults within a generation is due to persistent differences in financial behavior, and that 30 percent of this behavioral component is transferred across generations. These findings suggest that persistent differences in financial behavior and the transmission of such behavior across generations matter quantitatively for observed financial problems.

The second strategy is to elicit key preference parameters, using established survey instruments, for a small subset of the population and to link this survey data at the individual level to the register data in order to analyse whether preferences and financial trouble are related. Indeed, we find that the elicited preference parameters predict real-life financial trouble of both parents and children and that preferences correlate across the two generations. These findings are also consistent with the existence of persistent differences in financial behavior passed on from generation to generation. Overall, the different pieces of evidence collectively point towards the transfer of financial behavior as an important factor in explaining the intergenerational correlation in financial trouble.

Our third set of findings address whether the interest rate setting on loans incorporates the differences in the probability of default predicted by the intergenerational dependency. We select all loans for individuals who were not in default on any loan in 2004 and divide them into groups of loans carrying the same interest rate. We then subdivide each of these groups into two subgroups according to whether the parents are in default or not in 2004. Finally, we follow the loans of the individuals forward in time and compute the share of the loans, which become delinquent during the period 2005-2011. The evidence shows that the loan-specific interest rate predicts default but, more importantly, that the default rate within each group of loans carrying the same interest rate is substantially higher for the group where the parents are in default. This points to the existence of private information in the credit market for personal loans creating an interest rate externality: interest payments of individuals with a low default probability, due to low risk-taking behavior inherited from parents, partly cover losses incurred by individuals with a high default probability, caused by high risk-taking behavior adopted from their parents.

Our results relate to different strands of literature. The empirical literature studying consumer delinquency and bankruptcy has mainly focused on the the importance of adverse shocks, strategic motives in relation to bankruptcy arrangements and default costs as drivers of defaults on loans (Agarwal and Liu 2003, Agarwal et al. 2003, Fay et al. 2002, Gross and Souleles 2002). The conclusions from this literature are mixed, but there appears to be a consensus that adverse shocks can only explain a fraction of the default events. Our study contributes with evidence indicating that differences in financial behavior is an important reason why some individuals default on their loans while others do not.

In a recent study, Ghent and Kudlyak (2017) follow the credit records of more than 300,000 Americans from age 18/19 and ten years forward. They document a negative association between parental credit score at child age 18/19 and the risk of default of the child ten years later. This result is complementary to the IGC findings reported here. It suggests that our results are not specific to the Danish setting, where among other things borrowers are subject to full recourse in the event of default. Our results are also in line with Kuhnen and Melzer (2018) who use data from the National Longitudinal Survey of Youth (NLSY) to show that self-efficacy measured during childhood predicts differences in the likelihood of being in financial distress in adulthood. This is remarkable because it shows that financial distress is related to factors measured very early in life, and is consistent with our finding that financial distress is related to very persistent factors. Consistent with these results Parise and Peijnenburg (2016) and Gathergood (2016) find that individual level noncognitive abilities are predictive for ending up in financial distress, highlighting the importance of personal traits in determining financial decision making.

Our results are also related to the literature using survey and experimental methods to elicit preference parameters. This literature has demonstrated significant heterogeneity in risk and time preferences (e.g. Bruhin et al. 2010, Epper et al. 2018) and also a strong correlation in these preference parameters across generations (e.g. Alan et al. 2017, Dohmen et al. 2012, Kimball et al.

2009). Our evidence on intergenerational preference correlation is consistent with these results. In addition, by linking survey and register data, we show that people who characterize themselves as risk willing are more prone to be in financial trouble in real-life than individuals who characterize themselves as risk averse. A related literature has documented that preference heterogeneity is needed in order to rationalize the observed heterogeneity in consumption and wealth levels across individuals (e.g. Alan and Browning 2010, Carroll et al. 2017, Bozio et al. 2017, Epper et al. 2018). Since preferences are thought to be relatively fixed throughout adulthood, this is consistent with the persistence of financial trouble in our study.

Finally, our results are broadly related to recent papers studying intergenerational wealth correlations. Using Norwegian adoption data, Fagereng et al. (2018) find that being raised by parents who take financial risks lead adoptees to also take risks when making financial decisions. Black et al. (2017) use Swedish adoption data with information about riskiness in portfolio choices to demonstrate a strong intergenerational correlation in risky financial behavior, and also point to nurture being the most important driver of the intergenrational correlation. Our results suggest that transmission of financial behavior also plays an important role for understanding financial trouble, but our data does not allow us to enter the nature versus nurture debate.

The next section describes the data and the institutional environment. Sections 3-5 present the results. The final section discusses broader implications of our results. The appendix provides various robustness analyses.

2 Description of institutional environment and data

2.1 Measurement of financial trouble and the Danish institutional environment

We define a person as being in financial trouble if having made insufficient payments to service debt obligations. We think of this 0-1 outcome as being a result of (ex ante) financial behavior/risk willingness and (ex post) adverse shocks. This is formalized theoretically in Section 4.

In practice, the measurement of default and the degree of risk taking also depend on the institutional setting. The Danish tax law requires all banks and other financial intermediaries offering interest-bearing personal loans to report to the Danish Tax Agency (SKAT), for each loan of each individual, whether the person has defaulted on the loan, defined as being at least 60 days late with payments on the loan at the end of the year.[2] This is our primary measure of financial trouble on which we have obtained detailed longitudinal data for the period 2004-11 from the Danish Tax Agency. The records are collected annually and contain all loan accounts of all Danes and also contain information about the level of debt on each account at the end of the year and the interest payments accrued during the year. The Danish tax authorities collect this third-party information to crosscheck whether tax deductions for interest payments are correct and to estimate changes in net-wealth, which is used in the process of selecting taxpayers for audit (see Kleven et al. 2011). The information on loan balances allows us to work with different degrees of severity of financial trouble by, for example, confining our default definition to delinquencies on large loans.[3]

To corroborate our main analysis based on loan defaults, we also study another measure of financial trouble based on other data obtained from the two credit bureau companies—Experian and Debitor Registret—that specialize in running files on bad payers in Denmark. A person is recorded in these files if a creditor, e.g. a bank or a shop, has reported him as not having fulfilled payment obligations. This allows other potential creditors to buy access to these files to verify that a potential customer is not in default. There are regulations about who can be recorded in these registers and for how long they can be recorded.[4] Being recorded in the register effectively removes the possibility of obtaining new loans or credit (at least in the short run) and it is therefore a signal of severe financial trouble. We have gained access to a snapshot of the people registered in 2009, which has been collected by the Danish Ministry of Economics and Business (Økonomi- og Erhvervsministeriet 2010).

The bankruptcy system in Denmark, as in many continental European countries, is creditor-friendly compared to the US (Livshits et al. 2007). In year 2011, about 1,500 individuals were granted personal bankruptcy (Domstolsstyrelsen 2011), corresponding to 1 out of 3,000 of the adult

[2]Bank regulatory systems work with different definitions when defining performing and non-performing loans. According to the Bank for International Settlements, for banks to be advanced and use risk weights "Banks must be able to access performance in formation on the underlying pools on an ongoing basis in a timely manner. Such information may include, as appropriate: exposure type; percentage of loans 30, 60 and 90 day past due ..." (BIS 2014 p. 13). For banks using the standardised approach "Delinquent underlying exposures are underlying exposures that are 90 days or more past due ..." (BIS 2014 p. 26).

[3]As the data is collected for tax-purposes, it does not hold any information about the type of loan or credit except that mortgage loans can be identified because they are supplied in separate files. Neither does the data contain information about whether default has been associated with any punishment, for example a fee, nor information about internal credit scoring used by the banks nor information about personal bankruptcy.

[4]People can be recorded in the files if they have received at least three reminders and a letter warning them that they will be recorded in the file if they do not pay their dues. People can at most be recorded in the files for five years for each missing payment.

population (18+ years), and even when bankruptcy is granted it can be associated with wage garnishment for up to five years. In this system, where debt discharge is rare, people may stay in financial trouble for a long time if they continue not to service their debt obligations.

2.2 Other data, sample selection and summary statistics

All Danes have a unique personal identification number (CPR), and our data sets on financial trouble include this identification number of the account holder. This enables us to link the data to the population register and, thereby, link individuals to their parents. We also link the data to the income-tax register and other public administrative registers giving information about labor market history, annual income and level of financial wealth going back to 1987. These data have also been used in previous studies of household financial behavior (Leth-Petersen 2010; Chetty et al. 2014). By virtue of being based on administrative records for the entire population there is no attrition apart from what derives from death and migration.

We consider all individuals who are 18-45 years old in the sample period 2004-2011 and with at least one living parent. We exclude all individuals with family-owned enterprises.[5] We organize the data so that each unique parent-child-year cell provides the unit of observation. This implies that for a child with two parents, there will be a child-mother and a child-father observation for each year.[6] If parents are divorced and have found new partners then we do not consider the new partners.

Table 1 presents summary statistics for the sample. There are 28,027,610 unique parent-child observations in our data set, and 5 percent of the children and 6 percent of the parents are recorded as having defaulted on unsecured loan payments during the data period. Very few are recorded as having defaulted on a mortgage loan. The default risk on Danish mortgage loans is generally low due to credit screening based on the availability of collateral and the ability to service the loan, first lien status, a maximum loan-to-value ratio of 80 percent of the house value when taking up the mortgage loan, as well as several other regulatory features (see Jensen et al. 2015 for a more detailed

[5] We do this to avoid including loans more related to firm finance than family finance. However, Figure 1 is more or less unchanged if we do not exclude these individuals.

[6] We have two observations per child if both parents are alive in a given year, but only one observation for children with only one parent alive. This difference is not important because both parents are alive for nearly all children in this age segment. For example, if children with two parents alive and one parent alive are weighted equally then the overall default rate remains the 5 percent reported in Table 1 and Figure 1 is close to identical. Figure 1 is also almost unchanged if we base the unit of analysis on households instead of individuals where a household is defined as being in default if one of the children are recorded as being in default if themselves or their partner are in default and parents are recorded as being in default if one parent is in default.

Table 1: Summary statistics for full sample 2004-2011

	Mean	Median	SD
Main persons			
Default on bank/credit card debt (d)	0.05	0.00	0.21
Bank/credit card debt	190,367	126,807	204,702
Delinquent bank/credit card debt	84,768	43,071	129,577
Default on mortgage (d)	0.00	0.00	0.02
Bank/credit card debt	118,747	39,677	192,169
Mortgage debt	321,718	0	500,447
No. of bank/credit card loans	3.08	3.00	2.83
No. of mortgages	0.61	0.00	0.90
Financial assets	68,363	18,675	146,657
Homeowner (d)	0.40	0.00	0.49
Housing assets	420,798	0	662,247
Affected by unemployment (d)	0.05	0.00	0.22
Age	31.99	32.00	8.17
Female (d)	0.51	1.00	0.50
Gross income	294,264	282,128	185,004
College degree (d)	0.22	0.00	0.42
Married or cohabiting (d)	0.57	1.00	0.50
No. of children	0.99	1.00	1.15
Number of individuals		2,501,088	
Number of observations		28,027,610	
Parents			
Default on bank/credit card debt (d)	0.06	0.00	0.24
Bank/credit card debt	253,963	168,718	265,344
Delinquent bank/credit card debt	130,133	63,812	194,468
Default on mortgage (d)	0.00	0.00	0.02
Bank/credit card debt	113,748	12,670	207,106
Mortgage debt	307,568	0	492,264
No. of bank/credit card loans	2.49	2.00	2.83
No. of mortgages	0.72	0.00	1.01
Financial assets	181,834	44,957	365,578
Homeowner (d)	0.53	1.00	0.50
Housing assets	708,752	418,500	945,381
Affected by unemployment (d)	0.03	0.00	0.18
Age	58.35	58.00	10.54
Female (d)	0.56	1.00	0.50
Gross income	315,883	285,405	181,170
College degree (d)	0.19	0.00	0.39
Married or cohabiting (d)	0.75	1.00	0.43
No. of children	2.56	2.00	1.08
Number of parent individuals		1,802,251	
Number of observations		25,194,524	

Notes: All amounts in 2011-DKK. A dummy variable is denoted by (d).
Sources: Loan register from the Danish Tax Agency (SKAT) and various registers from Statistics Denmark.

description of the Danish mortgage system). Therefore, default and foreclosure on mortgage loans are not so common in Denmark and were less of a problem during the recent financial crisis than in many other countries as described by Campell (2012).

Danish households generally have a high level of debt compared to many other countries (IMF 2012), which may reflect a low need for precautionary savings due to a high universal public pension benefit level, substantial labor market pension savings and an extensive social safety net. The average level of bank debt is DKK 118,747 (median DKK 39,677), and the average level of mortgage debt is DKK 321,718.[7] Debt is highly unequally distributed as is witnessed by the significant differences between average and median debt levels. Individuals who are recorded as defaulters on unsecured debt have a higher level of bank and credit card debt, on average, but they have less mortgage debt reflecting that they are more likely to be renters. While highly unequally distributed, the mean balance on defaulting accounts is economically significant at DKK 190,367, suggesting that defaults are not confined to small loans only.[8]

In a sub-analysis, we use information about the grade point average (GPA) obtained in middle school (9^{th} grade). The school grades are only available for people completing middle school in 2001/2002 or later. When we use this information, we confine the sample to those cohorts where the information is available.

Administrative data lack subjective information about financial behavior and attitudes that may help explain why some people are in financial trouble while others are not. In order to learn whether key preference parameters are correlated with the propensity to get into financial trouble, we issued a survey to 1,748 individuals in January 2014, where we asked people about their own preferences (risk willingness, patience and impulsivity) and the preferences of their parents using established survey questions. We merge these data at the individual level to the administrative register data described above and investigate in Section 4.2.2, whether the subjectively stated preference indicators correlate with our measures of financial trouble from the administrative registers.

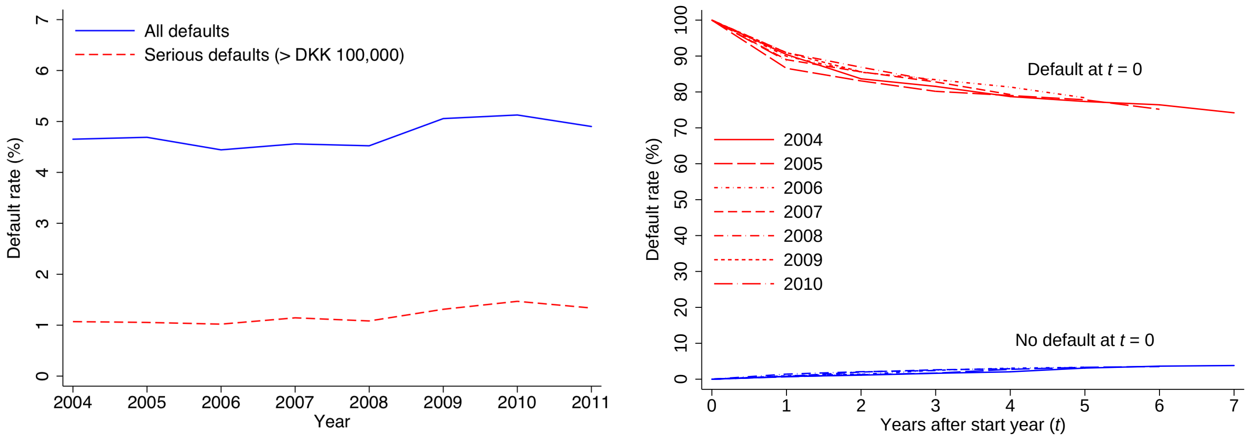
[7] The exchange rate has been in the range of 5-6 DKK per USD in the period from 2004 to 2011.

[8] Summary statistics by default status are reported in the Appendix Table 3. Compared to non-defaulters, defaulters tend to be slightly older, slightly more likely to be male, have a lower level of education, a lower level of income, are less likely to be home owners and, as a result, they hold less mortgage debt. However, defaulters have more non-mortgage debt and hold fewer financial assets. Table 3 also shows that the balance on the defaulted bank/credit card loans is more than eight times bigger than available financial assets on average, and the total debt balance is more than 15 times higher than the level of financial assets. This suggests that default is not merely the result of carelessness concerning repayment of the debt. In fact, 87 percent the children in default have a balance on the defaulted loan, which is larger than their financial wealth by the end of the year.

Figure 2: Aggregate default rate over time and persistence in default

(a) Aggregate default rate

(b) Survival curves



Notes: Panel A shows the development over time in the aggregate default rate for people of age 18-45 in each year. Along with the overall default rate the graph shows the default rate when default only counts for loans with a loan balance>DKK 100,000. For both categories the individual is defined as being in default if defaulting on at least one loan with the given characteristics. Obs: 2,501,088. In Panel B individuals are grouped by their default state in the initial year, 2004-2010, and followed until 2011. The curves in the top of the panel show the default rate for people who were in default in the initial year, while the curves in the bottom show the default rate for people who were not in default in the initial year. Default status can be tracked for 7 years using 2004 as initial year down to 1 year when using 2010 as initial year. Each curve represents a given initial year. Obs: 1,743,743.
Sources: Loan register from the Danish Tax Agency (SKAT).

3 Financial trouble: Basic facts and correlation across generations

The solid line in Panel A of Figure 2 shows the development over time in the share of 18-45 year old people who are registered as having defaulted on a loan payment. It shows that the aggregate default propensity is relatively constant over the period at a level of about 5 percent, with the level being somewhat lower before 2008 and a little higher afterwards with a difference of about 0.5 percentage points. Thus, the default rate increased after the financial crisis, but the change is moderate. In particular, it seems difficult to rationalize the reasonably stable level of defaults with a theory of financial trouble based only on adverse shocks to unemployment, income and asset prices, which have fluctuated substantially over the period. White (2007) makes a similar point in the context of personal bankrupticies in the US in the 1980s and 1990s.

The broken line in Panel A shows the aggregate propensity to default on large loans with a balance of at least DKK 100,000. The level of default is obviously smaller, but at a level of about 1 percent it is still significant. This shows that defaults are not concentrated only on small and insignificant loans.

The stable default rate in Panel A may reflect a high flow of individuals defaulting on a loan each year and quickly moving out of the default state again, or it may reflect a high persistency with people being in default for many years and only few people moving across the two states. In Panel B of Figure 2, we follow the default propensities of individuals over time. Specifically, we identify individuals who were in default/not default in a given year and then follow them forward as long as we can. For example, the upper solid line starting at 100 percent in 2004 follows individuals who were in default in 2004 and plots the fraction of this group of individuals who are in default in the subsequent years. The graph shows that almost 3/4 of those who default on loan payments in 2004 are also defaulting on loans seven years later. Half of those who defaulted initially have defaulted on a different loan seven years later (not reported) showing that the persistency is not simply related to a single account.

The curves at the top of Panel B may be compared to the lower level curves showing the risk of defaulting for individuals who were not in default in the initial years. The solid curve shows that less than 5 percent of this group default on a loan seven years later. The large difference of around 70 percentage points after seven years, depending on the initial default status in 2004, shows that individual default rates are more persistent than the duration of standard business cycles. Note, finally, that all the curves at the top follow a similar pattern over time, as do all the curves at the bottom, showing that the degree of persistency is stable.[9]

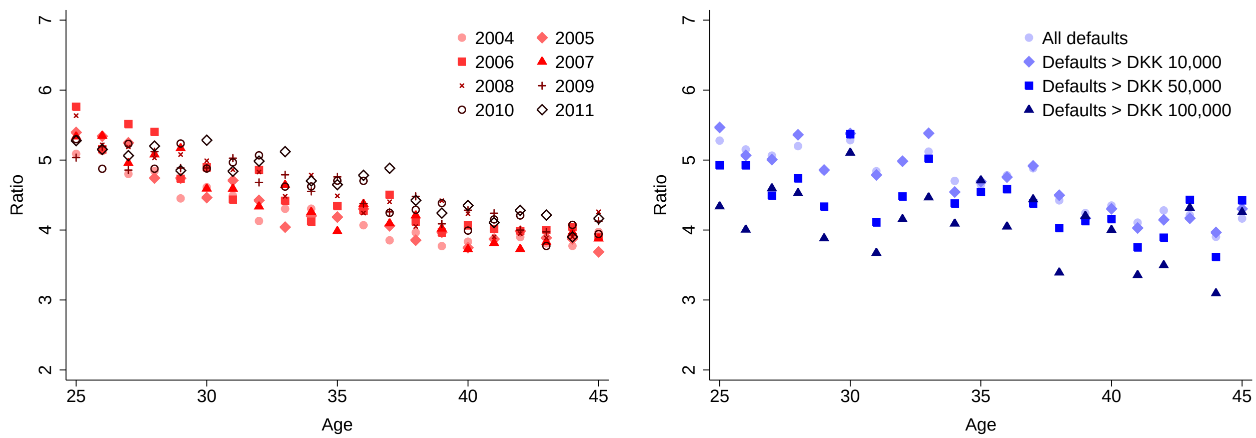
A strong kind of persistency exists if financial trouble is related across generations. Figure 1, discussed in the Introduction, documents a striking intergenerational dependency in the propensity to default. This relationship is stable. In Panel A of Figure 3, we plot the ratio of default for children with parents in default to children with parents not in default for each of the eight years in our sample. The ratio is quite stable across the years, starting at 5-6 for the youngest age groups and converging to a level of 4-5 from age 30. Panel B shows the ratio of defaults of the two groups when we vary the criteria for financial trouble by only including delinquency of large loans ($\geqq$ DKK 10k, 50k and 100k, respectively) in the definition of default. Along this dimension, the ratio is also

[9]Default rates are strongly correlated with birth weight within each cohort-gender combination. For example, for men who are 30 years old in 2011 the average birth weight is 110 gram lower for those who have defaulted on a loan in 2011 compared to those who have not defaulted. This shows that the high persistency in default rates reflects, at least to some extent, predetermined differences across individuals. It is well-known that birth weight is correlated with many economic outcomes (Currie 2011) and that many different explanations may underlie such correlations. The only point we want to make here is that some of the variation in financial trouble across individuals has to be predetermined.

Figure 3: Intergenerational correlation by year and loan balance

(a) Ratio of default propensities by year

(b) Ratio of default propensities by loan levels



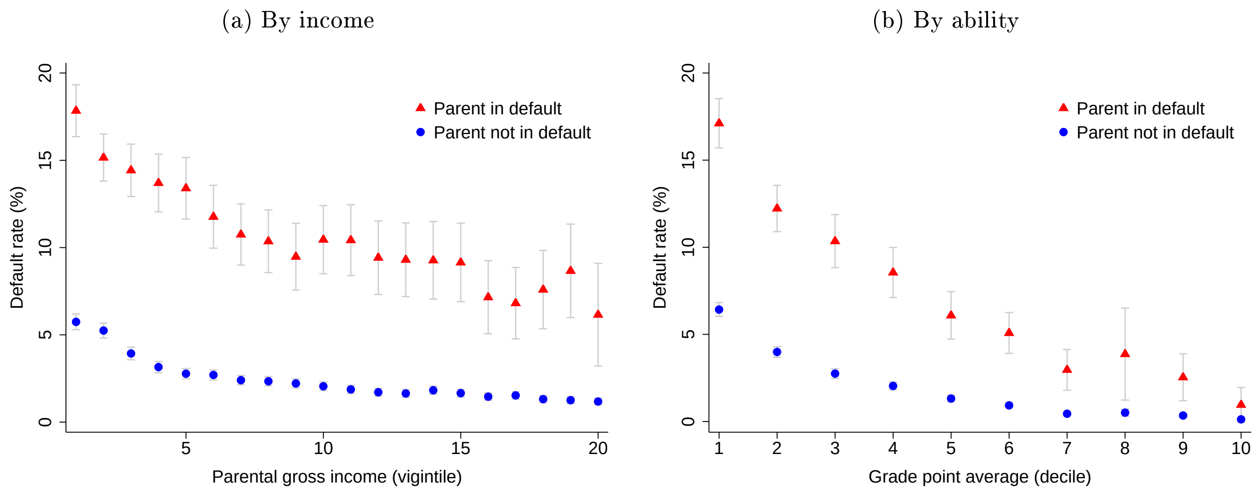
Notes: The graphs show the ratio between the default propensity for individuals where the parent is in default relative to the default propensity for individuals of the same age where the parent is not in default. In Panel A the ratio is calculated for each year, 2004-2011. Obs: 1,791,489. In Panel B the graph displays the ratio for defaulting at loan levels exceeding DKK 0, DKK 10,000, DKK 50,000 and DKK 100,000, respectively. The default loan level may reflect defaults on several smaller loans that, in total, add up to the defined amount. The default status for both the individual and the parent is measured in 2011 and the default loan level threshold applies for both parent and individual. Obs: 2,552,493. For the younger age groups, especially at high loan levels, the default rate is low and consequently the ratio is not well-defined. For this reason we display the ratio only from age 25 and up.
Sources: Loan register from the Danish Tax Agency (SKAT).

stable at a level of 4-5. We find a similar intergenerational pattern when using the credit bureau files on bad payers, which is a different measure of financial trouble and from a different data source (see Appendix B). We therefore conclude that the intergenerational correlation in Figure 1 is not confined to the specific measure of financial trouble that we use throughout the paper.

Figure 1 shows that the intergenerational relationship appears soon after children turn 18 years old and become eligible to establish debt. We obtain the same result if we follow young individuals over time (not reported). This shows that the relationship is not driven by cohort effects. Moreover, if we restrict the sample to children and parents not living together, we also find the same pattern (not reported). This suggests that the intergenerational correlation is not simply the result of parents and children living together and deciding jointly on household finances.

It is natural to expect that financial trouble is related to income and cognitive ability, implying that our finding of an intergenerational dependency in financial trouble may just reflect the well-established intergenerational correlations in income levels and ability measures (Solon 1999, Black and Devereux 2011). In Panel A of Figure 4 we rank parents (within their cohort) by their average gross income in the five years leading up to 2004 binned into vigintiles, and plot the default rate by

Figure 4: Intergenerational correlation by income and ability



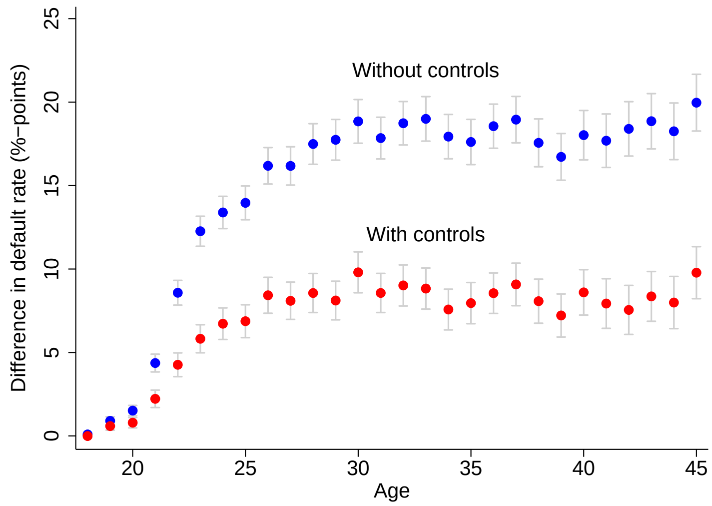
Notes: Panel A shows the default rate with 95% CIs for individuals aged 22-24 in 2011, grouped by parental default status in 2004 and by vigintile of average parental income over the period 1989-2003. Income vigintiles are constructed separately for each parental cohort. Obs: 276,254. Panel B groups the same sample by parental default status in 2004 and plots the average default rate within deciles of grade point averages (GPA) from the 9th grade graduation exam in Danish and Mathematics. Deciles of GPA are constructed separately for each cohort. Obs: 262,390. Standard errors in both panels are clustered at the child level. *Sources*: Loan register from the Danish Tax Agency (SKAT) and various registers from Statistics Denmark.

parental default status in 2004 within each vigintile of parental income.

As expected, the overall tendency for children to get into financial trouble is declining in parental income, i.e. children with more affluent parents tend to be less likely to get into financial trouble. However, the level of default is significantly higher for children with parents who are in default, and this is the case for all levels of parental income. The ratio between the default rate of children with parents in and out of default is in the range 4-7, which is of the same magnitude as for the basic intergenerational correlation in Figure 1.

Panel B displays the default propensity against deciles of the middle school (9th grade exam) grade point average (GPA) of the child. We only consider the subsample who completed the 9th grade in 2001/2002 or later because we only have middle school GPAs available for this subsample. Previous studies have demonstrated that IQ and cognitive ability, in particular mathematical knowledge, predict financial distress, a lower incidence of mortgage delinquency, fewer mistakes in credit card usage and loan choices (Zagorsky 2007, Gerardi et al. 2013, Agarwal and Mazumder 2013, Stango and Zinman 2009). Our data also show that financial hardship is negatively correlated with cognitive ability, measured by middle school GPA. However, the graph also shows that children with parents in default are much more likely to be in default than other children at all levels of

Figure 5: Intergenerational correlation with controls



Notes: The figure shows the difference in the mean default rate with 95% CIs in 2011 between individuals with a parent in default in 2011 and individuals with a parent not in default in 2011. The intergenerational relationship is shown with and without controls, where the included controls are within-cohort deciles of gross income (dummies), within-parental cohort deciles of parental gross income (dummies), within-cohort deciles of GPA for those cohorts where GPA is available (dummies), gender of individual and of parent (dummy), college education, employment status and industry of individual and parent (dummies), residential region for individual and parent (dummy), parental cohort (dummies for 5-year intervals) and bank of child and parent (dummies). All control variables are measured in 2011. Standard errors are clustered at the child level. Obs: 2,533,844. *Sources*: Loan register from the Danish Tax Agency (SKAT) and various register from Statistics Denmark.

GPA. The difference exists for all cohorts, and is therefore not related to grade inflation, and it also exists when considering only grades from the math exam (results not reported).[10]

In Figure 5, we look at the difference in default rates between children of parents in default and children of parents not in default, before and after including a large number of control variables. We include dummy variables measuring the within cohort income decile of children and parents, respectively, the within cohort GPA decile of the child, college education of both child and parents, gender, parent cohort, region of residence and, finally, bank fixed effects.

The graph shows that 30 year old children with parents in default are, on average, 18 percentage points more likely to be in default compared to children without parents in default, corresponding to the vertical difference between the curves in Figure 1. After including all the controls, the difference is close to 10 percentage points. Thus, parental default is still a very strong predictor of child default showing that a major part of the intergenerational correlation in financial trouble is not captured

[10] Parental default could impact GPA directly. If parental default affects child GPA negatively then it would be a channel through which parental default would cause child default. Later, we shall control explicitly for GPA along with a host of other control variables to show that the intergenerational correlation exists beyond what can be explained by GPA and other control variables.

through intergenerational transmission mechanisms related to income, education etc. Note, finally, that education and income may be related to preference parameters, which also determine financial behavior. If this is the case, the control variables may also be removing variation in default that is related to variation in behavior and preferences across people.[11]

4 Factors that may explain intergenerational correlation in financial trouble

This section explores factors that may explain the finding of a significant intergenerational correlation in financial trouble. First, we provide a simple theory of financial trouble where the variation across individuals in defaults on loans may be due to both random shocks and persistent differences in risk taking behavior. The theory points to three possible explanations of intergenerational persistence in financial trouble. Afterwards, we provide empirical evidence on the relative importance of these three explanations of intergenerational persistence.

4.1 Basic theory

4.1.1 Distinction between adverse shocks and risky behavior

We consider a simple two-period model of individual consumption where c_1 and c_2 are the consumption levels in the two periods. Preferences are characterized by the utility function

$$u = (1 + \theta)\, c_1 + c_2, \tag{1}$$

where $\theta \in (0, 1)$ is supposed to capture the degree of impatience and risk willingness of the individual. More generally, it may also reflect behavioral biases and cognitive limitations leading to high risk taking behavior (Angeletos et al. 2001).

The interest rate is normalized to zero and the average income of an individual over the two periods is normalized to 1, implying that amounts of consumption and loan are measured in proportion to permanent income. The average (permanent) income is known to the individual but the distribution of income across the two periods is unknown when deciding consumption in the first

[11] We have also considered an approach where we split the vector of control variables into two groups of variables and control for them individually. One group includes variables related to job and income while the other group includes variables capturing education and cognitive ability. These two groups of control variables can be thought of as mediator variables in the sense that they are themselves the result of a deep underlying determinant of financial behaviour (which we label the 'fixed latent risk factor' in the theory section). Controlling for either subset produces a graph which looks almost identical to Figure 5 in the paper. These results are not reported but available upon request.

period. The income realization in the first period is determined by a stochastic variable ε distributed on the domain $(0,1)$ according to the density function $f(\varepsilon \mid \theta)$ and the cumulative distribution function $F(\varepsilon \mid \theta)$. In this formulation, we allow the probability of income shocks ε to be related to the type parameter θ, reflecting that the risk type of an individual may also influence income risk, for example through job choices.

Consumption c_1 takes place at the beginning of the first period while income ε is received at the end of this period, with the remaining income equal to $2-\varepsilon$ being received at the beginning of period two. Consumption in the first period is therefore financed by borrowing the amount $\alpha \equiv c_1$ and the loan has to be repaid at the end of the first period. This implies that the individual defaults on the loan repayment if $\varepsilon < \alpha$. In this case, the person will have to repay the loan in period two and pay default costs. The cost of default is modelled as a resource cost but may also represent a utility loss from being in financial trouble. The expected consumption in period two of a type θ individual then becomes

$$c_2^e = 2 - \alpha - \int_0^\alpha (\alpha - \varepsilon) f(\varepsilon \mid \theta) \, d\varepsilon, \tag{2}$$

where the last term is the costs of default and where the cost per dollar of the delinquent loan is normalized to one unit of consumption in period two.

The individual maximizes expected utility, which is solved by inserting $c_1 = \alpha$ and c_2^e from eq. (2) into the utility function (1) and maximizing with respect to α. This gives the optimality condition

$$F(\alpha^*(\theta) \mid \theta) = \theta, \tag{3}$$

where $\alpha^*(\theta)$ denotes the optimal level of credit relative to permanent income of a type-θ individual. In this optimum, the probability of default equals $F(\alpha^*(\theta) \mid \theta)$ and the default risk of a type-θ individual therefore equals θ according to eq. (3). Thus, default is determined both by the degree of riskiness in behavior — captured by the latent risk type factor θ — and by adverse shocks — captured by the stochastic variable ε. Note that the risk type parameter θ fully characterizes the risk of default in this model, implying that the default risk is independent of the correlation between the distribution of income shocks and the risk type parameter embodied in $F(\cdot)$. For example, a higher risk of job loss due to a higher θ does not influence the probability of default, which is still θ. The reason is that the individual responds to the higher risk of income loss by adjusting the amount of credit $\alpha^*(\theta)$.

The population consists of a continuum of individuals with risk types θ distributed on the unit interval according to a density function $h(\theta)$ and we assume shocks ε are idiosyncratic. The aggregate default rate of the population then becomes

$$d = \int_0^1 F(\alpha^*(\theta) \mid \theta) h(\theta) d\theta = \int_0^1 \theta h(\theta) d\theta. \tag{4}$$

The role of financial behavior and shocks in explaining the variation in observed defaults across individuals may be illustrated by considering two special cases of the model, both giving rise to the same aggregate default rate d: Shocks: All individuals are homogenous with $\theta = d$, in which case all the variation in defaults across individuals are caused by differences in the realization of shocks ε. Risk types: A share d of the population is characterized by $\theta = 1$ and the rest of the population is characterized by $\theta = 0$, in which case all the variation in defaults across individuals is caused by differences in risk taking behavior θ.[12] In the general case, the variation in defaults across individuals is due to both shocks and heterogeneity in financial behavior, and the relative importance of these two explanations is an empirical question.

4.1.2 Explanations of intergenerational correlation in financial problems

The simple theory points to three possible explanations for why financial trouble may be correlated between parents and children:

#1 **Financial behavior**: Financial behavior differs across individuals and is transmitted from generation to generation. In the model, this corresponds to a correlation between θ_g and θ_{g-1}, and, therefore, in the choices of credit α_g^* and α_{g-1}^*, where g denotes the generation.

#2a **Common shocks**: Shocks faced by children and parents may be correlated, for example, because they have similar skills or sort into similar occupations, and because shocks vary across these characteristics. In the model, this corresponds to a correlation between ε_g and ε_{g-1}.

#2b **Resource pooling**: Generations may pool resources and insure each other against adverse shocks (or, related, parents may help children in financial trouble). For example, parents and children

[12] Related to the business cycle variation in defaults shown in Figure 2, we may also consider the case where ε represents common shocks to all individuals—macro shock—instead of idiosyncratic shocks. In this interpretation, the Shock model described above predicts that the aggregate default rate switches between 0 and 1 over the business cycle with an average default rate of d. In contrast, the Risk type model predicts that the aggregate default rate stays constant at d over the business cycle. The observed moderate increase in the aggregate default rate following the Great Recession is consistent with the general model explaining variation in defaults by both shocks and heterogeneity in risk attitudes.

may jointly maximize a family utility function of the form $u_g + u_{g-1}$. In this extreme example, they only experience financial troubles if $\alpha_g + \alpha_{g-1} > \varepsilon_g + \varepsilon_{g-1}$, in which case both generations default at the same time, while in the opposite case, none of them default.

The first explanation is based on heterogeneity and inheritability of financial behavior, while the two other explanations are related to income shocks. Each of the three explanations are distinct and may explain the intergenerational correlation in financial problems independent of the other explanations. For example, in the third explanation, individuals may have the same risk parameter θ and parents and children may face independent shocks ε, but defaults on loans become correlated because ressources are pooled within the family. On the other hand, the three possible explanations are not mutually exclusive and may complement each other in explaining the intergenerational correlation documented in Figure 1.

4.2 Empirical evidence

The theory of default operates with two causal factors, shocks and behavior, and motivates three channels through which default can be correlated across generations. In this section, we provide different types of evidence to shed light on the importance of the different channels. We exploit the longitudinal dimension in our data to analyse differences in the timing of default across children and parents and to study the effects of severe unemployment shocks. We also include historical information about financial asset holdings, which is used to measure the relative importance of differences in financial behavior for default and the intergenerational transmission of this behavior. Finally, we link the register data to survey data where we use standard questionnaire techniques to elicit key preference parameters, and analyse the correlation with financial trouble.

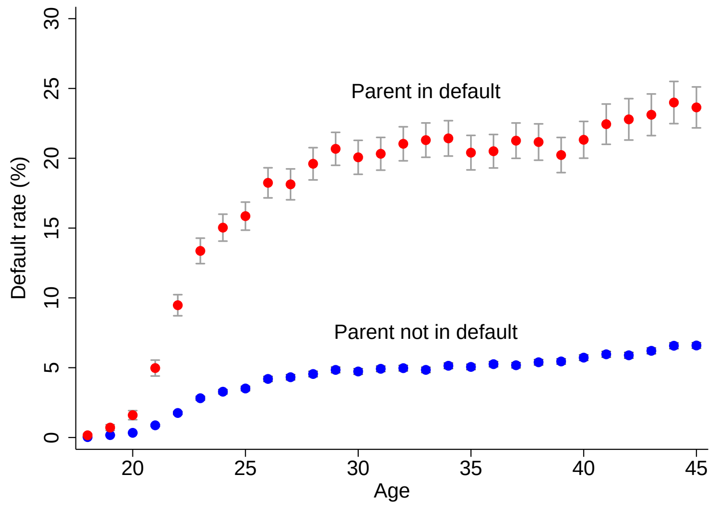
4.2.1 Common shocks and resource pooling

Different timing of default across children and parents

We start with a simple analysis where we reproduce the intergenerational correlation in Figure 1, but measure parental default seven years earlier than child default, that is we measure parental default in 2004 and child default in 2011. The result is illustrated in Figure 6 and provides the first piece of evidence related to the common shock hypothesis.

The idea is that if contemporaneous arrival of temporary shocks to both parents and children is important, then we should observe that the intergenerational correlation attenuates when introducing

Figure 6: Default propensity in 2011 by age and by parental default in 2004



Notes: The figure shows the mean default rate surrounded by 95% CIs for each age group in 2011. Each age group is categorized into two groups according to parental default in 2004. Standard errors are clustered at the child level. Obs: 2,649,161
Sources: Loan register from the Danish Tax Agency (SKAT) and population register from Statistics Denmark.

a difference in the time of measurement. For example, if consequences of shocks die out over a seven-year period then we should not see any intergenerational correlation. As is evident from the figure, the pattern is almost identical to Figure 1, which suggests that contemporaneous transitory shocks are not a main driving factor behind the intergenerational correlation. This evidence does not exclude the possibility of more long-term shocks, say permanent reductions in income because of health shocks, that are correlated across generations, but the result suggests that shocks at business cycle frequencies are not crucial in understanding the intergenerational correlation.

Appendix C contains a number of additional analyses looking at the timing of defaults of children and parents: (*i*) We show that the conclusion is the same if we include the full set of controls used in Figure (5). (*ii*) Using the pooled sample over the period 2004-11, we show that the intergenerational correlation vanishes when controlling for a fixed intergenerational component. (*iii*) We show that parental default predicts future default of children moving into adulthood and thereby becoming eligible for taking up loans. (*iv*) We provide suggestive evidence that the severity of parental financial trouble, rather than the timing of their default, matters for the default rates of children. Together these results align better with a correlation in latent risk types across generations than a correlation in the timing of shocks of parents and children.

Unemployment event analysis

Next, we look directly at the consequences of shocks. We focus on unemployment shocks, which may have large, unanticipated economic consequences at the individual level without being rare events. In addition, this type of shock is well identified in our data, which contains the unemployment histories for all individuals.

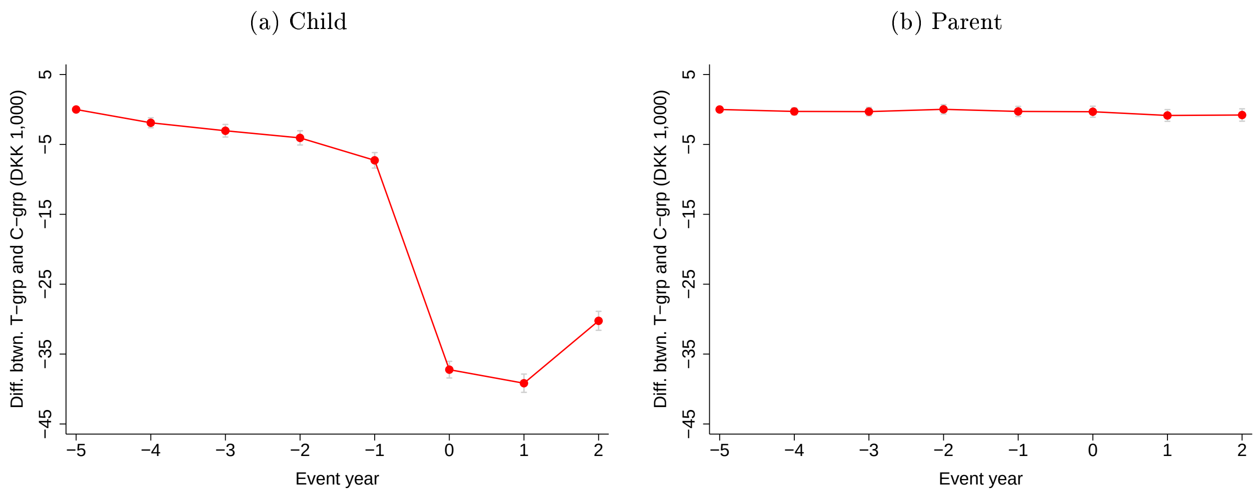
Our approach is very similar to the classical unemployment event study by Jacobson et al. (1993). We consider individuals experiencing unemployment shocks in 2007, 2008 and 2009 (event year t), respectively, defined as an unemployment spell of at least three months, and we consider only individuals who are employed, and without any unemployment spells in the five years up to the unemployment shock (t-5, t-4,...,t-1).[13] This will be our treatment group. The control group consists of individuals who are employed, and without any unemployment spells in the five years up to time t, and who do not experience any unemployment shock in the event year t. We select people who are 18-38 years old five years before the shock ($t-5$) and follow them up to two years after the shock ($t+2$). For this balanced panel, we study the impact of the unemployment shock on the disposable income, the default propensity and the financial wealth of both children and parents. All amounts are index-adjusted to 2009-DKK by computing $x_{y,c,i} * \bar{x}_{2009,c}/\bar{x}_{y,c}$, where $x_{y,c,i}$ is the original amount for individual i in cohort c observed in year y, $\bar{x}_{2009,c}$ is the sample average of cohort c in year 2009, and $\bar{x}_{y,c}$ is the sample average of cohort c in year y.

Figure 7 displays the impact of the unemployment shock on the disposable income of children (Panel A) and parents (Panel B). The graphs plot the coefficients from a regression of annual disposable income on T-group dummy variables and individual fixed effects. It is clear that disposable income drops considerably at the unemployment event. However, the drop in disposable income of around DKK 40,000 in Panel A is considerably lower than the drop in gross earnings, which is around DKK 125,000 (see Appendix D) because of the insurance incorporated in the tax-benefit system. When looking at the graphs for the parents in Panel B, we see no change in disposable income around the time children become unemployed. There is thus no indication that the children and parents are hit by shocks at the same time.

In Figure 8, we analyse the effect on the default propensity by looking at the difference in default rates between the treatment and control group. Panel A indicates that the default rate of the children increases after the unemployment shock by about 1.5 percentage points. The graph in

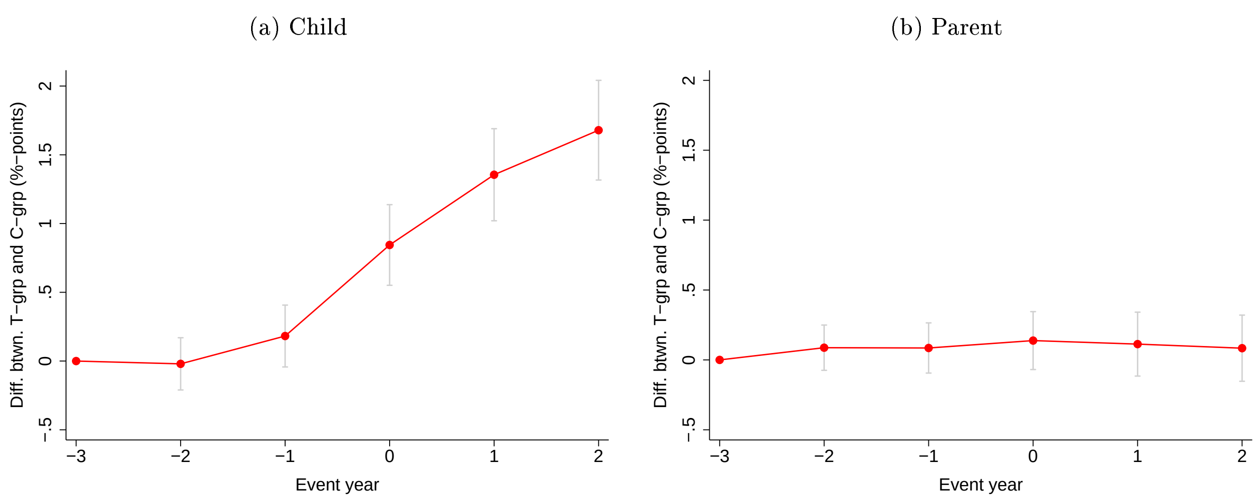
[13] Some of the unemployment shocks may be anticipated by the individuals. We are unable to use plant closures as a way to better isolate unanticipated shocks because of its low frequency.

Figure 7: Effect of child unemployment on disposable income



Notes: Panel A plots the coefficients, with 95% CIs, from a regression of annual disposable income on T-group dummy variables and individual fixed effects. The T-group consists of individuals affected by more than 3 months unemployment in year 2007, 2008 or 2009 ($t = 0$), who were employed and not affected by unemployment in any of the five years prior to the shock and of age 18-38 five years before the shock. The same selection criteria are used for the C-group with the exception that they have experienced less than 3 months of unemployment in the event year. This gives 12,384 individuals in the T-group and 1,399,746 individuals in the C-group. Individuals with missing parental information in any year 2002-2011 are excluded from both groups. The C-group is reweighted to account for age asymmetries between the two groups and to give each shock year the same weight in the pooled regression. All amounts are index-adjusted to 2009-DKK by computing $x_{y,c,i} * \bar{x}_{2009,c}/\bar{x}_{y,c}$, where $x_{y,c,i}$ is disposable income for individual i from cohort c in year y, $\bar{x}_{2009,c}$ is the sample average of disposable income for cohort c in year 2009, and $\bar{x}_{y,c}$ is the sample average of disposable income for cohort c in year y. Panel B is constructed in the same way as panel A, but with annual disposable income of parents as the outcome variable. In both panels standard errors are clustered at the child level.
Sources: Loan register from the Danish Tax Agency (SKAT) and population and income register from Statistics Denmark.

Figure 8: Effect of child unemployment on propensity to default



Notes: Panel A plots the coefficients, with 95% CIs, from a regression of default on T-group dummy variables and individual fixed effects. Panel B is constructed in the same way as panel A, but with default of parents as the outcome variable. The construction of the T-group and C-group is described in the notes to Figure 7. In both panels standard errors are clustered at the child level.
Sources: Loan register from the Danish Tax Agency (SKAT) and population register from Statistics Denmark.

Panel B, displaying the default rate of parents, is almost completely flat. Thus, we do not find any evidence indicating that children and parents simultaneously start defaulting on loans when children are hit by unemployment events. To summarize, none of the evidence points to common shocks as the main reason behind the intergenerational correlation in default.

The resource pooling hypothesis implies that parents transfer resources to their children if they are hit by a shock and the parents have the means to help. To measure whether parents help out their children, we construct a dummy variable taking the value one if parental financial wealth amounts to less than one month of disposable income, where disposable income is calculated as an average over five years of disposable income before the unemployment event. If parents help out their children then we should expect to see an increase in the fraction of parents with a low ratio of financial wealth to income.[14] For comparison, we do the same for the children.

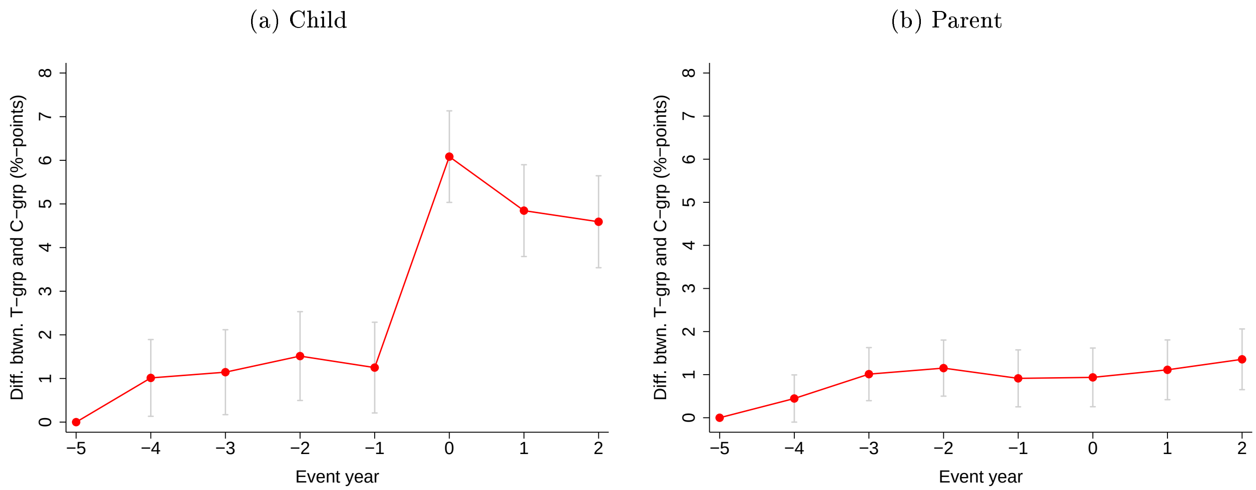
The results are displayed in Figure 9, which plots the coefficients from a regression of a low financial wealth indicator on T-group dummy variables and individual fixed effects. We observe a significant increase of more than 4 percentage points in the share of children with low financial wealth after the unemployment shock compared to the control group, but do not observe a similar increase for parents, as we might have expected if significant resource pooling takes place.

In Appendix D, we provide a number of sensitivity analyses: (*i*) We examine the consequences of more severe unemployment shocks. (*ii*) We investigate whether the results change if we use a two month income threshold for the definition of low financial wealth. (*iii*) We restrict the sample to parents not in default at any time and who should therefore be more able to help their children financially. (*iv*) We investigate the sensitivity of the results to using pooled resources of the parents instead of looking separately at each child-parent pair. (*v*) We investigate whether the share of child financial wealth drops in proportion to the sum of child-parent financial wealth. (*vi*) We examine common shock and resource pooling effects with respect to unemployment shocks of parents instead of children.[15] Other important life events such as adverse health shocks and family break-ups may also put household finances under strain. In Appendix E, we provide similar event study results

[14] Wealth measures are generally noisy and wealth is very unequally distributed across the population. This makes it difficult to obtain precise estimates using the raw wealth data, which is the reason for using a threshold approach. This has also been done in the empirical consumption/savings literature, where it is common to use a threshold approach (see for example Chetty et al. 2014). In Appendix D, we display the results from using two months of disposable income as the threshold, which gives the same results.

[15] We have also made sensitivity analyses with respect to other types of financial outcomes such as number of loans and debt levels without finding any resource pooling effects (these results are available upon request).

Figure 9: Effect of child unemployment on propensity to hold low levels of financial wealth



Notes: Panel A plots the coefficients, with 95% CIs, from a regression of a low financial wealth indicator on T-group dummy variables and individual fixed effects. The low financial wealth indicator equals one if the individual has financial assets at the end of the year less than what corresponds to one month's worth of the individual's average disposable income in the five years preceding the shock year. Panel B is constructed in the same way as panel A, but with a low financial wealth indicator of parents as the outcome variable. Financial wealth is the sum of stocks, bonds and bank deposits. All amounts in the calculation are indexed as described in the notes to Figure 7. Construction of T-group and C-group is described in the notes to Figure 7. In both panels standard errors are clustered at the child level.
Sources: Population and income register from Statistics Denmark.

for health shocks identified by receivement of sickness benefits. In addition, we show that the intergenerational correlation shown in Figure 1 is virtually unaffected when individuals experiencing unemployment, unstable family patterns or adverse health events are left out of the sample. The results from all these robustness analyses support our previous conclusions that the common shock and resource pooling hypotheses are unlikely to be the main underlying explanations for the observed intergenerational correlation in financial trouble.

4.2.2 Financial behavior

Historical financial behavior of parents

This section exploits historical information about asset holdings of parents observed two decades before the default outcomes (i) to provide an estimate of the intergenerational correlation in financial trouble that is less likely to be influenced by shocks; (ii) to provide an estimate of the importance of differences in financial behavior (differences in the latent risk factor θ in the theory) relative to shocks (ε in the tehory); (iii) and to measure the correlation in financial behavior between parents and children. To accomplish this, we impose more structure on the data.

The basic idea is that historical choices about financial liquidity (measured in proportion to income) are governed by the fixed latent risk-factor, but are orthogonal to recent shocks that may drive parents and children into default. Standard consumption-savings models (Deaton 1991, Carroll 1997) suggest that impatient and risk-willing individuals tend to persistently hold low levels of precautionary savings relative to their permanent income. Consistent with these models, empirical studies have found that people with low levels of precautionary savings, measured by financial assets relative to income, exhibit stronger spending responses to stimulus policies (e.g. Johnson et al. 2006, Leth-Petersen 2010, Kreiner et al. 2018). Building on these insights, we construct an estimate of the intergenerational correlation where we predict parental default in 2011 with a measure of the financial asset path in the period 1987-1996. The parents are, on average, 35 years old at the beginning of this period and 44 years old by the end of the period, meaning that the instrument is measured at a phase in life where financial assets and income are expected to be relatively stable. Specifically, we calculate the ratio of average financial assets to average disposable income for the parents for each of the years 1987-1996, and then divide the parents into behavioral types based on the within-cohort decile they belong to with respect to their average asset-income ratio over the ten year period. By predicting parental default using the financial asset-to-income paths observed almost two decades earlier, we are attempting to isolate the part of parental default that is related to (persistent) behavioral differences rather than shocks that have occurred close to when we observe financial default.

We assume that the latent risk-factor of the children is related to the latent risk-factor of parents according to the intergenerational relationship

$$\theta^C = \alpha_0 + \alpha_1 \theta^P + \omega, \tag{5}$$

where α_0 and α_1 are parameters, and ω is an independent noise term. The key parameter of interest is α_1, which quantifies how much of the parental risk-factor is passed on to the child.

Next, we assume that the default outcome can be approximated by the linear relationship

$$D_t^j = \theta^j + \varepsilon_t^j, \tag{6}$$

where $j = C$ for children, $j = P$ for parents, t indicates the year of observation, and ε_t^j is an independent shock component which is specific to period t such that $E\left[D_t^j\right] = \theta^j$ as in eq. (3) of the theory. Finally, we assume that the within-cohort decile of the ratio of average financial assets to average disposable income for the parents across the years 1987-1996, Z^P_{t-k}, is related to the fixed latent risk-factor of the parent, θ^P, in the following way

$$Z^P_{t-k} = \gamma_0 + \gamma_1 \theta^P + \mu_{t-k}, \tag{7}$$

where γ_0 and γ_1 are parameters, and μ_{t-k} is an independent error term. From the three equations above it is possible to derive the following relationships (see Appendix G):

$$\hat{\alpha}_1^{\text{OLS}} = \frac{\text{cov}(D^P_t, D^C_t)}{\text{var}(D^P_t)} = \alpha_1 \frac{\text{var}(\theta^P)}{\text{var}(\theta^P) + \text{var}(\varepsilon^P_t)}, \tag{8}$$

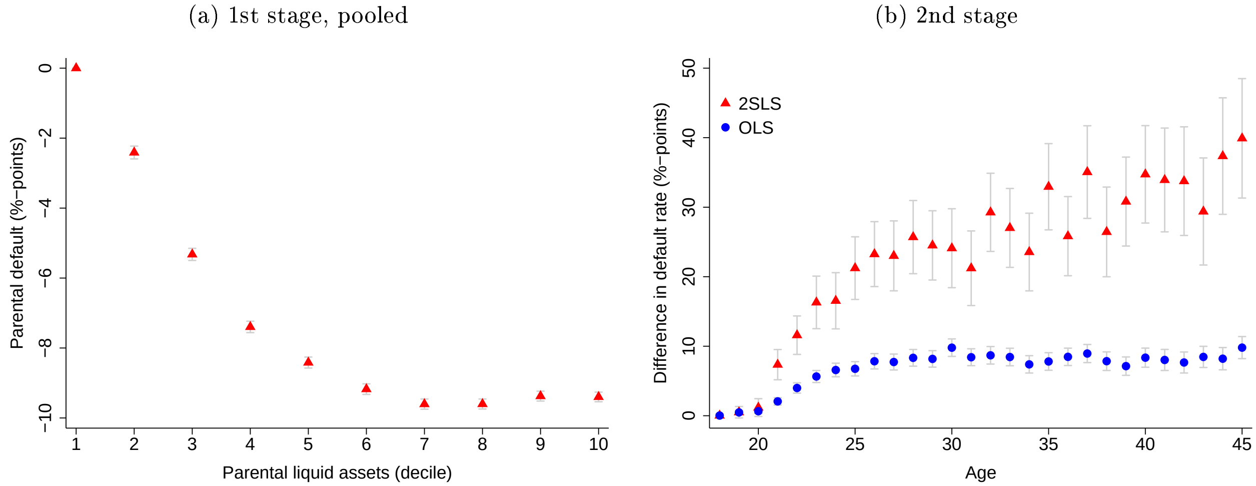
$$\hat{\alpha}_1^{\text{IV}} = \frac{\text{cov}(Z^P_{t-k}, D^C_t)}{\text{cov}(Z^P_{t-k}, D^P_t)} = \alpha_1, \tag{9}$$

$$\frac{\hat{\alpha}_1^{\text{OLS}}}{\hat{\alpha}_1^{\text{IV}}} = \frac{\text{var}(\theta^P)}{\text{var}(\theta^P) + \text{var}(\varepsilon^P_t)}. \tag{10}$$

Eq. (8) shows that simple OLS regressions of D^C_t on D^P_t give a biased estimate of the intergenerational parameter α_1 because of the unobservable noise component in parental default ε^P_t. However, the IV estimator in eq. (9) is able to identify the intergenerational correlation in the latent risk factors. Finally, the ratio of the OLS and IV estimates in Eq. (10) measures the relative importance of variation in the latent risk factor θ^P across parents in explaining the total variation in parental default relative to shocks ε^P_t. The validity of this variance decomposition and of the IV-estimate rests on two critical assumptions, $cov\left(\mu_{t-k}, \varepsilon^P_t\right) = cov\left(\mu_{t-k}, \varepsilon^C_t\right) = 0$. This means that factors, which temporarily affected financial assets of parents during 1987-1996, should not be correlated with transitory components influencing default of the parents and the children in 2011. The identifying assumption would, for example, be violated if parents received a shock to liquidity during 1987-1996, say a massive lottery win, implying that they or their children were effectively not at risk of defaulting in 2011. It should also be noted that although the method is able to filter away the impact of short-lived shocks occuring after 1996, it cannot distinguish between fixed differences in behavioral types and very persistent or permanent shocks occuring before 1997 and affecting default propensities in 2011.

Panel A in Figure 10 provides a graphical representation of the ability of the historical financial asset holdings (or to be precise, the within-cohort decile of the ratio of financial assets to average disposable income for the parents across the years 1987-1996) to predict parental default in 2011.

Figure 10: Default correlation when instrumenting parental default with historical financial wealth



Notes: For individuals aged 18-45 in 2011, Panel A shows the difference in the default rate in 2011 between parents in a given decile of financial wealth compared to parents in the bottom decile. Financial wealth for the parent is measured as the ratio of average financial wealth to average disposable income in 1987-1996 where financial wealth is the sum of stocks, bonds and bank deposits. Deciles are calculated within-parental cohort. For each age group of children in 2011, Panel B shows the difference in the average default rate for children where the parent was/was not observed to default in 2011 using two different specifications. In one specification the difference is the result of an OLS-regression of child default on parental default, in the other specification parental default is instrumented with deciles of parental financial wealth before regressing child default on instrumented parental default. All regressions in panel B are performed separately for each age group of the children while the first stage regression presented in Panel A is performed on children aged 18-45 pooled together. In both cases a large set of covariates are included, see notes to Figure 5. All estimates are shown with 95% CIs. In both panels standard errors are clustered at the child level. Obs: 2,376,036.
Sources: Loan register from the Danish Tax Agency (SKAT) and various registers from Statistics Denmark.

This non-parametric evidence reveals a strong negative relationship: parents with financial assets in the top five deciles are more than 10 percentage points less likely to default than parents in the bottom decile. The graph shows the result when pooling across the age groups of children, but the same conclusion applies when doing the analysis for each age group, which is used for the IV estimates in panel B.[16]

Panel B in Figure 10 shows the difference in default propensities between children with parents in default and children with parents not in default in 2011. The bottom curve repeats the OLS estimates of α_1 including the same set of controls as in Figure 5. The top curve shows the corresponding relationship estimated using the IV estimator where the historical level of financial assets of parents is used to predict their default in 2011. The IV estimate shows a much larger impact of parental default than the OLS estimate. This is consistent with the theoretical conjecture that OLS gives a downward biased estimate of the intergenerational correlation in financial behavior, while the IV

[16]The relationship in panel A is shown for the pooled sample to avoid cluttering. The relationship is also strongly significant when considering each child age group separately (F-tests close to 100 or above for all age groups).

estimate is able to remove the role of current shocks and therefore provide a better estimate.

By comparing the OLS and IV estimates reported in Figure 10, we see that $\hat{\alpha}_1^{\text{OLS}}/\hat{\alpha}_1^{\text{IV}} \approx 1/2$. This suggests that the fixed latent risk factor, θ^P, is responsible for approximately 50 percent of the parental defaults observed in 2011. In mid-life the IV-estimate of α_1 is around 0.3 suggesting that about 30 percent of the fixed latent risk factor of the parents is transferred to the next generation conditional on control variables. Therefore, the intergenerational dependency goes beyond intergenerational correlation in ability—captured by income, education and other controls—and is therefore likely to reflect significant inheritability in behavior.

Appendix F shows that the results are robust to using different time periods for the measurement of the historical financial asset holdings of parents.

Correlation between elicited preference parameters and financial trouble

The analysis presented so far relies on observed choices and default realizations. In this section, we focus on direct measures of behavioral parameters. For a subsample consisting of 1,748 individuals, we issued a telephone survey in which we asked respondents to self-assess their behavioral type along three dimensions: risk willingness, patience and impulsivity. Risk willingness and patience are traditional neoclassical parameters, while the question about impulsivity may capture that some people get into financial trouble because of self-control problems.

The survey took place in January 2014 and asked the following questions:

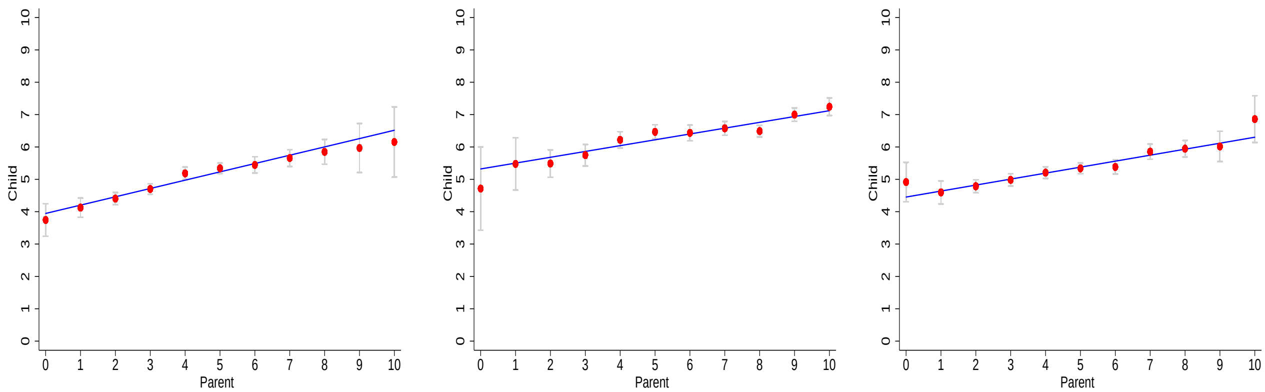
- How do you view yourself: Are you in general ready to take a risk or do you try to avoid risk taking?
- How do you view yourself: Are you in general impatient or do you always exhibit high patience?
- How do you view yourself: Are you in general impulsive or are you not impulsive at all?

In all cases, respondents have to provide an answer on a scale from 1 to 10. This simple survey methodology to elicit behavioral parameters has been used in other studies and validated in large-scale experiments (Dohmen et al. 2011, Vischer et al. 2013). Following the self-assessment, respondents are asked to assess their parents along the same dimensions.

The subjective data from the questionnaire are merged on to the administrative data at the individual level enabling us to correlate the self-assessed behavioral characteristics with the third-party reported data about default on loans. Figure 11 shows three graphs where we plot each of the

Figure 11: Child behavioral characteristic on parental behavioral characteristic

(a) Risk Willingness (b) Patience (c) Impulsivity



Notes: Panel A shows the average value of self-reported child risk willingness with 95% CIs for each possible level of self-reported parental risk willingness. The line in Panel A is the result of a linear regression of child risk willingness on parental risk willingness. Panel B and Panel C show the same relationship for the two other behavioral parameters, patience and impulsivity. Information about behavioral type is obtained from a survey issued in 2014, where the respondents were asked to place themselves and both of their parents on a scale from 1 to 10 for each behavioral characteristic. In all panels standard errors are clustered at the child level.
Obs=2,798 unique child-parent links based on answers from 1,748 children.
Sources: Survey data collected in 2014 and population register from Statistics Denmark.

behavioral characteristics of the child against the corresponding measure of the parents.

The graphs reveal significant positive intergenerational correlation across all three behavioral parameters. In our setup, where we ask children to assess the behavioral characteristics of both themselves and their parents, the relationships in Figure 11 may be spurious. However, the relationships are consistent with the results reported by Dohmen et al. (2012), who show that preference measures reported in the German SOEP are correlated across generations in a setup where children and parents are asked separately about their own preference parameters, and results in Brenøe and Epper (2018), who show that preferences elicited four decades apart exhibit a strong intergenerational correlation in the Danish Longitudinal Study of Youth, thereby eliminating concerns regarding reverse causality.

More importantly, we investigate whether the reported behavioral characteristics are correlated with the observed default on loans, which is third-party reported and hence collected independently of the behavioral measures. Table 2 reports results from a linear probability model where we regress the 2011 default indicator for the parents against the behavioral characteristics of the parents and the 2011 default indicator for the children against the behavioral characteristics of the children.

Columns 1-3 report the bivariate correlations between the default indicator for the parent and

Table 2: Default dummy on behavioral characteristics

	Parents				**Children**			
Risk Willingness	0.825***			0.530**	0.595***			0.487**
	(4.37)			(2.76)	(3.31)			(2.77)
Patience		-0.304		-0.009		0.00836		0.012
		(-1.84)		(-0.07)		(0.07)		(0.11)
Impulsivity			0.559**	0.165			0.537**	0.189
			(2.92)	(0.85)			(3.21)	(1.29)
Constant	-0.567	4.641***	0.232	-17.81*	-1.688*	1.204	-1.567*	89.28***
	(-0.84)	(3.89)	(0.29)	(-2.52)	(-2.29)	(1.46)	(-2.14)	(19.46)
Controls				X				X
Obs:	2,798	2,798	2,798	2,798	1,748	1,748	1,748	1,748

Notes: Shows results from a LPM where we regress a default dummy on covariates. t-statistics based on robust standard errors in parentheses. In col. 1-3 standard errors are clustered at the child level. *(p<0.05), **(p<0.01), ***(p<0.001). The control variables in col. 4 and 8 are within cohort deciles of gross income (d), gender (d), college education (d), employment status (d), industry (d), residential region (d), cohort (dummy per 5-year interval) and bank (d), where "d" denotes dummy variables.
Sources: Survey data collected in 2014, loan register from the Danish Tax Agency (SKAT) and various registers from Statistics Denmark.

each of the behavioral indicators of the parent. The reported measure of patience is insignificant but both risk willingness and impulsivity are strongly significant. For example, moving up one unit on the 1-10 scale on risk willingness increases the average propensity of default by 0.8 percentage points, which is large compared to a baseline default rate of parents of 2.7 percent in the sample. In column 4 we include the three behavioral measures simultaneously and together with the same types of covariates as in Figure 5. In this case impulsivity is no longer significant but risk willingness is still strongly significant and large; moving up one unit on the 1-10 scale on risk willingness increases the average propensity of default by 0.5 percentage points.

In columns 5-8 we perform the corresponding analysis for the children. This gives basically the same picture as for the parents with respect to the different behavioral characteristics. Risk willingness is still strongly significant and large, both in the univariate regression and in the multivariate regressions with controls.

The evidence presented here is suggestive. The telephone survey is collected after the default data and may thus, in principle, be adapted to the default realizations. The sample size is limited and the behavioral parameters are therefore not estimated precisely. However, the fact that subjectively stated data about inherent behavioral characteristics collected by telephone interview correlate with default data collected independently from the subjective data is compelling, and the results are consistent with our other findings suggesting that parents and children share behavior and attitudes when making financial decisions, hence, causing financial trouble to be correlated across generations.

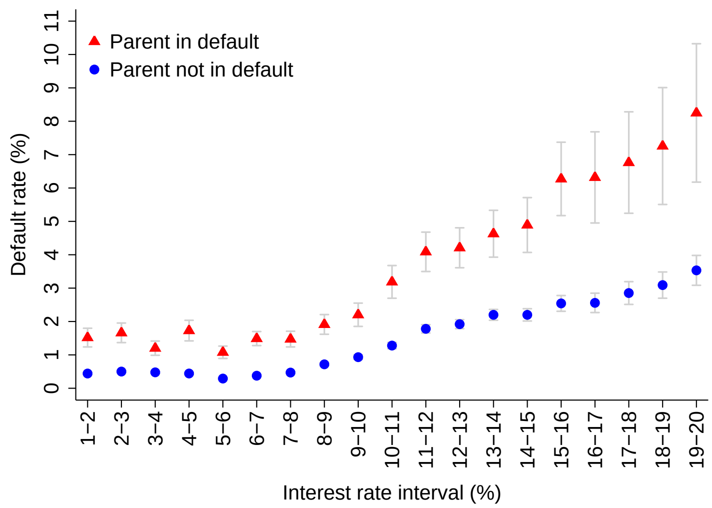
5 Is intergenerational dependency in financial trouble incorporated in interest rate setting?

In this section, we analyse whether the intergenerational dependency in default rates is incorporated in interest rate setting in order to learn whether the intergenerational correlation is indicative of the existence of an interest rate externality. The externality arises if differences across individuals in financial behavior, established in Section 4.2, (endogenously) generate differences in default probabilities, which are not priced in by banks. This amounts to a case where consumers facing similar interest rates have systematically different default rates. In this case, interest payments of individuals with a low default probability, due to low risk-taking behavior inherited from parents, partly cover losses incurred by individuals with a high default probability, caused by high risk-taking behavior adopted from their parents. In Appendix H, we show this formally in a modified version of the simple model in Section 4.1.

In the model, banks either predict behavioral types perfectly and set the interest rates on loans to match the latent risk type of each individual or they cannot identify the individual type and set the same interest rate on all loans. Thus, in the first case without an externality, we should expect to observe a positive relationship between interest rates on loans and future default rates and, conditional on the interest rate, it should be impossible to predict default with other information. In particular, information about financial trouble of the parents should be uninformative about the default rate of the children after conditioning on the interest rate on each loan. On the other hand, if financial trouble of the parents predict whether children default on loans in the future—for loans carrying the same interest rate—then this is an indication that a systematic component of the default risk has not been priced into the loan. In Figure 12, we study this relationship empirically.

To construct the graph, we have selected all loans of persons who were not in default on any loan in 2004 and divided them into two groups dependent on whether the parents are in default or not in 2004. We then follow the loans of the individuals and compute the share of the loans that become delinquent at some time during the period 2005-2011. This is displayed as a function of the interest rate on the loans in 2004, which is approximated by dividing the total interest payments

Figure 12: Future default probability by loan specific interest rate and parental default



Notes: The figure shows the average loan-level default rate in 2005-2011, along with 95% CIs, by loan specific interest rates in 2004, binned into one-percentage point interest rate intervals. Sample is restricted to loan accounts of individuals who are not in default on any loan in 2004. Loan accounts are grouped by the individual-level default status of the debtor's parent in 2004. A loan is classified as becoming delinquent if the individual has defaulted on loan payments in any of the years 2005-2011. The ex ante interest rate on a specific loan in 2004 is computed as interest payments during the year divided by nominal debt at the end of the year. Interest rates are censored at the 5th and 95th percentiles and loans with nominal debt below DKK 10,000 in 2004 are excluded. Standard errors are clustered at the child level. Obs: 3,408,588.
Sources: Loan register from the Danish Tax Agency (SKAT) and population register from Statistics Denmark.

during the year with the loan balance at the end of the year. We divide all the loans into one percentage point interest rate intervals and compute for each group of loans, and conditional on parental default in 2004, the average future default rate on the loans. For the case of parents not in default, Figure 12 shows that the future average default rate increases gradually from 0.5 percent to 3.5 percent when going from loans with an interest rate of 2 percent to an interest of 20 percent, consistent with banks being able to predict delinquency when setting interest rates. We also obtain a clear increasing relationship between the interest rate and the future default rate for the loans of individuals where parents are in default. However, this relationship lies considerably higher in the diagram. For example, for loans with an interest rate of 5 percent the probability of default within the next seven years is 0.5 percent if the parents are not in default in 2004, but 1.75 percent if parents are in default. Banks are thus unable to fully account for the intergenerational relationship in default propensities when setting the interest rates, and with a difference in the range of 0.7-4.7 percentage points across the interest rates levels, the effect not accounted for is quite large. As argued above, this indicates that the market for personal loans suffers from a significant interest rate externality because banks are not able to price into the loans a systematic component of the default risk.[17]

6 Concluding remarks

This paper documents a strong intergenerational persistency in default propensities. The intergenerational correlation appears soon after children move into adulthood, and it exists after controlling for different measures of ability.

We show theoretically that the correlation across generations can be explained by contemporaneous shocks to children and parents, by risk sharing between children and parents in response to shocks and by persistent differences in financial behavior transmitted from generation to generation. We do not find support for the common shock and the risk sharing hypotheses in our data. However, the channel operating through financial behavior appears very important. According to one of the analyses, differences in risk-taking behavior across people within a cohort explain around 50 percent of the variation in defaults, while the other half of the variation is explained by random shocks. 30 percent of the differences in risk-taking behavior is transmitted from one generation to the next.[18]

Finally, we find that financial institutions are unable to fully price in the systematic risk of default related to family background. This finding points to the existence of an interest rate externality in the market for personal loans.

Our analysis is limited in a couple of respects. For example, we are unable to completely rule out that parents have experienced very persistent shocks that have propagated to the children before we begin to observe them. In any case, this does not change the conclusion that financial trouble is an extremely persistent state.

The fact that our analysis is based on Danish data raises the question of external validity,

[17]For a subsample of the loans, we have information on the actual interest rate charged on the loan. In Appendix I, we demonstrate that the computed interest is close to the actual interest rate for this subsample. We also reconstruct Figure 12 for this subsample of loans and construct another diagram where we use the actual interest rate on the X-axis instead of the computed interest rate. These graphs are similar and mirror Figure 12 suggesting that measurement error in the computation of the interest rate is of minor importance for the relationships in Figure 12.

[18]In general, we cannot rule out the co-existence of the reverse channel where behavior is transferred from child to parent. We do however, provide several pieces of evidence that the parent-to-child channel does exist. The perhaps most direct example is reported in Appendix Figure 15. Here, children aged 13-18 years old in 2004 (the first year in our data period) are tracked over the sample period 2004-2011, and the sample is split according to whether the parents are in default or not in 2004. It is not possible to establish a loan before age 18, so we know that children turning 18 are not in default in the beginning of the observation period. The figure shows that the share of children defaulting increases from zero to 18 percent for children with parents in default in 2004, while it increases to only 3 percent for the group of children whose parents are not in default in 2004. Thus, parental default is a strong predictor of future default for children moving into adulthood.

i.e. whether our results apply to other developed economies. For example, we find that risk sharing is not important for explaining the intergenerational correlation in loan default. This could be related to the fact that there is a high degree of social insurance embodied in the Danish tax-benefit system, free education as well as generous government student grants and guaranteed student loans for young people. In other countries where such institutions do not exist, risk sharing may play a bigger role. This would, however, imply an even bigger intergenerational correlation (holding everything else equal) than we have found in this study. This has also been documented for other economic outcomes in the Nordic countries compared to other countries (see Björklund and Jäntti 2011, Chetty et al. 2014).

Differences in risk-taking behavior would in a basic neoclassical setting be due to preference heterogeneity, but in reality it might also reflect differences in financial literacy, in degree of self-control problems or in other behavioral biases (Laibson 1997, Lusardi and Mitchell 2014, Chetty 2015). Unfortunately, our data does not enable us to distinguish between these characteristics of the individuals.

In spite of these caveats, we believe our findings have implications for modeling default on personal loans and for thinking about policy. Our results suggest it is important to incorporate fixed heterogeneity in household behavior in micro- and macroeconomic theories of financial problems. The finding of an externality in credit markets for personal loans would normally call for a policy response. Our results suggest that interest payments of individuals with a low default probability, due to low risk-taking behavior inherited from parents, partly cover losses incurred by individuals with a high default probability, caused by high risk-taking behavior adopted from their parents. A policy response could, in principle, be to include information about parental credit history in credit registers and allow banks to exploit this type of information. However, this indirectly implies that children pay for their parents mistakes, which presumably is deemed unfair by most policy makers.[19] Without this option, debt relief policies would potentially worsen the problem and, in isolation, our results therefore point to less debtor-friendly bankruptcy laws. However, moving in this direction would have to be balanced against social insurance benefits from a more debtor-friendly system. Our analysis does not allow us to estimate this trade-off. This would require a structural approach, for example along the lines of Livshits et al. (2007), extended with heterogeneity in preferences. Finally,

[19] This point is reminiscent of the critique of tagging in optimal taxation, which implies that you should tax tall people more than short people (Mankiw and Weinzierl 2010).

note that if risk taking, and therefore default propensity, is high for some people because they are financially illiterate or have self-control problems then policy responses might be to provide financial training, prevent high-interest loans or set limits on loan balances. Thus, a deeper understanding of the underlying reasons for differences in risk-taking behavior is of first-order importance for optimal design of bankruptcy policy.

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Appendices (FOR ONLINE PUBLICATION)

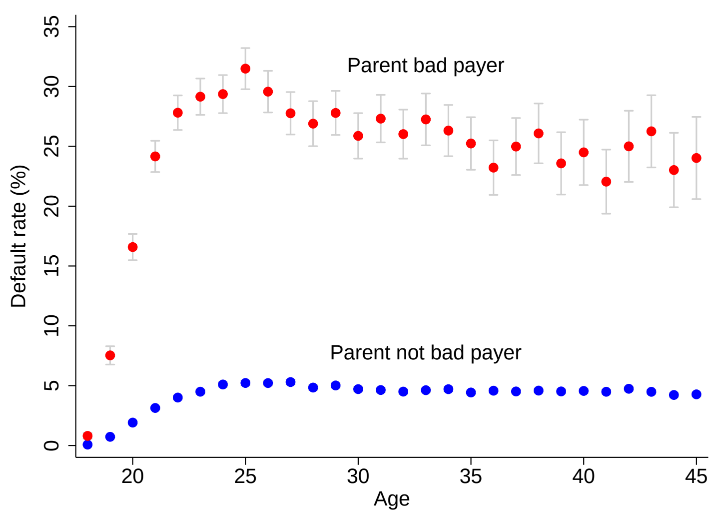
A Summary statistics

Table 3 on the next page shows summary statistics for all variables in 2011 conditional on whether the main individual is in default.

B Intergenerational correlation in financial trouble using the bad payer register

In this appendix, we repeat the analysis in Figure 1, but use the bad payer files of the credit bureaus. The measure of financial trouble is different and from another data source as described in sub-section 2.1. Figure 13 shows the result from this exercise. The graph is very similar to Figure 1. In fact, the conclusion that the intergenerational correlation appears already at a very young age is only reinforced.

Figure 13: Default propensity by age and by parental default: bad payer files



Notes: The figure shows the mean default rate surrounded by 95% CIs for each age group in 2009. Each age group is categorized into two groups according to parental default in 2009. An individual is defined as being in default if the individual is registered as "a bad payer". Standard errors are clustered at the child level.
Sources: Experian and Debitor Registeret (the two credit bureau companies that specialize in running files on bad payers in Denmark) and population register from Statistics Denmark.

Table 3: Summary statistics for defaulters and non-defaulters in 2011

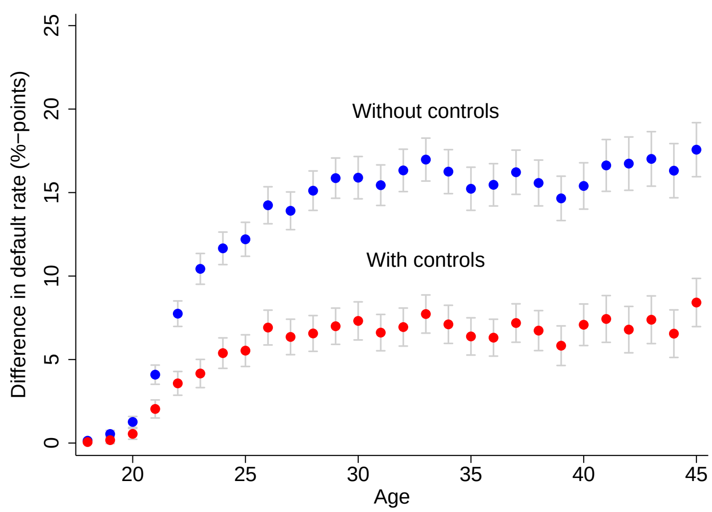
	Defaulters			Non-defaulters		
	Mean	Median	SD	Mean	Median	SD
Main persons						
Default on bank/credit card debt (d)	0.99	1.00	0.08	0.00	0.00	0.00
Bank/credit card debt	188,662	122,157	207,777			
Delinquent bank/credit card debt	90,672	46,702	133,962			
Default on mortgage (d)	0.01	0.00	0.12	0.00	0.00	0.00
Bank/credit card debt	189,707	122,625	209,153	112,353	21,239	189,927
Mortgage debt	51,950	0	233,856	327,576	0	519,059
No. of bank/credit card loans	5.83	5.00	3.72	2.66	2.00	2.53
No. of mortgages	0.12	0.00	0.47	0.54	0.00	0.84
Financial assets	11,330	6,398	42,511	67,737	19,476	141,744
Homeowner (d)	0.07	0.00	0.26	0.38	0.00	0.49
Housing assets	54,585	0	240,577	380,970	0	605,663
Affected by unemployment (d)	0.06	0.00	0.25	0.04	0.00	0.20
Age	35.11	36.00	6.91	31.41	32.00	8.38
Female (d)	0.42	0.00	0.49	0.51	1.00	0.50
Gross income	214,231	194,083	117,665	288,310	274,777	196,865
College degree (d)	0.04	0.00	0.21	0.25	0.00	0.43
Married or cohabiting (d)	0.42	0.00	0.49	0.55	1.00	0.50
No. of children	1.40	1.00	1.35	0.92	0.00	1.12
Number of observations		176,242			3,344,986	
Parents						
Default on bank/credit card debt (d)	0.23	0.00	0.42	0.06	0.00	0.23
Bank/credit card debt	218,549	150,544	219,462	259,401	176,123	263,278
Delinquent bank/credit card debt	115,998	68,262	147,835	136,818	72,843	191,015
Default on mortgage (d)	0.00	0.00	0.04	0.00	0.00	0.02
Bank/credit card debt	130,806	56,143	192,439	125,681	19,798	213,387
Mortgage debt	195,535	0	398,525	359,255	0	543,051
No. of bank/credit card loans	3.68	3.00	3.78	2.46	2.00	2.73
No. of mortgages	0.44	0.00	0.80	0.76	0.00	1.01
Financial assets	77,041	14,931	197,962	189,125	51,085	352,921
Homeowner (d)	0.33	0.00	0.47	0.58	1.00	0.49
Housing assets	328,736	0	616,597	723,184	500,000	905,332
Affected by unemployment (d)	0.03	0.00	0.17	0.03	0.00	0.16
Age	60.22	61.00	8.20	58.96	59.00	8.80
Female (d)	0.57	1.00	0.50	0.55	1.00	0.50
Gross income	247,289	205,874	131,418	334,925	304,006	189,716
College degree (d)	0.08	0.00	0.28	0.22	0.00	0.42
Married or cohabiting (d)	0.61	1.00	0.49	0.77	1.00	0.42
No. of children	2.84	3.00	1.34	2.51	2.00	1.05
Number of observations		118,040			2,415,935	

Notes: All amounts in 2011-DKK. A dummy variable is denoted by (d).
Sources: Loan register from the Danish Tax Agency (SKAT) and various registers from Statistics Denmark.

C Different timing of default across children and parents: sensitivity analysis

This appendix provides additional analyses looking at the timing of default of children and parents. (i) Figure 14 is the same graph as Figure 5, but with parental default measured in 2004 instead of 2011. This has almost no impact on the graph. (ii) In Table 4 below, we analyse the correlation between child default and parental default in the pooled sample 2004-2011 for individuals age 35 or older in 2011 (we restrict the sample to this age group to avoid mixing the effects with the sharp increase in default for the young individuals). The first column in the table shows that children on average have a 16 percentage point higher default propensity if their parents are in default. In the second column, we include individual fixed effects, in which case the intergenerational correlation almost vanishes. This shows that changes in the default outcomes of children and parents are not synchronous.

Figure 14: Same graph as Figure 5, but with parental default measured in 2004



Notes: The graph is identical to Figure 5, but with parental default measured in 2004 instead of 2011.
Sources: Loan register from the Danish Tax Agency (SKAT) and population register from Statistics Denmark.

(iii) Next, we study whether parental default predicts future default of children. In Figure 15, we follow children who are 13-18 years old in 2004 (the first year in our data period) over the sample period 2004-2011 conditional on whether the parents are in default or not in 2004. It is not possible to establish a loan before age 18, so we know that children turning 18 are not in default in the beginning of the observation period. The figure shows that the share of children defaulting increases

Table 4: Intergenerational effect in pooled sample w. individual fixed effects

	OLS	FE
Parental default dummy	16.10 pct.point	0.43 pct.point
	(96.06)	(9.62)
Number of observations	8,444,058	8,444,058
Number of individuals		969,511

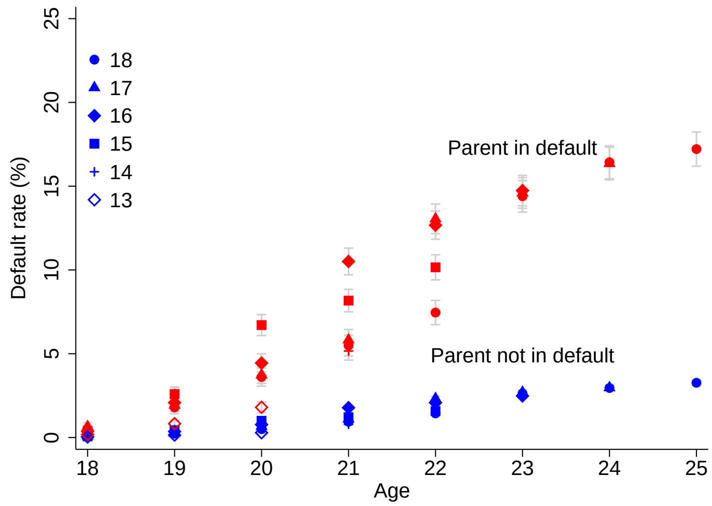
Notes: We consider the subsample of individuals who are 35 or older in 2011. The regressions include time dummies.

from zero to 18 percent for children with parents in default in 2004, while it increases to only 3 percent for the group of children whose parents are not in default in 2004. Thus, parental default is a strong predictor of future default for children moving into adulthood.

(*iv*) In Figure 16, we examine the relationship between parents transitioning in/out of default and the default rate of children. The dark blue graph shows the child default rate over time for parents not in default in each of the years 2004-2011. The dark red curve shows the child default rate over time for parents in default in each of the years 2004-2011. The light blue curve displays the child default rate over time for parents not in default 2004-2006, but going into default in 2007 and staying in default the remaining period. The light red curve displays the child default rate over time for parents in default 2004-2006, but going out of default in 2007 and staying out of default the remaining period. The main take away from this exercise is the persistent differences over time in the child default rate depending on parental default patterns. The highest default rates are observed for children with parents consistently in default, while the lowest default rates are observed for children with parents never in default, and with the middle default groups of children being those where parents are in default some of the time.[20]

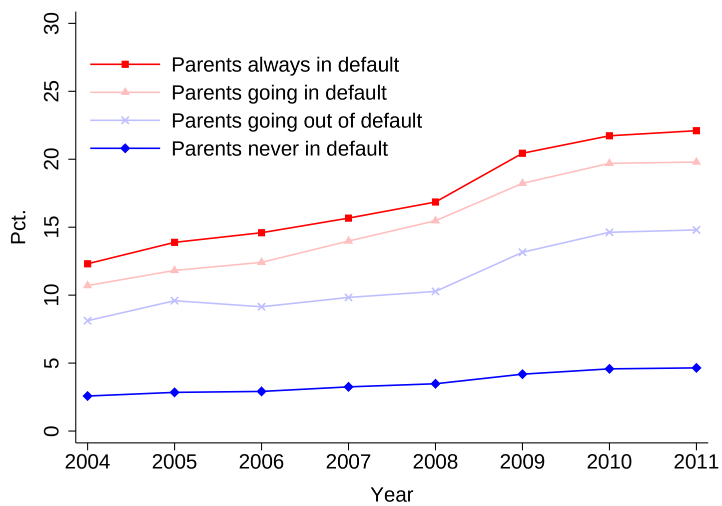
[20] All curves increase after the financial crisis in line with the overall development in default rates shown in the paper. Note, however, that the overall pattern of the children is not related to the timing of default of the parents. For example, for the children with parents in default until 2006 and then going out of default in 2007 and staying out of default, we observe the same development over time for the children with parents continuously in default. The only difference is a more or less fixed difference over time.

Figure 15: Future default of children entering adulthood, by parental default in 2004



Notes: Default of children over time conditional on parents being in default or not in 2004 for children who are 13-18 years old in 2004.
Sources: Loan register from the Danish Tax Agency (SKAT) and population register from Statistics Denmark.

Figure 16: Relationship between parents going in/out of default and the default rate of children



Notes: The dark red curve shows the child default rate over time for parents in default in each of the years 2004-2011. The light blue curve displays the child default rate over time for parents not in default 2004-2006, but going into default in 2007 and staying in default the remaining period. The light red curve displays the child default rate over time for parents in default 2004-2006, but going out of default in 2007 and staying out of default the remaining period.
Sources: Loan register from the Danish Tax Agency (SKAT) and population register from Statistics Denmark.

D Unemployment event study: sensitivity analysis

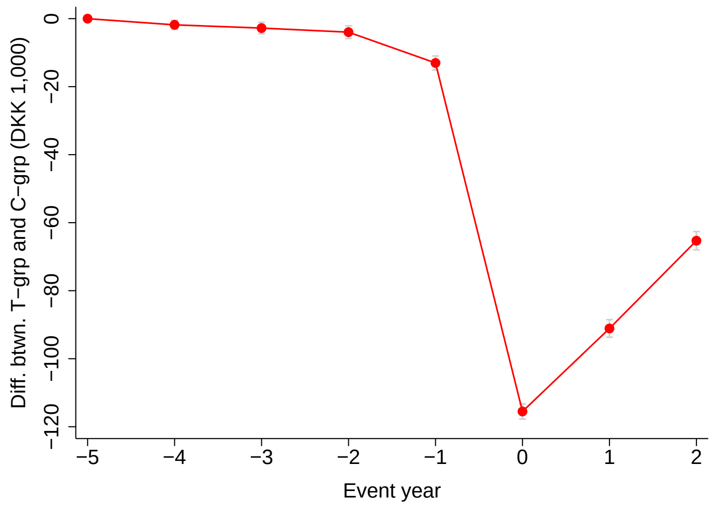
This appendix provides additional results from the unemployment event study on the role of common shocks and resource pooling studied in sub-section 4.2.1. We start in Figure 17 by deriving the effect of unemployment shocks on gross earnings using the same method as in Figure 7, which studies the impact on disposable income. Figure 17 shows that gross earnings decrease by around DKK 100,000, as stated in the main text, which is 2.5 times the effect on disposable income of around 40,000 in Figure 7.

In Figure 8, showing the effect of unemployment shocks on the default rate, we can only study default up to three years before the unemployment event because the data starts in 2004 and we study unemployment shocks in 2007-2009. In Figure 18, we show the result in isolation for those individuals who become unemployed in 2009. This enables us to study the pre-trend up to five years before the event. Figure 18 shows that the curves for both children and parents are flat prior to the unemployment shock, in accordance with similar trends for treatment and control groups. As in Figure 8, the default rate increases for the child and is unchanged for the parents after the unemployment shock to the child.

Figure 19 is similar to Figure 7, but here we look at more severe unemployment shocks by only letting individuals belong to the treatment group if they have experienced more than 6 months of unemployment in the event year. The figure shows that the drop in disposable income of the children becomes larger and that disposable income of parents is completely unchanged. Thus, the evidence does not provide support for the common shocks hypothesis.

Figures 20–24 provide a number of sensitivity analyses related to the resource pooling hypothesis: (i) In Figure 20, we re-examine the consequences of unemployment on financial wealth for more severe unemployment shocks. The graphs are very similar to Figure 9. (ii) In Figure 21, we investigate whether the results change if we use a two month income threshold for the definition of low financial wealth. The graphs are, in this case, also very similar to the ones in Figure 9 (the same conclusion applies if we use a three month income threshold instead). (iii) In Figure 22, we restrict the sample to parents not in default at any time and who should therefore be more able to help their children financially. Again, the graph is very similar to Figure 9. (iv) In Figure 23, we investigate the sensitivity of the results to using pooled resources of the parents instead of looking separately at each child-parent pair. Again, the graphs are very similar to Figure 9. (v) In Figure 24, we investigate

Figure 17: Effect of child unemployment shock on gross earnings

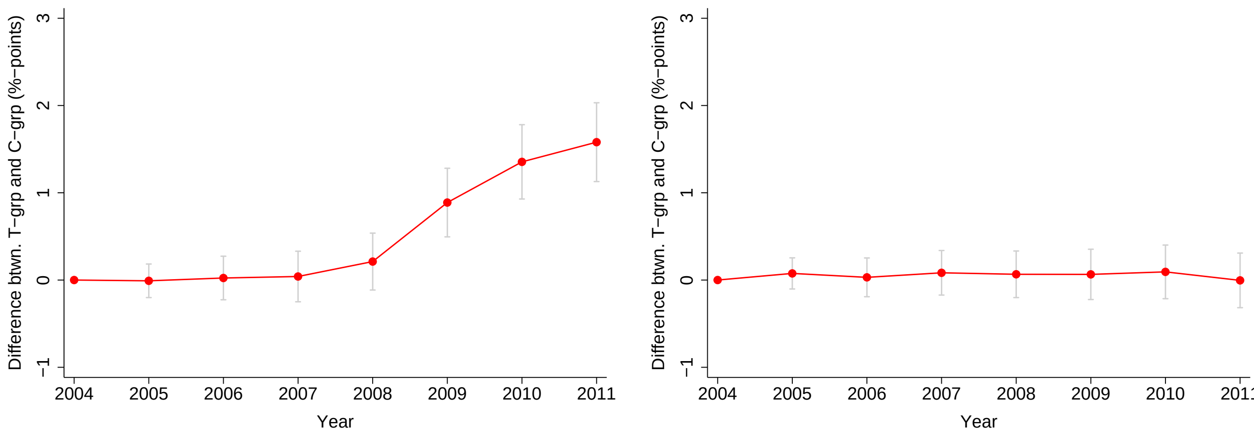


Notes: The figure shows the impact of an unemployment shock at t=0 on gross earnings. The graph is related to Figure 7, studying the impact on disposable income of unemployment, and uses the same method but with gross earnings as outcome instead of disposable income. Standard errors are clustered at the child level.
Sources: Population and income register from Statistics Denmark.

whether child financial wealth drops in proportion to the sum of child-parent financial wealth. If the consequence of the shock is shared equally by children and parents, in proportion to their initial levels of financial wealth, then the child share of overall financial wealth would not change following the shock. This is in contrast to the evidence in Figure 24 showing that the child share of overall financial wealth drops significantly. (*vi*) In Figures 25 and 26, we consider unemployment shocks to parents. Figure 25 shows that parental income drops sharply when parents become unemployed, but we observe no effect on the income of the children, and therefore there is no indication of common shocks. Figure 26 shows that the share of parents with low liquidity increases following unemployment of parents, while the share of children with low liquidity is unaffected, and therefore there is no indication of resource pooling. To conclude, none of these cases provide evidence in favor of strong common shock or resource pooling effects.

Figure 18: Effect of child unemployment shock in 2009 on default propensities

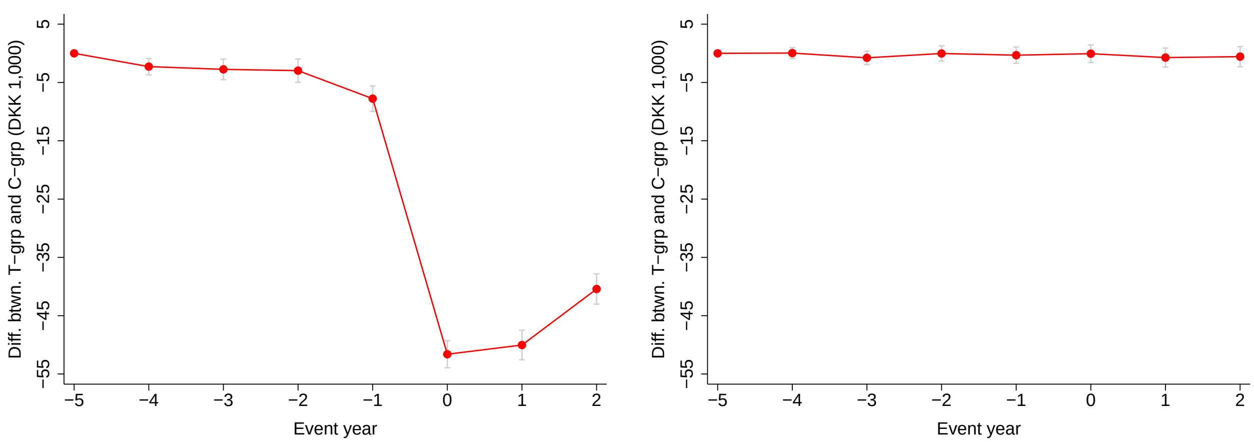
(a) Child (b) Parent



Notes: The figure resembles Figure 8, but is created for a subsample where the T-group is confined to individuals who become unemployed in 2009, while the control group are individuals who do not become unemployed in 2009. In both panels standard errors are clustered at the child level.
Sources: Loan register from the Danish Tax Agency (SKAT) and population register from Statistics Denmark.

Figure 19: Effect of severe unemployment shock ($>$ 6 months) on disposable income

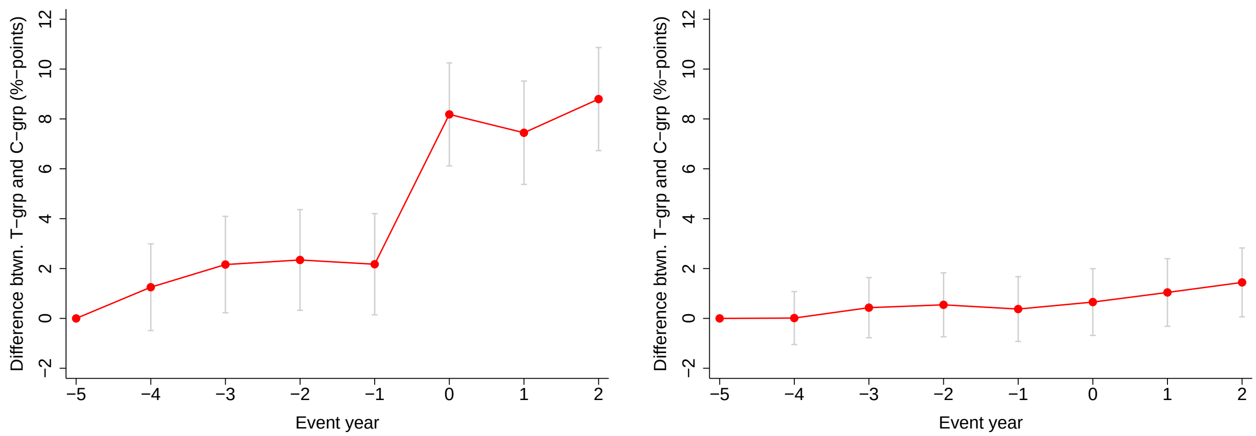
(a) Child (b) Parent



Notes: The figure is similar to Figure 7, but here we look at more severe unemployment shocks by only letting individuals belong to the treatment group if they have experienced more than 6 months of unemployment in the event year. In both panels standard errors are clustered at the child level.
Sources: Loan register from the Danish Tax Agency (SKAT) and population and income register from Statistics Denmark.

Figure 20: Effect of severe unemployment shock (> 6 months) on propensity to hold low financial wealth

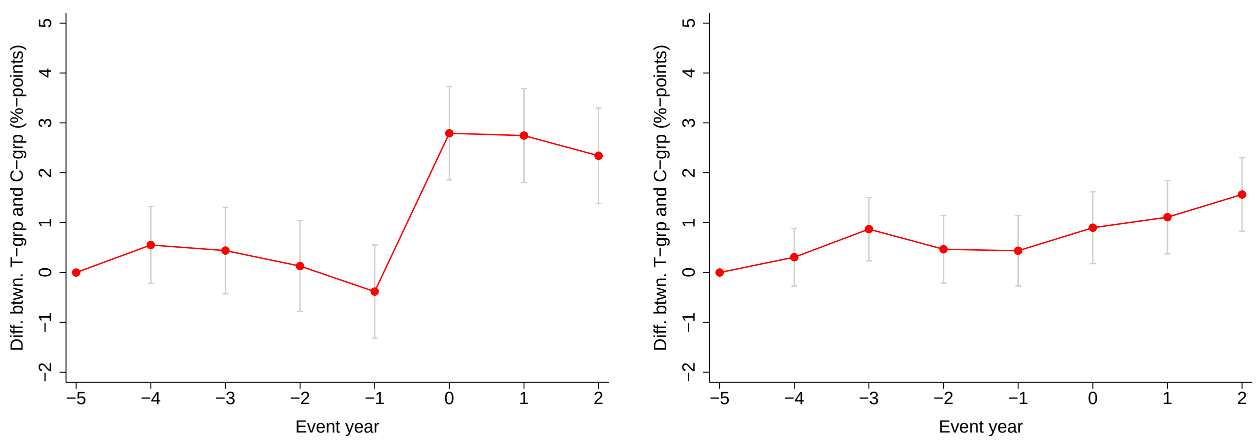
(a) Child (b) Parent household



Notes: The figure is similar to Figure 9, but here we look at more severe unemployment shocks by only letting individuals belong to the treatment group if they have experienced more than 6 months of unemployment in the event year. In both panels standard errors are clustered at the child level.
Sources: Population and income register from Statistics Denmark.

Figure 21: Effect of child unemployment shock on propensity to hold low financial wealth: less than two months of disposable income in financial assets

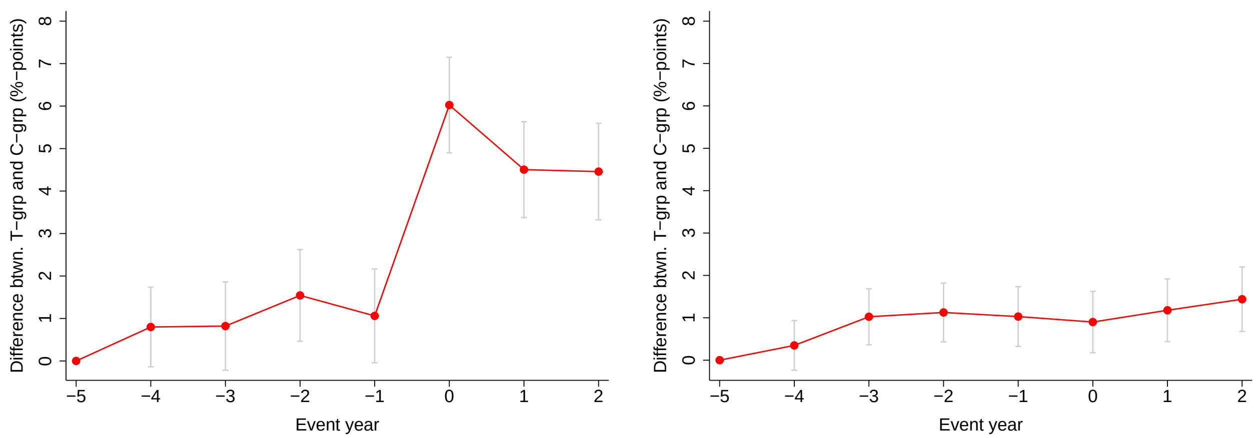
(a) Child (b) Parent



Notes: The figure is similar to Figure 9, but here we use a two month income threshold for the definition of low financial wealth. In both panels standard errors are clustered at the child level.
Sources: Population and income register from Statistics Denmark.

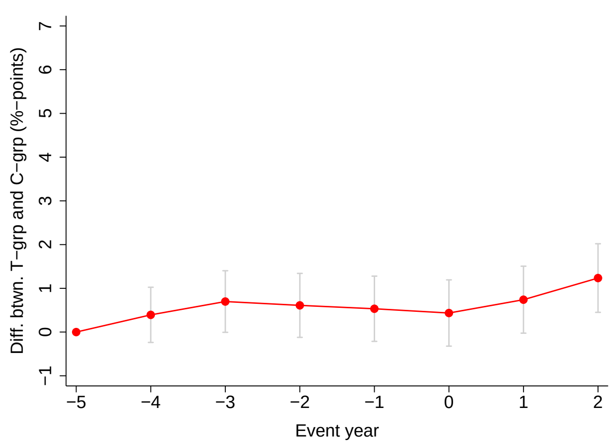
Figure 22: Effect of child unemployment shock on propensity to hold low financial wealth: parents never in default

(a) Child (b) Parent



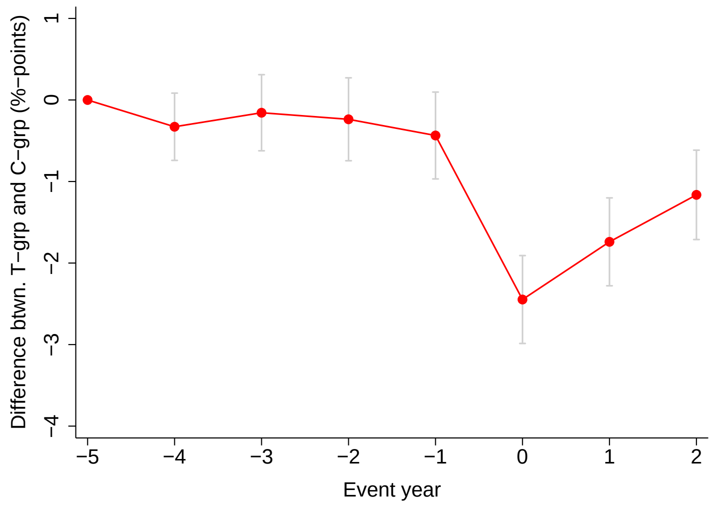
Notes: The figure is similar to Figure 9, but here we restrict the sample to child-parent pairs where parents are not in default at any time. In both panels standard errors are clustered at the child level.
Sources: Population and income register from Statistics Denmark.

Figure 23: Effect of child unemployment on parental propensity to hold low financial wealth: Pooled financial wealth of parents



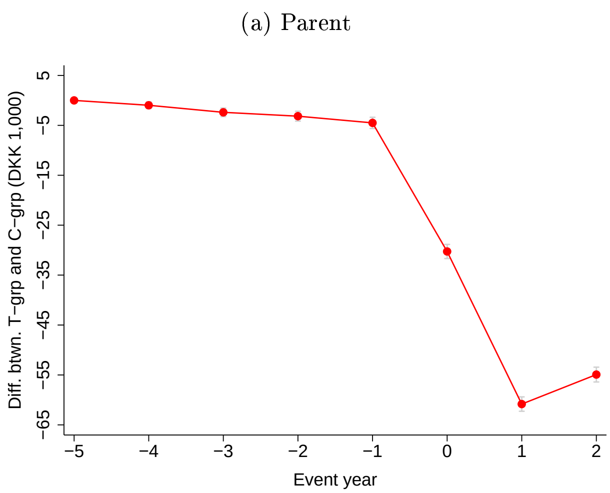
Notes: The figure is similar to Panel B in Figure 9, but here we consider the pooled resources of the parents instead of each parent separately.
Sources: Population and income register from Statistics Denmark.

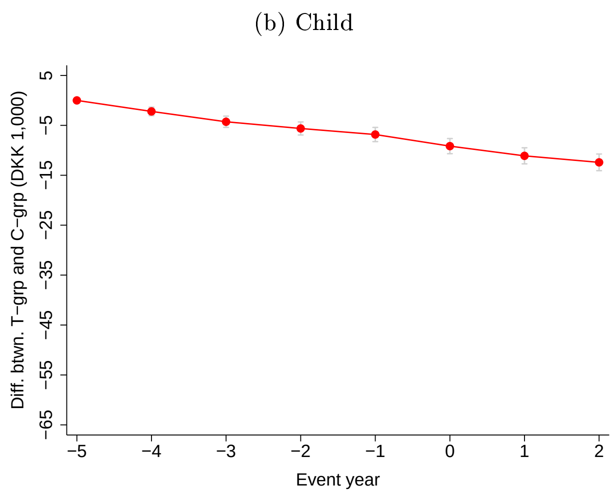
Figure 24: Effect of unemployment on child's share of total child-parents financial wealth



Notes: This figure shows the impact of a child unemployment shock at t=0 on child financial wealth as a share of total child-parent financial wealth. In both panels standard errors are clustered at the child level.
Sources: Population and income register from Statistics Denmark.

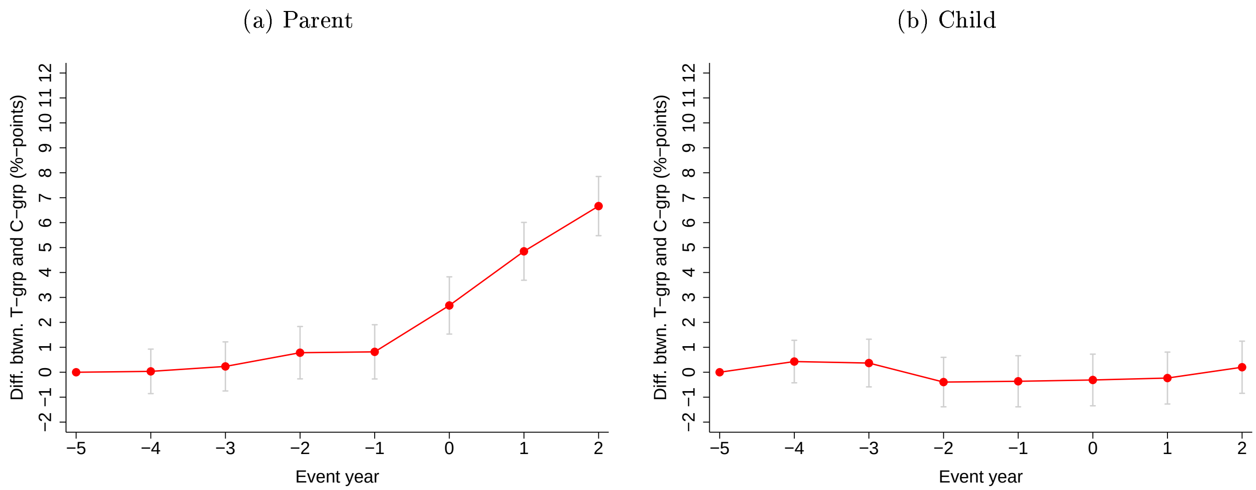
Figure 25: Effect of parental unemployment shock on disposable income





Notes: The figure is similar to Figure 7, but where we look at unemployment of parents. In both panels standard errors are clustered at the parental level.
Sources: Population and income register from Statistics Denmark.

Figure 26: Effect of parental unemployment shock on propensity to hold low financial wealth



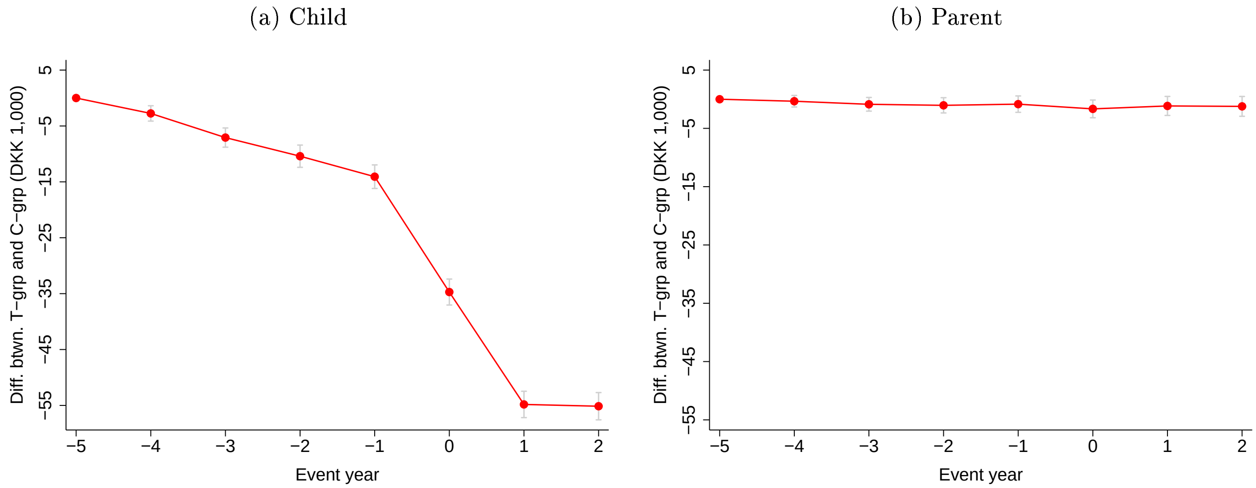
Notes: The figure is similar to Figure 9, but where we look at unemployment of parents. In both panels standard errors are clustered at the parental level.
Sources: Population and income register from Statistics Denmark.

E Other types of shocks

Figures 27 and 28 report the results from an event study where the child has an adverse health event. The health event is defined as as a situation where the child starts receiving sickness benefits, and have not received sickness benefits in the five preceding years. Sickness benefits are received if an individual is out of work for more than two weeks for health reasons. Figure 27 shows the effects on income of children and parents. Panel A shows that income of the child drops when the health event hits. Panel B shows no sign that parental income is affected (no common shock). Figure 28 shows the effect on the propensity to hold liquid assets worth less than one months of income. In panel A, we see a slight increase for the children in the propensity to end up with limited liquid assets around the time of the health event. Panel B reveals no corresponding increase in the parent's propensity to hold few liquid assets. Consistent with the unemployment event analysis, this suggests that the risk sharing channel is unlikely to be a major factor in explaining financial trouble.

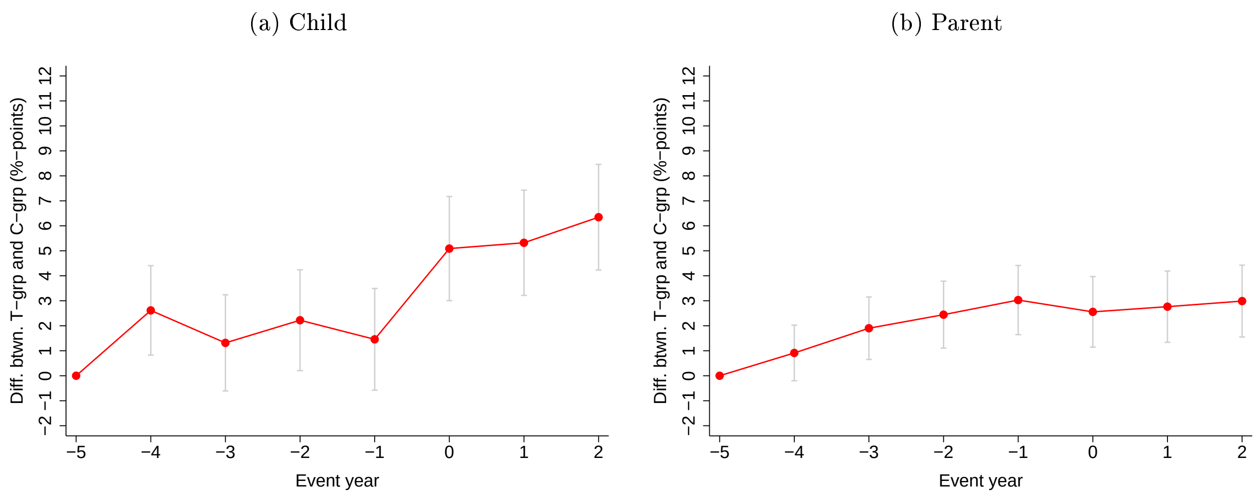
Finally, figure 29 shows that the intergenerational correlation shown in Figure 1 is virtually unaffected when individuals experiencing unemployment, unstable family patterns or adverse health events are left out of the sample.

Figure 27: Effect of health shock on disposable income



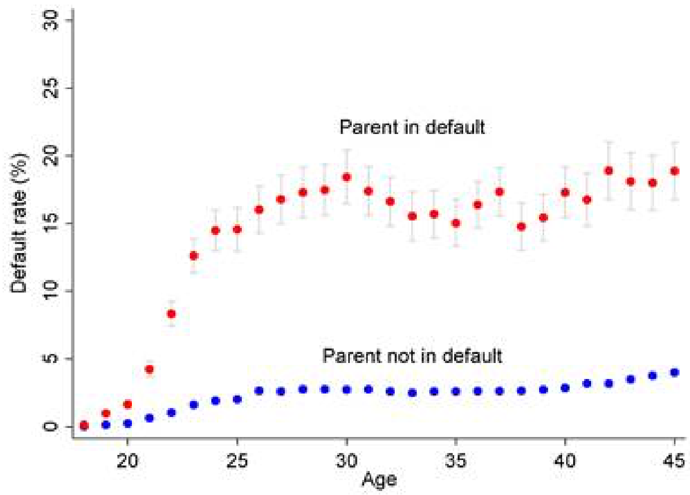
Notes: The figure is similar to Figure 7, but where we look at health events identified by receivement of sickness benefits. In both panels standard errors are clustered at the child level.
Sources: Population and income register from Statistics Denmark.

Figure 28: Effect of health shock on propensity to hold low financial wealth



Notes: The figure is similar to Figure 9, but where we look at health events identified by receivement of sickness benefits. In both panels standard errors are clustered at the child level.
Sources: Population and income register from Statistics Denmark.

Figure 29: Default propensity by age and by parental default status for individuals with a stable family pattern and experiencing no unemployment or health shocks.



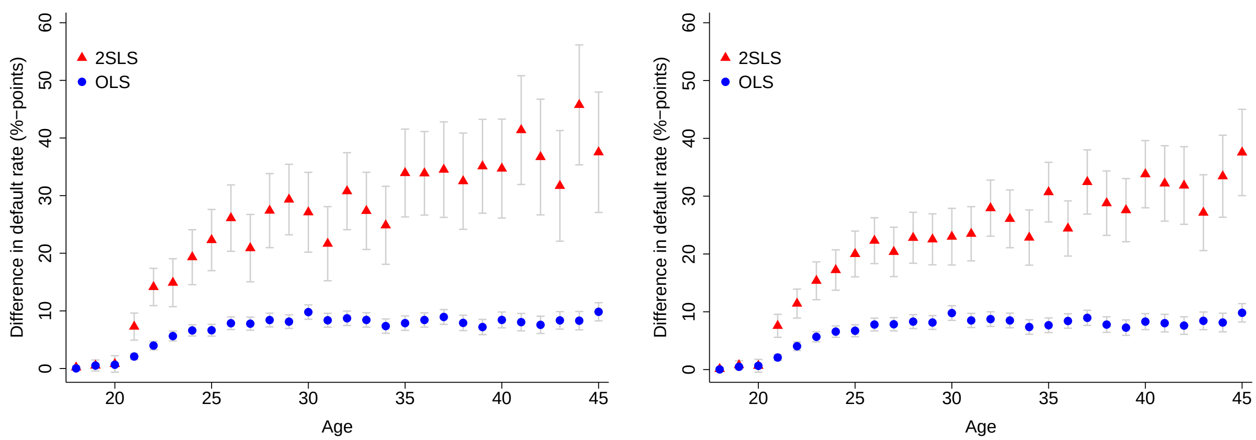
Notes: The figure shows the mean default rate surrounded by 95% CIs for each age group in 2011. Standard errors are clustered at the child level. Each age group is categorized into two groups according to parental default in 2011. An individual is defined as being in default if having at least one delinquent loan at the end of the year. Individuals with unstable family patterns or experiencing adverse health or unemplyment shocks during the period 2007-2011 have been omitted. A health shock occurs if the person is recorded as receiving sickness benefits. An unemployment shocks is defined to occur if the individual experiences unemployment amounting to more than 3 months during the year. Obs: 1.241.546.
Sources: Loan register from the Danish Tax Agency (SKAT) and population register from Statistics Denmark.

F Financial behavior: variations on the instrument

In this appendix we complement the analysis on parental financial behavior in Figure 10 with two variations on the instrument that we employ. Here we measure the historic financial assets of the parents both over a shorter period of time, 5 years, and over a longer period of time, 15 years. When measured over a longer period, the instrument will more precisely identify parents with persistently low liquid assets to income which provides a stronger signal on financial behavior. However, the instrument can only eliminate shocks occurring after the end date of the period when the instrument is measured. In Panel A in Figure 30, the instrument is measured from 1987-1991 which potentially removes shocks occurring after 1991. In Panel B, the instrument is measured over a period of 15 years from 1987 to 2001. Since this can only remove the attenuation bias from shocks occurring between 2002 and 2011, the IV-estimates in Panel B are slightly closer to the OLS-estimates than the corresponding IV-estimates in Panel A. In both cases, however, the results are in line with the results in Figure 10.

Figure 30: Intergenerational relationship with parental default 2011 instrumented with parental financial wealth measured over two different periods

(a) 5 years: 1987-1991 (b) 15 years: 1987-2001



Notes: Panel A corresponds to Panel B in Figure 10 when the IV-instrument for the parent, decile of financial assets to income, is measured over the 5 year period 1987-1991. Panel B is the same graph but with the instrument measured over the 15 year period 1987-2001. In both panels standard errors are clustered at the child level.
Sources: Loan register from the Danish Tax Agency (SKAT) and population and income register from Statistics Denmark.

G Derivation of eqs (8)-(10)

The OLS estimator of α_1 equals

$$\hat{\alpha}_1^{\text{OLS}} = \frac{\text{cov}(D_t^P, D_t^C)}{\text{var}(D_t^P)} = \frac{\text{cov}(\theta^P + \varepsilon_t^P, \alpha_0 + \alpha_1\theta^P + \omega + \varepsilon_t^C)}{\text{var}(\theta^P) + \text{var}(\varepsilon_t^P)} = \alpha_1 \frac{\text{var}(\theta^P)}{\text{var}(\theta^P) + \text{var}(\varepsilon_t^P)},$$

where we have used equations (5) and (6). The IV estimator of α_1 is

$$\hat{\alpha}_1^{\text{IV}} = \frac{\text{cov}(Z_{t-k}^P, D_t^C)}{\text{cov}(Z_{t-k}^P, D_t^P)} = \frac{\text{cov}(\gamma_0 + \gamma_1\theta^P + \mu_{t-k}, \alpha_0 + \alpha_1\theta^P + \omega + \varepsilon_t^C)}{\text{cov}(\gamma_0 + \gamma_1\theta^P + \mu_{t-k}, \theta^P + \varepsilon_t^P)} = \alpha_1 \frac{\gamma_1 \text{var}(\theta^P)}{\gamma_1 \text{var}(\theta^P)} = \alpha_1$$

where we have used eqs (5), (6) and (7). Eq. (10) follows directly from the two expressions above.

H A simple theory of interest rate determination and externality in the credit market for personal loans

We extend the basic model in Section 4.1 with supply of credit, but simplify the model by assuming the shock ε and the risk parameter θ are each uniformly distributed on the unit interval. We consider a competitive bank sector that supplies credit but cannot observe the degree of risk taking of each individual, reflected by the choice of credit in proportion to permanent income α.[21] In the event of

[21] This is a strong assumption. In practice, the creditor knows the size of the loan given to the borrower and may have an idea of the permanent income. On the other hand, it seems realistic to assume that the information is not

default of the borrower, we assume the total costs of defaults are shared by the borrower and the bank with a share γ paid by the borrower and a share $1-\gamma$ paid by the bank. Thus, the costs of defaults faced by the banks cannot be passed on to the borrower in the default state. Instead, the banks charge a risk premium r on all loans (in addition to the risk free rate normalized to zero). With a consumption level equal to α in the first period, the second period consumption level of the borrower becomes

$$c_2 = 2 - \alpha(1+r) - \gamma \int_0^{\alpha} (\alpha - \varepsilon)\, d\varepsilon, \tag{11}$$

which is identical to eq. (2) in the special case where $r = 0$ and $\gamma = 1$. By inserting the consumption level in eq. (11) into the utility function (1) and optimizing with respect to α, we obtain

$$\alpha(\theta) = \begin{cases} \frac{\theta - r}{\gamma} & \theta \geq r \\ 0 & \theta < r \end{cases}, \tag{12}$$

where $\alpha(\theta)$ is the optimal loan, and also the expected default rate, of a type θ borrower. The default rate is decreasing in the risk premium charged by the banks, and individuals with $\theta < r$ do not borrow at all.

The expected profits of banks from giving credit to individuals of type θ equals

$$\pi(\theta) = r\alpha(\theta) - (1-\gamma) \int_0^{\alpha(\theta)} (\alpha(\theta) - \varepsilon)\, d\varepsilon, \tag{13}$$

where the first term is the revenue from charging the risk premium on all loans, while the last term is default costs. After solving the integral and using (12) to substitute for $\alpha(\theta)$, we obtain

$$\pi(\theta) = \frac{1+\gamma}{2\gamma^2}(\theta - r)\left(r - \frac{1-\gamma}{1+\gamma}\theta\right). \tag{14}$$

If the banks could identify the borrower type θ then in a perfectly competitive equilibrium, where $\pi(\theta) = 0$, banks would charge the risk premium[22]

$$r(\theta) = \frac{1-\gamma}{1+\gamma}\theta, \tag{15}$$

perfect. For example, a borrower may have loans in many financial institutions making it difficult to screen the borrowers perfectly.

[22] To see that this is the equilibrium and not $r = \theta$, note that profits are positive when $\frac{1-\gamma}{1+\gamma}\theta < r < \theta$, implying that a small reduction in r when $r = \theta$ raises both profits and utility of borrowers, implying that it cannot be a competitive equilibrium.

which is increasing in the risk type θ, and thereby also increasing in the probability of default, and increasing in the share of default costs paid by the banks $1-\gamma$. In this case, all individuals borrow and high-risk borrowers do not impose an interest rate externality on low-risk borrowers. [23]

When banks cannot observe θ, they have to charge the same risk premium r on each dollar of credit. In this case, the average profit per borrower equals

$$\pi = \frac{\int_r^1 \pi(\theta)\, d\theta}{\int_r^1 d\theta} = \frac{1+\gamma}{2\gamma^2 \int_r^1 d\theta} \int_r^1 (\theta - r)\left(r - \frac{1-\gamma}{1+\gamma}\theta\right) d\theta, \tag{16}$$

where we have used eq. (14). In a competitive equilibrium, profits π equal zero if $\tilde{\pi} = 0$ where

$$\begin{aligned}
\tilde{\pi} &\equiv \int_r^1 (\theta - r)\left(r - \frac{1-\gamma}{1+\gamma}\theta\right) d\theta \\
&= \int_r^1 \left(\frac{2}{1+\gamma}\theta r - r^2 - \frac{1-\gamma}{1+\gamma}\theta^2\right) d\theta \\
&= \left[\frac{1}{1+\gamma}\theta^2 r - r^2\theta - \frac{1-\gamma}{1+\gamma}\frac{1}{3}\theta^3\right]_r^1 \\
&= \frac{1}{1+\gamma}r - r^2 - \frac{1-\gamma}{1+\gamma}\frac{1}{3} + r^3\left(\frac{\gamma}{1+\gamma} + \frac{1-\gamma}{1+\gamma}\frac{1}{3}\right) \\
&= \frac{1+2\gamma}{3}\frac{(1-r)^2}{\gamma+1}\left(r - \frac{1-\gamma}{1+2\gamma}\right),
\end{aligned}$$

which is zero if the market value of the risk premium r^* is

$$r^* = \frac{1-\gamma}{1+2\gamma}, \tag{17}$$

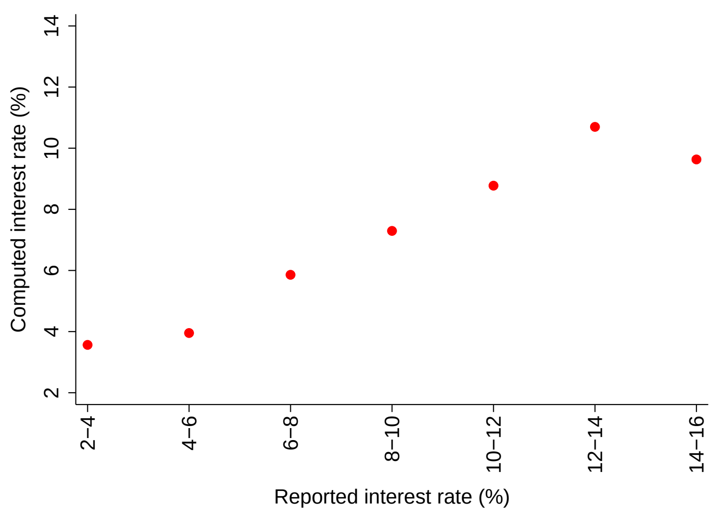
and positive (negative) if $r > r^*$ ($r < r^*$), showing that r^* is the competitive equilibrium. The risk premium r^* lies in the interval $(0,1)$. It then follows from the relationship (14) that the equilibrium is characterized by borrowers with high risk willingness θ paying a risk premium below the expected cost of default of the bank while borrowers with low values of θ pay a higher risk premium than the expected costs they inflict on the banks, and finally individuals with $\theta < r$ do not borrow at all. It also implies that policies that move some of the burden of default from borrowers to banks (reduction in γ) raise the equilibrium risk premium paid by all borrowers. This increases the interest rate externality and increases the number of low-risk individuals who choose not to borrow at all.

[23] The banks do not face an adverse selection problem in this case, but the competitive equilibrium is still characterized by moral hazard in the form of excessive borrowing compared to the social optimum because banks cannot charge borrowers the full costs of defaults, i.e. when $\gamma < 1$. From eqs (12) and (15), we have $\alpha(\theta) = 2\theta/(1+\gamma)$, which is larger than θ in (3), showing that borrowing is higher than the social optimum θ.

I Analysis of a subsample of loans where actual interest rates are known

This appendix repeats the analysis in Figure 12 for a subsample of the loans, where we have information on the actual interest rate charged on the loan. Financial institutions have to report the interest rate (rounded down to the nearest integer value) on the loan in special circumstances, but in many cases the institutions report the interest rate anyway. This evidence may be subject to selection bias (e.g. interest rates on loans with a non-fixed interest rate are not reported), but should not be subject to measurement error. Figure 31 shows that the computed interest rates match reported interest rates reasonably well for this subsample. Panel A in Figure 32 corresponds to Figure 12 for the subsample. Panel B is the same graph, but with the actual interest rate on the X-axis. The two graphs are very similar and mirror the original graph Figure 12, suggesting that measurement error in the computation of the interest rate is of minor importance for the findings.

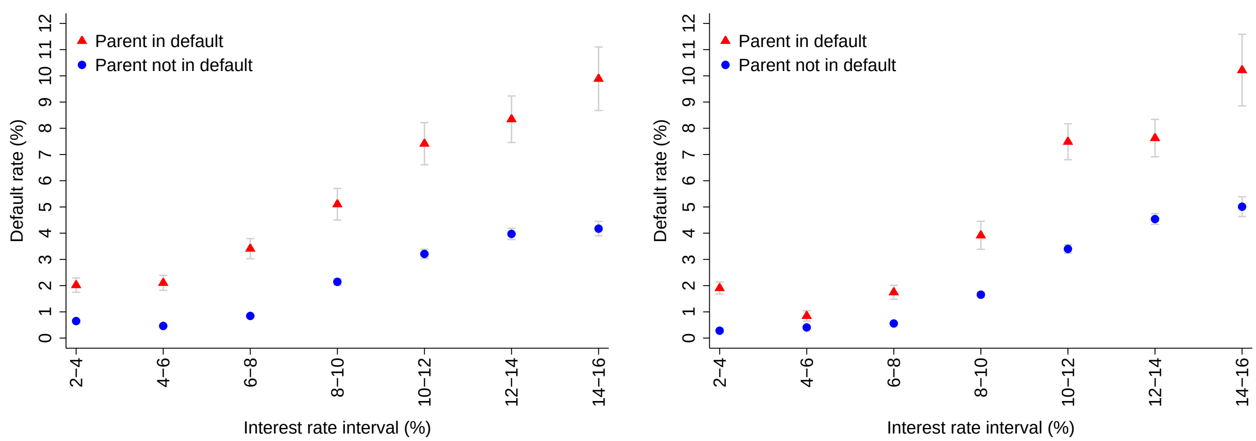
Figure 31: Computed interest rates against reported interest rates



Notes: The figure shows average computed interest rates for binned values of reported interest rates on the same loans.
Sources: Loan register from the Danish Tax Agency (SKAT) and population register from Statistics Denmark.

Figure 32: Default probability on loan-specific interest rate: Subsample with information on actual interest rates

(a) Computed interest rate (b) Reported interest rate



Notes: Panel A corresponds to Figure 12 for the subsample where actual interest rates are known. Panel B is the same graph but with the actual interest rate on the X-axis. In both panels standard errors are clustered at the child level.
Sources: Loan register from the Danish Tax Agency (SKAT) and population register from Statistics Denmark.