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The Added Worker Effect for Married Women and Children in Brazil: A Propensity Score Approach

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Dissertação de Mestrado

Dissertation presented to the Programa de Pós–graduação em Economia of the Departamento de Economia, PUC–Rio as partial fulfillment of the requirements for the degree of Mestre em Economia

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Abstract

Silva, Daniel Gomes da; Gonzaga, Gustavo Maurício (Advisor). **The Added Worker Effect for Married Women and Children in Brazil: A Propensity Score Approach**. Rio de Janeiro, 2016. 40p. MSc. Dissertation — Departmento de Economia, Pontifícia Universidade Católica do Rio de Janeiro.

The added worker effect (AWE) is the increase in the likelihood of an individual to enter the labor force in response to the household head's job loss. This dissertation estimates the AWE for married women and children and young adults in Brazil using propensity score matching methods. We find evidence of a significant AWE for both groups, in particular for children and young adults. We also investigate some heterogeneities in the AWE for children and young adults. Our results suggest that the magnitude of the AWE for them is higher for females and for those out of school. This AWE magnitude is also related to other household members' characteristics, specially the household head's earnings and access to unemployment insurance.

Keywords

Labor Supply; Added Worker Effect; Propensity Score; Married Women; Children; Young Adults; NEET.

Resumo

Silva, Daniel Gomes da; Gonzaga, Gustavo Maurício. **O Efeito Trabalhador Adicional para Mulheres Casadas e Filhos no Brasil: Uma Abordagem Utilizando Propensity Score**. Rio de Janeiro, 2016. 40p. Dissertação de Mestrado — Departamento de Economia, Pontifícia Universidade Católica do Rio de Janeiro.

O efeito trabalhador adicional (AWE, em inglês) é o aumento na probabilidade de um indivíduo ingressar na força de trabalho em resposta a uma perda de emprego do chefe de família. Essa dissertação estima o AWE para mulheres casadas e filhos no Brasil utilizando métodos de propensity score matching. Encontramos evidência de um AWE significante para ambos os grupos, em particular para os filhos. Também investigamos algumas heterogeneidades no AWE para filhos. Nossos resultados sugerem que a magnitude do AWE para eles é maior para mulheres e para aqueles fora da escola. A magnitude desse AWE também está relacionada a outras características de membros do domicílio, especialmente os rendimentos do chefe de família e acesso ao seguro-desemprego.

Palavras–chave

Oferta de Trabalho; Efeito Trabalhador Adicional; Propensity Score; Mulheres Casadas; Filhos; Nem-nem.

Sumário

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1
Introduction

Theoretical models of family labor supply show that individuals have a number of coping mechanisms to smooth consumption levels of the household in the event of a job loss. Not only unemployed individuals can dispose of such mechanisms but other family members can support the household increasing their labor supply. The response of other family members has been referred to as the added worker effect (AWE) in the literature. In other words, the AWE is the increase in the likelihood of an individual to enter the labor force in response to the household head's job loss.

The objective of this dissertation is to estimate the AWE in Brazil using data from the Pesquisa Mensal de Emprego (PME), a Brazilian monthly employment survey. This topic is useful in order to understand the labor force participation of married women, children, young adults and other specific groups of individuals. For Brazil, this investigation is relevant to help explaining the historically low levels of the unemployment rate observed in the beginning of the 2010s despite the recent economic downturn. Moreover, the investigation of the AWE in Brazil is especially relevant due to the few number of studies available, all of which use an older version of the PME.

We estimate the AWE as a treatment effect. The main contribution of this dissertation is the use of propensity score for the AWE estimation instead of a linear probability model as performed in the majority of studies in the AWE empirical literature. We adopt this alternative methodology motivated by some important differences observed in the characteristics of control and treatment group households in our sample.

The propensity score estimation in this dissertation is benefited by the inclusion of variables concerning the household head's employment status experience in the PME. Following Kudlyak and Lange (2014), we argue that these variables are potentially useful to control for some of the unobserved characteristics of the household head. The estimated propensity score is then used to perform a non-parametric AWE estimation with different matching methods. Our propensity score matching results point to an AWE estimate of around 5.5% for married women. This estimate is smaller in relation to the one obtained using a linear probability model and highlight the importance of considering other methodologies when estimating the AWE.

Another important contribution of this dissertation is the AWE estimation for individuals aged between 10 and 24 years old in household. This is an additional departure in relation to the AWE empirical literature which is mostly focused on how the labor supply of married women is affected by their husbands' job loss. The inclusion of children and young adults in our analysis offers us the possibility of gaining some insights about the dynamics of their labor force participation. In turn, these insights are useful because of the important role the labor force participation of young people can play in households – particularly in Brazil due to their low schooling levels.

Using propensity score matching, our results point to a lower AWE estimate of around 4.5% for children and young adults. This possibly reflects their higher opportunity cost to enter the labor force at the young age of the individuals in our sample. Further exploring the AWE for children and young adults, the second part of this dissertation investigates heterogeneities in our AWE estimates according to different household characteristics. This investigation generates results in line with the predictions in the AWE theoretical literature. The magnitude of the AWE estimate is higher for females and for those out of school. This magnitude is also related to other household members' characteristics, in particular those of the household head such as his previous earnings and access to unemployment insurance.

This dissertation is organized as following. Chapter 2 reviews the AWE empirical literature and main theoretical concerns. Chapter 3 describes the data, descriptive statistics and the construction of the sample, also presenting our empirical strategy. Chapter 4 presents the results of the AWE estimation for married women and individuals aged between 10 and 24 years old. Chapter 5 investigates heterogeneities in the AWE estimates for children and young adults according to household members' characteristics. Chapter 6 presents our concluding remarks.

2 Literature Review

In a simple household utility maximization model the household head's job loss affects the labor supply of all other household members. This impact occurs mainly because of the income effect generated by the fact that the household head's job loss represents a negative income shock for the household as a whole[1]. Consequently, other household members are induced to offset such income loss, helping in an attempt to smooth the household's consumption levels. This phenomenon has been referred to as the added worker effect (AWE) in the literature.

The understanding of the AWE as an income effect brings forth the fact that its magnitude is closely linked to the household's ability to smooth its consumption levels in the event of a negative income shock. In other words, it is the relative ease with which the household can adjust the wife's labor force participation instead of recurring to other alternatives to handle this shock that will ultimately determine the AWE magnitude. For instance, the presence of liquidity constraints is expected to increase the AWE magnitude since they prevent a perfect smoothing of the household's consumption levels. On the other hand, access to unemployment insurance is expected to reduce the AWE magnitude by providing some income to the household head at least for a few months.

These theoretical predictions are confirmed in the empirical literature in light of the diversity of AWE estimates when analysing studies for different countries. More specifically, the results point to an evidence of small or statistically not significant effects in developed countries (Pietro-Rodriguez and Rodriguez-Gutierrez (2003), Kohara (2010), Bredtmann et al (2014)). In turn, for developing countries, the results point to the evidence of a larger and statistically significant effect in developing countries (Başlevent and Onaran (2003), Parker and Skoufias (2004, 2006), Bhalotra and Umaña-Aponte (2010)). This difference in the results is usually attributed to differences in the welfare system between these two groups of countries. Another explanation for these findings is the presence of liquidity constraints, which are more likely

[1]There is also a cross-substitution effect. This secondary effect occurs due to the household head's greater availability of hours to spend on other non-work activities now that he is unemployed. His greater availability of hours, in turn, reduces other household members' opportunity cost of working.

to be a problem for households in developing countries than for those in developed ones. For instance, Gruber and Cullen (2000) in their work argued that access to unemployment insurance reduced the relative importance of credit constraints thus reducing AWE estimates[2].

Still, there are some significant divergences in AWE estimates even in studies for a same country[3]. These differences call the attention to the difficulty involved in the identification of the AWE due to the influence of household members' unobserved characteristics or local labor market conditions. An early identification issue was recognized in Layard et al (1980) and Maloney (1987). These studies pointed to the important role the discouraged worker effect (DWE) can play in the AWE identification, acting in the opposite direction of the AWE. This happens because the DWE induces individuals to leave the labor force or stay out of it when labor market conditions are unfavorable. These unfavorable conditions are signalled for the wives by the household head's job loss so that AWE estimates will be poorly identified if the DWE is not correctly accounted for.

More importantly, the household head's job loss must be exogenous not only in what concerns the non-anticipation of the job loss itself but in relation to the wife's characteristics as well. This requirement will not be satisfied, for instance, in the presence of correlation in the couple's preference for leisure or of matching on labor force volatility (Lundberg (1985), Spletzer (1997)). Ultimately, this concern refers to how well control group wives can be compared to treatment group wives. This is an issue only superficially investigated in the literature and that may not be correctly accounted for using the framework found in the majority of the empirical studies which is a relatively simple linear regression. In order to handle this issue, we propose an alternative methodology in this dissertation which is based on propensity score matching and that will be further explained in the next chapter.

Adittionally, the AWE literature has focused its attention on the labor force participation of married women in response to a job loss of the household head. These studies adopt the convention of assuming husbands as the household heads and primary workers while their wives are considered to be secondary workers. However, note that the AWE theoretical framework applies to any secondary individual in the household. In other words, there is no reason to limit our attention to the labor force participation of married women as

[2]This finding is also useful to highlight the importance of considering how long the household head expects to be unemployed for the AWE magnitude since unemployment insurance is usually granted only for a limited time.

[3]In the United States, for example, some studies do not find any statistical evidence of the AWE (Layard et al (1980), Maloney (1987, 1991)) while others find evidence of a statistically significant effect (Lundberg (1985), Stephens (2002)).

studies in the AWE literature usually do. This dissertation also investigates the AWE for individuals aged between 10 and 24 years old in the household. To our knowledge, there are only two studies that analyze the AWE for a demographic group other than married women. One is Parker and Skoufias (2006) for Mexico and the other is Oliveira et al (2014) for Brazil. Both studies are interested in how the household head's job loss influences child work in the household. Their results, however, are opposite: Parker and Skoufias (2006) does not find any evidence of the AWE for children aged between 12 and 19 years old while Oliveira et al (2014) finds evidence of it for male children aged between 10 and 18 years old.

Finally, in what concerns other important studies in the small Brazilian AWE literature, it is important to mention Fernandes and Felicio (2005) and Gonzaga and Reis (2011). Both studies analysed the AWE for married women in Brazil and used data from a previous version of the Pesquisa Mensal de Emprego (PME), which was discontinued in 2002 giving place to an improved survey. Their results using the usual framework in the literature showed evidence of a large and statistically significant AWE.

3
Data and Empirical Strategy

3.1
Data

This dissertation uses data from the Pesquisa Mensal de Emprego (PME), a Brazilian monthly employment survey collected by the Instituto Brasileiro de Geografia e Estatística (IBGE). The PME is a household survey quite similar to the Current Population Survey (CPS) in the United States. More specfically, it is a rotating panel in which households are interviewd for two periods of four consecutive months, with an eight-month break between them. The PME collects data on labor, income and demographic characteristics of households and its members above 10 years of age in the six main Brazilian metropolitan regions. This results in approximately 100,000 individuals from 35,000 households every month.

In 2002, IBGE implemented significant changes in the PME's methodology, adopting a larger questionnaire and updating the definition of labor market participation as well as its rotation scheme. These changes are the reason why the PME after 2002 is sometimes referred to as New PME, while the survey with the previous methodology is sometimes referred to as Old PME. In light of this difference in the methodology, our sample covers the period comprehended between the middle of 2002 and the beginning of 2015. All nominal income variables available in the PME are converted to real income variables using January of 2016 as the base year.

Finally, the PME does not have an unique identifier for each individual. A simple way to circumvent this issue is to identify each individual in the household by his birthday. Note, however, that doing so will result in some attrition in our data due to problems such as recall bias or input errors. Hence, in order to reduce this attrition bias we use the algorithm developed by Ribas and Soares (2008) to match individuals within households in this dissertation[4].

[4]This algorithm allows for the match of individuals with different answers between households interviews if these answers are sufficiently similar according to some specific criteria. Ribas and Soares (2008) provided the codes for their algorithm in their study, which was further implemented in Data Zoom (a STATA package) by the Department of Economics at PUC-Rio which we used in this dissertation. The STATA package and more information about it can be found at `http://www.econ.puc-rio.br/datazoom/english/index.html`.

We have two populations of interest so that we have two samples in this dissertation. The married women sample is focused on married women and is composed of households in which both husband and wife are aged between 25 and 60 years old. We require that husbands be reported as the household head in these households. The children and young adults sample has the same characteristics of the first but requires the presence of at least one individual aged between 16 and 24 years in addition to husband and wife. We further restrict our samples to only include households in which individuals are present in all eight interviews. For reasons that will be clearer when discussing the empirical strategy, we only retain observations from the last three interviews of each household in the PME.

3.2
Empirical Strategy

Control and Treatment Groups

Our empirical strategy for the AWE estimation follows the traditional framework found in the literature. The AWE definition used in this dissertation refers to a reaction in the labor force decision of individuals only in the extensive margin. That is, we do not analyze whether individuals already in the labor force increase their number of hours worked in response to the household head's job loss. Other notions used in this dissertation are employment, unemployment and out of the labor force (OLF)[5], all of which follow the standard definitions. We will refer to them as employment status henceforth.

To empirically estimate the AWE it is first necessary to define an arbitrary reference interview. Our sample only contains households in which the husband is employed and the wife or child (depending on the population of interest) is out of the labor force in the reference interview. Given the PME rotation scheme and the large time gap between the fourth and fifth household interviews, we take the fifth household interview as our reference interview. This allows us to analyze the labor force participation decisions of individuals in consecutive months. This choice is the reason for the restriction of our sample to the last three interviews of each household in the survey as mentioned earlier.

[5]Individuals out of the labor force are also referred to as inactive individuals as opposed to active individuals (or in the labor force). Active individuals can be either employed or unemployed.

Next, households are allocated to the control or treatment group depending solely on the husband's employment status in the sixth household interview. The control group is composed of households in which the husband remains employed, while the treatment group is composed of households in which the husband suffers a job loss in the sixth household interview. Therefore, the classification of a given household into the control or treatment group does not change in our sample[6].

This rule was chosen because it enables the detection not only of a prompt entry in the labor force in the sixth household interview but also a delayed entry in the following interviews. A delay in the individuals' entry in the labor force can occur if there are restraints on their ability to promptly enter the labor force such as the presence of kids in the household. Besides, even if the husband manages to quickly get another job, his new earnings may be lower[7] so that the labor force participation decisions of wives, children and young adults will still be under the influence of the AWE. Finally, we exclude from our sample treated households in which the husband's job loss reason was retirement or quit since these reasons for separation are clearly not exogenous.

Standard Approach

Our analysis measures the AWE by the difference in the likelihood of entering the labor force for individuals in the treatment group and the corresponding likelihood for those in the control group. The AWE estimation in this dissertation is performed using two different methodologies. The first one, which we will refer to as standard approach, consists in the estimation of the following equation:

$$H_{it} = \beta_1 D_i + \beta_2 X_{jt} + u_{it} \tag{3-1}$$

In this equation, H_{it} is a dummy variable indicating whether the wife or child i at the time t is in the labor force or not. Similarly, D_i is a dummy variable that indicates if the wife or child i is in the treatment group. In this context, the AWE estimate is given by β_1. X_{jt} refers to a set of economic and demographic variables of the household members j (including the wife or child i) used as controls.

[6]For instance, if a household is initially allocated to the treatment group but the household head is reemployed in the following interviews, it will still be in the treatment group rather than be reallocated to the control group.

[7]In their analysis for Brazil, Fernandes and Felicio (2005) found some evidence suggesting that unemployment in Brazil signalled a substantial permanent income loss.

It is important to discuss the exact interpretation of β_1. Since D_i is time-invariant as opposed to H_{it}, this coefficient is not simply the additional entry rate in the labor force for individuals in the treatment group. Instead, β_1 represents the additional mean entry rate in the labor force in the remaining three household interviews after the husband's job loss for individuals in the treatment group.

We estimate Equation 3-1 using a linear probability model (LPM). The identification hypothesis behind this empirical strategy assumes selection on observables. That is, individual's labor force participation decision is orthogonal in relation to the husband's job loss is exogenous after controlling for the observed variables at our disposal X_{jt}. Given the importance of unobserved characteristics of the household and its members, selection on observables is not likely to be a valid hypothesis in the AWE framework. Taking advantage of the PME structure, in this dissertation we use a set of employment status history variables intended to mitigate the influence of these unobserved factors.

These variables are dummy variables that indicate if, in any of the first four household interviews, the individual was employed, unemployed or out of the labor force. Following Kudlyak and Lange (2014), we argue that these variables are useful to control for at least some unobserved variables of the household and its members[8]. Take for example the employment status history variables of the husband when comparing two seemingly identical households in the treatment group. Additionally, suppose that the husband in one of these households does not have any recent experience of unemployment or being out of the labor force, while the husband in the other household does. According to our approach, we expect the husband with no previous experience of unemployment or out of the labor force to be a worker of greater ability in comparison to the another husband. Hence, this difference in ability or preferences for work can be signalled by their employment status history in the PME.

Descriptive Statistics and Propensity Score Approach

Table 1 reports some descriptive statistics concerning the characteristics of household members included in the control group or in the treatment group for our two samples. In what concerns the married women sample, we verify the

[8]In their study, Kudlyak and Lange (2014) analysed the job finding rate of unemployed and out of the labor force individuals in CPS. Their findings using these individuals history in the CPS indicate that there are important heterogeneities in their job finding rates according to these histories in the CPS that would be otherwise overlooked.

presence of younger and more educated wives in the control group. We observe these same findings for the husband in these households which suggests some assortative matching in terms of education.

The proportion of children aged 10 or less in the household is not much different in the two groups. This is also true for the employment status history of the married women in our sample: a small and similar share of them had an employment or unemployment experience in both groups. This finding reinforces their status as secondary workers in the household just as studies in the AWE literature assume.

On the other hand, differences in the husband past average earnings as well as differences in his employment status history observed in table 1 are more worrisome. Important differences also arise when we look upon husband's characteristics concerning his job in the fifth household interview. More specifically, that job is more likely to be in the formal sector for husbands in the control group, which also displayed a longer work experience. These same differences overall hold for the children and young adults sample.

As previously stated, the standard approach is the methodology largely used in the empirical AWE literature. However, in light of the differences observed in table 1, it is possible that the standard approach may not be able to correctly compare control and treatment group individuals by just controlling for their observed characteristics. If this is the case, AWE estimates obtained using this methodology will be biased. This issue motivates the use of a matching approach for the AWE estimation in order to perform a better comparison of control and treatment group individuals.

Ideally, in order to estimate the AWE using matching, we would be able to allocate the individuals in our sample into a number of different cells according to their characteristics. Next, we would compute the treatment effect of the husband's job loss for control and treated individuals inside a same cell and then compute a weighted average of the treatment effects in all cells to obtain our AWE estimate. This is not possible in our case because it would result in a huge number of cells due to the many characteristics based on which we match the individuals. Besides, we would incur in other problems due to the use of continuous variables and the fact that we would end up having cells with a very thin number of observations.

Despite these issues we are still able to perform a matching in our framework. This is made possible by the propensity score theorem in Rosenbaum and Rubin (1983). This theorem states that if potential outcomes are independent of the treatment status after conditioning on a set of variables X_{jt}, then this independence holds after conditioning on a scalar function of these variables $p(X_{jt})$ as well. More specifically, we can use the propensity score, the probability of the husband's job loss, as the scalar function $p(X_{jt})$. Hence, after estimating the propensity score, we can use it to perform a propensity score matching for the AWE estimation. This matching methodology will be referred to as propensity score approach in this dissertation.

The propensity score approach can be divided in two steps. The first step consists of the propensity score estimation itself. That is, in this step we estimate the likelihood of the husband's job loss using a set of observed variables. Once again, despite our dependence upon observable variables at our disposal for the propensity score estimation, we add the husband's employment status history among our set of variables in order to control for some of his unobserved characteristics. This step highlights the fact that the propensity score approach assumes selection on observables as the identification hypothesis, just as the standard approach. On the other hand, an advantage of this approach is that it performs a non-parametrical AWE estimation instead of requiring an additional normality assumption as the standard approach does.

After the propensity score estimation, there are some additional procedures that must be made. Firstly, we require the common support assumption to be satisfied: $0 < P(D_i = 1|X_{jt}) < 1$. This assumption means that the probability of receiving treatment (and the probability of not receiving treatment as well) is necessarily positive. In other words, it means that there is sufficient overlap in the characteristics of the control and treatment group individuals in our sample. Next, we take note of the highest and the lowest values of the estimated propensity score for treated individuals in our sample. We then stratify our sample into ten different stratas with the same length according to these propensity score values.

In the second step of the propensity score approach, we estimate the AWE in each of these stratas. The AWE estimation in each strata involves the comparison of the entry rate in the labor force of treated individuals and the corresponding entry rate for the matched control group individuals. Note that there is a number of methods we can use to perform this matching between control and treatment group individuals.

In this dissertation we use three different matching methods. Nearest neighbor matching, just as the name suggests, picks to the control group those N individuals whose estimated propensity score value is closest to that of the treated individual. On the other hand, kernel and local linear regression matching methods pick to the control group a weighted average of all control group individuals. In this weighted average, higher weights are given to those individuals whose estimated propensity score values are closest to that of the treated individual. In order to use these last two methods, we choose three different kernel functions (Normal, Epanechnikov and Biweight) as well as a bandwidth parameter (0.01).

After estimating the AWE for each strata, we compute a weighted average of these AWE estimates. The resulting average will be our AWE estimate using the propensity score approach. Our AWE estimates' standard errors are calculated using bootstrap following the convention in the propensity score matching literature.

Finally, it is necessary to check if the matching was indeed successful in finding a comparison group with characteristics similar enough to those of the treatment group individuals. This is important because the search for a better comparison group was the motivation for using matching in the first place and if this task is not accomplished then our estimates may remain biased. Rubin (2001) proposed two parameters in order to evaluate the propensity score matching results, Rubin's B and R.

Rubin's B is the absolute standardized difference of the means of the propensity score between the treatment group and the matched control group. In turn, Rubin's R is the ratio of variance of the propensity score of the treatment group to that of the matched control group. According to Rubin (2001), B should be less than 25 and R should be between 0.5 and 2 for the groups to be considered sufficiently balanced. In this dissertation we use these parameters to assess the goodness of our propensity score matchings.

4
Results

4.1
Married Women

Standard Approach Results

In this section we present the results of our AWE estimation for married women. We begin examining the results using the standard approach, which are provided in Table 3. Standard error estimates are corrected for the presence of clusters of observations at the household level.

The first specification only includes a dummy variable indicating whether the wife is in the treatment group. It is the coefficient of this dummy variable that represents our AWE estimate. The results presented point to a large and statistically significant AWE estimate of 10.4%[9]. The magnitude of this preliminary finding highlights the importance of the AWE as a household coping mechanism in the event of the household head's job loss for wives in Brazil.

Specifications 2 and 3 add a set of control variables in our regression. We first control for sociodemographic characteristics of both the husband and the wife such as age, education and the proportion of children in the household. A set of dummy variables for the husband's employment sector in the fifth household interview, time and linear trends are added in order to control for local labor market conditions and the influence of the DWE. Variables concerning the employment status history of wives are also added and their coefficients are statistically significant.

The remaining variables are all related to the husband and are mostly intended to control for his unobserved characteristics. Besides the husband's employment status history, an example worth mentioning is the inclusion of the husband's average earnings in the first four household interviews. The idea behind using this information as a control variable is that, once we control for his education, work experience and local labor market conditions, differences in average earnings among husbands are mainly caused by unobservable

[9] In this specific specification the constant can be interpreted as the average entry rate of wives whose husbands did not suffer a job loss. Thus, this initial AWE estimate means that the husband's job loss nearly doubles the average entry rate of wives.

characteristics. The addition of all these control variables contribute to gradually reduce our AWE estimate to 7.6%.

Finally, specification 4 adds dummy variables similar to the husband's employment status experience but referring to his employment status after his job loss instead[10]. When both these variables are zero, they indicate that the husband continued employed in the seventh and eighth household interviews. For treatment group husbands, this means that they shortly managed to get another job and remained employed, thus indicating a mostly transitory job loss. The results point to a further reduction in our AWE estimate to 5.5%. This finding is in line with the theoretical prediction that the AWE magnitude is decreasing when the husband's job loss is only transitory.

Propensity Score Approach Results

As previously mentioned, the standard approach may not be able to correctly account for the different characteristics of control and treatment group households. This is especially relevant given the differences presented in Table 1 between control group and treatment group individuals. In turn, the propensity score approach is directly concerned about how well the control group households are representative of those in the treatment group.

This comparison between households is done based on the propensity score which is the likelihood of the household head's job loss conditional on his observed characteristics. In order words, the propensity score approach shifts attention from the AWE estimation to the propensity score estimation. The results of this estimation for each of our samples using a logit model is presented in Table 2.

The set of control variables used for the propensity score estimation is more parsimonious since they are intended to explain only the likelihood of the husband's job loss. Nevertheless, we are still able to add variables potentially useful as control for some of his unobserved characteristics such as his average earnings in the first four household interviews and employment status history. We store this model's predicted values as our estimated propensity score based on which we perform our matching between control and treatment group individuals.

The results of our AWE estimation obtained using the propensity score approach are presented in Table 4. In addition to the AWE estimates, we also report their t-statistic as well as Rubin's B and R, used to assess the goodness

[10]These variables refer to the period after the sixth household interview and indicate if the husband is unemployed or OLF in the seventh or eight household interview.

of the matching performed. As a rule of thumb, Rubin (2001) recommends values lower than 25 for B and between 0.5 and 2 for R so that the groups can be considered sufficiently balanced.

The estimated Rubin's B and R show us that the different combinations of matching methods and specifications are successful in balancing the two groups in our sample. In particular, we find evidence of a statistically significant AWE estimate of 5.2% using 25 nearest neighbors as the matching method. The remaining estimates remain statistically significant and their magnitude is quite robust to the chosen matching method.

These AWE estimates can be compared to those reported in the first three specifications of the standard approach. The smaller AWE estimates obtained using the propensity score approach can be partly explained in light of the fact that matching is able to identify a better comparison group to the individuals in the treatment group. However, it is possible to show that the standard approach can be seen as some sort of matching as well, reducing the importance of this first explanation.

The main difference between these two methodologies are the different weights each one uses to compute the weighted average that represents our AWE estimate. More specifically, the propensity score approach gives more weight to those cells that contain individuals more likely to be treated. On the other hand, the standard approach puts more weight to those cells in which the proportion of control group individuals is equal or similar to the proportion of treatment group individuals. Hence, an additional interpretation of our results can be done in light of this difference.

In particular, the difference between our AWE estimates indicate that the additional mean entry rate in the labor force is smaller for those wives in households in which the husband is more likely to lose his job. A possible explanation for this finding is that, since the husband's job loss was already likely in these households, if the wife intended to enter the labor force to help the husband, she would have taken this decision already. Of course, this does not mean that the husband's job loss has no effect on her participation decisions as the statistically significant AWE estimates in Table 4 make clear. However, this effect is relatively lower in relation to the effect on the participation decisions of wives in other households, in which the husband's job loss represents a shock more meaninful and less likely to happen.

4.2

Children and Young Adults

In this section, we present the results of our AWE estimation for individuals aged between 10 and 24 years old. According to theory, the household head's job loss is expected to affect the labor force participation decisions of other individuals in the household besides his wife. This happens because her transition to the labor force may not directly translate into a transition into employment. Additionally, even if she is successful in this transition, her relatively low earnings potential may not be enough to smooth the household's income needs.

Standard Approach Results

Here we follow the structure of the previous section, briefly commenting our results using the standard approach and then the corresponding results using the propensity score approach. Table 5 presents the results of our AWE estimation for children and young adults using the standard approach. The first specification points to a smaller unconditional AWE estimate of 7.3%. This finding once again highlights the importance of the AWE as a household coping mechanism in the event of the household head's job loss in Brazil – not only for wives but for children and young adults as well, although in a smaller magnitude.

The next two specifications include control variables at our disposal to the regression. Note that sociodemographic variables now include not only the husband's, children's and young adults' characteristics but those of the wife's as well. This is important due to young age of these individuals. In other words, they may not be the first individuals in the household to react in response to the husband's job loss due to their relatively low earnings potential at this age. Just as observed for wives, the addition of these controls contributes to a reduction in the AWE estimates to 2.7% which become statistically significant only at the 10% level of significance. Finally, the AWE estimate for children and young adults becomes not statistically different from zero in specification 4, presenting evidence that the AWE magnitude is decreasing when the husband's job loss is only transitory.

Propensity Score Approach Results

The results of our AWE estimation for children and young adults using the propensity score approach are presented in Table 6. The propensity score estimation is done in the exact same way as we did for the married women sample and can be found in Table 2. Our results continue providing evidence of statistically significant and robust AWE estimates using different matching methods and specifications. Moreover, the estimated Rubin's B and R again present evidence that the different combinations of matching methods and specifications are successful in balancing the two groups in our sample.

An important difference of these results in relation to those obtained for married women is in the magnitude of our AWE estimates. More specifically, when analyzing children and young adults, the magnitude of these estimates using the propensity score approach are not further reduced as was the case for married women. In fact, we find evidence of a statistically significant AWE estimate of 4.4% when using 25 nearest neighbors as the matching method. The remaining estimates remain statistically significant and their magnitude is even greater when using some matching methods.

We can interpret the difference in the AWE estimates obtained according to which methodology we used for the AWE estimation in light of the same discussion made in the previous section. In this case, our results for children and young adults show evidence that the additional mean entry rate in the labor force is smaller for those individuals in households in which the husband is more likely to lose his job.

In other words, the labor force participation of children and young adults seem to be more relevant as a household coping mechanism in the event of the household head's job loss in those households in which this shock is more likely. Still, it is also important to note that despite the higher dependence upon the labor force participation of children and young adults, the AWE remains higher for married women than for children and young adults in these households. In sum, the results in this section highlight the relevance of the AWE for children and young adults as well as the importance of considering different estimation methods when investigating the AWE.

5
Heterogeneities in the AWE for Children and Young Adults

The statistically significant AWE estimates for children and young adults reported in the previous chapter show that the AWE is relevant for their labor force participation decisions. These findings are particularly relevant given the age group we analyzed, in which they are expected to be accumulating human capital instead of rushing to enter the labor force to help the household to cope with a negative income shock. However, despite its importance, this issue has been little explored in the literature.

In this section we analyze some heterogeneities in our AWE estimates for children and young adults. We do this separating our sample into two or three subsamples according to each heterogeneity and then estimating the AWE for children and young adults in each of these subsamples. The AWE estimation is done using the propensity score approach with 25 nearest neighbors as the matching method.

These results are presented in Table 7, which gathers the results of six different heterogeneities investigated, each in a different line of the table. They are intended to be an initial effort of further investigating the influence that the husband's job loss can have on their labor force participation decisions.

The first heterogeneity we analyze is how our AWE estimates are affected according to these children and young adults' age. A priori, we would expect to find evidence of an increasing relationship between the AWE magnitude and their age due to the low earnings potential of younger individuals in light of their age and education. In fact, our results seem to confirm this hypothesis. More specifically, we find evidence of a statistically not significant AWE for individuals aged between 10 and 16 years, while the AWE estimates are statistically significant and increasing in magnitude for those individuals above 16 years old.

We already mentioned the convention of considering women as secondary individuals in the household while men are considered to be more permanently attached to the labor force. In light of this discussion, we the next heterogeneity investigates the AWE for children and young adults according to their gender. Our AWE estimates do provide some evidence of this hypothesis although the difference in the magnitudes is not large.

Next, we investigate the AWE for children and young adults depending on whether they are studying or not. This is quite important because of the recent surge in the Brazilian NEET population – young people not in work, employment or training. This phenomenom has been usually attributed to the improved conditions of the labor market in recent years that would have made it possible a longer stay of these individuals in this condition.

In fact, our results are somewhat supportive of this explanation since the AWE estimate for children and young adults out of school is much higher than for those in school. Of course, this difference also reflects the higher opportunity costs of individuals currently in school to enter the labor force (specially taking into consideration that in most cases they would have to abandon school). Finally, note that despite the small AWE estimate for children and young adults currently in school, its magnitude is still statistically significant.

The remaining heterogeneities concern how our AWE estimates for children and young adults is affected by the characteristics of other household members. The first of these characteristics are the husband's earnings in the job he currently held in the fifth household interview. More specifically, we investigate if there is a difference in the AWE magnitude for children and young adults if the husband's earnings were below or above the median.

According to the theory, children and young adults in households in which the husband's earnings were above the median should have smaller AWE estimates. Despite the greater income loss that the husband's job loss represents, these households are also more likely to have accumulated more savings and, therefore, are more likely to be better able to smooth the household's consumption levels. This prediction is confirmed by our results, which point to a smaller AWE estimate for children and young adults in households where the husband earnings were above the median.

The next heterogeneity investigated is closely related to the previous one. Here, we analyze how the AWE estimate for children and young adults is affected according to whether the husband had access to unemployment insurance or not in the job he currently held in the fifth household interview. Once again, according to the theory, children and young adults in households in which the husband had access to unemployment insurance should have smaller AWE estimates. The access to unemployment insurance is important in the sense that it provides some income to the household while the husband remains unemployed. It thus helps the household's consumption smoothing and reduces children and young adults' need to enter the labor force.

Finally, the last heterogeneity is related to whether the wife is already in the labor force or not at the moment of the husband's job loss. The idea here is to allow for the possibility of a hieararchical structure of the household's labor supply. If this is the case, and assuming that the wife's participation in the labor force is prioritized over the children and young adults', then a weaker AWE estimate is expected when the wife is not already in the labor at the moment of the husband's job loss. Our results are also supportive of this hypothesis, with a large difference between the AWE estimates for each subsample.

6
Conclusion

The AWE is the increase in the likelihood of an individual to enter the labor force in response to the household head's job loss. The AWE estimation faces some empirical issues that may compromise its proper identification among which controlling for relevant unobserved characteristics of the household. This is an important consideration to be made for the main methodology used in the literature which estimates the AWE as a treatment effect. More specifically, it does not investigate how balanced are the characteristics of control group and treatment group households.

This dissertation estimated the AWE for married women and individuals aged between 10 and 24 years old in Brazil using PME data. Our analysis is relevant because we offer an alternative methodology for the AWE estimation which is based on the propensity score of a household head's job loss. Additionally, we take advantage of the PME rotation scheme in order to create variables potentially useful as controls in our regressions and propensity score estimation. Our results present evidence of a statistically relevant AWE for both married women, children and young adults.

The results for children and young adults are of particular interest in light of their low schooling levels in Brazil. We also analyze some heterogeneities in our AWE estimates for these children and young adults. The results of our investigation suggest that the magnitude of the AWE estimate is higher for females and for those out of school. This magnitude is also related to other household members' characteristics, in particular those of the household head such as his previous earnings and access to unemployment insurance. It is important to note that these results represent only an initial effort in this direction of studying the AWE for children and young adults and encourage further research.

Bibliography

ARULAMPALAM, W.; BOOTH, A. L. ; TAYLOR, M. P.. **Unemployment persistence**. Oxford Economic Papers, 52(1):24–50, 2000.

ASHENFELTER, O.. **Unemployment as disequilibrium in a model of aggregate labor supply**. Econometrica: Journal of the Econometric Society, p. 547–564, 1980.

BAŞLEVENT, C.; ONARAN, Ö.. **Are married women in Turkey more likely to become added or discouraged workers?** Labour, 17(3):439–458, 2003.

BEYLIS, G.. **Looking under the right lamppost: A large and significant added worker effect in a developing country**. 2012.

BHALOTRA, S. R.; UMANA-APONTE, M.. **The dynamics of women's labour supply in developing countries**. 2010.

BINGLEY, P.; WALKER, I.. **Household unemployment and the labour supply of married women**. Economica, 68(270):157–186, 2001.

BREDTMANN, J.; OTTEN, S. ; RULFF, C.. **Husband's unemployment and wife's labor supply – The added worker effect across Europe**. Ruhr Economic Paper, (484), 2014.

CABANAS, P. H. F.; KOMATSU, B. K. ; MENEZES-FILHO, N. A.. **A condição "nem-nem" entre os jovens é permanente?** São Paulo: Insper, 2013.

CABANAS, P. H. F.; KOMATSU, B. K. ; MENEZES-FILHO, N. A.. **Crescimento da renda e as escolhas dos jovens entre os estudos e o mercado de trabalho**. 2015.

CAMARANO, A. A.; KANSO, S.. **O que estão fazendo os jovens que não estudam, não trabalham e não procuram trabalho?** 2012.

COSTA, JOÃO SIMÕES DE MELO E ULYSSEA, G.. **O fenômeno dos jovens nem-nem**. In: DESAFIOS A TRAJETORIA PROFISSIONAL DOS JOVENS BRASILEIROS. Instituto de Pesquisa Econômica Aplicada - IPEA, Brasília, 2014.

CUNNINGHAM, W. V.. **Breadwinner or caregiver? How household role affects labor choices in Mexico**, volumen 2743. World Bank Publications, 2001.

FERNANDES, R.; DE FELÍICIO, F.. **The entry of the wife into the labor force in response to the husband's unemployment: A study of the added worker effect in Brazilian metropolitan areas**. Economic Development and cultural change, 53(4):887–911, 2005.

FERNANDES, A. L.; GABE, T.. **Disconnected youth: A Look at 16-to 24-year olds who are not working or in school**. DIANE Publishing, 2009.

GONG, X.. **The added worker effect for married women in Australia**. Economic Record, 87(278):414–426, 2011.

GONZAGA, G.; REIS, M. C.. **Oferta de trabalho e ciclo econômico: Os efeitos trabalhador adicional e desalento no Brasil**. Revista Brasileira de Economia, 65(2):127–148, 2011.

GREGG, P.; TOMINEY, E.. **The wage scar from male youth unemployment**. Labour Economics, 12(4):487–509, 2005.

GRUBER, J.; CULLEN, J. B.. **Does unemployment insurance crowd out spousal labor supply?** Journal of labor Economics, 18(3):546–572, 2000.

HECKMAN, J. J.; MACURDY, T. E.. **A life cycle model of female labour supply**. The Review of Economic Studies, p. 47–74, 1980.

HECKMAN, J. J.; MACURDY, T. E.. **Corrigendum on a life cycle model of female labour supply**. Review of Economic Studies, 49(4):659–60, 1982.

HUMPHREY, D. D.. **Alleged "additional workers" in the measurement of unemployment**. The Journal of Political Economy, p. 412–419, 1940.

JACOBSON, L. S.; LALONDE, R. J. ; SULLIVAN, D. G.. **Earnings losses of displaced workers**. The American Economic Review, p. 685–709, 1993.

KIND, M.. **Start me up: How fathers' unemployment affects their sons' school-to-work transitions**. Technical report, Ruhr Economic Papers, 2015.

KOHARA, M.. **The response of Japanese wives' labor supply to husbands' job loss**. Journal of Population Economics, 23(4):1133–1149, 2010.

LAYARD, R.; BARTON, M. ; ZABALZA, A.. **Married women's participation and hours**. Economica, p. 51–72, 1980.

LUNDBERG, S.. **The added worker effect**. Journal of Labor Economics, p. 11–37, 1985.

MALONEY, T.. **Employment constraints and the labor supply of married women: A reexamination of the added worker effect**. Journal of Human Resources, p. 51–61, 1987.

MALONEY, T.. **Unobserved variables and the elusive added worker effect**. Economica, p. 173–187, 1991.

MARCENARO-GUTIERREZ, O.; VIGNOLES, A.. **Parental status influence on students' labour market success: An insight from the vocational track**. Unpublished manuscript, 2009.

MATTINGLY, M. J.; SMITH, K. E.. **Changes in wives' employment when husbands stop working: A recession-prosperity comparison**. Family Relations, 59(4):343–357, 2010.

MINCER, J.. **Labor force participation of married women: A study of labor supply**. In: ASPECTS OF LABOR ECONOMICS, p. 63–106. Princeton University Press, 1962.

MONTEIRO, J.. **Quem são os jovens nem-nem? Uma análise sobre os jovens que não estudam e não participam do mercado de trabalho**. 2013.

DE OLIVEIRA, E. L.; RIOS-NETO, E. G. ; DE OLIVEIRA, A. M. H. C.. **O efeito trabalhador adicional para filhos no brasil**. Revista Brasileira de Estudos de População, 31(1):29–49, 2014.

PARKER, S. W.; SKOUFIAS, E.. **The added worker effect over the business cycle: Evidence from urban Mexico**. Applied Economics Letters, 11(10):625–630, 2004.

PARKER, S. W.; SKOUFIAS, E.. **Job loss and family adjustments in work and schooling during the Mexican peso crisis**. Journal of Population Economics, 19(1):163–181, 2006.

PISSARIDES, C. A.. **Loss of skill during unemployment and the persistence of employment shocks**. The Quarterly Journal of Economics, p. 1371–1391, 1992.

POSADAS, J.; SINHA, N.. **Persistence of the added worker effect: Evidence using panel data from Indonesia**. Technical report, Mimeo, World Bank, Washington, DC, 2010.

PRIETO-RODRÍGUEZ, J.; RODRÍGUEZ-GUTIÉRREZ, C.. **Participation of married women in the European labor markets and the "added worker effect"**. The Journal of Socio-Economics, 32(4):429–446, 2003.

RIBAS, R. P.; MACHADO, A. F.. **A imputação da renda não-trabalho na Pesquisa Mensal de Emprego (PME/IBGE) e seu proveito em análises dinâmicas de pobreza e desigualdade**. Technical report, Texto para Discussão, Instituto de Pesquisa Econômica Aplicada (IPEA), 2008.

RIBAS, R. P.; SOARES, S. S. D.. **Sobre o painel da Pesquisa Mensal de Emprego (PME) do IBGE**. 2008.

RIBAS, R. P.; SOARES, S. S. D.. **O atrito nas pesquisas longitudinais: O caso da Pesquisa Mensal de Emprego (PME/IBGE)**. Estudos Econômicos (São Paulo), 40(1):213–244, 2010.

ROSENBAUM, P. R.; RUBIN, D. B.. **The central role of the propensity score in observational studies for causal effects**. Biometrika, 70(1):41–55, 1983.

RUBIN, D. B.. **Using propensity scores to help design observational studies: application to the tobacco litigation**. Health Services and Outcomes Research Methodology, 2(3-4):169–188, 2001.

SERNEELS, P.. **The added worker effect and intrahousehold aspects of unemployment**. Technical report, Center for the Study of African Economies, 2002.

SPLETZER, J. R.. **Reexamining the added worker effect**. Economic Inquiry, 35(2):417–427, 1997.

STEPHENS JR., M.. **Worker displacement and the added worker effect**. Journal of Labor Economics, 20(3):504–537, 2002.

STEVENS, A. H.. **Persistent effects of job displacement: The importance of multiple job losses**. Journal of Labor Economics, p. 165–188, 1997.

WOYTINSKY, W. S.. **Additional workers on the labor market in depressions: A reply to Mr. Humphrey**. The Journal of Political Economy, p. 735–739, 1940.

A
Tables

Table A.1: Descriptive Statistics

	Married Women		Children & YA	
	Control Group	Treatment Group	Control Group	Treatment Group
Age	41.75	45.30	15.38	15.68
Education 1-3 yrs	.07	.11	.04	.05
Education 4-7 yrs	.30	.38	.48	.50
Education 8-10 yrs	.21	.18	.32	.28
Education +11 yrs	.39	.27	.15	.14
Employment Experience	.15	.15	.06	.04
Unemployment Experience	.02	.02	.01	.02
Husband Age	44.42	47.93	42.91	44.31
Husband Education 1-3 yrs	.07	.10	.05	.10
Husband Education 4-7 yrs	.29	.39	.26	.38
Husband Education 8-10 yrs	.19	.18	.20	.20
Husband Education +11 yrs	.42	.28	.46	.27
Husband Work Experience 1 mo-1 yr	.10	.17	.10	.21
Husband Work Experience 1-2 yrs	.07	.10	.08	.11
Husband Work Experience +2 yrs	.82	.71	.82	.66
Husband in the Formal Sector	.53	.37	.53	.41
Husband Past Avg. Earnings (log)	7.42	6.97	7.46	6.96
Husband Unemployment Experience	.02	.07	.03	.10
Husband OLF Experience	.11	.43	.07	.36
Proportion of Children in the Household	.14	.11	.11	.12
Observations	130891	3686	94046	1896

Source: PME, own calculations.

Table A.2: Propensity Score Estimation

	(1) Husband Job Loss (Married Women)	(2) Husband Job Loss (Children & YA)
Husband Education 1-3 yrs	-0.208	-0.333*
	(0.133)	(0.198)
Husband Education 4-7 yrs	-0.277**	-0.421**
	(0.123)	(0.179)
Husband Education 8-10 yrs	-0.357***	-0.504***
	(0.131)	(0.186)
Husband Education +11 yrs	-0.506***	-0.714***
	(0.134)	(0.189)
Husband Work Experience 1 mo-1 yr	-0.524**	-0.337
	(0.253)	(0.325)
Husband Work Experience 1-2 yrs	-0.427*	-0.342
	(0.259)	(0.338)
Husband Work Experience +2 yrs	-0.636***	-0.611*
	(0.243)	(0.319)
Husband Past Avg. Earnings (log)	-0.270***	-0.320***
	(0.046)	(0.062)
Husband Unemployment Experience	0.984***	1.158***
	(0.134)	(0.160)
Husband OLF Experience	1.523***	1.483***
	(0.080)	(0.123)
Husband in the Formal Sector	-0.484***	-0.259***
	(0.067)	(0.092)
Constant	0.177	1.182
	(1.060)	(1.443)
Observations	134,577	95,942
Pseudo R-squared	0.127	0.129
Month and Year Dummies	Y	Y
Employment Sector Dummies	Y	Y
Metropolitan Region Dummies	Y	Y
Metropolitan Region x Year Linear Trend	Y	Y

Source: PME, own calculations. Notes: *** p<0.01; ** p<0.05; * p<0.1.
– Robust standard errors in parentheses (clustered at household level).

Table A.3: AWE Estimates for Married Women (Standard Approach)

	(1) Wife Active	(2) Wife Active	(3) Wife Active	(4) Wife Active
Husband Job Loss	0.104***	0.079***	0.076***	0.055***
	(0.012)	(0.011)	(0.013)	(0.013)
Wife Employment Experience		0.181***	0.181***	0.181***
		(0.006)	(0.006)	(0.006)
Wife Unemployment Experience		0.212***	0.211***	0.211***
		(0.016)	(0.016)	(0.016)
Husband Past Avg. Earnings (log)		-0.021***	-0.021***	-0.021***
		(0.002)	(0.002)	(0.002)
Husband Work Experience 1 mo-1 yr		-0.015	-0.014	-0.016
		(0.023)	(0.023)	(0.023)
Husband Work Experience 1-2 yrs		-0.029	-0.028	-0.027
		(0.023)	(0.023)	(0.023)
Husband Work Experience +2 yrs		-0.036	-0.035	-0.034
		(0.022)	(0.022)	(0.023)
Husband in the Formal Sector			-0.006**	-0.005*
			(0.003)	(0.003)
Husband Job Loss due to Firing			0.015	-0.002
			(0.028)	(0.028)
Husband Unemployment Experience			0.003	0.000
			(0.012)	(0.012)
Husband OLF Experience			-0.004	-0.007
			(0.006)	(0.006)
Husband Unemployment after Job Loss				0.107***
				(0.018)
Husband OLF after Job Loss				0.031***
				(0.009)
Constant	0.116***	0.408***	0.414***	0.402***
	(0.001)	(0.101)	(0.101)	(0.100)
Observations	134,577	134,577	134,577	134,577
R-squared	0.002	0.073	0.073	0.074
Sociodemographic Variables	N	Y	Y	Y
Month and Year Dummies	N	Y	Y	Y
Employment Sector Dummies	N	Y	Y	Y
Metropolitan Region Dummies	N	Y	Y	Y
Metropolitan Region x Year Linear Trend	N	Y	Y	Y

Source: PME, own calculations. Notes: *** p<0.01; ** p<0.05; * p<0.1.
– Robust standard errors in parentheses (clustered at household level).

Table A.4: AWE Estimates for Married Women (Propensity Score Approach)

Matching Method	AWE	t	B	R
Nearest neighbors (N = 5)	0.050	6.64	10.1	1.00
Nearest neighbors (N = 10)	0.050	6.86	7.6	0.99
Nearest neighbors (N = 25)	0.052	7.22	6.0	0.97
Kernel (Normal)	0.057	8.14	14.9	0.71
Kernel (Epanechnikov)	0.054	7.65	6.2	0.91
Kernel (Biweight)	0.053	7.60	5.5	0.94
Local linear regression (Normal)	0.054	7.72	13.0	0.57
Local linear regression (Epanechnikov)	0.055	5.76	18.7	1.00
Local linear regression (Biweight)	0.053	7.56	8.2	0.73

Source: PME, own calculations.

Table A.5: AWE Estimates for Children and Young Adults (Standard Approach)

	(1) Child Active	(2) Child Active	(3) Child Active	(4) Child Active
Husband Job Loss	0.073***	0.035***	0.027*	0.012
	(0.014)	(0.012)	(0.014)	(0.014)
Child Employment Experience		0.154***	0.154***	0.154***
		(0.011)	(0.011)	(0.011)
Child Unemployment Experience		0.192***	0.192***	0.192***
		(0.021)	(0.021)	(0.021)
Husband Past Avg. Earnings (log)		-0.018***	-0.017***	-0.017***
		(0.002)	(0.002)	(0.002)
Husband Work Experience 1 mo-1 yr		-0.005	-0.005	-0.006
		(0.017)	(0.018)	(0.018)
Husband Work Experience 1-2 yrs		0.001	0.001	0.001
		(0.018)	(0.018)	(0.018)
Husband Work Experience +2 yrs		-0.004	-0.004	-0.004
		(0.017)	(0.017)	(0.017)
Husband in the Formal Sector			0.001	0.002
			(0.003)	(0.003)
Husband Job Loss due to Firing			0.028	0.017
			(0.027)	(0.028)
Husband Unemployment Experience			0.010	0.008
			(0.009)	(0.009)
Husband OLF Experience			-0.006	-0.008
			(0.006)	(0.006)
Husband Unemployment after Job Loss				0.056***
				(0.016)
Husband OLF after Job Loss				0.021**
				(0.010)
Wife Unemployment after Husband's Job Loss				0.020***
				(0.008)
Wife OLF after Husband's Job Loss				-0.001
				(0.002)
Constant	0.074***	0.015	0.015	0.005
	(0.001)	(0.092)	(0.092)	(0.092)
Observations	95,942	95,942	95,942	95,942
R-squared	0.001	0.165	0.166	0.166
Sociodemographic Variables	N	Y	Y	Y
Month and Year Dummies	N	Y	Y	Y
Employment Sector Dummies	N	Y	Y	Y
Metropolitan Region Dummies	N	Y	Y	Y
Metropolitan Region x Year Linear Trend	N	Y	Y	Y

Source: PME, own calculations. Notes: *** p<0.01; ** p<0.05; * p<0.1.
– Robust standard errors in parentheses (clustered at household level).

Table A.6: AWE Estimates for Children and Young Adults (Propensity Score Approach)

Matching Method	AWE	t	B	R
Nearest neighbors (N = 5)	0.037	3.87	13.5	0.84
Nearest neighbors (N = 10)	0.041	4.62	10.0	0.87
Nearest neighbors (N = 25)	0.044	5.28	9.2	0.92
Kernel (Normal)	0.051	6.26	21.7	0.94
Kernel (Epanechnikov)	0.049	5.97	9.7	0.94
Kernel (Biweight)	0.048	5.94	7.7	0.92
Local linear regression (Normal)	0.048	5.89	8.6	0.79
Local linear regression (Epanechnikov)	0.048	3.41	17.5	0.83
Local linear regression (Biweight)	0.048	5.92	10.9	0.78

Source: PME, own calculations.

Table A.7: Heterogeneities in the AWE Estimates for Children and YA (Propensity Score Approach: Nearest Neighbors (N = 25))

AWE estimates according to...	(1)	(2)	(3)
... child age is less than 16 (1),	0.000	0.054	0.089
between 16 and 18 (2)	t = -0.10	t = 2.87	t = 3.14
or above 18 (3)	B = 12.2	B = 11.9	B = 16.7
	R = 0.88	R = 1.17	R = 1.35
... child is male (1) or female (2)	0.037	0.054	
	t = 3.17	t = 4.32	
	B = 6.1	B = 8.0	
	R = 1.00	R = 1.04	
... child is studying (1) or not (2)	0.019	0.138	
	t = 2.71	t = 4.53	
	B = 9.7	B = 11.1	
	R = 0.87	R = 1.34	
... husband's earnings were below the	0.058	0.044	
R$1000 median (1) or above it (2)	t = 4.58	t = 3.97	
	B = 8.0	B = 17.1	
	R = 0.87	R = 0.72	
... husband had access to unemployment	0.034	0.040	
insurance (1) or not (2)	t = 2.47	t = 3.50	
	B = 8.1	B = 7.3	
	R = 0.90	R = 0.91	
... wife initially in the labor force (1)	0.064	0.035	
or not (2)	t = 4.97	t = 3.10	
	B = 11.7	B = 6.3	
	R = 1.01	R = 0.99	

Source: PME, own calculations.