Mothers' Labor Supply and Conditional Cash Transfers: Evidence from Chile

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Abstract

This paper uses a difference-in-difference strategy to test how a Chilean conditional cash transfer program (CCT) affects mothers' labor supply. I find that the program leads to a significant decline in labor supply for single mothers. This reduction is particularly sharp for young single mothers ages 18 to 24, who experience a 4.1% fall in labor force participation and an 6.5% fall in working hours. These results highlight an unintended and policy-relevant behavioral response to CCTs. It is also the first time these effects are studied for a population with high baselines on secondary schooling and health care utilization.

I Introduction

Conditional Cash Transfers (CCT) have become very popular over the last twenty years. A report by the World Bank estimates that in 2018 a total of 60 countries had active CCT programs, with a combined 105 million beneficiaries of this type of program. The same report points to one likely reason of their popularity: CCTs seem to outperform all other types of social safety instrument in targeting the poorest two quintiles (World Bank, 2018). Their simplicity contributes to their popularity too, even poor states can use CCTs successfully.

In this paper, I will focus on measuring the labor supply distortions created by one of these CCTs. The Chilean *Subsidio Unico Familiar* (SUF, 'unique family subsidy') was significantly expanded between 2007 and 2010, period in which it doubled it reach from one million to two million beneficiaries.

My results suggest that both young mothers (18 to 24) and single mothers are responding to the policy change by reducing their labor supply, with the first group being the most affected. Unexpectedly, older women (25 to 50), also with children, seem to increase their labor force participation due to the extra generosity of the SUF, although only if part of a couple.

The principal contribution of this work is to provide a measure of labor supply distortions for CCTs on a relatively high educated population. A secondary, but still very relevant contribution, is to provide statistically significant results due to having an uncommonly rich dataset.

The relevance of the first contribution requires understanding of the sources of distortions of the labor market that may stem from a CCT program. Alzúa et al. (2013) suggest three, besides general equilibrium effects.

The first source of distortion is the pure income effect from the non-earned income being received. It should lead to lower labor supply and will depend on the size of the transfer relative to the beneficiary's income. This will be the first study that can claim to identify mostly this distortion by itself.

The second and third are generated by changes in people's behavior, and would lead to increased labor supply. For the second, because children are going to school, their mothers' time is liberated from childcare, leading to some of that time likely be used to increase working hours. For the third, children that may have been working before the program was in place will have to stop working, leading to a decrease in family total income that could force the mother to increase her labor supply.

The mothers in my sample have two to five times more schooling than previous studies looking for these distortions. Their children are at least 90% likely to be in school if under the age of 17, before the policy change under study. This means that mothers are not originally spending their time taking care of children that should be at school (zero effect two), and these children are not providing work income either (zero effect three). As a result, my estimates will be less affected by the second and third distortion, reflecting purely the effect of the non-earned income being transfered to these families.

The rest of the paper is organized as follows. Section II discusses the current state of knowledge on the effects CCTs have on labor supply. Section III is devoted to explaining thoroughly the SUF subsidy and its recent evolution, including the event that will provide me with an identification strategy. Section IV describes the data used, Section V defines treatment and control and Section VI presents the difference-in-difference model. Section VII shows results for labor supply outcomes. Finally, Section VIII concludes and suggests ways forward.

II Literature Review

Banerjee et al. (2017) review seven CCT evaluations using randomized controlled trials for four developing countries, finding no evidence that any of these programs affected labor supply negatively. However, the research they consider is not precise, failing to conclude even with relatively large estimates. Additionally, these studies are likely identifying the combination of many distortions, that depend on each country particular situation at the time of the evaluation.

The studies considered include CCTs in Argentina, Brazil, Cambodia, Colombia, Honduras, Mexico, Nicaragua, Pakistan, and Philippines; where the latter four correspond to randomized control trials. Notably, children health and educational outcomes in all of these countries at the time of the evaluation are far below those of the developed world (*World Bank Open Data*, 2018).

This means that the CCT programs can successfully improve any of these metrics by modifying people's behavior. Effectively, CCTs have been proven very successful welfare programs on reducing poverty (Fiszbein & Schady, 2009), improve children's educational outcomes (Schultz, 2004; Maluccio & Flores, 2005), and access to health services (Gertler, 2004; Attanasio et al., 2005).

This paper is the first to look at the effects on labor supply generated by a CCT received by a population with high schooling and healthy children. The importance of this distinction is that it allows us to identify the effect of the non-earned income on labor supply by itself. Previous results mixed this effect with at least two other opposite effects, biasing results to zero. Since these other distortions depend on the preponderance of schooling among children, their size likely differs for different schooling rates, which makes them less generalizable.

As mentioned above, an important weakness in the existing body of research relates to its precision. Typically they fail to reject the null even with relatively large estimates, that can sometimes represent more than 10% of the pre-treatment levels. Many follow the methodology of Mexico's PROGRESA, that introduced the program selecting counties at random to benefit, leaving others as control, in an attempt to facilitate future policy evaluations.

Alzúa et al. (2013) find that CCTs in Honduras, Nicaragua, and Mexico have no significant effect on labor supply of their beneficiaries. Nonetheless, according to their fixed effects model's results, women reduce their employment 5% in Honduras (1.8 percentage points, ITT), 5-11% in Nicaragua (1-2.3 percentage points, ITT), and 0-10%in Mexico (0.1-2 percentage points, ATE), in response to the CCT. Further, Skoufias & Di Maro (2008) find age heterogeneity in responses to Mexico's PROGRESA, with results that are consistent with mine: negative responses for the youngest mothers and positive responses for older women.

Research in Brazil and Argentina (Brazil: De Brauw et al., 2015; Ribas & Soares, 2011; Argentina: Garganta & Gasparini, 2015) has shown no effect on labor force participation. However, these countries make the benefits a function of current income, while a standard CCT would use some indirect measure (neighbourhood, income generating capacity). As a result, in other countries, working more after being selected has no consequence for people's CCT benefits, but in this two nations it could reduce them.

In summary, the existing body of research on labor supply distortions generated by CCTs is not very precise. Most papers fail to reject the null, while at the same time providing very consistent mostly negative results. More importantly, these analyses may not even provide an insight on what type of distortions can be expected for better educated populations, because of the externalities the CCTs bring with them. Chilean data can provide these insights, as well as the precision needed to make statistical inference.

III The SUF program

The SUF program was established in 1981 with the explicit goal of increasing parents' investment in their children, and today reaches about 15% of the country's households. The program provides a monthly transfer per child and mother conditional on children up to six being taken to regular medical controls, and those older attend school full time, up to 24. If a family qualifies for the program, the per capita amount is the same for everyone.

These conditions are easily controlled for by the authorities, making the system efficient and relatively simple to enforce. However, the SUF also requires families to be part of the poorest 40 percent as measured by an index called *income generating capacity.* However, this index is built using self-reported information, making it very manipulable (Herrera et al., 2010; Irarrázabal et al., 2010).

From 2007 to 2010, this subsidy was made more generous and more popular. The former was achieved by an increase in the transfer's value. The amount transfered in 2007 was 31% larger than the previous year, and its subsequent growth was increase as well. From 2006 to 2015 the nominal value of the SUF grew at an average annual rate of 10%, 2.5 times faster than during the period 1998-2006 (Table 1). At the same time, it was turned into an entitlement, which lead to the program's doubling its reach by 2010 (Figure 1). The reason it takes some time for the CCT to grow is that the authorities need to estimate the income generating capacity of the beneficiaries in order to add them to the program, which means interviewing each family.

[Table 1]

[Figure 1]

Overall, this overhaul to the SUF program could have important unintended effects as long as the program also meets two other requirements: being big with respect to some generally definable universe; and important enough to have noticeable effects on people's budget constraints.

Chile's SUF is very popular, reaching large sections of the country's families. It currently benefits over two million people in about 850 thousand different families, according to official data for 2016 (Subsecretaría de Seguridad Social, 2018). In a country with 18 million people, and 5.5 million households, this represents more than 10% of the population, and 15% of families. Furthermore, by decile of income, the SUF reached over 25% of the first two deciles and 17% of the third, according to survey data from 2015 (even with 20-30% sub-estimation of SUF recipients).

[Table 2]

On the second requirement, the SUF makes only a modest contribution to the average family's budget. The transfer awarded to any particular *cause* would represent only 4.1% of the national minimum wage in 2015, and even less in previous years. However, Table 2 shows that the benefits gotten through the SUF can represent a very substantive part of some people's income.

Table 2 shows three statistics, for three groups of SUF recipients. The first statistic shows the value of the monetary transfer with respect to the families work income on average; the second shows how many SUF recipients, with positive work income, receive between 20% and 100% of said income through the SUF; finally, the last column shows how likely is the SUF transfer to be larger than the recipient's declared work income, including those with zero work income.

I show these statistics for the general population and also for two other groups that could be expected to be more exposed to the CCT. These groups are mothers in the age range 18 to 24, and families that are not the nuclear family of the household head (therefore *guests*). What Table 2 shows is that there are some individuals that rely heavily on the SUF benefits. There is an important part of the SUF beneficiaries that would lose more than 20% of their family's income if the SUF is discontinued, ranging from 25% in general, to almost 60% for *guests*.

IV Data

The data used comes from seven editions of a survey created to evaluate public policy in Chile, called *Encuesta de Caracterización Socioeconómica Nacional* (CASEN, 'national socio-economical characterization survey'), covering the years 1998 to 2015. This is a household survey first conducted in 1987, meant to be nationally representative of the population, that in 2015 reached almost 270 thousand people in 84 thousand households, and 100 thousand different nuclear families; effectively interviewing 1.5% of Chilean population.

The survey's purpose is to measure poverty, describe the poor, and guide and evaluate public policy, which is why it contains detailed personal demographic information, sources of income and labor force participation, among other things. Because it is meant to be repeated indefinitely there is a substantive effort in making versions comparable and the survey trustworthy. By 1998 it has been repeated five times before, giving people no specific reasons to believe the survey would be used against them if they admitted to improper behavior.

The analysis is based upon four surveys before the 2007 policy change: 1998, 2000, 2003, and 2006; and three surveys after the SUF's modification: 2011, 2013, and 2015. There is a 2009 survey that will not be used, because the expansion of the program is still incomplete at this point.[1].

Our relevant population are women between 18 and 60 years old, with at least one child younger than 18, or 24 if full time student. This results in a sample of 362,796 observations (including 2009) for which some general statistics can be seen in Table 3. This table shows how the change in the SUF led to a sharp increase in the probability of having the SUF subsidy after 2006.

[Table 3]

Table 4 shows the same basic statistics for the subgroup that declares to receive SUF. These women are younger, less schooled, have more children, they have their first child sooner, are more likely to be single, work less and earn less than the overall population. However, their trends are those of the general population, the table does not suggest a change in the composition of SUF beneficiaries. The biggest difference is as expected, a rather significant jump in schooling, likely a result of expanding the subsidy's reach.

[Table 4]

There is one trend that seems to differ between the tables in a way that is not warranted, and that is labor force participation. Figure 2 shows how the labor force participation of the two groups (with SUF and without SUF) trend together only before the policy change. This graph includes a grey area, meant to signify the SUF expansion period, and circles around the 2009 data points, meant to signify quality concerns[2].

[Figure 2]

The data also includes detailed information about other outcomes related to labor supply that we will use to study the program's effects: labor force participation, average hours worked and average hours worked by the spouse (attributing zero to those without a job), average hours worked by

[1]Nevertheless, the results are robust to the inclusion of this survey, taking 2007 as the critical event year

[2]The CASEN 2009 was excecuted by Universidad Alberto Hurtado, the four before and the three after by Universidad de Chile, This led to a sub-representation of 50% for SUF recipients in 2009, double the standard.

those with positive hours, probability of working extra hours, and hourly wages. This six outcomes allow me to identify how individuals choose to respond to the change in the CCT program.

V Empirical Approach

Any modification of the SUF could potentially affect any woman that has children eligible for the program. Nominally, this would be limited to mothers in the first forty percentiles of per capita income, as the SUF should not be received by wealthier people. However, there is evidence that recipients misrepresent their situation in order to improve their chances.

Indeed, according to Herrera et al. (2010) the data used to determine elegibility to the SUF differs importantly to survey data for the same population. The head of household is older and more likely to be woman, and the family is smaller and much more likely to have someone with disability. Similarly, Irarrázabal et al. (2010) show in their table 4.2.1 that according to the data used to determine SUF elegibility, with two thirds of the country surveyed, 35% belong to the first decile of income. That would mean that at least 22% of Chilean population belong to the first income decile, which is only possible because the data is self-reported with the intent to improve chances of being eligible to the program.

Schooling cannot be used to discard mothers either. The survey data used shows that for all schooling levels mothers experience an important change in probability of receiving the subsidy after 2007 (Figure 3). The probability of benefiting from the SUF are very significant for any mother with 12 years of schooling or less (high school diploma), but are still relevant for 15 or 16 years of schooling.

[Figure 3]

Therefore, the only group of women who can be used as a pure control in this situation is the group of women with no eligible children. I also limit my attention to the age range 18 to 50. The lower limit corresponds to the minimum age for mothers to benefit from the SUF, making this a necessary restriction. The upper limit helps keeping demographics between treatment and control more balanced, since older women typically no longer live with young children. However, the results are not overly affected by eliminating the latter age restriction.

[Table 6]

Table 6 shows some general demographics for mothers and women without children. We can see here some differences between the groups: women without children are on average younger, more educated, work more and are more likely to be single. These are all expected differences, but it raises the obvious issue that maybe it is not a good control group for mothers.[3]

However, Figure 4 shows the evolution of labor force participation for both groups from 1998 to 2015. We can see clearly that the two groups have very different levels of labor force participation, as the table also shows. But we can also see plainly that they trend together prior to 2007, which is the fundamental assumption that needs to hold for the difference-in-difference analysis I will describe later. Women without children are more likely to work, but do not seem to have reached a ceiling on labor force participation by 2015, which means there is no reason for the series to separate after 2007 other than the treatment.

[Figure 4]

For the group that is less educated, the concern seems more important, as Table 5 shows. In this case, the group of mothers seem to have a slightly larger slope than the group of not mothers. If this is the case it could mean that the distance between the two groups would be naturally shrinking over time, biasing estimates toward zero. However, it could also mean that the determinants of changes in labor force participation are different for the two groups, which could potentially lead to biases in any direction.

[Figure 5]

VI The Model

I have identified treatment and control groups, and the time at which treatment comes into effect. I will use a difference-in-difference methodology to identify labor supply effects attributable to the SUF program extra generosity. The preferred specification controls for several relevant covariates parsimoniously. Every regression includes controls for whether the individual has work experience, whether she is family head, whether her family is the household head's (i.e. not the family of a son or daughter), and whether she is married; as well as year of survey (6 dummies), age, family

[3] To address this concern further I also tried alternative specifications, selecting mothers as control based on how exposed they were to the CCT program. The results proved robust to these tests.

size, number of children, and fixed effects for neighborhood (359 dummies). If the regression is conditional on working I add to these controls another, for time in current job[4]. I also use heteroskedastic robust errors on estimation, given that differences-in-differences models are prone to underestimate them (Bertrand et al., 2004). Below I show the equation for the model.

$$y_{it} = \beta_0 + \beta_1 mom_i + \beta_2 \cdot post_t \cdot mom_i + \gamma_t + \Gamma X_{it} + \varepsilon_{it}$$

Where y_{it} is one of several outcomes of interest: labor force participation, weekly working hours or log of weekly working hours, extra hours, and hourly wage; and $post_t$ is zero for surveys before 2007, and one for the complement. I also run this regression with three different interactions in order to evaluate possibly heterogeneous responses: whether the woman is single, whether she is old (defined as in the age range 25 to 50), and whether she has a high school diploma (12 or more years of schooling).

As the results seem to be driven by two characteristics in particular, being single and being young, I run the regression with both interactions together. This allows me to identify exactly which groups are responding to the policy, as responses by single/couple status may vary by age, as indeed they do, and those by age may vary by being single or in a couple, which is also the case.

This difference-in-difference model's validity rests in the assumption of parallel trends. To show that this assumption is sustained, Figure 4 plots the trends before and after the policy change, for both treatment and control groups.

If the groups' trends are not parallel then we would not be identifying solely the effect of treatment when we use the difference-in-difference model. Instead, we would be identifying the effect of treatment $\pm$ the difference in trends. This also leads me to be careful with regressions with interactions on treatment. Adding interactions increases the number of groups very fast, and the parallel trends assumption likely loses validity in some of these subgroups. On top of that, some groups may become small leading to failure to reject the null because of statistical power, and not for a lack of effect. Instead, using a strategy of minimum subdivision, I get to the groups that are being affected by the policy.

Parallel trends mean generally that both series follow each other. More specifically we would want the fundamentals that determine their movement to be the same, so as to ensure they will not drift apart for any reason other than the shock under analysis. Whenever their fundamentals are

[4]Alternative specifications including these covariates do not significantly alter the results

different, we could see the trends diverge because of a shock that only affects the fundamentals of one of the groups. This leads to choosing treatment and control groups that are as similar as possible, in this case it means choosing only women for both categories, even if there are other possibly important differences between them. Nevertheless, as Figure 4 shows, these other differences, whatever they may be, seem to have no relevance on the groups' labor force participation long term trends, which is what concern us particularly.

VII Results

I start by looking at the results on the extensive margin. Table 7 shows labor force participation effects for the treated. Each column shows the marginal effect for the treated with a different interaction. Column (1) shows the overall response with no interaction, column (2) interacts with whether the mother is single (not in a couple), column (3) distinguishes between mothers that are young (18 - 24) and the older group (25 - 50), and column (4) compares women with and without high school diploma. Additionally, results from these columns motivate a fifth column, which combines interaction for couple/single and young/old. Finally, columns (6) and (7) explore the possibility that the effects may be driven primarily by the less educated mothers, by separating women with 0 to 11 years of schooling from those with 12 or more years of schooling.

[Table 7]

Table 7 shows that even though there is no significant change in labor force participation due to treatment overall, there are some significant results, together with large heterogeneity, for some subgroups. In particular, it shows that single or young mothers tend to reduce labor force participation due to treatment, while mothers in couples or older increase it, albeit marginally.

However, young mothers are much more likely to be single than older mothers (43% v. 25% in 2006), introducing an important correlation between the groups single and young, and between couples and older mothers. This means that we have not fully identified the group or groups that are driving the responses.

The difference in the negative response from young and single mothers is more important than it looks, as young mothers have a labor force participation of only 44% in 2006, compared to 74% for single mothers. Nevertheless, columns (2) and (3) fail to identify properly whether the effect is being driven by age, being single, or both. Column (5) provides the answer, it shows that the characteristic that leads to a negative response is being single, not young. However, being young is critical, as it amplifies the effect of the policy greatly for single mothers. Taking into account the 2006 baselines, a reduction of 2.1 percentage points for young single mothers in labor force participation is a 4.1% drop due to treatment, while the effect for the older group of single mothers represents only a 1.1% reduction from the 2006 baseline.

According to these results, a family with three causes (two children and a mother) would have experienced an increase of approximately 140% between 2006 and 2015, that is a 10.2% annual growth, compared to an annual growth of only 4.5% on average in the previous years (1998 to 2006). This suggests a decline in labor force participation of 0.7% for the younger group and 0.2% for the older group of single mothers, when the program growth rate is increased 1%.

The positive response we observe in Table 7 seems to come specifically from older women in a couple (column 5). The mechanism that explains this result is harder to ascertain, as standard labor theory would predict a non positive response. This positive response suggests that the transfer of unearned income to families is producing some type of externality that is more than enough to offset any negative responses due to the pure income effect from said transfer. One explanation, suggested by Alzúa et al. (2013), is that mothers may work more due to the CCT if their children increase school attendance, because this either increases their leisure time, or creates lost income from child labor.

This explanation would imply that the effects on schooling are still relevant, even with school attendance being around 90% before the policy change. It is not clear why this would impact only mothers within couples, but it is possible that single mothers suffer more negative pressure leading them to an overall negative response, while women in couples show an overall positive response.

Tabe 7 also shows that education attainment plays almost no role in these responses. Columns (6) and (7) show that the point estimates are very similar for groups with different education levels, and not very different from those found in columns (2), (3) and (5). This may be due to the high level of education that the sample in general exhibits. Only 7% of the women in the sample had zero to eight years of schooling in 2015, down from 22% in 1998. Similarly, while less than 50% had at least twelve years of schooling in 1998, by 2015 almost 72% were in this situation. Therefore, slicing the data to take a closer look at lower levels of education, as in columns (6) and (7) of Table 7, does not seem necessary in this case (and will not be done for other outcomes).

[Table 8]

[Table 9]

However, since we only observe a positive response for women in couples, there may be another explanation for it. We are not seeing the entirety of the couple's labor supply, while we are seeing the entirety of single mothers' labor supply. Therefore, it is possible that the couple's labor supply is not increasing due to treatment, and what we are seeing is the rearranging of the work load due to the change in the CCT. In this case we would observe an effect on complementary labor supply in these women's families. Table 9 seems to confirm this theory, showing that while women ages 25 to 50 in couples increase their labor force participation, their spouses reduce average unconditional working hours. This can be further rationalized by taking into account that the probability of working extra hours in this population, at 29%, was 8 percentage points higher than the sample average in 2006. Still, the reason why these couples require the change in the welfare program to rearrange their labor supply is not completely clear.

Neither of these results is completely novel. Foguel & Barros (2010), for Brazil, and Skoufias & Di Maro (2008), for Mexico, find small positive employment effects for women, even though they dismiss them on account of being too small. Alzúa et al. (2013), Galiani & McEwan (2013), and Skoufias & Di Maro (2008), find some negative estimates for Mexico, Honduras, and Nicaragua, even though most times they cannot reject the null, or if they can, the effect is lost over time. However, this is the first time that these results are found to be significant, and relevant in the long-term.

Not everyone will find it optimal to leave the labor force due to treatment. When the benefits are relatively small, as the SUF is, leaving work might not be a realistic option to most, but some workers might still be able to alter their working hours. Table 8 shows responses for average weekly working hour, attributing zero hours to mothers that did not work. This variable seems mostly unaffected by the policy, except for the case of women ages 25 to 50 in a couple. This subgroup shows a significant reduction of 0.3 hours of work a week, that is a decline of 1.6% from their 2006 baseline. The policy seems to have a much larger effect on this outcome for the spouses of these women, outcome shown in the following table. Table 9 shows an overall decline of 0.77 hours, 2.3% of the baseline for the treated, with the larger response being that of the spouses of women 25 to 50, that nevertheless only represents a marginally larger reduction of 2.7% from their 2006 baseline.

We can see that mothers already working are lowering their working hours more significantly, in Table 10. We again observe that being single or young, and especially being single and young, makes women susceptible to the policy change, but now having a lower educational attainment also factors in. In this case, some self-selection issues may cloud the table's results, as more productive people choose to work, leading them to maybe lowering their hours, as they do not need to work as much as the less productive workers. Nevertheless, the results seem to follow more closely the analysis done for labor force participation than what self-selection on productivity considerations would predict. In particular we might have expected significant results for other groups in the case of self-selection, and maybe a larger point estimate for people that do not finish high school. Overall, these results suggest and intensive margin response to treatment by single mothers, accentuated by their age, together with some self-selection, as all but one of the estimates is negative.

This response is expected and reasonable. Single mothers are very likely to be reliant on own work income for their subsistence. This naturally limits their ability to stop working, specially when considering a transfer that is far from enough to sustain a family. Some mothers may be able to rely in their parents, which would allow them to leave the labor force, but others, maybe even most, will have no choice of leaving the labor force, but can certainly work a few less hours a week if they receive a small cash transfer every month. This explanation would also fit with the fact that younger mothers show stronger responses to treatment.

[Table 10]

This reduction in working hours by workers could be explained at least in part by a negative effect on extra hours, which I define as working over 50 hours a week, with results in Table 11. Overall, probability of working extra hours goes down by one percentage point, but since most of these women do not work extra hours, this represents a reduction of almost 14% of the treated group's 2006 baseline. Mothers in the age range 18 to 24 are the most affected and at the same time less likely to work extra hours, meaning their probability of working extra hours experiences a fall of 27% of their 2006 baseline do to treatment. Table 11 overall shows a similar image to what we have seen for other outcomes.

[Table 11]

To complete the picture, Table 12 shows effects on wages, that to some extent follow a similar pattern as observed in prior results, with more pronounced increases for the more responsive groups.

The estimates from Table 12 are large, in particular those for young mothers. However, this table no longer shows only the same pattern as previous tables, but includes a generalized increase, suggesting higher reservation wages and self-selection issues may be important. The story seems to be that these effects are larger for the least productive workers. To confirm this I ran a quantile regression, Table 13 shows that the coefficients are indeed larger for lower percentiles. A t-test also shows that $\beta_{0.2}$ is statistically different from $\beta_{0.8}$ at 90% significance.

It is unlikely that the SUF may be raising equilibrium wages for the economy, given its size relative to wages (4% of the minimum wage in 2015). However, it is reducing labor supply for some groups in the extensive margin. Therefore, it is not unreasonable to believe that the people that abandoned the labor force were likely less productive than those that remained, increasing the averages in that way. This would explain why the wage responses are larger for the more responsive to treatment and for the least productive. Meantime, the generally positive wage response for all groups could be related to higher reservation wages motivated by the transfer.

This is not the first time that CCTs are related to wage increases, Alzúa et al. (2013) finds the same effect for Mexico's CCT program, albeit only for men in benefiting households.

[Table 12]

[Table 13]

VIII Conclusions

This paper provides the first evidence of significant distortions created by CCT programs in the labor market. I show here than these programs have both negative and positive labor supply externalities.

The most significant effects are being experienced by young mothers, between 18 to 24. This is reasonable, as this group is more likely to consider the SUF a more important source of income. It is also a concern, as this is a critical time for these women's future. Deciding to dely their entering the labor market, or to diminish their exposure to it, can have long lasting effects on their lifetime earnings and general career prospects.

Older single mothers experience a marginal negative effect on their labor supply, possibly driven by people reducing their over time hours. Although it is possible to see this effect as a 'positive' (as in desirable) externality, the problem is that this is not the objective of the program. If the government wants people to reduce overtime hours, it could establish a policy possibly more efficient, with the ability to reach men and women, with and without children.

Women with couples on the other hand experience similar reductions in over time work probability, but also an increase probability of labor force participation, a positive externality on the extensive margin. This could result from some rearrangement of labor between couples, or another vehicle that the current analysis fails to elucidate.

In the coming years research could look for similar effects on other countries. Mexico has today a much higher secondary enrollment that it had in 1997 for example, and PROGRESA tends to deliver much larger transfer with respect to household consumption than the SUF does.

Progress needs to be made on studying other distortions as well. The incipient research on CCTs distortions has concentrated in labor supply, as this study itself. However, my results suggest that young mothers may be particularly affected by this type of welfare program. It would be interesting to see whether this demographic is not reacting to the CCT by changing their education choices, fertility timing, and even family composition.

References

Alzúa, M. L., Cruces, G., & Ripani, L. (2013). Welfare programs and labor supply in developing countries: experimental evidence from latin america. *Journal of Population Economics*, *26*(4), 1255–1284.

Attanasio, O., Battistin, E., Fitzsimons, E., & Vera-Hernandez, M. (2005). How effective are conditional cash transfers? evidence from colombia.

Banerjee, A. V., Hanna, R., Kreindler, G. E., & Olken, B. A. (2017). Debunking the stereotype of the lazy welfare recipient: Evidence from cash transfer programs. *The World Bank Research Observer*, *32*(2), 155–184.

Bertrand, M., Duflo, E., & Mullainathan, S. (2004). How much should we trust differences-in-differences estimates? *The Quarterly journal of economics*, *119*(1), 249–275.

De Brauw, A., Gilligan, D. O., Hoddinott, J., & Roy, S. (2015). Bolsa família and household labor supply. *Economic Development and Cultural Change*, *63*(3), 423–457.

Fiszbein, A., & Schady, N. R. (2009). *Conditional cash transfers: reducing present and future poverty*. The World Bank.

Foguel, M. N., & Barros, R. P. d. (2010). The effects of conditional cash transfer programmes on adult labour supply: an empirical analysis using a time-series-cross-section sample of brazilian municipalities. *Estudos Econômicos (São Paulo)*, *40*(2), 259–293.

Galiani, S., & McEwan, P. J. (2013). The heterogeneous impact of conditional cash transfers. *Journal of Public Economics*, *103*, 85–96.

Garganta, S., & Gasparini, L. (2015). The impact of a social program on labor informality: The case of auh in argentina. *Journal of Development Economics*, *115*, 99–110.

Gertler, P. (2004). Do conditional cash transfers improve child health? evidence from progresa's control randomized experiment. *American economic review*, *94*(2), 336–341.

Herrera, R., Larrañaga, O., & Telias, A. (2010). *La ficha de protección social* [Work Document].

Irarrázabal, I., Candia, A., Castro, R., Codina, G., Delgado, R., Herrera, R., ... Valdés, S. (2010). *Comite de expertos ficha de protección social* [Work Document].

Maluccio, J., & Flores, R. (2005). *Impact evaluation of a conditional cash transfer program: The nicaraguan red de protección social.* Intl Food Policy Res Inst.

Ministerio de Desarrollo Social. (1999). *Encuesta CASEN 1998.*

Ministerio de Desarrollo Social. (2001). *Encuesta CASEN 2000.*

Ministerio de Desarrollo Social. (2004). *Encuesta CASEN 2003.*

Ministerio de Desarrollo Social. (2007). *Encuesta CASEN 2006.*

Ministerio de Desarrollo Social. (2010). *Encuesta CASEN 2009.*

Ministerio de Desarrollo Social. (2012). *Encuesta CASEN 2011.*

Ministerio de Desarrollo Social. (2014). *Encuesta CASEN 2013.*

Ministerio de Desarrollo Social. (2016). *Encuesta CASEN 2015.*

Ribas, R., & Soares, F. V. (2011). Is the effect of conditional transfers on labor supply negligible everywhere?

Schultz, T. P. (2004). School subsidies for the poor: evaluating the mexican progresa poverty program. *Journal of development Economics*, *74*(1), 199–250.

Skoufias, E., & Di Maro, V. (2008). Conditional cash transfers, adult work incentives, and poverty. *The Journal of Development Studies*, *44*(7), 935–960.

Subsecretaría de Seguridad Social. (2018). *Estadísticas anuales, 2016.* Retrieved from `https://www.suseso.cl/608/w3-propertyvalue-10364.html`

World Bank. (2018). The state of social safety nets 2018. *Washington, DC: World Bank. doi:10.1596/978-1-4648-1254-5. License: Creative Commons Attribution CC BY 3.0 IGO*.

World bank open data. (2018). Retrieved from `https://data.worldbank.org/`

Table 1: SUF benefit per cause, by year

Year	**SUF**	**Growth**
1998	$3,025	-
2000	$3,310	4.60%
2003	$3,716	3.93%
2004	$3,797	2.18%
2005	$3,930	3.50%
2006	$4,126	4.99%
2007	$5,393	30.71%
2008	$5,765	6.90%
2009	$6,500	12.75%
2010	$6,776	4.25%
2011	$7,170	5.81%
2012	$7,744	8.01%
2013	$8,626	11.39%
2014	$9,242	7.14%
2015	$9,899	7.11%

Figure 1: SUF is liberated from its budget and doubles its reach

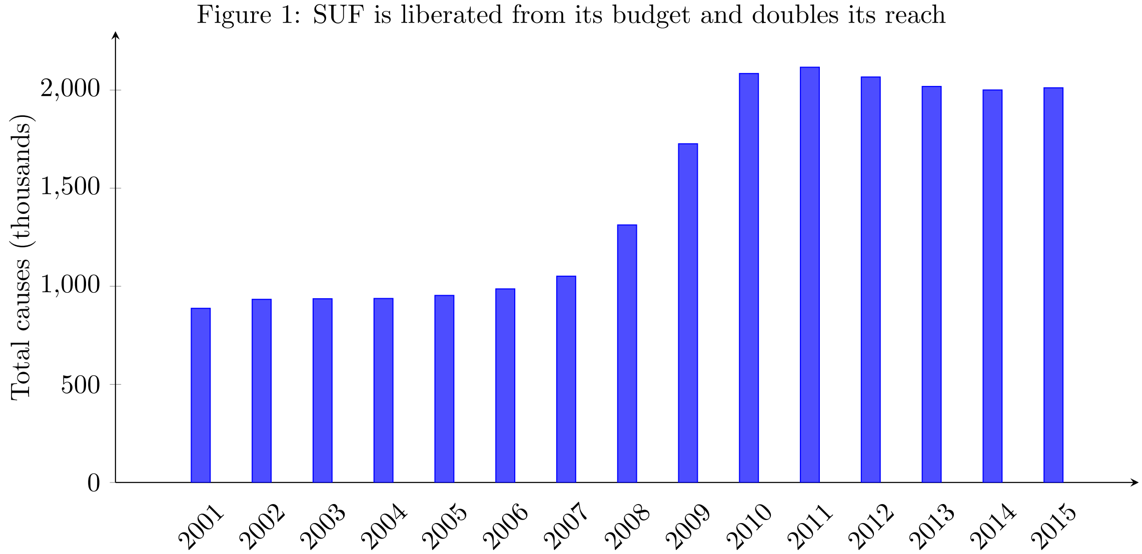

Figure 2: Mother's Labor Force Participation

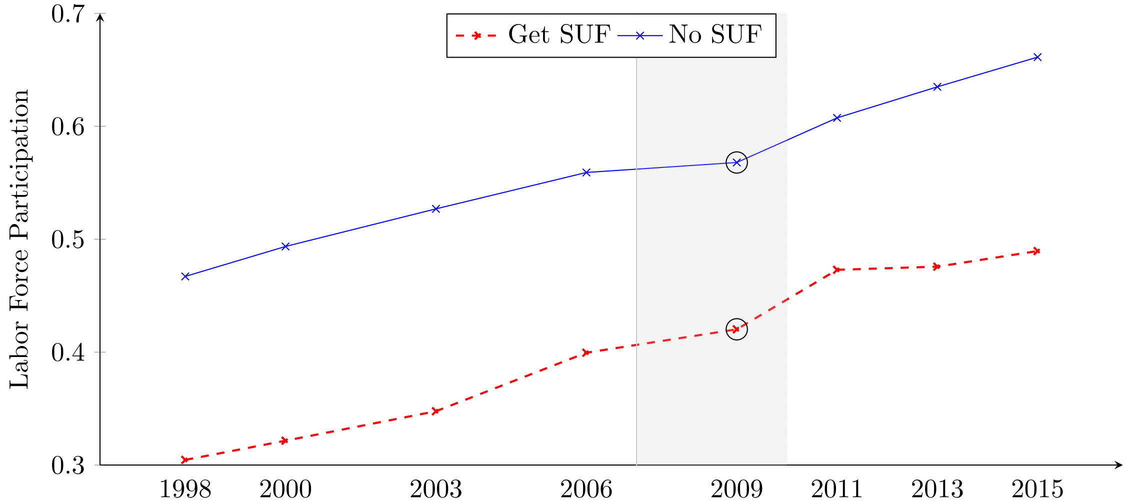

Figure 3: Probability of Receiving SUF by Schooling level

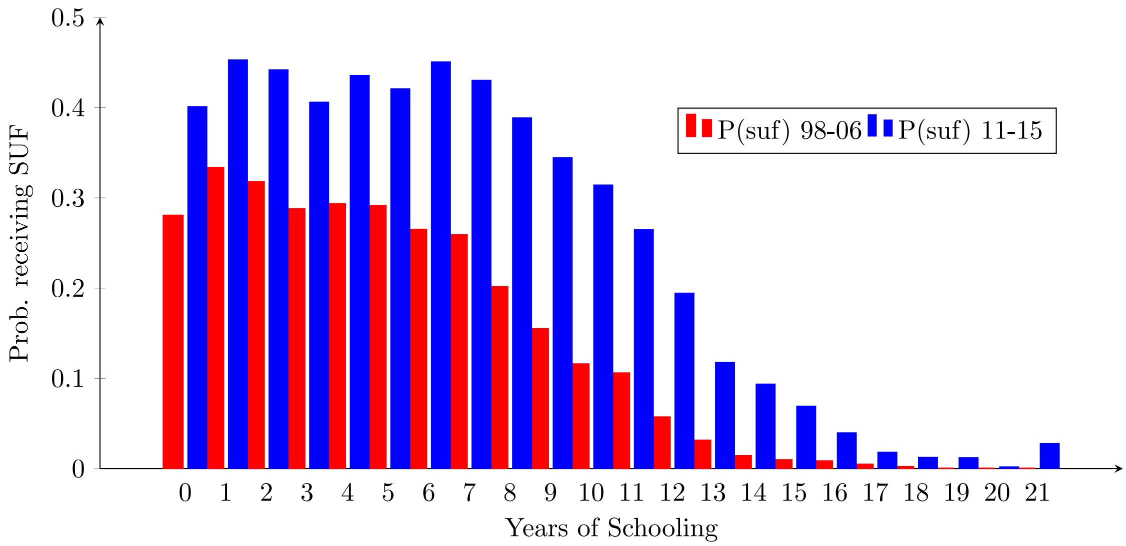

Figure 4: Labor Force Participation - Not mothers v. Mothers

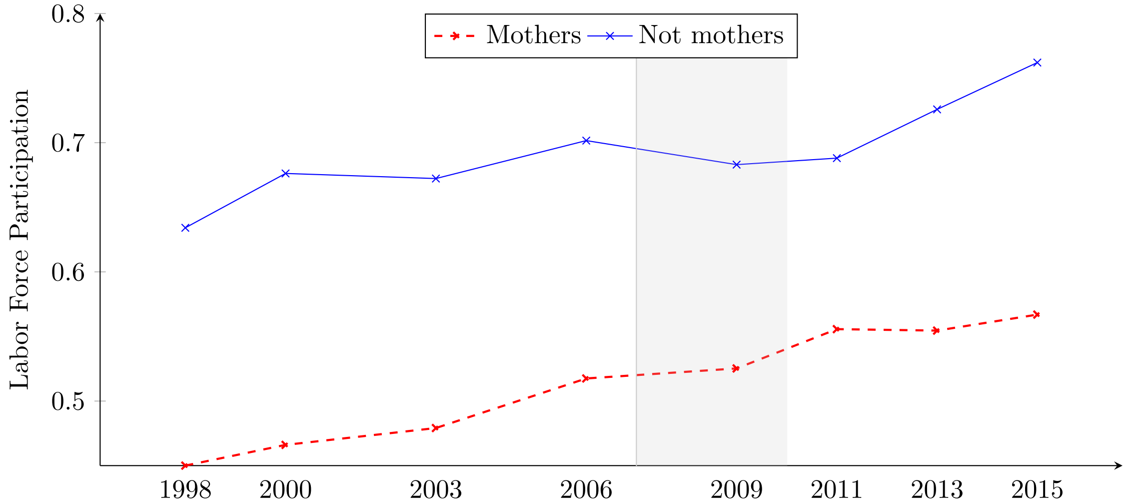

Figure 5: Labor Force Participation - Not mothers v. Mothers, 0-11 years of school

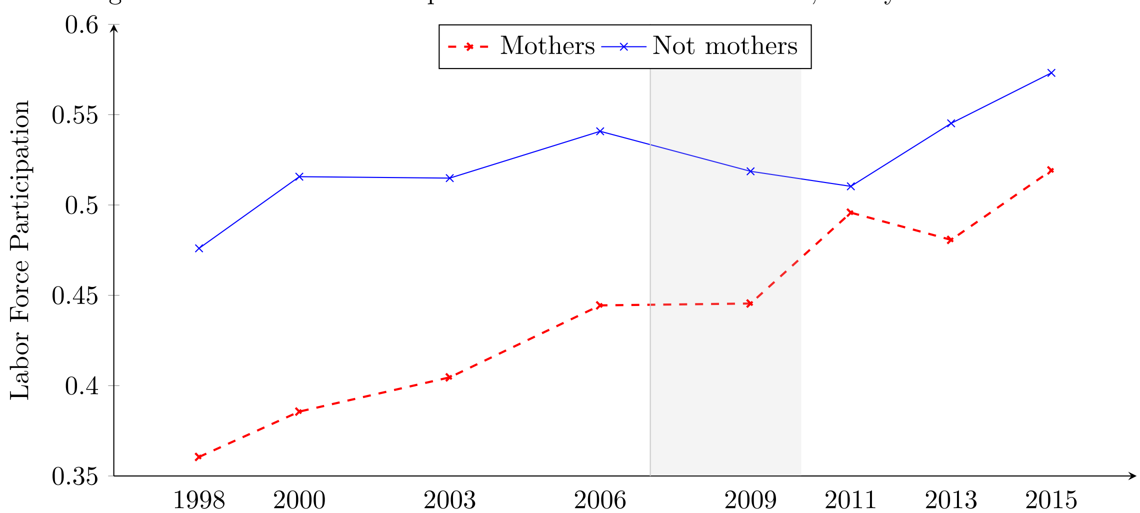

Table 2: SUF benefits and Family Income

Year 2015	**SUF/Income**	**0.2<SUF/income<1**	**SUF≥income**
General	7.5%	14.9%	10.7%
Age 18-24	8.2%	20.3%	26.2%
House guest	9.6%	25.6%	31.7%

The first column shows average value of SUF subsidy in terms of work income
The second column shows, for SUF recipients with positive income, what percentage of them gets over 20% of their income via the SUF
The third column shows, for all SUF recipients, what percentage gets more income through the SUF than through work

Table 3: Sample General Statistics

Year	Obs	Age	Years Educ.	# children	First Mom	% Single	% SUF	LF partic.	Work Income	Work Hours
1998	35,095	36.9	10.0	2.07	24.1	21.4	11.2	44.7	658,369	17.0
2000	46,677	37.0	10.3	2.02	24.1	22.2	11.0	47.3	588,017	18.5
2003	47,703	37.6	10.6	1.98	24.3	23.6	11.4	50.5	544,443	17.7
2006	48,479	38.3	10.7	1.94	24.6	26.5	10.5	54.0	525,382	20.1
2009	43,506	38.9	11.0	1.90	24.8	29.4	13.3	54.5	512,965	19.2
2011	54,256	38.8	11.2	1.83	25.1	33.6	19.7	57.8	480,057	20.4
2013	39,985	38.9	11.5	1.79	25.3	35.6	20.5	60.0	425,274	21.4
2015	47,095	39.0	11.8	1.77	25.4	35.9	18.9	62.6	412,465	23.2

Table 4: SUF recipients' General Statistics

Year	Obs	Age	Years Educ.	# children	First Mom	% Single	% SUF	LF partic.	Work Income	Work Hours
1998	5,851	33.9	7.2	2.46	22.5	24.7	100	30.4	216,858	9.5
2000	10,223	34.1	7.5	2.31	22.7	27.6	100	32.0	183,378	10.1
2003	10,844	34.4	7.8	2.23	22.8	28.9	100	34.7	191,780	8.9
2006	9,885	35.0	8.1	2.17	23.2	31.4	100	39.8	197,561	11.6
2009	9,110	35.0	9.1	2.02	23.2	35.7	100	41.7	244,490	11.6
2011	12,708	35.0	9.5	1.95	23.5	40.3	100	46.9	209,973	13.4
2013	9,686	35.6	9.6	1.92	23.8	41.4	100	47.2	198,267	14.2
2015	10,745	35.6	9.9	1.95	23.7	40.0	100	48.7	183,421	14.7

Table 5: Subample General Statistics - Schooling 0 - 11

Year	Obs	Age	Years Educ.	# children	First Mom	% Single	% SUF	LF partic.	Work Income	Work Hours
1998	22,419	38.0	7.2	2.20	23.8	20.0	17.8	35.1	328,255	13.0
2000	30,439	38.1	7.4	2.14	23.8	21.3	18.1	37.7	307,067	14.2
2003	29,273	38.9	7.5	2.09	24.1	22.1	19.7	40.2	268,866	13.3
2006	27,685	40.2	7.6	2.04	24.6	24.4	18.2	43.7	293,880	15.8
2009	22,956	40.6	7.7	1.98	24.9	27.4	21.1	43.5	275,008	14.3
2011	23,068	40.9	7.8	1.93	25.1	30.4	31.4	47.7	250,821	15.7
2013	15,267	41.4	7.9	1.90	25.5	33.2	33.8	47.6	224,383	16.3
2015	16,315	41.5	8.0	1.86	25.6	33.2	33.0	51.1	216,189	17.4

Table 6: Descriptive Statistics for treatment/control

Year	Obs	Age	Years Educ.	# children	First Mom	% Single	% SUF	LF partic.	Work Income*	Work Hours*
Treatment										
1998	31,969	35.1	10.2	2.08	23.2	21.0	11.8	45.6	686,844	43.3
2006	43,159	36.3	10.9	1.96	23.7	26.5	11.2	54.7	528,650	40.8
2015	40,025	36.2	12.0	1.80	24.1	36.4	20.7	63.5	422,429	39.9
Control										
1998	3,495	34.4	11.0	-	-	35.4	0.7	62.8	882,660	45.3
2006	5,050	34.7	11.8	-	-	35.7	1.0	69.6	734,406	43.5
2015	7,109	34.5	13.1	-	-	35.5	1.4	75.8	550,901	41.3

*refers to values for mothers working at least 1 weekly hour

Table 7: Results for Labor Force Participation

	Regression:						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
treated	0.003	0.008*	-0.017**	0.004	-0.006	0.010	-0.011
	54.7%	*48.0%*	*41.3%*	*49.8%*	*33.1%*	*37.4%*	*35.2%*
treated×Single		-0.015**					
		73.3%					
treated×25-50			0.006^{+}				
			56.3%				
treated×HS				0.002			
				72.2%			
treated×18-24×Single					-0.021*		
					50.8%		
treated×25-50×Couple					0.011**		
					49.2%		
treated×25-50×Single					-0.012*		
					78.5%		
treated×inc. HS×Single						-0.020*	
						66.7%	
treated×HS×Couple						0.011*	
						56.5%	
treated×HS×Single						-0.015**	
						77.6%	
treated×inc. HS×25-50							0.002
							45.4%
treated×HS×18-24							-0.011*
							45.1%
treated×HS×25-50							0.004
							64.8%
Observations				308,993			

*** significant at 0.001, ** significant at 0.01, * significant at 0.05, + significant at 0.1. HS stands for High School. In *italics*, below each coefficient, is the group's baseline for 2006. All regressions control for whether individuals have work experience, whether she is family head, whether her family is primary in the household, whether she is married, year of survey, age, family size, neighborhood, and years in current job.

Table 8: Results for weekly Working Hours

	Regression:				
	(1)	(2)	(3)	(4)	(5)
treated	-0.005	-0.042	0.264	-0.311	1.043
	20.2	*17.6*	*13.2*	*18.3*	*10.3*
treated×Single		-0.232			
		27.6			
treated×25-50			-0.069		
			21.1		
treated×hs diploma				0.185	
				27.2	
treated×18-24×Single					-0.489
					16.7
treated×25-50×Couple					-0.309*
					18.2
treated×25-50×Single					-0.105
					30.1
Observations			308,993		

*** significant at 0.001, ** significant at 0.01, * significant at 0.05, + significant at 0.1
In *italics*, below each coefficient, is the group's baseline for 2006.
All regressions control for whether individuals have work experience, whether she is family head, whether her family is primary in the household, whether she is married, year of survey, age, family size, neighborhood, and years in current job.

Table 9: Results for weekly Working Hours of Spouse

	Regression:				
	(1)	(2)	(3)	(4)	(5)
treated	0.072	-0.621	2.409	0.148	3.267
	33.5	*45.5*	*23.4*	*33.6*	*43.7*
treated×Single		-			
treated×25-50			-0.415*		
			34.7		
treated×hs diploma				-0.156	
				33.0	
treated×18-24×Single					-
treated×25-50×Couple					-0.037
					45.7
treated×25-50×Single					-
Observations			308,993		

*** significant at 0.001, ** significant at 0.01, * significant at 0.05, + significant at 0.1
In *italics*, below each coefficient, is the group's baseline for 2006.
All regressions control for whether individuals have work experience, whether she is family head, whether her family is primary in the household, whether she is married, year of survey, age, family size, neighborhood, and years in current job.

Table 10: Results for Working Hours conditional on working (logs)

	Regression:				
	(1)	(2)	(3)	(4)	(5)
treated	-0.013	-0.011	-0.014	-0.036*	0.047
	40.8	*40.1*	*40.1*	*40.9*	*39.3*
treated×Single		-0.022			
		42.0			
treated×25-50			-0.018*		
			40.8		
treated×hs diploma				-0.008	
				40.5	
treated×18-24×Single					-0.065+
					40.7
treated×25-50×Couple					-0.026*
					40.1
treated×25-50×Single					-0.017
					42.2
Observations			126,404		

*** significant at 0.001, ** significant at 0.01, * significant at 0.05, + significant at 0.1
In *italics*, below each coefficient, is the group's baseline for 2006.
All regressions control for whether individuals have work experience, whether she is family head, whether her family is primary in the household, whether she is married, year of survey, age, family size, neighborhood, and years in current job.

Table 11: Results for the probability of working Extra hours, for workers

	Regression:				
	(1)	(2)	(3)	(4)	(5)
treated	-0.010*	-0.007	0.011	-0.022*	0.028
	13%	*12.3%*	*11.6%*	*15.0%*	*8.9%*
treated×Single		-0.018*			
		14.6%			
treated×25-50			-0.016**		
			13.2%		
treated×hs diploma				-0.002	
				8.5%	
treated×18-24×Single					-0.002
					13.6%
treated×25-50×Couple					-0.016*
					12.4%
treated×25-50×Single					-0.021**
					14.7%
Observations			126,404		

*** significant at 0.001, ** significant at 0.01, * significant at 0.05, + significant at 0.1
In *italics*, below each coefficient, is the group's baseline for 2006.
All regressions control for whether individuals have work experience, whether she is family head, whether her family is primary in the household, whether she is married, year of survey, age, family size, neighborhood, and years in current job.

Table 12: Results for Hourly Wage (logs), for workers

	Regression:				
	(1)	(2)	(3)	(4)	(5)
treated	0.038***	0.035*	0.117**	0.075**	0.009
	$2,517	*$2,774*	*$1,385*	*$1,663*	*$1,607*
treated×Single		0.046**			
		$2,048			
treated×25-50			0.035**		
			$2,602		
treated×hs diploma				0.024+	
				$4,500	
treated×18-24×Single					0.252***
					$1,214
treated×25-50×Couple					0.043**
					$2,831
treated×25-50×Single					0.027
					$2,152
Observations			126,404		

*** significant at 0.001, ** significant at 0.01, * significant at 0.05, + significant at 0.1
In *italics*, below each coefficient, is the group's baseline for 2006. All regressions control for whether individuals have work experience, whether she is family head, whether her family is primary in the household, whether she is married, year of survey, age, family size, neighborhood, and years in current job.

Table 13: Results for Hourly Wage (logs), for workers - Quantile regression

	τ	β	s.e.
treated	0.2	0.068**	0.022
	0.4	0.059**	0.018
	0.6	0.050*	0.022
	0.8	0.014	0.027

*** significant at 0.001, ** significant at 0.01, * significant at 0.05, + significant at 0.1