Trick or treat? Maternal involuntary job loss and children’s non-cognitive skills

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Abstract

Negative effects of job loss on adults such as considerable fall in income have long been examined. These effects may spread to their children via parental stress and discouragement or via income loss. This paper uses propensity score matching to examine involuntary job loss and its causal effect on children’s non-cognitive skills. Job loss is identified as end of employment first and foremost due to plant closure, yet I also consider dismissals/layoffs by employer. Using a rich and representative data set, namely the German Socio-Economic Panel Study (SOEP), I estimate associations for preschool children aged five/six and for adolescents aged seventeen. Children whose mothers experience an involuntary job loss are more likely to have behavioural problems and are less likely to believe in self-determination.

JEL classifications: J13, J63, J65
Keywords: child development, maternal job loss, non-cognitive skills, propensity score matching

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Introduction

Negative effects of job loss on adults such as a considerable fall in income, persistence of unemployment, or even divorce have been discussed widely in the literature (Charles and Stephens 2004; Ruhm 1991). If job loss has negative consequences for adults it may spread to their children. These potential effects on children have been mainly studied for their academic performance, likelihood of grade repetition, or for earnings (Huff-Stevens and Schaller 2011; Kalil and Ziol-Guest 2008; Oreopoulos et al. 2008; Rege et al. 2011). Maternal involuntary job loss opposed to job loss of the main income earner has so far been less examined or only in addition to effects of main income earners (for example Kalil and Ziol-Guest 2008; Rege et al. 2011). This paper investigates effects of maternal involuntary job loss on children’s non-cognitive skills. Although mothers are in most cases second earners in households, they are still the main caregivers of children and therefore a shock experienced by mothers may be more closely related to children’s non-cognitive skills. Job loss is identified as end of employment first and foremost due to plant closures, yet I also consider dismissals/layoffs by employer to be involuntary. Doing so, effects of maternal job loss on children’s non-cognitive outcomes are estimated while accounting for mothers’s selection to work based on the propensity score method.

One mechanism by which maternal job loss may influence outcomes of preschool children and adolescents is through stress. Children’s emotional security and their relationship with their parents may be deeply affected by maternal stress and unstable bonds may then lead to problematic behavior of children (Fomby and Cherlin 2007; Hill et al. 2001; Sweeney 2007). Maternal job loss could also result in a drop in income which may cause economic hardship which may lead to an overall deterioration of a child’s environment, and which may impede a child’s progress (Eliason 2011; Kalil and Ziol-Guest 2008).

Given that, this paper is interested in maternal job loss influencing non-cognitive outcomes of children. Research on human capital formation examines aside form academic achievement, cognitive and non-cognitive skills. Whereas cognitive skills have been widely studied non-cognitive skills have received less attention in the literature. The development of skills is a dynamic process occurring over the life course (see Cunha and Heckman 2007). Other than cognitive skills, non-cognitive skills are more malleable at later stages of a child’s life. Non-cognitive skills are traits that can be developed through interventions.
enabling a person to communicate and interact with other people. They depict people’s social ability. Motivation, socio-emotional regulation, or personality traits are examples of non-cognitive skills (see Heckman, 2008). This paper focuses on two non-cognitive outcome measures assessed at age five/six and at age seventeen. For preschool children I analyze maternal job loss on socio-emotional behaviour using the SDQ measure developed by Goodman (1997), and for adolescents on locus of control based on the concept by Rotter (1966).

In addition non-cognitive skills are important for later economic success (Blan- den et al., 2007; Carneiro et al., 2007). Therefore I am particularly interested in measuring the relationship between maternal job loss and children’s non-cognitive skills. First because a mother’s job loss is often considered with a substitution of her working time in time spent on care. However stress or frustration associated with job loss might either directly reduce the actual time spent with children or indirectly aggravate the quality of time spent with children. Second non-cognitive skills are considered valuable assets for labor market participation. Locus of control, measuring belief in fate or self-determination, is, for instance, negatively related with job search. Hence mothers’ experience may affect their own non-cognitive skills which in turn may influence the development of their children.

A large body of research on maternal employment decision and its effect on children’s abilities during early exists. Yet the direction of potential effects remains unclear. Some studies find a negative influence of mothers’ employment on children’s outcomes focusing mainly on cognitive outcomes (see for example Hill et al., 2005; James-Burdumy, 2005; Ruhm, 2004), whereas other analyses find both negative and positive results (Waldfogel et al., 2002). These results indicate that the mere association of maternal employment and child well-being might be spurious, since childcare settings, maternal preferences, and maternal background determine a mother’s decision to work. Consequently any paper interested in identifying an effect of maternal employment on child outcomes has to correct selection bias. Here job loss can only be observed for working mothers and whether a mother works or not is correlated with her own characteristics as well as with those of her child.

This paper uses the German Socio-Economic Panel Study (SOEP), which comprises information on characteristics of mothers and children, so that I am able to

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Caliendo et al. (2010) find that individuals who believe in fate are less likely to leave unemployment. And a study by Helneck and Anger (2010) shows that if people have an external locus of control, it may reduce their wages.
obtain bias-corrected estimates of involuntary job loss on children’s non-cognitive skills. Different methods can be used to correct for selection bias: either using “selection on unobservables” applying a Heckman correction model or an instrumental variable approach, or using “selection on observables” by the propensity score method. This paper utilizes propensity scores assuming that heterogeneity of mothers who experience a job loss to those who keep their job can be observed. In a seminal paper [Rosenbaum and Rubin (1983)] show that the probability of receiving treatment (here involuntary job loss) is a vector of observed characteristics, called propensity score. And matching based on this “univariate” propensity score can remove the bias. Predicting mothers’ propensity score implements a “random sample”, where mothers who work and lose a job do not differ from mothers who work and keep their job in terms of observables, e.g., education, income, marital status amongst others. Other methods to solve selectivity such as the Heckman correction model or an instrumental variable approach are not applied in this paper, since a valid instrument correlated with mothers’ job loss but not with children’s non-cognitive skills is hard to obtain.

So far propensity score matching has been mainly applied for evaluating participation in job training programs (see the work by Ashenfelter (1978), Dehejia and Wahba (2002), Heckman et al. (1997), LaLonde (1986)). Yet the empirical literature increasingly uses propensity score matching to account for various selection biases. For example, Jiang et al. (2010) estimate the effect of breast feeding on child cognitive outcomes using propensity score matching, or Eliason (2011) analysing job loss effects on income. Caponi and Plesca (2009) argue that “given identification assumptions and available data” propensity score matching opposed to “selection on unobservables” is preferable.

Related literature

A prolific body of literature documents potential effects of maternal employment on child well-being. In general, papers analyzing maternal employment and its association with early child outcomes assess timing of mother’s return to work (see for example Berger et al. (2005)). Or they focus on paternal job loss and its influence on children’s academic achievement relating child well-being to an exogenous income shock. The analysis of the present paper aims at determining potential influence of maternal involuntary job loss on children’s non-cognitive skills. Both strands of the literature - maternal employment and exogenous job loss - are related to my
analyses and are discussed to identify relevance for the present study.

Research on maternal employment affecting child outcomes is confronted with selection, since mothers who work differ in terms of their preferences and backgrounds from mothers who do not work. Apart from “complete” ordinary least squares estimations, matching is an alternative method to account for endogeneity. Propensity score matching has only recently been applied to estimate effects of maternal employment on child development (Ruhm 2008, 2009). Ruhm (2009) discusses several methods to measure causal effects of parental employment amongst others family fixed effects, instrumental variables, and propensity score matching.

A few other studies (Berger et al., 2005; Hill et al., 2005) have discussed matching methods as estimation technique to identify causal impact of maternal employment on early child outcomes. Both papers apply the propensity score method in addition to ordinary least squares with a “complete” set of covariates. Hill et al. (2005) use US data from the National Longitudinal Study of Youth (NLSY) analyzing the effect of maternal employment during the first year after birth on children’s cognitive and behavioural outcomes between ages three and eight. Based on propensity score matching they find that children’s cognitive outcomes are less developed if mother return to work full-time within a year after childbirth. Berger et al. (2005) also examine data from the NLSY focusing on health and developmental outcomes of children. The authors investigate mothers return to work using variations in women’s maternity leave taking and its effect on child outcomes, e.g., externalizing behaviour problems or the Peabody Picture Vocabulary Test. Contrary to Hill et al. (2005) the paper finds that the obtained propensity score estimates are consistent with OLS results and are “generally stronger for mothers returning full-time within 12 weeks” (Berger et al. 2005, p. F45).

Another possibility to assess parental employment effects on child outcomes uses job loss experience defined as exogenous income shocks (see Oreopoulos et al., 2008; Rege et al., 2011). The study by Rege et al. (2011) analyses the effect of parental job loss on teenager’s academic performance using Norwegian register data. As natural experiment setup they assume that plant closures in Norway between 1999 and 2005 are determined by exogenous shocks and are independent of unobservable determinants of children’s school performance. For maternal job loss the authors find that the grade point average of children aged 16 is marginally increased. A study based

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3 Rege et al. (2011) find that fathers’ exposure to plant closure imposes stress on a father. If future employment is discouraging this stress causes children to perform in school.
on Canadian data finds that fathers’ job loss from plant downsizing lowers annual earnings of their children compared to those children whose fathers were not laid off (Oreopoulos et al., 2008). Exogenous shock on the other hand can also be identified in survey data. Kalil and Ziol-Guest (2008) estimate children’s academic performance as a function of parental employment patterns using US data from the Survey of Income and Program Participation. They determine involuntary job ends due to quitting, dismissal, or illness amongst others (p. 6 Kalil and Ziol-Guest, 2008). They find no significant correlation between mothers’ employment experiences and children’s grade repetition or exclusion/suspension. Huff-Stevens and Schaller (2011) analyze job loss and children’s likelihood of grade repetition based on the same data as Kalil and Ziol-Guest (2008), yet they define involuntary job ends more narrow focusing only on dismissals or plan closure. Applying child fixed effects they show that exogenous displacements of parents are detrimental for children’s academic performance in the short-run.

Within the large body of research maternal job loss and its effect on non-cognitive outcomes has to my knowledge been examined less or not at all. I argue that correcting for selection by using propensity score techniques distinguishes my research from other papers examining these influences. This paper analyzes maternal experiences on non-cognitive skills, as these skills are known to be important for later success and might be affected by experiences of labour market “failure”. Papers associated with involuntary shocks and child outcomes (see Huff-Stevens and Schaller, 2011; Kalil and Ziol-Guest, 2008; Rege et al., 2011) do not explicitly analyze maternal job loss nor do they account for mothers’ decision to work. Thus I infer effects of maternal involuntary job loss whilst correcting potential selection bias.

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4Based on Norwegian employer-employee data, Bratberg et al. (2008) find no effect of fathers’ displacement on earnings of children more than ten years after the employment shock.

5Parental job loss significantly increases children’s likelihood of grade repetition.
Data

Using data from the German Socio-Economic Panel Study (SOEP), my analysis is based on a representative and rich data set. The SOEP started in 1984 and is an annual household panel\(^6\) that comprises a series of mother-child questionnaires as well as a youth specific questionnaire. The child-specific modules of the SOEP contain detailed information on children, i.e. non-cognitive skills, birth weight, child care usage, school attendance, and grade repetition amongst others. In addition the SOEP has rich information on individual characteristics of children’s mothers as well as on family characteristics. The SOEP accumulates information on current household compositions as well as on past formations. Based on this vast data set mothers’ probability of involuntary job loss is estimated.

The sample of children aged five/six in the SOEP consists of 661 observations. I restrict my preschool sample to children whose mothers answered the mother-child questionnaire, whose mothers were 20 years and older at childbirth, who have non-missing information on the measured non-cognitive skills, and whose mothers participated in the survey prior 2003, and therefore have non-missing information prior childbirth. These restrictions reduce the sample to 555 observations. For the implementation of propensity score matching, I determine a point in time at which mother’s are observed to lose their jobs. Since mothers are entitled to three years of parental leave in Germany, I assess mothers’ working status after a child’s third birthday. In period \( t \geq 3 \) when children are aged three and older, I observe whether mothers are working and thus may be prone to involuntary job loss. I calculate the exact distance of three years between a child’s birth and mothers reported employment status to account for parental leave regulations. A detailed discussion of variables used for modeling the selection decision is given in the next section. Thus the sample used to examine effects of maternal job loss for children aged five/six includes 315 observations of mothers who are observed to be working after age three of the child.

In the youth sample of the SOEP 3,679 observations of children aged 17 and older are pooled. The sample reduces to 1,148 observations due to the following restrictions. Children who are no longer living with their parents are dropped. Those who are born between 1984 and 1993 and thus are 17 years old at the time of the sur-

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\(^6\) A general overview of the SOEP is given by [Wagner et al. (2007)](#), whereas [Schupp et al. (2008)](#) and [Siedler et al. (2009)](#) describe the mother-child questionnaires used in this paper. [Frick and Lohmann (2010)](#) document the youth questionnaire.
vey are kept, as well as those who are still in school, have non-missing non-cognitive skill information, whose mothers were 20 years and older at childbirth, and whose mothers have reported their employment status during early childhood. Unlike in the preschool sample maternal employment patterns prior childbirth cannot be observed for all birth cohorts, since the household panel started in 1984. Thus I use another cut-off date to predict mothers’ propensity scores. In addition, for some mothers earlier working information coincides with unification and its transition year 1990/1991 and for some mothers a comprehensive measure capturing involuntary job loss is only available since 1995. Hence the period during which maternal job loss is observed ranges from age ten until age seventeen of the child \( t \geq 10 \). Thus the final sample of adolescents aged seventeen comprises 812 observations of mothers who are observed to be working after age ten of their child. Similar to the preschool sample I predict maternal likelihood of job loss using a vast set of covariates (see next section for detailed discussion).

**Involuntary job loss**

This paper focuses on involuntary job loss experienced by mothers and its influence on non-cognitive development of children. Opposed to other studies maternal experiences are inferred, because mothers are still the main caregivers of children. And although mothers are often second earners, non-cognitive skills could be affected due to job loss, as mothers are said to substitute working time for caring time. In particular non-cognitive skills may be more responsive to maternal stress and thus time spent for caring may be of meagre quality.

Involuntary job loss is first and foremost identified as job ending due to *plant closure*. This particular job loss is experienced by mothers within a survey year and is reported by stating that they “left a job after December 31st and how this job was terminated” since the last interview. Mothers can choose among eight categories for job ends, including resignation, retirement, or suspension. Another reason is *dismissal by employer or end of temporary contract*. Since plant closure occurs less frequent I define another variable, which includes both, plant closure and dismissals. By adding dismissals to mothers’ involuntary job loss, I follow (p. 291 Huff-Stevens and Schaller, 2011) who define job ends based on the following answer categories: “the person was fired or discharged, if the employer was sold or went bankrupt, or if the job loss was due to slack work or business conditions”.

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Thus, analogue to previous works\textsuperscript{7}, this paper considers these two categories to be involuntary job ends in which plant closure is a “truly” exogenous shock. In both samples job loss is analysed using a comprehensive measure including the relevant incidences of job loss. In the pooled sample of children aged five/six, 6 percent of working mothers lose their job in the observation period, whereas in the pooled sample of children aged seventeen 12 percent of mothers experience an involuntary job loss (see Table 1).

[Table 1 about here]

For a first descriptive summary of the potential association between non-cognitive skills and involuntary job loss, Table 2 depicts characteristics comparing job losers to non job losers. Preschool children whose mothers lose their job have a higher total difficulties score and are rather boys than girls. Whereas in the adolescents sample more girls experience an involuntary job loss of their mothers. The internal locus of control of children experiencing maternal job ends is below mean zero of this standardized score, indicating that they are more likely to not believing in self-determination. Thus a first glance at the descriptives suggests that there might be negative effects on children’s non-cognitive skills when a job loss occurs.

[Table 2 about here]

Non-cognitive skills

In the SOEP non-cognitive skills are measured at different childhood stages using divergent scales. Non-cognitive outcomes often include behavioral, social and emotional skills. This is true for the outcomes used in this paper as well. The socio-emotional behavior measures non-cognitive skills of preschool children, whereas locus of control is used for adolescents’ non-cognitive outcome.

\textbf{Socio-emotional behavior (SEB)} describes a child’s behavior in terms of feelings or relationships with family and peers. Goodman (1997) developed the Strength and Difficulties Questionnaire (SDQ), which assesses children’s socio-emotional regulation. The SOEP uses a modified version of the SDQ to collect information on preschool children aged five/six. The construction of children’s overall SEB accounts for the fact that mothers answer the questionnaire related to children’s emotional

\textsuperscript{7}See among others the studies by Coelli (2011); Huff-Stevens and Schaller (2011); Kalil and Ziol-Guest (2008)
symptoms, peer problems or conduct problems and others\textsuperscript{8}. The reliability of this total difficulties score has also been shown by other studies (see for example \cite{Ermisch2008}). In the preschool sample children’s SEB ranges from 0 to 30 with a higher score representing a negative outcome of the child, e.g., having peer problems. In addition children can be grouped in different behavioral categories: normal, borderline, and abnormal\textsuperscript{9}.

**Locus of control** is the non-cognitive outcome in the adolescence sample based on the concept developed by \cite{Rotter1966}. The locus of control is part of the youth questionnaire since 2001 and adolescents report on a scale from 1 (completely disagree) to 7 (completely agree) regarding “what happens in life depends on me” or “what you achieve is a matter of luck”. Factor analysis is used to extract two factors determining whether adolescents believe that their life depends on their own action (internal locus of control) or whether they believe that life is determined by others (external locus of control). In this paper the analyses focus on internal locus of control, which may be affected by maternal involuntary job loss, as children who experience instability in their family environment through exogenous shocks might more likely stop believing that life depends on their own actions or success. This in turn could lead them to belief in fate, hence these adolescents may become externalizers. Some studies show that having an external locus of control is associated with negative labor market outcomes \cite{Caliendo et al. 2010, Heineck and Anger 2010}\textsuperscript{10}.

**Empirical strategy**

Estimating the effect of maternal involuntary job loss on children’s non-cognitive skills is summarized by the following general equation:

\[ S_{ij} = \beta_{ij}JOBL_{ij} + \gamma_{ij}X_{ij} + \nu_{ij} \]  \hspace{1cm} (1)

where \( S_{ij} \) comprises non-cognitive outcome of child \( i \) at age \( j \), \( JOBL_{ij} \) is a variable capturing involuntary job loss, \( X_{ij} \) represents our measured covariates and \( \nu_{ij} \) is an error term. The coefficient of interest is \( \beta_{ij} \) and it will render causal estimates if the

\textsuperscript{8}Information on the reliability and construction of the SEB, as well as the categorization into different behavioral groups can be found at \url{http://www.sdqinfo.org}

\textsuperscript{9}Within the preschool sample 73 percent are in the group “normal”, 12 percent in “abnormal” and the remaining 15 percent in “borderline”. The sample mean of the total difficulties score is 10.26.

\textsuperscript{10}\cite{Caliendo et al. 2010} show that individuals who have an external locus of control are less likely to leave unemployment.
following assumptions are satisfied. The estimates of $\beta_{ij}$ are “true” if maternal job loss is uncorrelated with children’s non-cognitive outcomes, i.e. $E(\upsilon \mid JOBL_{ij}) = 0$. Estimating Equation 1 yields unbiased estimates in case there is no correlation of involuntary job loss with the error term $\upsilon_{ij}$ and thus job loss is exogenous with respect to non-cognitive skills. But since maternal involuntary job loss is only observed for working mothers, selectivity may bias the OLS estimates of $\beta_{ij}$.

Any estimation of maternal job loss has to consider mothers’ selection into employment, or that endogeneity due to omitted variables may bias the results. Mothers’ decision to work is correlated with $JOBL_{ij}$, since only a working mother can experience this exogenous shock. But mother’s participation on the labour market is not independent of her child’s development, of her educational background, of her preferences, or of her own skills. If the “selection to work” is ignored in the analyses, selectivity captured in the error term $\upsilon_{ij}$, will therefore bias any OLS estimates of $\beta_{ij}$. Different techniques are possible to correct for selection bias, where this paper utilizes “selection on observables” by applying propensity score matching.

In the preschool sample maternal probability of job loss is predicted after a child’s third birthday, since parental leave regulation in Germany entitles mothers to a leave of absence for three years. The data used in this paper comprise pooled cross-sections and only those children whose mothers have the “most complete” information are utilized in the analyses. The same is true for the adolescence sample, but mothers’ probability of job loss is predicted after age ten of the child.

For predicting maternal propensity scores the following “observables” are used in the preschool sample: employment status two years prior childbirth, employment status in the birth-year of the child, partner present at childbirth, years of education around birth, number of children <16 present in the household in the birth-year of observed child, logarithmic household income around birth, whether the mother is satisfied with “only being a mother”, living in East Germany around childbirth, living in an urban area around childbirth, care settings at childbirth, and age of mother at child birth using age group dummies.

In the adolescents sample I utilize: employment status as well as working hours at age six of child, employment status at age three of child, partner present at age six, years of education around age six, number of children <16 present in the household at age six of the observed child as well as logarithmic household income at that time, living in East Germany in 1989, overall life satisfaction when the child is six years old, tenure and size of firm, living in an urban area, and age of mother at childbirth using age group dummies.
Propensity score matching

Propensity score matching (Rosenbaum and Rubin, 1983, 1984) is a well-established method to correct selection bias. It is a quasi-experimental approach, comparing outcomes of those who are “treated” to those who are “untreated”, simulating a random sample design. Similar to ordinary least squares, propensity score matching relies on the assumption that selection is based on observable characteristics. By using a rich set of variables predicting mothers’ likelihood of job loss after age three or age ten respectively, this paper assumes that all relevant information related to maternal selection to work can be observed (for an overview of application of matching see Caliendo and Kopeinig, 2008). The assumption that selection only exists on observables is known as conditional independence assumption (CIA). Under the conditional independence assumption, the outcome variable - children’s non-cognitive skills - and maternal job loss, i. e. exposure to treatment, are independent given characteristics X. Given the data quality at hand, I argue that the analyses in this paper are able to meet this requirement and that relevant observable characteristics that affect mothers’ decision to work are accounted for.

\[ Y_1, Y_0 \perp T | X \] (2)

Following Rosenbaum and Rubin (1983) mothers’ probability of job loss is predicted based on the relevant X, obtaining a comprehensive measure of all covariates for each person, i.e. the propensity score: \( P(D = 1|X) = P(X) \), where X represents the set of observed maternal characteristics as well as relevant child and household characteristics, \( D=1 \) is the “treatment condition”, here maternal involuntary job loss after age three or age ten of the child respectively, and \( P(X) \) is the estimated propensity score.

A second requirement is the common support condition, which implements that a match between mothers of the treatment group and those of the control group is obtained. By applying this restriction those children whose mothers do not overlap with regards to the relevant observables are discarded from the analysis.

\[ 0 < P(X) < 1, \forall X \] (3)
Equation three simply states that the sample does not consist of only working mothers who kept their job \( P(X)=0 \) or of only working mothers who experienced an involuntary job loss \( P(X)=1 \).

After predicting mothers’ propensity score, the observations are matched based on the obtained \( P(X) \). All observations who do not comply with the overlap condition are discarded from the sample. Hence the sample used for examining maternal involuntary job loss consists only of those working mothers who have a balanced match based on the same characteristics set \( X \). Two different matching techniques are applied: nearest neighbor and kernel matching\(^{11}\). Each method assigns different weights to the mothers that are “eligible matches” for working mothers who experienced an involuntary job loss, i.e. for the “treated”. By using different weights the matching algorithms face trade-offs in terms of bias and variance (see Caliendo and Kopeinig, 2008).

Nearest neighbor matching simply chooses the mother of the comparison group who is identical to the mother of the “treatment” group based on their estimated propensity score. Different techniques can be applied: “with replacement”, “without replacement”, or using more than one neighbor called “oversampling” (Caliendo and Kopeinig, 2008). For instance the option “with replacement” uses those mothers of the comparison group with a high propensity score more than once matching them with “treated” mothers who have a high propensity score as well\(^{12}\). The nearest neighbor technique renders bad matches if the “best” fit in the control group is far away. Other than nearest neighbor and caliper matching, the kernel matching method uses weighted averages of those mothers in the control group depending on the choice of the kernel function (see for an in depth discussion Imbens, 2000; Stuart, 2010). Whilst the usage of nearly “all” untreated mothers is an advantage, it may cause bad matches. Thus applying the common support restriction is important when utilizing kernel matching\(^{13}\). Here mothers who lose their job are matched with “similar” mothers who keep their job based on kernel matching using a gaussian/normal kernel distribution in order to obtain as many mothers as possible for the control group. In the Appendix a summary table depicts the balance of the used \( Xs \) between treatment and control group before and after matching (see Table A1).

\(^{11}\)Matching is implemented in Stata11 using the program psmatch2 provided by Leuven and Sianesi (2003).

\(^{12}\)By applying “oversampling” in the nearest neighbor algorithm one decides how many “untreated” mothers are used for each “treated”.

\(^{13}\)Kernel matching requires a decision on the kernel function and on a bandwith parameter. The former requirement is less important compared to the latter (Caliendo and Kopeinig, 2008).
Propensity score matching allows then to identify different effects, i.e. the average treatment effect of the treated (ATT), which renders estimates of the difference in child outcomes for those whose mothers’ worked and experienced an involuntary job loss

$$ATT = E(Y_1|D = 1, P(X)) - E(Y_0|D = 1, P(X))$$ (4)

This average treatment effect of the treated can also be identified by propensity score weighted regressions (see Hirano and Imbens, 2001). Since this paper is interested in an effect on non-cognitive skills of children, weighting the regressions using the predicted propensity of job loss, will render moderate estimates. To estimate the ATT the regression of non-cognitive skills on involuntary job loss is weighted by assigning $w = 1$ to mothers who lost their job ($D = 1$), and $w = 1/(1 - P(X))$ to mothers of the control group ($D = 0$). By weighting the estimated OLS regression, omitted variable bias can be corrected14.

Results

Each table presents the results in three steps: the OLS estimates without correcting for maternal employment decisions, i.e. regressing maternal job loss on children’s non-cognitive skills, second the results obtained from propensity score matching (kernel matching) are shown. In column 2 the estimates of the ATT after matching are reported and in column 3 those of the ATT using propensity score weighted regression. In a second specification column 2 presents the estimates obtained from OLS “complete” comparing them to the propensity score estimates. Only the main coefficient is depicted: involuntary job loss.

Involuntary job loss and non-cognitive skills of preschoolers

In Table 3 the results of involuntary job loss affecting children’s socio-emotional behavior are presented. In column 1 the OLS estimates without correcting omitted variable bias are shown. Maternal involuntary job loss is not significantly correlated with children’s socio-emotional behavior. Using the matched sample renders the estimates displayed in column 2. Including the same controls as in the OLS esti-

14 Berger et al. (2005) argue that using the propensity score as weight depends, similar to the conditional independence assumption (CIA), on the specification of observables used to correct selection bias.
mation the negative effect on children’s total difficulties score becomes marginally significant. This effect is negative since an increase in the score implies an increase in a child’s likelihood of having behavioral problems. Accounting for selection bias substantially increases the effect size compared to the OLS estimate in column 1. Correcting the selection bias due to mothers decision to work, doubles the potential effect of maternal involuntary job loss: A child’s total difficulties score increases by 3.5 score points, which “lifts” the mean child closer to “abnormal” behavior. The sample size decreases slightly from column 1 to 2 because not all mothers are matched and the sample is restricted to “common support mothers”. The findings in column 3 compared to column 2 suggest that estimating the average treatment effect of the treated using propensity score weighted regression is slightly more moderate in terms of effect size. But the overall negative effect of involuntary job loss on non-cognitive skills remains significant.

[Table 3 about here]

Another possibility to account for omitted variable bias would be to include employment behavior of mothers prior childbirth as well as other relevant pre-treatment characteristics that correlate job loss with the error term. Therefore I also estimate an OLS model with “complete information” to compare a more detailed OLS examination to the propensity score method. Maternal involuntary job loss increases children’s socio-emotional behavior by 3 score points using OLS with prior information (see column 2 of Table 4). An effect which is similar to the effect obtained by propensity score weighted regressions. Findings shown in Table 4 suggest that selection biases the “normal” OLS analysis of involuntary job loss and its influence on children’s non-cognitive skills. But it also shows that the obtained OLS results are close to those from the propensity score method. Yet, propensity score matching assumes that selection is only based on observables and does not account for unobserved heterogeneity. Children’s non-cognitive skill formation may be correlated with maternal non-cognitive skills which in turn may be affected by experiencing an involuntary job loss. Thus in a second step I control for potential unobserved heterogeneity between the matched mothers by including maternal personality traits in my analysis. Controlling for mothers’ personality traits further reduces the sample size and the marginal significant effect of maternal involuntary job loss on children’s socio-emotional behavior is no longer significant (see Table 5).

[Table 4 and 5 about here]
Involuntary job loss and non-cognitive skills of adolescents

Table 6 summarizes the relationship of adolescents’ internal locus of control and maternal job loss. No significant association can be found when using OLS without prior information as it is depicted in column 1. However the potential direction of the effect already indicates that maternal job loss decreases the likelihood of believing in self-determination. The results based on propensity score matching show a marginal significant average treatment effect of the treated. Meaning that adolescents whose mothers experience plant closure or dismissal by employer are less likely to believe that working hard or striving for one’s own success helps to achieve one’s goals. An involuntary job loss decreases adolescents belief in self-determination by 1/3rd of a standard deviation also controlling for covariates such as household income, household composition and maternal education. The size of the effect of job loss is substantial compared to column 1. This effect remains stable and only decreases slightly in size when using propensity score weighted regressions (see column 3). Again due to the common support requirement unmatched mothers are discarded from the analysis and thus the sample size decreases from column 1 to column 2.

In Table 7 findings comparing complete ordinary least squares to propensity weighted regressions are presented. The effect of maternal job loss on adolescents internal locus of control is similar to the effect obtained by propensity score matching, suggesting that the propensity score method corrects the selection problem. Other than in the preschool sample, when including maternal personality traits in the analysis the significance of the effect of an experienced job loss on internal locus of control increases. Moreover, the size of the effect also increases to nearly 1/2 of a standard deviation. Both, including maternal personality traits and running a “complete” ordinary least squares analysis, indicate that the findings obtained by the propensity score method are robust and suggest a causal relationship between maternal involuntary job loss and children’s non-cognitive skills.
Conclusion

This paper is interested in the potential effect of maternal involuntary job loss on children’s non-cognitive skills. Although mothers are still second earners in German households, they are on the other hand the main caregivers of children. Thus an exogenous shock might not affect the household’s financial situation in a substantial way, yet it may effect the emotional stability of mothers causing stress and discouragement at home. The weakening of maternal “mental” stability may be closely related to children’s development and in particular to the development of non-cognitive skills, such as motivation or socio-emotional regulation.

A potential problem for the analysis of maternal involuntary job loss on child outcomes is selection. Maternal employment depends on maternal preferences, maternal background, available child care or on children’s development which biases any results obtained from OLS. Meaning that mothers whose children are more independent and socio-emotional “stable” are more likely to work. Thus mothers’ decision to work is not independent of children’s skills. This paper therefore estimates the relationship between job loss and child outcomes whilst accounting for selection bias by using propensity score matching. Propensity score matching can be used to correct for selection bias. This method assumes that selection is based on observables which are used to match “similar mothers”, i.e. in terms of observed characteristics, who do not experience a job loss with those who are prone to plant closure or dismissal by employers.

When comparing OLS estimates with those obtained in the matched samples, the effects of maternal job loss on non-cognitive outcomes are similar, but they vary significantly in effect size. I find a negative association between maternal job loss and children’s non-cognitive skills. Experiencing maternal involuntary job ends during early childhood increases children’s socio-emotional problems. Children are more likely to have peer problems or emotional problems. The hypothesis that mothers substitute lost working time with more time for caring might not result in “better” quality of time due to stress or discouragement. The stress theory indicates that emotional bonds may be weakened by maternal stress exposure. Children’s total difficulties score increases by 3 score points, which lifts the mean child closer to “abnormal” behavior.

For adolescents’ outcome the same negative effect of maternal job loss can be found. Children are less likely to believe in self-determination if their mother ex-
experienced an involuntary job loss due to plant closure or dismissal. The effect of maternal job loss is substantial, since adolescents internal locus of control decreases by $1/3^{rd}$ of a standard deviation using the propensity score method and correcting the selection bias. Including maternal personality traits in the analysis to account for unobserved heterogeneity confirms this negative result. The results become even more statistically significant indicating that an involuntary job loss “causes” adolescents to believe less in self-determination, i.e. to be less motivated or striving for success.

The theory of stress is strongly linked to the non-cognitive skill formation of pre-schoolers and adolescents. However, further research is needed to disentangle the mechanisms by which maternal stress affects children’s non-cognitive skills. It could be either due to “meagre” quality of time spent with children or due to mental instability. The propensity score method suggest a potential causal relationship between the child outcomes and maternal involuntary job loss, since the estimates are consistent with the OLS results. Although the propensity score method reduce potential biases resulting from mothers’ selection to work, it does not account for unobserved heterogeneity. Yet, including maternal personality traits, potential unobserved heterogeneity biasing the results is considered, and the findings remain robust.

Given the literature on negative effects of maternal employment on child well-being, this paper argues that maternal job loss and thus additional time for caring might be beneficial for cognitive outcomes, i.e. test score ([Rege et al., 2011]), but not for non-cognitive skills. As the negative effects of maternal involuntary job loss on non-cognitive skills may impede children’s progress in school or on the labor market. Thus, further analyses regarding non-cognitive development and potential influences should be carried out.
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## Tables

Table 1: Means of maternal involuntary job loss

<table>
<thead>
<tr>
<th></th>
<th>Preschool sample</th>
<th>Adolescents sample</th>
</tr>
</thead>
<tbody>
<tr>
<td>Involuntary job loss</td>
<td>0.0644</td>
<td>0.1239</td>
</tr>
<tr>
<td></td>
<td>[0.2459]</td>
<td>[0.3297]</td>
</tr>
<tr>
<td>Plant closure</td>
<td>0.0203</td>
<td>0.0512</td>
</tr>
<tr>
<td></td>
<td>[0.1414]</td>
<td>[0.2206]</td>
</tr>
<tr>
<td>Dismissal by employer</td>
<td>0.0441</td>
<td>0.0727</td>
</tr>
<tr>
<td></td>
<td>[0.2056]</td>
<td>[0.2599]</td>
</tr>
</tbody>
</table>

*N*  
295  
742

Note: Standard deviation in parentheses. SOEP v27 (2001-2010). Author’s calculations. Samples only include working mothers.
Table 2: Means of covariates in samples

<table>
<thead>
<tr>
<th></th>
<th>All</th>
<th>Job losers</th>
<th>Non job losers</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Preschool sample</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Total difficulties score</td>
<td>10.26</td>
<td>11.89</td>
<td>10.13</td>
</tr>
<tr>
<td>Age of child in months</td>
<td>67.02</td>
<td>65.53</td>
<td>67.23</td>
</tr>
<tr>
<td>Gender (Female=1)</td>
<td>0.49</td>
<td>0.47</td>
<td>0.50</td>
</tr>
<tr>
<td>Migration background</td>
<td>0.14</td>
<td>0.26</td>
<td>0.12</td>
</tr>
<tr>
<td>Child care</td>
<td>0.77</td>
<td>0.84</td>
<td>0.76</td>
</tr>
<tr>
<td>Grandparent care</td>
<td>0.59</td>
<td>0.72</td>
<td>0.59</td>
</tr>
<tr>
<td>Relative care</td>
<td>0.07</td>
<td>0.00</td>
<td>0.07</td>
</tr>
<tr>
<td>Logarithmic household income</td>
<td>8.12</td>
<td>7.85</td>
<td>8.11</td>
</tr>
<tr>
<td>Region (East Germany)</td>
<td>0.32</td>
<td>0.42</td>
<td>0.32</td>
</tr>
<tr>
<td>Number of children &lt;16</td>
<td>1.90</td>
<td>1.79</td>
<td>1.89</td>
</tr>
<tr>
<td>Partnered</td>
<td>0.89</td>
<td>0.74</td>
<td>0.89</td>
</tr>
<tr>
<td><strong>Ref. Vocational degree</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>No degree</td>
<td>0.06</td>
<td>0.11</td>
<td>0.06</td>
</tr>
<tr>
<td>University degree</td>
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<td>0.11</td>
<td>0.28</td>
</tr>
<tr>
<td><strong>Ref. Not employed</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Full time</td>
<td>0.26</td>
<td>0.37</td>
<td>0.25</td>
</tr>
<tr>
<td>Part time</td>
<td>0.53</td>
<td>0.37</td>
<td>0.53</td>
</tr>
<tr>
<td>Minor employed</td>
<td>0.09</td>
<td>0.11</td>
<td>0.11</td>
</tr>
<tr>
<td><strong>Adolescence sample</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Internal locus of control</td>
<td>-0.002</td>
<td>-0.079</td>
<td>0.009</td>
</tr>
<tr>
<td>Gender (Female=1)</td>
<td>0.49</td>
<td>0.55</td>
<td>0.47</td>
</tr>
<tr>
<td>Migration background</td>
<td>0.19</td>
<td>0.18</td>
<td>0.17</td>
</tr>
<tr>
<td><strong>Ref. Lower school track</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Middle school track</td>
<td>0.27</td>
<td>0.31</td>
<td>0.27</td>
</tr>
<tr>
<td>Upper school track</td>
<td>0.38</td>
<td>0.31</td>
<td>0.39</td>
</tr>
<tr>
<td>Comprehensive school</td>
<td>0.06</td>
<td>0.02</td>
<td>0.07</td>
</tr>
<tr>
<td>Vocational school</td>
<td>0.21</td>
<td>0.26</td>
<td>0.20</td>
</tr>
<tr>
<td>Logarithmic household income</td>
<td>7.90</td>
<td>7.74</td>
<td>7.92</td>
</tr>
<tr>
<td>Region (East Germany)</td>
<td>0.33</td>
<td>0.40</td>
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<td>Number of children &lt;16</td>
<td>1.52</td>
<td>1.45</td>
<td>1.53</td>
</tr>
<tr>
<td>Partnered</td>
<td>0.88</td>
<td>0.86</td>
<td>0.89</td>
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<td><strong>Ref. Vocational degree</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>No degree</td>
<td>0.16</td>
<td>0.13</td>
<td>0.15</td>
</tr>
<tr>
<td>University degree</td>
<td>0.25</td>
<td>0.25</td>
<td>0.24</td>
</tr>
<tr>
<td><strong>Ref. Not employed</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Full time</td>
<td>0.38</td>
<td>0.35</td>
<td>0.38</td>
</tr>
<tr>
<td>Part time</td>
<td>0.42</td>
<td>0.39</td>
<td>0.43</td>
</tr>
<tr>
<td>Minor employed</td>
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<td>0.07</td>
<td>0.07</td>
</tr>
<tr>
<td><strong>N</strong></td>
<td>295</td>
<td>19</td>
<td>276</td>
</tr>
</tbody>
</table>

Note: SOEP v27 (2001-2010). Author’s calculations. Samples only include working mothers.
Table 3: Estimation of socio-emotional behavior and maternal involuntary job loss

<table>
<thead>
<tr>
<th></th>
<th>OLS</th>
<th>PSM overlap</th>
<th>PSM weighted</th>
</tr>
</thead>
<tbody>
<tr>
<td>Involuntary job loss</td>
<td>1.346</td>
<td>3.529*</td>
<td>3.060*</td>
</tr>
<tr>
<td></td>
<td>[1.3878]</td>
<td>[1.9652]</td>
<td>[1.6608]</td>
</tr>
<tr>
<td>N</td>
<td>276</td>
<td>207</td>
<td>211</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.095</td>
<td>0.125</td>
<td>0.128</td>
</tr>
<tr>
<td>adj. $R^2$</td>
<td>0.031</td>
<td>0.036</td>
<td>0.046</td>
</tr>
</tbody>
</table>

Standard errors in second row, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note that all models include as additional covariates age of child, gender (female=1), migration background, region (East Germany=1), logarithmic household income, partner present (yes=1), number of children <16, maternal employment status (ref. category: not employed/full time, part time, minor employed, maternal education (ref. category: vocational degree/university degree, no degree), child care setting, and time dummies. Author’s calculations, SOEP v27 (2008-2010).

Table 4: Estimation of socio-emotional behavior and maternal involuntary job loss

<table>
<thead>
<tr>
<th></th>
<th>OLS</th>
<th>OLS</th>
<th>PSM weighted</th>
</tr>
</thead>
<tbody>
<tr>
<td>Involuntary job loss</td>
<td>1.346</td>
<td>3.126*</td>
<td>3.062*</td>
</tr>
<tr>
<td></td>
<td>[1.3878]</td>
<td>[1.7039]</td>
<td>[1.6544]</td>
</tr>
<tr>
<td>$N$</td>
<td>276</td>
<td>211</td>
<td>210</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.095</td>
<td>0.212</td>
<td>0.124</td>
</tr>
<tr>
<td>adj. $R^2$</td>
<td>0.031</td>
<td>0.054</td>
<td>0.042</td>
</tr>
</tbody>
</table>

Prior treatment covariates

$✓$

Standard errors in second row, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note that all models include as additional covariates age of child, gender (female=1), migration background, region (East Germany=1), logarithmic household income, partner present (yes=1), number of children <16, maternal employment status (ref. category: not employed/full time, part time, minor employed, maternal education (ref. category: vocational degree/university degree, no degree), child care setting, and time dummies. Author’s calculations, SOEP v27 (2008-2010).
Table 5: Estimation of socio-emotional behavior and maternal involuntary job loss

<table>
<thead>
<tr>
<th></th>
<th>OLS</th>
<th>PSM overlap</th>
<th>PSM weighted</th>
</tr>
</thead>
<tbody>
<tr>
<td>Involuntary job loss</td>
<td>2.303</td>
<td>2.379</td>
<td>2.455</td>
</tr>
<tr>
<td></td>
<td>[1.4039]</td>
<td>[1.7965]</td>
<td>[1.6205]</td>
</tr>
<tr>
<td>Maternal personality traits</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
</tbody>
</table>

N | 257 | 211 | 213
R² | 0.193 | 0.207 | 0.214
adj. R² | 0.113 | 0.104 | 0.119

Standard errors in second row, * p < 0.10, ** p < 0.05, *** p < 0.01
Note that all models include as additional covariates age of child, gender(female=1), migration background, region(East Germany=1), logarithmic household income, partner present(yes=1), number of children <16, maternal employment status(ref. category: not employed/full time, part time, minor employed, maternal education(ref. category:vocational degree/university degree, no degree), child care setting, and time dummies. Author’s calculations, SOEP v27 (2008-2010).

Table 6: Estimation of internal locus of control and maternal involuntary job loss

<table>
<thead>
<tr>
<th></th>
<th>OLS</th>
<th>PSM overlap</th>
<th>PSM weighted</th>
</tr>
</thead>
<tbody>
<tr>
<td>Involuntary job loss</td>
<td>-0.150</td>
<td>-0.324*</td>
<td>-0.288*</td>
</tr>
<tr>
<td></td>
<td>[0.1067]</td>
<td>[0.1685]</td>
<td>[0.1596]</td>
</tr>
</tbody>
</table>

N | 697 | 412 | 417
R² | 0.136 | 0.162 | 0.162
adj. R² | 0.106 | 0.108 | 0.111

Standard errors in second row, * p < 0.10, ** p < 0.05, *** p < 0.01
Note that all models include as additional covariates attended school track(ref. category: lower school track/middle school track, upper school track, comprehensive school track, vocational school track), gender(female=1), migration background, region(East Germany=1), logarithmic household income, partner present(yes=1), number of children <16, maternal working hours, maternal education (ref. category: vocational degree/university degree, no degree), and time dummies. Author’s calculations, SOEP v27 (2001-2010).
Table 7: Estimation of internal locus of control and maternal involuntary job loss

<table>
<thead>
<tr>
<th></th>
<th>OLS</th>
<th>OLS</th>
<th>PSM weighted</th>
</tr>
</thead>
<tbody>
<tr>
<td>Involuntary job loss</td>
<td>-0.150</td>
<td>-0.350**</td>
<td>-0.288*</td>
</tr>
<tr>
<td></td>
<td>[0.1067]</td>
<td>[0.1627]</td>
<td>[0.1596]</td>
</tr>
</tbody>
</table>

Prior treatment covariates

|                      | ✓            |

N: 697 417 417
R²: 0.136 0.210 0.162
adj. R²: 0.106 0.119 0.111

Standard errors in second row, * p < 0.10, ** p < 0.05, *** p < 0.01
Note that all models include as additional covariates attended school track(ref. category: lower school track/middle school track, upper school track, comprehensive school track, vocational school track), gender(female=1), migration background, region(East Germany=1), logarithmic household income, partner present(yes=1), number of children <16, maternal working hours, maternal education (ref. category: vocational degree/university degree, no degree), and time dummies. Author’s calculations, SOEP v27 (2001-2010).

Table 8: Estimation of internal locus of control and maternal involuntary job loss

<table>
<thead>
<tr>
<th></th>
<th>OLS</th>
<th>PSM overlap</th>
<th>PSM weighted</th>
</tr>
</thead>
<tbody>
<tr>
<td>Involuntary job loss</td>
<td>-0.171 *</td>
<td>-0.438**</td>
<td>-0.355**</td>
</tr>
<tr>
<td></td>
<td>[0.1086]</td>
<td>[0.1746]</td>
<td>[0.1635]</td>
</tr>
</tbody>
</table>

Maternal personality traits

|                      | ✓            | ✓             | ✓             |

N: 673 400 405
R²: 0.152 0.194 0.193
adj. R²: 0.114 0.129 0.130

Standard errors in second row, * p < 0.10, ** p < 0.05, *** p < 0.01
Note that all models include as additional covariates attended school track(ref. category: lower school track/middle school track, upper school track, comprehensive school track, vocational school track), gender(female=1), migration background, region(East Germany=1), logarithmic household income, partner present(yes=1), number of children <16, maternal working hours, maternal education (ref. category: vocational degree/university degree, no degree), and time dummies. Author’s calculations, SOEP v27 (2001-2010).