Identification issues in the Public/Private wage gap with an application to Italy

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Abstract

This paper reviews some of the standard assumptions imposed to estimate the average public/private wage gap, namely random sorting and possible selection of the sector. There are two contributions to the existing literature. One is a better understanding of the identified parameters: standard estimators identify a *local* effect (LATE), which in general cannot be generalized to the entire population, as is almost always done. One is a departure from untestable hypotheses made by standard approaches, although at the cost of losing point identification. This is the first paper employing bounds in this literature. The technique is applied to Italy. For compliers, LATE estimates a wage advantage from public sector of 50% for women and 25% for men. These returns are within the most narrow bounds, although data are consistent even with a much smaller gap (10% for women, 6% for men).

JEL classification: J31, J38, C26

Keywords: public/private wage gap, bounds, instrumental variable

*I am grateful to Erich Battistin, Aureo de Paula, Cristina Gualdani, Enrico Rettore, Santiago Pereda, Jeffrey Wooldridge ... Replication files and additional results will be available at the webpage: http://sites.google.com/site/domdepalo/ The views expressed in this paper are those of the authors and do not imply any responsibility of their institution. Corresponding address: Domenico Depalo, Banca d'Italia, Economics and Statistics Department, Via Nazionale, 91 - 00184 Rome (Italy), Tel.: +39-06-4792 5989, e-mail: domenico.depalo@bancaditalia.it

1 Introduction

The interest in the public/private wage gap enjoyed a renewed interest during the recent economic recession, when some countries cut public sector wages (either in nominal or real terms) in an attempt to restore their fiscal positions. Understanding 1) whether a wage gap in favour of the public sector workers still exists with respect to the private sector counterparts, 2) under what circumstances and 3) how large it is are key questions for policy makers and researchers.

This paper tackles these issues proposing two contributions to the existing literature: the first is a better understanding of the point identification based on standard techniques; the second is a different approach, never investigated before in this literature, that uses only credible hypotheses met in the data. To this aim, I estimate bounds instead of single points.

The incredibly large existing literature on the public-private wage gap typically employs standard techniques without questioning the underlying hypotheses. Very few papers discuss the plausibility of such assumptions and even less cast doubts on (at least some of the) conclusions. Almost always, the choice is between sorting based on observable or unobservable (to the researcher) characteristics, with a preference for the latter over the former. Seminal papers imposed the assumption of independence between sector of employment and outcome (selection at random or ignorable). However, whether the employee works in the private or in the public sector can be the result of a individual utility maximization, thus the independence assumption might be unduly restrictive and accordingly has been removed in a number of studies (Dustmann and van Soest (1998) is probably the most complete treatment of this issue). When the sorting is based on unobservable characteristics, in general the wage gap can be identified only for specific sub-populations. This has never been emphasized before in this literature. Moreover, when assumptions necessary to implement standard approaches are not verifiable, it may be preferable to maintain only weaker hypotheses consistent with the data, even though the estimated parameter takes the form of a range of values ('bounds'). The more homogeneous the parameter within the population, the smaller the range.

Bounds are becoming increasingly popular for empirical studies. The methodological research initiated by Manski (1990) aims at relaxing strong, often untestable, hypotheses that allow point identification. However, it is only since recently that the advantage of relaxing undue assumptions is properly weighted against the disadvantage of having a set of admissible values for the parameter of interest instead of a single point.[1] One of the greatest merits of bounds is the clear connection between the structure imposed to the data through assumptions, credibility of results that follow and precision of the conclusions that may be drawn (where the smaller the set of the estimated effects, the higher the precision). To the best of my knowledge, this paper is the first application of bounds in the public/private wage gap literature.

Using point identification methods, in almost all developed countries a positive average wage gap is estimated in favour of the public sector workers, although with notable cross-country heterogeneity (Giordano et al. (2011)). When possible sorting is considered, the pay gap usually increases even by 30 percent for men and more for women.

In this paper I focus on Italy, which is a particularly interesting case to analyze because in 2010 a wage freeze for public sector was introduced for the period 2011-16 (Law 78/2010 and the late modifications). Consistent with the existing literature, I find a wage advantage for public sector workers as large as 5% for men and 15% for women imposing random selection. If some sorting mechanism is at work, the pay gap is much larger, above 25% for men and about 50% for women, a size comparable to previous studies on Italy (see Depalo and Giordano (2011) for a review of studies and an update of estimates). Using bounds greatly improves the picture. Standard estimates are close to the upper bounds, although data are also consistent with a smaller pay gap (6% for men and 10% for women), which is still larger than that estimated under ignorable selection, at least for men. It should be clear that, although wide bounds may be unpleasant for the policy maker, who typically prefers a single number summarizing everything, large bounds reflects the importance of heterogeneity in the working population (Horowitz and Manski (2000)). Not only are upper and lower bounds informative, but also their 'distance' is.

The paper is organized as follows. In Section 2, I briefly present a motivating example that shows how critical may be the random sorting assumption. I then analyze the techniques that will be used in the empirical application (Section 3) focusing on their advantages and disadvantages.

[1] Although the wording reflects the conventional wisdom, I do not believe that a range is a 'disadvantage' per se.

After a brief description of the data in Section 4, I apply the methods in Section 5. In Section 6 I offer some conclusions.

2 A motivating example

With only few exceptions (e.g., Holmlund (1993); Forni and Giordano (2003)), the existing literature in this field is mainly empirical in its nature. Even though this paper is not an exception, a motivating example may be of help to introduce the approaches adopted in the following sections and to interpret the results.

A worker may work in the public or in the private sector. The status is mutually exclusive. Early studies on the pay gap made the implicit assumption that workers are indifferent between the two sectors, so that the choice is made at random. In a more realistic setting, coherent with the Roy (1951) model, workers decide the employment sector that maximizes their utility. Heckman and Honore (1990) provide further generalizations of the original model. Most important, this breaks down the hypothesis of independence between sector and wage and requires an appropriate empirical approach that is analyzed in Section 3.

The maximization may depend on complex mechanism, including the non-monetary private benefit B associated to the job the worker does (see Gregory and Borland (1999); Lausěv (2014) for surveys). The benefit is unobservable to the researcher but the existing literature thinks of it as a broad definition of motivation, risk aversion and similar attitudes. For example, if B is a dichotomous indicator for motivated vs non-motivated workers to work in the public sector, then the probability to work in the public sector is higher for the former than for the latter group. Associated to benefits there are opportunity costs: continuing with the example of motivation, if the ability of the worker is high, the opportunity cost to join the public sector (the public competition to be admitted) would be lower and the individual utility will be higher. The interpretation in terms of cost-benefit analysis will be of much help to interpret the results and will be pushed further in Section 5.

3 Empirical strategy

In this section I describe the empirical strategies used in Section 5. To reduce notation, but without loss of generality, I do not explicitly condition on observable characteristics; however, everything should be conditioned on them. In contrast to the existing literature on public/private wage gap, I find convenient to consider the sector of employment as a treatment. Borrowing from that literature, a better understanding of what quantities are identified and under which conditions is immediate (Imbens and Wooldridge (2009)). This greatly improves over existing results. Define y the wage and $y_d = y(D)$ the wage a worker earns in sector $d \in D$, an indicator equal to 1 for public sector and 0 for private sector. The ultimate goal of the analysis is the evaluation of

$$\begin{aligned} \Delta_y &= E[y_1] - E[y_0] \\ &= \{E[y_1|D=1]\,P(D=1) + E[y_1|D=0]\,P(D=0)\} \\ &- \{E[y_0|D=1]\,P(D=1) + E[y_0|D=0]\,P(D=0)\}. \end{aligned} \tag{1}$$

If we had the opportunity to observe the outcome under both treatment status for the same individual, the estimation would be straightforward. This is the approach in Disney and Gosling (2008). However, in general for each workers we can observe either y_0 or y_1. In these situations, the key issue is recovering the wage in the unobservable status.

3.1 Standard approach

Under ignorable selection, sector sorting is not an issue (i.e., $D \perp (y_0, y_1)$), therefore $E[y_d|D=0] = E[y_d|D=1]$ and substituting in eq. 1 it follows that $\Delta_y = E[y_1|D=1] - E[y_0|D=0]$. This restriction implies that an OLS of wage on treatment indicator is consistent for the wage gap, provided the wage setting in the two sectors is equal up to a location shift (Imbens and Wooldridge (2009)).

If workers sort on the basis of their unobservable preferences, the OLS is an inconsistent estimator for the wage differential. Solving this drawback has been central in the existing literature. Standard approaches involve a IV estimator, based on a variable Z, called instrument, that affects the decision of sector, but not wage. To formalize the role of the instrument, define potential wages as $y(Z, D)$ and treatment as $D(Z)$, respectively. The decision mechanism is a flexible threshold crossing model

$$D = \mathbf{1}(s(Z, v) > 0), \tag{2}$$

with v a disturbance and $\mathbf{1}(i > 0)$ an indicator function taking value 1 if $i > 0$. Within this framework it is possible to identify a *local* average treatment effect (LATE) as proposed in Imbens and Angrist (1994) and Angrist et al. (1996). Under suitable conditions, notably monotonicity (such that an increase in the level of the instrument does not decrease the level of the treatment; formally, $D(1) \geq D(0)$ for all workers), the LATE is:

$$\begin{aligned} E[y(1) - y(0)] &= Pr((D(1) - D(0)) = 1)E[(y(1) - y(0))|(D(1) - D(0)) = 1] \\ E[(y(1) - y(0))|(D(1) - D(0)) = 1] &= \frac{E[y(1) - y(0)]}{E(D(1) - D(0))}. \end{aligned} \tag{3}$$

This is the treatment effect for *compliers*, i.e. the workers that are induced to work in the public sector by a change in the instrument. This quantity in general does *not* identify the average treatment effect for the entire population, because different instruments induce the change in the treatment for different subpopulations. As a consequence, using different instruments in general leads to different estimations of marginal return, each valid for different subpopulations. This well known result has not been emphasized before in the public/private wage gap literature, although it is key to correctly interpret the estimates. This is one contribution of this paper. Exploiting the local identification power of the estimator, Ichino and Winter-Ebmer (1999) propose an intriguing solution to bound the return on education in Germany. This represents a simple and important departure from point estimation.

Violation of monotonicity leads to a downward bias due to *defiers*, i.e. individuals that do the opposite with respect to what the instrument assignment would imply (Angrist et al. (1996)); violation of the exclusion restriction assumption induces a bias in unknown direction.

3.2 A different approach: bounds

All in all, standard approaches make strong hypotheses to recover the wage under the unobservable status and point identify the treatment effect. When these hypotheses fail, it is worth relaxing them. Typically this comes at the cost of losing point identification. Using basic statistical tools, Manski (1990) introduced a different perspective identifying a set of admissible marginal effects that depend on the underlying assumptions. Stronger assumptions on the unobserved components narrow the bound. A virtue of the approach is that hypotheses are clearly stated, so that one may check *i)* whether they are credible or not, and *ii)* whether some more structure may be imposed or not. In the simplest analysis, it is only required that the support $y \in [k_0, k_1]$, so that the bounds to the treatment derive directly from eq. 1 as:

No assumption bounds:

$$\begin{aligned} \text{lower:} \quad & [E[y_1|D=1]\,P(D=1) + k_0\,P(D=0)] - [k_1\,P(D=1) + E[y_0|D=0]\,P(D=0)] \\ \text{upper:} \quad & [E[y_1|D=1]\,P(D=1) + k_1\,P(D=0)] - [k_0\,P(D=1) + E[y_0|D=0]\,P(D=0)] \end{aligned} \tag{4}$$

The width of these bounds, obtained as the difference between the upper and the lower bound, is equal to $(k_1 - k_0)$, i.e. the larger the admissible values the larger the width. This is the first, not really satisfactory, indicator of heterogeneity in the population.

Workers may sort in the public sector. A situation where each person's wage function is higher in the public sector than in the private is consistent with the monotone treatment response (MTR; Manski and Pepper (2000)); it implies that $D = 1 \Leftrightarrow y_1 \geq y_0$ *for all workers* (Manski (1990)).[2]

Under MTR, the bounds to the treatment are

MTR:

$$\begin{aligned} \text{lower:} \quad & [E[y_1|D=1]\,P(D=1) + k_0\,P(D=0)] - E[y_0|D=0] \\ \text{upper:} \quad & E[y_1|D=1] - [k_0\,P(D=1) + E[y_0|D=0]\,P(D=0)]. \end{aligned} \tag{5}$$

[2] Manski and Pepper (2000) introduce also the monotone treatment selection (MTS) assumption. It implies that those who work in the public sector have a weakly higher mean wage function than those who work in the private sector. MTR and MTS can be exploited together (the empirical application is run imposing also this assumption; the interested reader will find it on my website).

The width of these bounds depends crucially on the distance between the largest admissible value of the wage and the unobservable outcomes. The reduction of this width with respect to the *no assumption bounds* may be understood as the gain from this specific assumption.

Although MTR is consistent with the few existing theoretical models on the pay gap, its validity *for all workers* may not be innocuous and accordingly has been relaxed in the existing literature that is exploited later in the paper. For example, by adding assumptions related to the selection mechanism, one may further shrink the bounds. Shaikh and Vytlacil (2011), hereby SV, impose 1) that $E[s(1,v)] \geq E[s(0,v)]$ or vice-versa, i.e. the treatment is monotone in the instrument although in an unknown direction –consistent with the idea that workers more motivated to work in the public sector are also more likely to work in this sector than in the private–, and 2) the rank similarity (Chernozhukov and Hansen (2005)). SV show that if $E[y|Z=1] > E[y|Z=0]$, the bounds are:

$$\begin{aligned} &SV: \\ &\text{lower:} \quad E[y_1|Z=1] - E[y_0|Z=0] \\ &\text{upper:} \quad E[y_1|D=1,Z=1]\,P(D=1|Z=1) + k_1\,P(D=0|Z=1) \\ &\qquad -E[y_0|D=0,Z=0]\,P(D=0|Z=0) - k_0\,P(D=1|Z=0). \end{aligned} \tag{6}$$

With respect to MTR, SV bounds are *i)* sign defined, because if the lower bound is positive, then the upper bound will be "more" positive (or vice versa, if the upper bound is negative the lower bound will be "more" negative), *ii)* narrower than bounds in Manski (1990), *iii)* less demanding than MTR, because the rank similarity allows the effect being positive for some workers and negative for others, and *iv)* agnostic about the direction of endogeneity of selection into treatment, which instead must be known a priori with MTR.

Furthermore, in the existing literature a wage gap in favour of the public sector is estimated at all quantiles of the wage distribution. This implies a form of stochastic dominance (the Positive Quadrant Dependence, PQD). Imposing this structure, Bhattacharya et al. (2008, 2012) show that if $E[y|Z=1] > E[y|Z=0]$, the bounds may further shrink to:

$$\begin{array}{rc} BSV: & \\ \text{lower:} & E[y_1|Z=1] - E[y_0|Z=0] \\ \text{upper:} & E[y_1|D=1,Z=1]\,P(D=1|Z=1) - E[y_0|D=0,Z=0]\,P(D=0|Z=0). \end{array} \tag{7}$$

The width of this bound may also be negative (due to the outcome of defiers), which would be a strong evidence against underlying hypotheses.

Related literature

An updated review of the literature on the public/private wage gap is in Giordano et al. (2011) and Lausěv (2014). A focus on Italy can be found in Depalo and Giordano (2011). Most of the early literature in this field imposes ignorable selection and estimates the gap by OLS. Seminal papers are mainly based on US data (Smith (1976)), although during the last 10-15 years increasing interest has been devoted to European countries (see Giordano et al. (2011) for a review). Evidence for Italy points towards a pay gap in favour of public sector workers of about 5-10% (e.g., Brunello and Dustmann (1997)). Considering the sorting mechanism nowadays is standard using mainly, but not exclusively, a IV technique. A complete treatment of selection mechanism can be found in Dustmann and van Soest (1998), where the participation in the labour market and the sector decisions are modeled for Germany. After the correction is made, results are consistent with a significantly higher pay gap than under ignorable selection. For Italy, Bardasi (1996) estimates a wage advantage in public sector up to 35% after correction, pooling men and women; Depalo and Giordano (2011) estimate a pay gap of 40% for women and lower at about 30-35 for men. The typical statements of papers using IV approach concern the entire population. As shown above, while these results are true for specific segments of the population, they might not hold for others.

Early treatment of bounds is in Manski (1990), whereas a general approach can be found in Manski (2003). Some recent fields where they have been used are health (e.g., Bhattacharya et al. (2012) for the effect of catheterization, Gundersen et al. (2012) or Gundersen and Kreider (2009) to evaluate the children's health), insurance (e.g., Kreider and Hill (2009)), schooling (e.g., Blanco et al. (2013)), wage inequality (e.g., Blundell et al. (2007)), crime (e.g., Manski and Pepper (2013)) or domestic violence (e.g., Siddique (2013)).

4 The data

The techniques in Section 3 are applied to data taken from the Survey on Household Income & Wealth (SHIW) which is conducted every two years by the Bank of Italy on a sample representative of the Italian population. The reference period is 2006–2012. The data contain information about a wide range of personal (age, gender, marital status, educational level, region of residency) and occupational (sector of economic activity, occupational level, firm size, part-time status, number of months worked in the year, average number of hours worked in a week) characteristics, wages (net of income and payroll taxes) and type of activity.

Three aspects that deserve attention are the definition of the public sector, the definition of wage, the existence of variables that may be used as appropriate instruments.

Following Lucifora and Meurs (2006), I define a public sector employee if his/her sector of activity is "public administration, defence, education, health and other public services". This definition is consistent with the figures from national accounts and allows a time series dimension. Nevertheless, it may induce some measurement errors, for example because workers of the health sector would be defined as public sector employees even though they work for private providers. In Table 1, I tabulate the share of public sector workers in total employment by year and gender. Public sector employment in Italy is sizable, with about 3.3 millions workers in 2012 down from 3.6 in 2006, and more widespread among women than among men. For women the share is relatively constant over time, whereas for men decreases from about 14% at the beginning of 2000s to 10% in the last available wave. From national accounts, the largest drop in the units of labour was recorded in 2010 and 2012, a trend that is found also in SHIW.

Having defined the public sector, a key aspect is related to the choice of the appropriate variable for wage comparison. Indeed, as the average number of hours worked in a week in the public sector

(35) is lower than that reported by workers in the private sector (40), using the monthly wage could underestimate the wage differential across sectors. Thus in our benchmark specification we approximate the hourly wage as $(YW/M)/(4*\bar{H})$, where YW is the yearly wage, M the number of months worked in the year, and $\bar{H}$ the average number of hours worked in a week. In Section 5 all the results are checked using also the monthly definition.

An advantage of SHIW over other dataset is the richness of variables that may be used as instruments. Appropriate instruments influence the decision to work in the public sector, but not wage. Existing literature emphasized the importance of motivation, ability and risk aversion. To this aim I investigate various possibilities, namely the sector of parents as an indicator for motivation, the education of parents for ability and a specific question for risk aversion.[3] When using family background indicators, I distinguish between fathers and mothers of the workers, in an attempt to gain flexibility to explain the sorting mechanism. The definition of the variables for individuals and their parents is identical.

Descriptive statistics

Descriptive statistics refer to employees aged 20–65, which I conventionally define as the working age population.

In Table 2, I report some relevant descriptive statistics for individual characteristics of the sample considered in this paper, pooling all the waves. Unconditionally, there exists a wage gap in favour of the public sector. Focusing on hourly wage, the gap is 25 percent for men and above 30 for women. Focusing on monthly wage, the gap is scaled down by 10 points, as a consequence that public sector workers on average work 5 hours less than private sector workers. The gender wage gap is substantially more pronounced in the private sector than in the public sector and for monthly than for hourly definition, as one would expect based on hours worked. At the same time, the variance of the wage distribution between the two sectors is roughly the same. I also investigated the minimum and the maximum wage by gender and sector, because the bounds are usually larger

[3] One question in the survey is "In managing your financial investments, would you say you have a preference for investments that offer: a) very high returns, but with a high risk of losing part of the capital; b) a good return, but also a fair degree of protection for the invested capital; c) a fair return, with a good degree of protection for the invested capital; d) low returns, with no risk of losing the invested capital."

when (k_0, k_1) are more faraway. With both definitions of wages, this measure of heterogeneity is higher for women than for men; for monthly definition, this heterogeneity is substantial for women but not for men.

Public sector workers are older than private sector workers and better educated (for women, lower education is achieved in more than 50% of the cases in the private sector and about 15 in the public sector; for men, the percentages are 50% and slightly less than 30%, respectively). Blu collars are almost in the same percentage between private and public sector for women, whereas in private sector the percentage is as large as twice that of the public sector for men; a huge difference is observed also in the statistics for managerial position which is larger by about 10 percentage points in the public sector than in the private. However, the greatest difference across the two sectors is in the percentage of the white collars, where the public/private proportion is 1 in 5 for both women and men.

As for variables used as instruments, 1 out of 4 of the public sector workers has the father working in the public sector at the same age of the interview, as opposed to those working in the private sector for whom the share is 1 in 10. Similarly, for public sector workers the share of high educated parents is higher than in the private sector. Finally, unconditional statistic show that individuals accepting only low risk are more in the private sector than in the public sector.

So far I have documented a pay gap by gender in favour of the public sector; the interesting question is whether it persists even after controlling for relevant characteristics determining the wage process. I do this in the next section.

5 Results

I begin the analysis with the classical approach under ignorability, soon relaxed to allow for sorting of the sector. Although there is nothing new in the latter approach, to the best of my knowledge, this is the first attempt to properly address a tight identification of the parameters in this field.

The novelty of this paper is the abandoning of the point identification in favour of the bounds. The data are consistent with 'some structure', therefore nonetheless I obtain economically relevant results.

5.1 Yet another estimate: standard approaches

Under random sector selection, there is a wage gap in favour of the public sector for men and women (Table 3). It is about 5 percent for men and 10 points higher for women. By year, the range is between 5–8 percent for men, and higher for women, in a range of about 10–15 percent. The gap is much erratic over time and a clear path cannot be identified. For women it decreases from more than 15 percent in 2006–2008 to 12–14 in 2010 and 2012; for men it is at about 7 percent in 2008 and 2012, and smaller in other waves. The gender gap (measured as the difference between the wage gaps for the sample of women and that of men) narrows from 13 percentage points in 2006 to 6 in 2012. Most important, these results are not consistent with our expectations based on the wage freeze in the public sector introduced by law at the end of 2010 (Law 78/2010 and those related) valid for the following 5 years. One possible reason is that the wages in the private sector diminished further because of the dramatic economic downturn.

The example of Section 2 suggests that workers may decide the sector upon a utility maximization. The sorting mechanism is unknown to the researcher: factors that influence the decision are thought to be motivation, ability and risk aversion. SHIW allows to explore them, using the parents' sector of occupation as an indicator of motivation (see Dustmann and van Soest (1998) and, for Italy, Bardasi (1996) and Brunello and Dustmann (1997)), the parents' education as a measure of ability (see Table 5 in Card (1999) for a review of studies using family background as instrument for it), and a question about a lottery as an indicator of risk aversion. While there is a well established tradition of using family background information as instrument for public sector sorting, with risk aversion it is doubtful that (with these data) the indicator is a good instrument satisfying the exogeneity and relevance assumptions; it is employed as a robustness check for other results and for completeness.

In Table 3, I impose the exclusion restriction assumption. Entries are the coefficients attached to the public sector indicator using the instrument defined in the row header, along with the related Hausman (1978) test and F-statistic from the first stage: in instance, 'Mother pub.' is the public/private pay gap using the sector of employment of the mother as instrument, the middle line is the relative Hausman (1978) test and the last entry is the first stage F-statistic from excluded instrument. I reject almost always the null hypothesis that OLS is a consistent estimator of the pay gap. This is evidence that the decision of the sector of employment is not random. The first stage F-statistic is about 20 or larger (Stock and Yogo (2002)) when using the parents' sector of occupation, namely the sector of the father, for the sample of men but somewhat smaller for women. Other instruments are less relevant to explain the sorting mechanism, as the first step F-statistic is small. This may be interpreted as if motivation is the major driver of the sector of working.[4]

In the spirit of Card (1999), the causal effect of working in the public sector can be viewed as a cost-benefit analysis with $\beta = B - C$, where B is individual return due, for example, to motivation, whereas C is the opportunity cost. The couple {B,C} defines benefits and costs for each individual, respectively. For simplicity, it is assumed that costs and benefits can take on only two values, high (H) or low (L).

With parents' sector of occupation used as instrument, I identify the pay gap for individuals {H,L}. Their ability is high (which makes low the cost to access the public sector), but they prefer to work in the public sector because their parents shape their utility (so the benefit is high). On the basis of the cost-benefit analysis, the return for these workers should be the highest. The estimated gap in favour of the public sector workers with father's sector of occupation is of magnitude much larger than under random sampling: point estimates are as large as 50% for women and 25% for men, pooling all the years. Quite interestingly, for women we estimate a turning point occurred between 2010 and 2012 (from 59 to 45%), whilst for men the gap increases over time.

Individuals of high ability can work in the public sector if highly motivated to do so, or in the private if not. Therefore, while the cost to access the public sector is low, nothing can be said about their benefit: instrumenting the sector with the high education of parents allows the estimation for individuals {H,L} or {L,L}. Being a weighted mean of individuals who enjoyed high and low benefits, I expect the associated β be lower than {H,L}. By the same arguments, low educational

[4]Moreover, I cannot reject the null hypothesis that instrument's coefficient is zero when using parents' sector of occupation to explain the mean wage function. On the contrary, for risk aversion I always reject the hypothesis at standard confidence level. This further reinforce the skepticism about the validity of the definition of risk aversion used as instruments, with these data.

attainment of parents identifies individuals {H,H} or {L,H}. Although the estimates are lower with educational attainment of the parents than with sector of occupation of the parents, the difference between the high and low educational attainment as instrument is small. I take this as evidence of homogeneity along this dimension and a supporting argument in favour of motivation (higher benefit) as the driving force to sort in the sector of employment.

The final dimension that I analyze is the risk aversion. The instrument allows to distinguish between individuals with high and low risk aversion. High risk averse workers pay attention to the lower occurrences of firings in the public sector, thus enjoy higher benefit from working in that sector, overall when with low ability (high cost to access), or {H,H}. Vice versa, workers of low risk aversion enjoy lower benefits from working in the public sector, but also high opportunity cost if they can earn more in the private sector, which is the case for the high ability workers, i.e. {L,H}. Hence LATE identified by low risk aversion should be the lowest among those considered, as indeed happens at least for men (for women the two coefficients are equal most of the times). It is worth stressing that this unobserved component is used only for completeness, because it is doubtful that this instrument is exogenous (a non constant-in-wage rate of risk aversion would break the exogeneity assumption; see Cocco et al. (2005) for a recent review) and certainly it has low relevance (almost always the first-stage F-statistic is smaller than 5 for men and women).

Since exogeneity may be defended only for family background indicators, I apply the method in Ichino and Winter-Ebmer (1999) considering only these dimensions. For women, the family background estimates a differential from 51% (father low educated) to 56% (mother worked in the public sector); for men, the range is between 21% (mother low educated) to 25% (father worked in the public sector). This signals substantial heterogeneity that bounds the least able and the most motivated workers, as predicted by a framework of cost-benefit analysis.

However, it should be understood that these bounds hold under maintained hypotheses, in particular on the wage in the unobservable status. Departures from these hypotheses have detrimental effects on the validity of the conclusions that may be drawn. This argument is the strongest motivation for a completely different approach that I exploit in the next section.

5.2 Yet another approach: bounds

The cost to remove untestable hypotheses, is to abandon point estimates in favour of bounds. For bounds where I need a finite support (k_0, k_1), I run in-sample statistics and set k_0 and k_1 equal to the minimum and the maximum observed in the data, respectively. Standard errors are obtained using the technique in Imbens and Manski (2004).

If one does not make any assumption beyond finite support, the data are consistent with wide bounds, estimating a huge disadvantage and a huge advantage (Table 4). With this approach, the width of the bounds is equal to $k_1 - k_0$. As expected from the descriptive statistics, it is larger for women than for men, thus pointing to a higher heterogeneity (defined as the difference between maximum and minimum wage) in the wages of women than in those of men. The economic theory may help shrink these bounds. Although the theoretical literature on the public/private wage gap is scant, all existing papers on developed economies predict that the public sector wage cannot be lower than private sector's (Lausěv (2014)). The reasons are related to the peculiarity of the public employer's objective function, which includes lobbying (Gunderson (1978)), electoral motives (Fogel and Lewin (1974)) or the exploitation by unions of the relatively inelastic labour demand curve in the public sector (Forni and Giordano (2003)). These arguments imply that $D = 1 \Leftrightarrow y_1 \geq y_0$ (or MTR). Imposing MTR, the bounds narrow by much (by half or so), but still *1)* are very large and *2)* say nothing about the *sign* of the gap (Table 5). As emphasized in Bhattacharya et al. (2012), with MTR one knows a priori that $y_0 \geq y_1$ for all individuals, thus the assumption imposes the answer to the question.

In fact, the data are consistent with more structure that that imposed so far. Invoking the MTR assumption plus *i)* the monotonicity in instrument and *ii)* the rank similarity, the gap estimated using the method in Shaikh and Vytlacil (2011) is much more informative. In particular, it is positive in all the years (Table 6). Because $E[y|Z = 1] > E[y|Z = 0]$, it follows that the upper bound with this approach is the same as in Manski (1990), therefore I consider only the lower bound. The lower bound of the gap is usually 10–12 percent for women and 5 or slightly higher for men. These estimates are about 5 times smaller than the LATE, estimated using parents' sector of occupation or the high educational achievement; the difference is even larger using low educational achievement of the parents. Recall that the presence of defiers implies a downward bias in the LATE, whereas the direction of the bias due to violation of other hypotheses is unknown. Since LATE is within bounds but faraway from the lower bound, it seems very unlikely that it is downward biased. Bounds allow to consider closer the heterogeneity in the wage generating process: for workers for whom the LATE assumptions on the wage generating process in the unobserved status are invalid, an appropriate estimate would be (somewhere towards) the lower bound. Thus, a single number summarizing everything is inappropriate to shed light on the mean generating process of the public/private wage gap: because of the heterogeneity of responses to treatment, and because of the strong assumptions on unobservable potential outcome that are necessary to obtain that number. Even though LATE is still within the possible ranges of the wage differential, the data are compatible with also a much smaller gap in favour of the public sector workers. At this point, one may be tempted to jump to the conclusion that the random allocation (OLS) is perfectly consistent with these new results and thus there is much ado about nothing in the literature about the importance of abandoning more sophisticated approaches. This would be simplistic and wrong. Indeed, in general the OLS estimates are smaller than the lower bound of SV method at least for men, thus pointing toward a non ignorable sector sorting. For women, the OLS estimates are within estimates of the SV bounds, in particular close to the lower bound.

The data are consistent even with even more structure, namely the PQD hypothesis (or first stochastic dominance), which allows to further tighten the bounds. Because the lower bound is the same as in SV, I now consider only the upper bound (Table 7). For women the upper bound of the gap is about 40 percent in favour of the public sector workers, whereas for men it is positive but still lower than that estimated for women (slightly higher than 30 per cent). For men the LATE estimates of Table 3 are within the bounds, whereas not always does this happens for women. What do these results suggest? In a paper using the same dataset (but other waves), Depalo and Giordano (2011) concluded that coefficients for women had to be viewed with caution. The estimates produced in this paper greatly enrich the picture because give a new credible measure of the gap for women and men: the wage gap in favour of women working in the public sector is in the range 10–40% with respect to their private sector counterpart, whereas for men is in the range 6–32%. Although a wide range may be unpleasant for the policy maker, it is of great interest to better understand the wage generating process in the two sectors and as a check for LATE (Nicoletti (2010)). Indeed, the width of the bound increases with the fraction of defiers and with the heterogeneity of the population. As LATE is closer to the upper bound in this analysis, for men and women, the presence of defiers is less likely. Our results rule out the possibility of random sector sorting for men; for women the mechanism is more complicated: for some, the results cast doubts on the faith in the LATE assumptions, for some, the random sorting is a correct hypothesis. I interpret this as if women pay attention to having a job, more than the sector of employment. This is consistent with the Italian labour market, where non-active women are about 50% in the age range considered in this paper, as opposed to 25% for men.

Moreover, using bounds instead of LATE or OLS it is possible to reconcile estimates to our expectations based on legislative provisions. Over time, for women the lower bound was about 12 percent in 2006 and went down to about 9 in 2012, although the pattern is not monotonic; as for the upper bound the pattern is much more striking with a monotonic decrease from about 45 percent to 39. For men the lower bound increased over time reaching the peak in 2010 (8 percent), but then it decreased to about 6 in 2012; as for the upper bound we estimate a monotonic increase from 27 percent to about 36. The inspection of the bounds helps much to understand where the legislation introduced in 2010 was more effective. For women and men the lower bound, which is consistent with expectations, was more affected than the upper bounds. Since the lower bound would be attained even though the PQD did not hold, one may argue that the wage freeze was more effective for the population of workers where PQD hypothesis is weaker. The existing literature on quantiles estimates a large gap at smaller quantiles, thus one may think that PQD is weaker at higher quantiles. Finally, it is worth mentioning that the width steadily increased over time, thus suggesting a always larger heterogeneity in the wage differential between private and public sector workers.

5.3 Some robustness checks

I run robustness checks to test whether results are driven by the decision to focus on hourly rather than on monthly wage definition and whether interesting differences emerge by age.

Monthly wage

As for monthly wage definition (Table 8), under random sampling the gap is smaller by 5–8 percentage points than with hourly definition: for women the wage advantage is as large as 8 percent pooling all the years (as opposed to 14 from hourly definition), whereas men are no longer at earning advantage (in 2006 there was a disadvantage by 4%). These point estimates are downward biased because do not consider the possible selection of the sample. In the spirit of a robustness check, I only consider the sector of the father as instrument (on my website, the interested reader will find the complete set of instruments and all the other results mentioned but not shown). The gap becomes about 30 percent for women and 7.5 for men. Hourly gap is about 20 percent higher than monthly gap and the difference is larger for women than for men. From bounds as in Bhattacharya et al. (2012), several aspects are worth emphasizing. First of all, the width is much smaller using monthly than hourly definition and the difference between the two definitions is larger for men (about 10 percentage points smaller with monthly than with hourly) than for women (5 or more). Second, both groups still enjoy a higher wage in the public sector than in the private sector as lower bounds are always positive. Third, for women most of the time LATE is within bounds but very close to the upper bound; in few cases it is higher than the upper bound. For men LATE is always within the bounds. Fourth, whilst for women the monthly lower bound is smaller than hourly lower bound by about 5 percentage point, it is about 10 for the upper bound; in the sample of men the difference of the lower bounds is inessential, whereas for the upper bound monthly definition is smaller by about 7 percentage points. An insight of the larger correction at the upper bound is obtained by looking at the distribution of hours worked. The difference in hours worked in the public and private sector at low quantiles of the hours distribution is larger than the difference at high quantiles. Since at low quantiles of the hour distribution the wage gap is higher than at high quantiles (i.e., it is the upper bound of the gap), considering monthly wage annihilate the wage difference and the larger correction at upper bound follows as a consequence.[5] Fifth, the mean difference of hours worked between public and private sector workers decreases over time between 2006 and 2010, although between 2010 and 2012 hours worked in the private sector decreases more than in the public. As a consequence, the turning point occurred in 2011 is not as sharp as it was with hourly definition: the lower bound is constant between 2010-12 as opposed to the upper bound which instead increases.

By and large, this robustness check confirms all the refinements over the existing literature that were found in Section 5.1-5.2.

Age

It has been argued that workers of younger age are more at wage advantage with respect to their private sector's counterparts because the Italian labour market is segmented. By splitting the sample based on age (less than 40 and greater than 40), I can check a possible form of dualism in the private sector labour market that may hurt younger workers. The hourly wage gap is higher for younger workers (not shown; available on the website) than for the oldest population, coherently with results in Depalo et al. (2015). The difference between the pay gap for the oldest and the youngest generations in the OLS is about 6 percentage points for women and 4.5 for men; with respect to the benchmark specification in Table 3, such a difference is symmetric about the benchmark (e.g., for women 3 more points for the youngest population; 3 less for the oldest).

When I allow for possible sorting in the public sector, it vanishes the wage gap in favour of oldest women who are induced to work in the public sector because their fathers worked in the public sector. However, the F-statistic from first stage is smaller than 10, thus the conclusion should be interpreted with caution. In contrast, for oldest men the gap is smaller than in the benchmark specification by 2.5%.

When I identify a set of wage gap instead of a single point, both OLS and LATE are within

[5] An example may help clarify this point. Let the monthly wages in the public and private sector be the same $w = w_G = w_p$, whereas the hours is $H_G = H$ in the public sector and $H_P = H + \epsilon$ in the private sector at low quantiles; $H_G = H + \epsilon$ and $H_P = H + 2\,\epsilon$ at high quantiles. It follows that the bounds are $[\frac{w\,\epsilon}{H+2\,\epsilon}; \frac{w\,\epsilon}{H+\epsilon}]$ with hourly definition, because $\frac{w}{H} - \frac{w}{H+\epsilon} = \frac{w\,\epsilon}{H+\epsilon} > \frac{w\,\epsilon}{H+2\,\epsilon} = \frac{w}{H+\epsilon} - \frac{w}{H+2\,\epsilon}$, and $[0, 0]$ with monthly definition, by construction. As a consequence, the correction is larger for upper bound than for lower bound.

bounds estimated as in Bhattacharya et al. (2008, 2012). However, the OLS is remarkably close to the lower bound, whereas for men LATE is indistinguishable from the upper bound. It confirms the benchmark analysis.

The width of the bounds is larger for women than for men (by 6.5 percentage points for the oldest population; the width for women is higher than 25 percentage points), still consistent with a larger heterogeneity in the former group than in the latter. Both the lower and the upper bound for the subsample of older workers is lower than in the benchmark case. Since the reduction of the upper bound is of a larger magnitude than for the lower bound, the smaller pay gap for the oldest generation is attributable to a larger difference at lower quantiles of wages, for which the pay gap from public sector is higher.

This robustness check supports the idea of a segmented labour market in Italy such that younger workers are underpaid in the private sector, overall at low wage levels.

6 Conclusions

A gap in favour of the public sector workers is estimated in (almost all) developed countries. Existing studies for Italy are in line with this finding. These results are valid under given assumptions. Unfortunately, underlying hypotheses are rarely spelled out and never questioned (to the best of my knowledge). This paper is the first tentative to shed light on what quantities of the public/private wage gap are identified and under what conditions. Italy is a interesting example to analyze in this context because the public sector employment is sizable, the wage bill is high, the country underwent a serious public finance difficulty during the latest economic crisis and the dozens existing papers on this issue estimate a large gap in favour of the public sector.

The classical approach would be consistent with a wage gap as large as 14% for women and about half for men; as soon as I allow for the possible sorting, the gap increases to above 50% for women and 25% for men. These results are those usually estimated in the existing literature (see Depalo et al. (2015) for a summary of the existing literature on the country). A first contribution of the paper is a better understanding of what parameter is identified: such a high gap is a *local* gap for individuals that are induced to work in the public sector because their fathers worked in the public sector (Imbens and Angrist (1994)). Using the method in Ichino and Winter-Ebmer (1999) the gap is heterogeneous across different subpopulations identified by the technique. The most motivated enjoy a larger gap with respect to the least able.

The novelty of this paper is to relax hypotheses that are questionable and untestable, preserving only those that are supported by the data. This comes at the cost of abandoning point identification in favour of bounds. By doing this I estimate a gap that is always higher than those imposing random sector sorting for men, whereas for women the mechanism is more complicated. The gap for compliers is close to the upper bound, although also a much smaller gap would be consistent with the data. In particular, for women the gap is consistent with a gap in the range 10–40%, for men 6–32%. As large as they are, these gaps seem much more credible than those obtained so far in the literature. The wide range should not be seen as unpleasant but simply as the measure of heterogeneity in the work force (Horowitz and Manski (2000)). Adding more structure, the researcher imposes hypotheses, more or less restrictive, often not met in the data. The cost of such assumptions in this study would overcome the benefits from a narrower range.

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Table 1: Evolution of public sector over time

Year	Women		Men		Total	
	Private	Public	Private	Public	Private	Public
2006	0.837	0.163	0.862	0.138	0.850	0.150
2008	0.844	0.156	0.869	0.131	0.856	0.144
2010	0.844	0.156	0.882	0.118	0.862	0.138
2012	0.848	0.152	0.893	0.107	0.870	0.130

Table 2: Summary statistics

Var.	Private					Public					Test
	Mean	SD	10th	50th	90	Mean	SD	10th	50th	90	
Women											
ln(Hour)	2.05	0.41	1.61	2.05	2.49	2.39	0.40	1.94	2.34	2.92	0.000
ln(Month)	6.93	0.49	6.34	6.99	7.42	7.22	0.38	6.82	7.26	7.60	0.000
Age	42.98	12.81	25.00	43.00	61.00	44.26	9.28	32.00	44.00	57.00	0.000
Basic ed.	0.15	0.35	0.00	0.00	1.00	0.01	0.12	0.00	0.00	0.00	0.000
Low ed.	0.40	0.49	0.00	0.00	1.00	0.16	0.37	0.00	0.00	1.00	0.000
High ed.	0.35	0.48	0.00	0.00	1.00	0.43	0.50	0.00	0.00	1.00	0.000
BA	0.10	0.31	0.00	0.00	1.00	0.39	0.49	0.00	0.00	1.00	0.000
Blu collar	0.18	0.38	0.00	0.00	1.00	0.13	0.34	0.00	0.00	1.00	0.000
White collar	0.13	0.33	0.00	0.00	1.00	0.73	0.44	0.00	1.00	1.00	0.000
Manager	0.01	0.11	0.00	0.00	0.00	0.09	0.29	0.00	0.00	0.00	0.000
Married	0.64	0.48	0.00	1.00	1.00	0.67	0.47	0.00	1.00	1.00	0.000
Mother pub.	0.09	0.29	0.00	0.00	0.00	0.14	0.35	0.00	0.00	1.00	0.000
Father pub.	0.14	0.35	0.00	0.00	1.00	0.23	0.42	0.00	0.00	1.00	0.000
Mother high ed.	0.19	0.39	0.00	0.00	1.00	0.23	0.42	0.00	0.00	1.00	0.000
Father high ed.	0.21	0.41	0.00	0.00	1.00	0.29	0.45	0.00	0.00	1.00	0.000
Mother low ed.	0.57	0.50	0.00	1.00	1.00	0.51	0.50	0.00	1.00	1.00	0.000
Father low ed.	0.53	0.50	0.00	1.00	1.00	0.41	0.49	0.00	0.00	1.00	0.000
Low risk	0.52	0.50	0.00	1.00	1.00	0.44	0.50	0.00	0.00	1.00	0.000
High risk	0.15	0.36	0.00	0.00	1.00	0.18	0.39	0.00	0.00	1.00	0.000
Men											
ln(Hour)	2.18	0.41	1.75	2.14	2.63	2.45	0.42	2.02	2.39	3.00	0.000
ln(Month)	7.24	0.40	6.82	7.22	7.70	7.41	0.41	6.99	7.39	7.82	0.000
Age	42.33	12.73	25.00	42.00	60.00	46.19	9.79	33.00	47.00	58.00	0.000
Basic ed.	0.09	0.29	0.00	0.00	0.00	0.02	0.13	0.00	0.00	0.00	0.000
Low ed.	0.45	0.50	0.00	0.00	1.00	0.25	0.43	0.00	0.00	1.00	0.000
High ed.	0.36	0.48	0.00	0.00	1.00	0.43	0.50	0.00	0.00	1.00	0.000
BA	0.10	0.30	0.00	0.00	0.00	0.30	0.46	0.00	0.00	1.00	0.000
Blu collar	0.35	0.48	0.00	0.00	1.00	0.14	0.35	0.00	0.00	1.00	0.000
White collar	0.13	0.33	0.00	0.00	1.00	0.62	0.49	0.00	1.00	1.00	0.000
Manager	0.04	0.19	0.00	0.00	0.00	0.18	0.39	0.00	0.00	1.00	0.000
Married	0.61	0.49	0.00	1.00	1.00	0.75	0.43	0.00	1.00	1.00	0.000
Mother pub.	0.08	0.27	0.00	0.00	0.00	0.10	0.30	0.00	0.00	0.00	0.000
Father pub.	0.12	0.33	0.00	0.00	1.00	0.27	0.44	0.00	0.00	1.00	0.000
Mother high ed.	0.16	0.36	0.00	0.00	1.00	0.17	0.38	0.00	0.00	1.00	0.707
Father high ed.	0.17	0.38	0.00	0.00	1.00	0.23	0.42	0.00	0.00	1.00	0.000
Mother low ed.	0.61	0.49	0.00	1.00	1.00	0.64	0.48	0.00	1.00	1.00	0.006
Father low ed.	0.57	0.50	0.00	1.00	1.00	0.53	0.50	0.00	1.00	1.00	0.000
Low risk	0.51	0.50	0.00	1.00	1.00	0.43	0.49	0.00	0.00	1.00	0.000
High risk	0.16	0.36	0.00	0.00	1.00	0.18	0.39	0.00	0.00	1.00	0.135

Table 3: Standard approaches: OLS & IV with various instruments

Gap	2006	2008	2010	2012	Pool
Women					
OLS	0.157 ***	0.161 ***	0.114 ***	0.139 ***	0.141 ***
Mother pub.	0.453 ***	0.606 ***	0.583 ***	0.555 ***	0.558 ***
Husman	14.402 ***	114.921 ***	118.722 ***	71.921 ***	281.255 ***
F-stat.	0.000	2.725	8.570	3.052	9.361
Father pub.	0.468 ***	0.532 ***	0.590 ***	0.447 ***	0.512 ***
Husman	19.731 ***	47.119 ***	111.417 ***	21.801 ***	157.858 ***
F-stat.	12.353	5.056	0.123	2.191	13.608
Mother High ed.	0.466 ***	0.602 ***	0.586 ***	0.537 ***	0.553 ***
Husman	15.614 ***	109.703 ***	119.969 ***	57.542 ***	255.724 ***
F-stat.	0.021	3.694	2.560	1.051	1.792
Father High ed.	0.429 ***	0.549 ***	0.596 ***	0.435 ***	0.512 ***
Husman	11.124 ***	58.990 ***	119.955 ***	19.536 ***	159.677 ***
F-stat.	5.277	0.780	0.044	1.218	1.430
Mother Low ed.	0.454 ***	0.616 ***	0.584 ***	0.533 ***	0.552 ***
Husman	12.125 ***	123.515 ***	117.892 ***	53.149 ***	248.025 ***
F-stat.	1.476	0.623	0.018	0.304	0.015
Father Low ed.	0.455 ***	0.540 ***	0.598 ***	0.426 ***	0.509 ***
Husman	17.124 ***	51.783 ***	119.446 ***	16.778 ***	152.767 ***
F-stat.	1.946	0.705	2.813	0.083	0.372
Low risk	0.376 ***	0.556 ***	0.567 ***	0.549 ***	0.519 ***
Husman	10.679 ***	152.408 ***	278.961 ***	137.738 ***	422.392 ***
F-stat.	3.745	2.833	4.800	0.000	7.474
High risk	0.370 ***	0.555 ***	0.567 ***	0.549 ***	0.518 ***
Husman	10.216 ***	149.879 ***	279.413 ***	138.506 ***	417.742 ***
F-stat.	0.048	1.337	0.581	0.003	0.014
Men					
OLS	0.024	0.070 ***	0.049 ***	0.079 ***	0.049 ***
Mother pub.	0.078	0.191 ***	0.345 ***	0.368 ***	0.227 ***
Husman	0.887	4.311 **	39.449 ***	44.430 ***	31.737 ***
F-stat.	0.082	0.395	2.262	5.600	0.136
Father pub.	0.137 **	0.229 ***	0.285 ***	0.369 ***	0.251 ***
Husman	3.122 *	8.379 ***	16.242 ***	49.071 ***	50.192 ***
F-stat.	9.140	18.865	54.307	17.547	85.744
Mother High ed.	0.075	0.175 ***	0.335 ***	0.368 ***	0.214 ***
Husman	0.825	2.629	31.233 ***	43.342 ***	23.979 ***
F-stat.	0.000	3.094	8.914	0.016	6.793
Father High ed.	0.144 **	0.253 ***	0.331 ***	0.325 ***	0.229 ***
Husman	3.679 *	9.286 ***	25.093 ***	25.602 ***	28.608 ***
F-stat.	0.702	0.068	5.304	3.472	1.612
Mother Low ed.	0.071	0.179 ***	0.356 ***	0.369 ***	0.217 ***
Husman	0.704	3.003 *	44.293 ***	43.281 ***	24.791 ***
F-stat.	1.504	0.935	0.006	0.989	1.176
Father Low ed.	0.145 **	0.253 ***	0.339 ***	0.328 ***	0.243 ***
Husman	3.601 *	9.223 ***	30.099 ***	27.117 ***	37.537 ***
F-stat.	0.743	0.061	0.011	2.714	0.245
Low risk	0.072	0.169 ***	0.266 ***	0.364 ***	0.205 ***
Husman	0.931	3.476 *	13.773 ***	69.660 ***	26.635 ***
F-stat.	3.061	9.661	2.131	0.555	9.559
High risk	0.090 *	0.182 ***	0.268 ***	0.360 ***	0.207 ***
Husman	1.768	4.434 **	14.095 ***	64.576 ***	28.482 ***
F-stat.	0.644	5.164	0.055	3.147	3.231

Notes: Weighted regressions. Variables denoted with * (**) [***] indicate statistical significance at the 10 (5) [1] percent level.

Table 4: Manski (1990) no assumption bounds - Various instruments

Gap	2006	2008	2010	2012	Pool
			Women		
			Mother pub.		
lower	-2.835 ***	-1.609 ***	-2.844 ***	-2.252 ***	-3.388 ***
upper	3.666 ***	2.195 ***	3.000 ***	2.577 ***	3.922 ***
			Father pub.		
lower	-2.741 ***	-1.639 ***	-2.917 ***	-2.319 ***	-3.417 ***
upper	3.599 ***	2.199 ***	3.043 ***	2.613 ***	3.938 ***
			Mother High ed.		
lower	-2.883 ***	-1.600 ***	-2.865 ***	-2.277 ***	-3.408 ***
upper	3.708 ***	2.200 ***	3.007 ***	2.599 ***	3.947 ***
			Father High ed.		
lower	-2.851 ***	-1.633 ***	-2.835 ***	-2.317 ***	-3.419 ***
upper	3.717 ***	2.225 ***	2.973 ***	2.646 ***	3.969 ***
			Mother Low ed.		
lower	-2.986 ***	-1.681 ***	-3.098 ***	-2.446 ***	-3.648 ***
upper	3.748 ***	2.295 ***	3.136 ***	2.725 ***	4.095 ***
			Father Low ed.		
lower	-2.819 ***	-1.652 ***	-2.912 ***	-2.368 ***	-3.455 ***
upper	3.752 ***	2.257 ***	3.012 ***	2.663 ***	4.018 ***
			Low risk		
lower	-2.756 ***	-1.626 ***	-3.126 ***	-2.479 ***	-3.544 ***
upper	3.613 ***	2.196 ***	3.245 ***	2.784 ***	4.060 ***
			High risk		
lower	-2.977 ***	-1.614 ***	-3.248 ***	-2.522 ***	-3.632 ***
upper	3.655 ***	2.104 ***	3.314 ***	2.807 ***	4.078 ***
			Men		
			Mother pub.		
lower	-2.940 ***	-1.975 ***	-2.575 ***	-2.116 ***	-3.103 ***
upper	2.575 ***	2.511 ***	2.860 ***	2.348 ***	3.047 ***
			Father pub.		
lower	-2.847 ***	-1.874 ***	-2.419 ***	-1.998 ***	-2.958 ***
upper	2.487 ***	2.409 ***	2.719 ***	2.263 ***	2.917 ***
			Mother High ed.		
lower	-2.963 ***	-1.941 ***	-2.611 ***	-2.120 ***	-3.112 ***
upper	2.600 ***	2.509 ***	2.895 ***	2.350 ***	3.064 ***
			Father High ed.		
lower	-2.960 ***	-1.949 ***	-2.609 ***	-2.146 ***	-3.121 ***
upper	2.601 ***	2.509 ***	2.900 ***	2.386 ***	3.074 ***
			Mother Low ed.		
lower	-2.882 ***	-1.968 ***	-2.645 ***	-2.110 ***	-3.102 ***
upper	2.480 ***	2.475 ***	2.904 ***	2.372 ***	3.019 ***
			Father Low ed.		
lower	-2.980 ***	-2.010 ***	-2.604 ***	-2.157 ***	-3.145 ***
upper	2.585 ***	2.530 ***	2.865 ***	2.357 ***	3.062 ***
			Low risk		
lower	-2.697 ***	-1.863 ***	-2.456 ***	-1.929 ***	-2.905 ***
upper	2.460 ***	2.479 ***	2.776 ***	2.258 ***	2.923 ***
			High risk		
lower	-2.743 ***	-1.941 ***	-2.544 ***	-2.038 ***	-2.992 ***
upper	2.469 ***	2.467 ***	2.789 ***	2.352 ***	2.958 ***

Notes: Weighted regressions. Variables denoted with * (**) [***] indicate statistical significance at the 10 (5) [1] percent level.

Table 5: Manski (1990) MTR bounds - Various instruments

Gap	2006	2008	2010	2012	Pool
			Women		
			Mother pub.		
lower	-1.303 ***	-0.801 ***	-1.903 ***	-1.392 ***	-1.938 ***
upper	1.347 ***	0.959 ***	1.624 ***	1.313 ***	1.633 ***
			Father pub.		
lower	-1.294 ***	-0.836 ***	-1.966 ***	-1.455 ***	-1.980 ***
upper	1.286 ***	0.937 ***	1.630 ***	1.305 ***	1.609 ***
			Mother High ed.		
lower	-1.328 ***	-0.796 ***	-1.931 ***	-1.417 ***	-1.958 ***
upper	1.357 ***	0.961 ***	1.614 ***	1.304 ***	1.631 ***
			Father High ed.		
lower	-1.321 ***	-0.819 ***	-1.930 ***	-1.446 ***	-1.979 ***
upper	1.353 ***	0.962 ***	1.579 ***	1.327 ***	1.626 ***
			Mother Low ed.		
lower	-1.439 ***	-0.825 ***	-2.122 ***	-1.541 ***	-2.137 ***
upper	1.314 ***	1.009 ***	1.643 ***	1.347 ***	1.642 ***
			Father Low ed.		
lower	-1.323 ***	-0.840 ***	-2.023 ***	-1.519 ***	-2.039 ***
upper	1.338 ***	0.963 ***	1.553 ***	1.297 ***	1.605 ***
			Low risk		
lower	-1.268 ***	-0.807 ***	-2.074 ***	-1.495 ***	-2.000 ***
upper	1.327 ***	0.955 ***	1.764 ***	1.440 ***	1.705 ***
			High risk		
lower	-1.274 ***	-0.730 ***	-2.152 ***	-1.504 ***	-1.974 ***
upper	1.425 ***	0.975 ***	1.812 ***	1.488 ***	1.784 ***
			Men		
			Mother pub.		
lower	-2.398 ***	-1.400 ***	-1.980 ***	-1.649 ***	-2.469 ***
upper	1.065 ***	0.753 ***	0.882 ***	0.761 ***	1.038 ***
			Father pub.		
lower	-2.337 ***	-1.348 ***	-1.899 ***	-1.580 ***	-2.382 ***
upper	0.997 ***	0.697 ***	0.806 ***	0.749 ***	0.966 ***
			Mother High ed.		
lower	-2.414 ***	-1.373 ***	-2.002 ***	-1.652 ***	-2.473 ***
upper	1.086 ***	0.795 ***	0.894 ***	0.753 ***	1.055 ***
			Father High ed.		
lower	-2.411 ***	-1.383 ***	-2.000 ***	-1.663 ***	-2.479 ***
upper	1.089 ***	0.790 ***	0.910 ***	0.809 ***	1.070 ***
			Mother Low ed.		
lower	-2.390 ***	-1.425 ***	-2.029 ***	-1.636 ***	-2.487 ***
upper	0.933 ***	0.658 ***	0.886 ***	0.786 ***	0.965 ***
			Father Low ed.		
lower	-2.432 ***	-1.430 ***	-2.016 ***	-1.679 ***	-2.504 ***
upper	1.057 ***	0.776 ***	0.865 ***	0.764 ***	1.040 ***
			Low risk		
lower	-2.224 ***	-1.333 ***	-1.930 ***	-1.515 ***	-2.347 ***
upper	1.003 ***	0.753 ***	0.797 ***	0.783 ***	0.970 ***
			High risk		
lower	-2.217 ***	-1.369 ***	-1.951 ***	-1.574 ***	-2.369 ***
upper	1.047 ***	0.729 ***	0.810 ***	0.943 ***	1.015 ***

Notes: Weighted regressions. Variables denoted with * (**) [***] indicate statistical significance at the 10 (5) [1] percent level.

Table 6: Shaikh and Vytlacil (2011) bounds - Various instruments

Gap	2006	2008	2010	2012	Pool
			Women		
			Mother pub.		
lower	0.121 ***	0.109 ***	0.122	0.115 ***	0.112 ***
upper	3.666 ***	2.195 ***	3.000 ***	2.577 ***	3.922 ***
			Father pub.		
lower	0.119 ***	0.077 ***	0.103 ***	0.091 ***	0.092 ***
upper	3.599 ***	2.199 ***	3.043 ***	2.613 ***	3.938 ***
			Mother High ed.		
lower	0.110	0.119	0.119 ***	0.114 ***	0.112 ***
upper	3.708 ***	2.200 ***	3.007 ***	2.599 ***	3.947 ***
			Father High ed.		
lower	0.131	0.105 ***	0.127 ***	0.124 ***	0.117 ***
upper	3.717 ***	2.225 ***	2.973 ***	2.646 ***	3.969 ***
			Mother Low ed.		
lower	0.036	0.126	0.039	0.081	0.019
upper	3.748 ***	2.295 **	3.136 ***	2.725 ***	4.095 ***
			Father Low ed.		
lower	0.143	0.106	0.121 ***	0.111 ***	0.116 ***
upper	3.752 ***	2.257 ***	3.012 ***	2.663 ***	4.018 ***
			Low risk		
lower	0.142 ***	0.096 ***	0.086	0.096	0.095 ***
upper	3.613 ***	2.196 ***	3.245 ***	2.784 ***	4.060 ***
			High risk		
lower	0.092	0.075 ***	0.021	0.041	0.052 ***
upper	3.655 ***	2.104 ***	3.314 **	2.807 ***	4.078 ***
			Men		
			Mother pub.		
lower	0.025	0.057	0.067	0.030	0.050 ***
upper	2.575 ***	2.511 ***	2.860 ***	2.348 ***	3.047 ***
			Father pub.		
lower	0.026	0.051 ***	0.076 ***	0.057	0.056 ***
upper	2.487 ***	2.409 ***	2.719 ***	2.263 ***	2.917 ***
			Mother High ed.		
lower	0.031	0.085 ***	0.063	0.026	0.057 ***
upper	2.600 ***	2.509 ***	2.895 ***	2.350 ***	3.064 ***
			Father High ed.		
lower	0.035	0.067 ***	0.067	0.031	0.054 ***
upper	2.601 ***	2.509 ***	2.900 ***	2.386 ***	3.074 ***
			Mother Low ed.		
lower	0.002	-1.968 **	0.032	0.039	0.006
upper	2.480 **	-0.015	2.904 ***	2.372 **	3.019 **
			Father Low ed.		
lower	0.006	0.030	0.037	-2.157 **	0.021
upper	2.585 **	2.530 ***	2.865 ***	-0.007	3.062 ***
			Low risk		
lower	0.158 ***	0.114	0.083 ***	0.131 ***	0.116 ***
upper	2.460 ***	2.479 ***	2.776 ***	2.258 ***	2.923 ***
			High risk		
lower	0.130 ***	0.093	0.050	0.123	0.092 ***
upper	2.469 ***	2.467 ***	2.789 ***	2.352 **	2.958 ***

Notes: Weighted regressions. Variables denoted with * (**) [***] indicate statistical significance at the 10 (5) [1] percent level.

Table 7: Bhattacharya et al. (2012) bounds - Various instruments

Gap	2006	2008	2010	2012	Pool
			Women		
			Mother pub.		
lower	0.121	0.109 ***	0.122 ***	0.115 ***	0.112 ***
upper	0.456 ***	0.428 ***	0.396 ***	0.403 ***	0.416 ***
			Father pub.		
lower	0.119 ***	0.077 ***	0.103	0.091 ***	0.092 ***
upper	0.447 ***	0.403 ***	0.387 ***	0.387 ***	0.401 ***
			Mother High ed.		
lower	0.110	0.119 ***	0.119 ***	0.114 ***	0.112 ***
upper	0.452 ***	0.437 ***	0.397 ***	0.401 ***	0.418 ***
			Father High ed.		
lower	0.131	0.105 ***	0.127 ***	0.124 ***	0.117 ***
upper	0.472 ***	0.431 ***	0.401 ***	0.418 ***	0.426 ***
			Mother Low ed.		
lower	0.036	0.126	0.039	0.081	0.019
upper	0.387 ***	0.461 **	0.343 ***	0.392 ***	0.351 ***
			Father Low ed.		
lower	0.143	0.106	0.121 ***	0.111 ***	0.116 ***
upper	0.495 ***	0.437 ***	0.404 ***	0.406 ***	0.430 ***
			Low risk		
lower	0.142 ***	0.096 ***	0.086	0.096	0.095 ***
upper	0.467 ***	0.415 ***	0.394 ***	0.403 ***	0.412 ***
			High risk		
lower	0.092 ***	0.075	0.021	0.041	0.052 ***
upper	0.412 ***	0.373 ***	0.344 **	0.388 ***	0.370 ***
			Men		
			Mother pub.		
lower	0.025	0.057	0.067	0.030	0.050 ***
upper	0.293 ***	0.331 ***	0.334 ***	0.327 ***	0.325 ***
			Father pub.		
lower	0.026	0.051 ***	0.076 ***	0.057	0.056 ***
upper	0.270 ***	0.310 ***	0.328 ***	0.362 ***	0.318 ***
			Mother High ed.		
lower	0.031	0.085	0.063	0.026	0.057 ***
upper	0.306 **	0.380 ***	0.335 **	0.319 ***	0.339 ***
			Father High ed.		
lower	0.035	0.067 ***	0.067	0.031	0.054 ***
upper	0.309 ***	0.375 ***	0.351 ***	0.361 ***	0.350 ***
			Mother Low ed.		
lower	0.002	-1.968 **	0.032	0.039	0.006
upper	0.234 *	-0.015	0.316 **	0.352 **	0.274 **
			Father Low ed.		
lower	0.006	0.030	0.037	-2.157 **	0.021
upper	0.269 *	0.343 ***	0.320 ***	-0.007	0.312 ***
			Low risk		
lower	0.158 ***	0.114 ***	0.083 ***	0.131 ***	0.116 ***
upper	0.367 ***	0.378 ***	0.322 ***	0.409 ***	0.358 ***
			High risk		
lower	0.130 ***	0.093	0.050	0.123	0.092 ***
upper	0.309 ***	0.309 ***	0.261 ***	0.510 *	0.315 ***

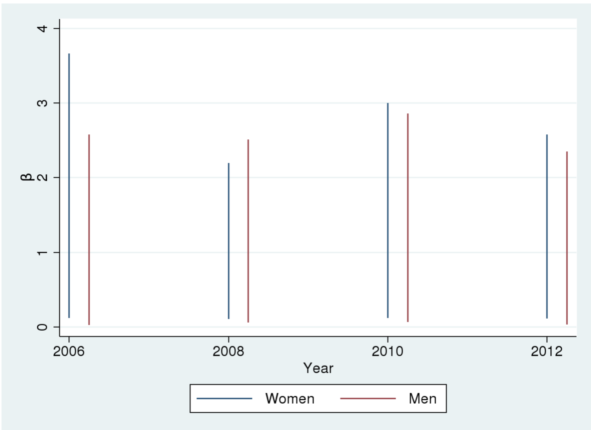
Notes: Weighted regressions. Variables denoted with * (**) [***] indicate statistical significance at the 10 (5) [1] percent level.

Table 8: Robustness check

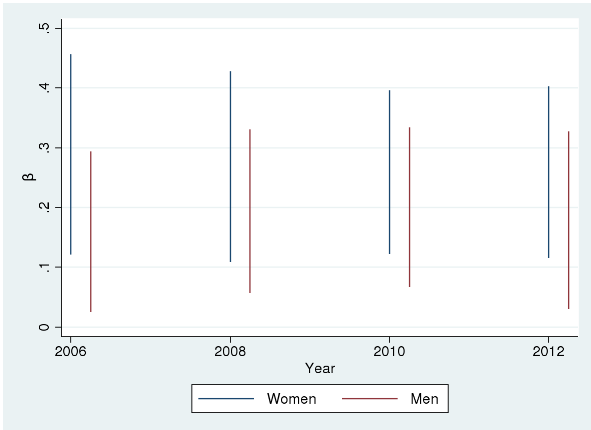
Gap	2006	2008	2010	2012	Pool
		Monthly wage definition			
		Women			
		OLS			
OLS	0.088 ***	0.095 ***	0.063 ***	0.089 ***	0.082 ***
		LATE			
Father pub.	0.010	0.212 *	0.427 ***	0.322 ***	0.281 ***
Husman	16.063 ***	1.155	76.855 ***	8.042 ***	21.103 ***
F-stat.	11.959	4.837	0.390	2.053	11.615
		Bhattacharya et al. (2012)			
lower	0.020	0.008	0.053	0.053	0.031
upper	0.284 **	0.285 **	0.307 ***	0.330 ***	0.299 ***
		Men			
		OLS			
OLS	-0.039 ***	0.004	0.000	0.001	-0.014 *
		LATE			
Father pub.	0.069	0.069 *	0.089 **	0.112 **	0.075 ***
Husman	2.940 *	3.327 *	4.480 **	4.621 **	13.976 ***
F-stat.	7.503	22.431	49.118	13.613	78.686
		Bhattacharya et al. (2012)			
lower	0.024	0.067 ***	0.072 ***	0.075 ***	0.061 ***
upper	0.156 ***	0.238 ***	0.241 ***	0.284 ***	0.229 ***
		Workers older than 40 years			
		OLS			
OLS	0.132 ***	0.125 ***	0.075 ***	0.119 ***	0.110 ***
		LATE			
Father pub.	0.547 ***	-0.228 ***	0.618 ***	-0.360 ***	-0.051
Husman	27.694 ***	18.049 ***	86.642 ***	46.016 ***	2.057
F-stat.	5.707	9.178	0.336	0.716	8.041
		Bhattacharya et al. (2012)			
lower	0.056	0.056	0.068	0.052	0.054 ***
upper	0.394 ***	0.356 ***	0.334 ***	0.346 ***	0.351 ***
		Men			
		OLS			
OLS	-0.007	0.023	0.037 *	0.067 ***	0.025 **
		LATE			
Father pub.	0.263 ***	0.256 ***	0.036	0.325 ***	0.234 ***
Husman	9.069 ***	5.825 **	0.000	12.819 ***	16.290 ***
F-stat.	3.896	1.658	56.334	6.792	44.789
		Bhattacharya et al. (2012)			
lower	-2.954 **	0.002	0.006	-2.118 **	0.005
upper	-0.000	0.220 *	0.244 *	-0.000	0.237 **

Notes: Weighted regressions. Variables denoted with * (**) [***] indicate statistical significance at the 10 (5) [1] percent level.

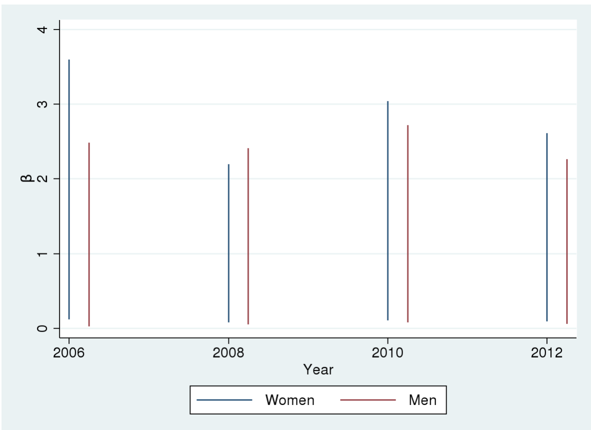
Figure 1: Plot of the estimates - Instruments: parents' sector of occupation



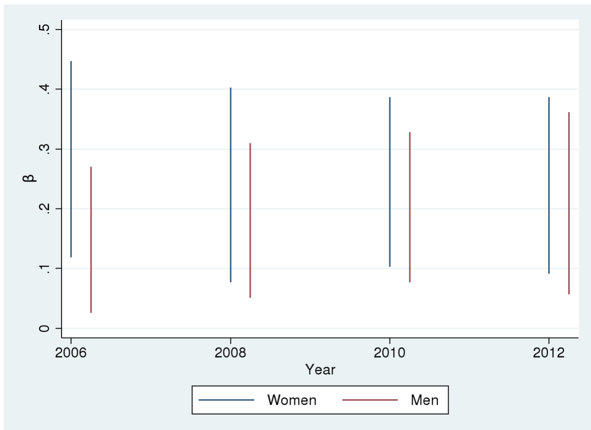
(a) SV - Mother pub.



(b) BSV - Mother pub.

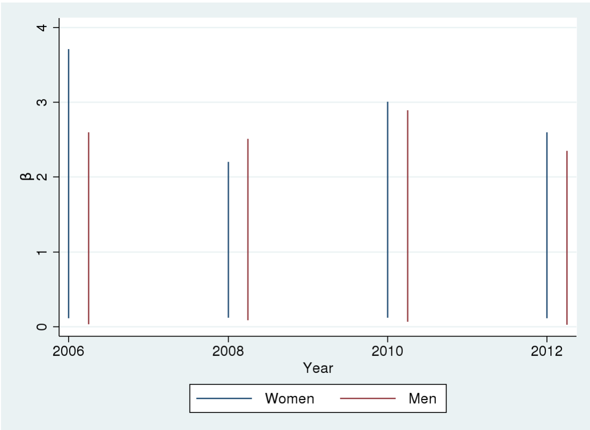


(c) SV - Father pub.

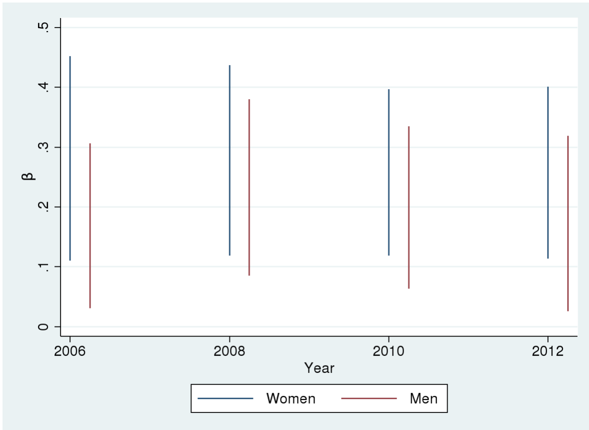


(d) BSV - Father pub.

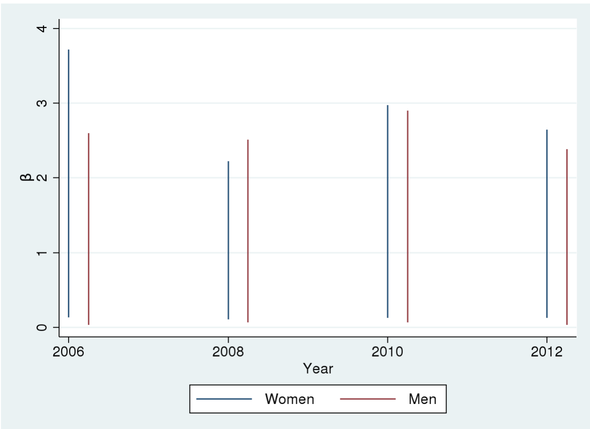
Figure 2: Plot of the estimates - Instruments: parents' education



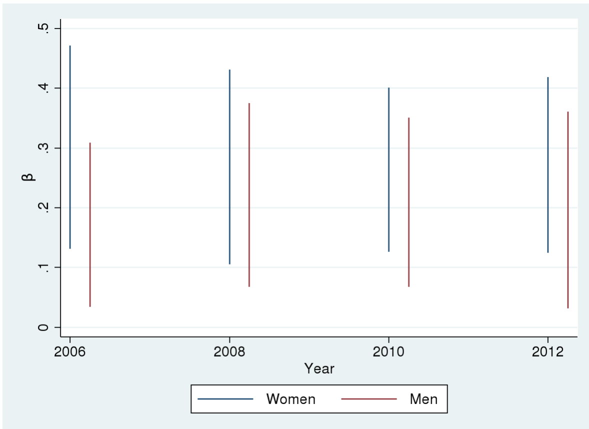
(a) SV - Mother High ed.



(b) BSV - Mother High ed.

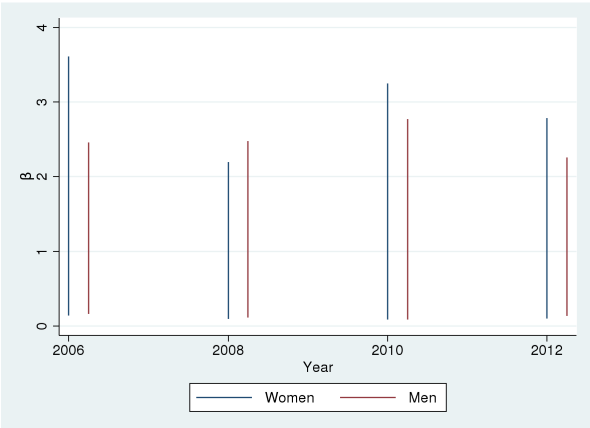


(c) SV - Father High ed.

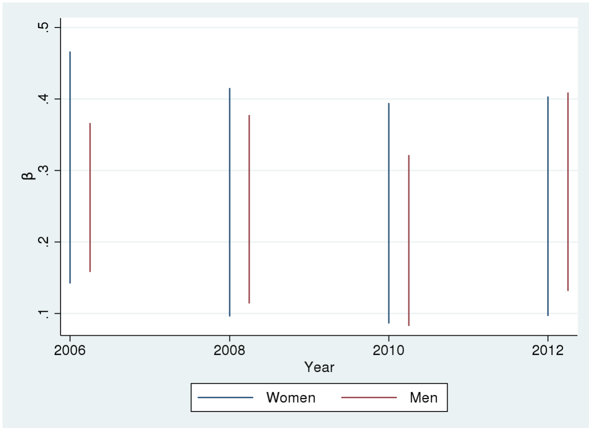


(d) BSV - Father High ed.

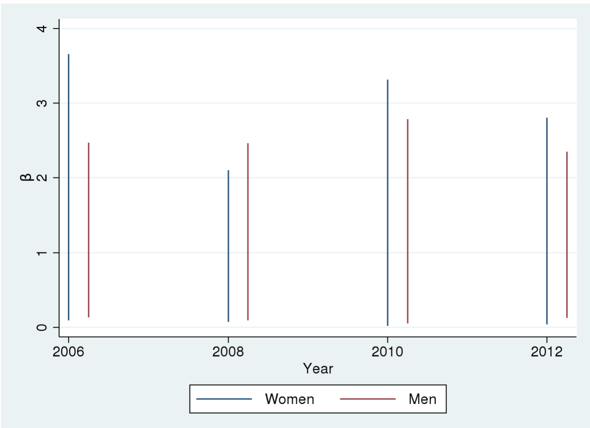
Figure 3: Plot of the estimates - Instruments: risk aversion



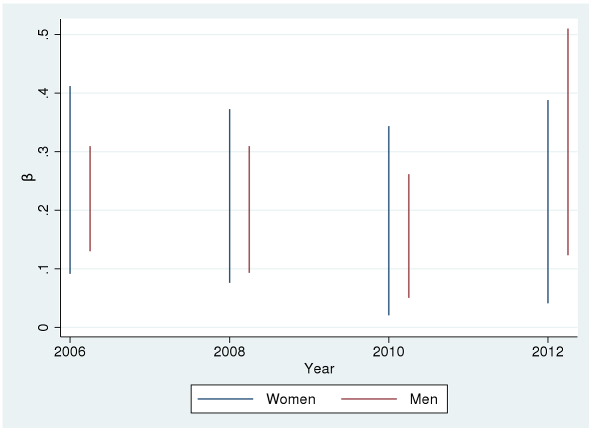
(a) SV - Low risk



(b) BSV - Low risk



(c) SV - High risk



(d) BSV - High risk