Public-Private Sector Wage Gap in Ghana

Single Spine Pay Policy to the Rescue?

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Master Essay II

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Dedicated to my Mother
Mercy Ayisah

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Abstract

This paper exploits the adoption of Single Spine Pay Policy (SSPP) as a natural experiment to investigate the potency of wage policies in addressing the pay differentials between the public and private sector in Africa. The Government of Ghana in 2010, implemented the SSPP to tackle the long-standing wage gap between the public and private sector and consequently improve productivity in the public sector. Using a quantile treatment estimate of the difference-in-difference research design, I show that the SSPP has a heterogeneous impact in reducing the wage gap. I find that there is no substantial evidence that the public-private wage gap is reduced across the entire distribution on earnings in Ghana. By linking the analysis to productivity, I find that the implementation of the SSPP is yet to improve productivity. I particularly uncover evidence that the policy has a negative impact on effort for female workers in the public sector.

Keywords: Wage Policy, Wage-Gap, Quantile treatment effect, Difference-in-Difference

1 Introduction

Public-private wage differentials has sparked global discussion in recent years. The impact of wage gap on worker's employment outcomes such as motivation, effort, productivity, and retention cannot be overlooked (Freeman, 2011). Adamchik and Bedi (2000) argue that the economic position of these different groups of people may cause resentment, and political disillusionment. Lower public sector wages may cripple public sectors ability to retain and attract workers, as well as induce the rate of

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moonlighting among workers which adversely affect public sector efficiency. Bridging the wage gap is therefore an important policy goal for both firms and governments. Bregn (2013) shows that approximately 80 percent of employers in the Organisation for Economic Co-operation and Development (OECD) countries have either used wage policies to close wage differentials and increase workers productivity (see also Bajirek & Baven, 2015). Surprisingly enough, not much has been done on the assessment of the impact of wage policies on the public-private wage gaps, especially in developing countries. Driven by the differences in labor market structures between countries and across regions, bulk of the studies have rather examined the sources or determinants of the these wage gaps[1]. That notwithstanding, extracting these sources of wage gaps and the awareness of level of bias in the labor market are crucial for examining the implementation of any wage policy.

However, the analysis of the wage gap between public and private sector in Africa has been quite problematic. A very unique characteristic of the labour market in Africa is that there exist a large pool of unproductive informal sector but a relatively smaller productive formal sector (ILO, 2002). This has lead to some studies in Africa concluding that public sector workers earn wage premium on average compared to private sector [2] (Finan et al, 2015). Interestingly, the public sector wage premium disappears when the comparison group is private formal employees. Also, not all public sector employees earn a premium over formal plus informal private workers (Younger & Osei-Assibey, 2017). Employees at the lower tail of the earnings distribution earn public sector pay premiums, while workers at the top tail rather face penalties (Younger & Osei-Assibey, 2017). This underlying differences between the formal and informal sector has posed a major caveat in the methodology for analysing the public-private sector wage gaps in Africa (Khaled, n.d).

In addition, there is an econometric challenge when one compares the wages of public-sector and private-sector workers independently. Such comparison may be biased by the fact that certain type of workers are more likely to self-select into a particular sector. The wage differential tend to be explained by individual workers attributes and heterogeneity in each sector of employment. For example, workers with relatively higher education and experience may more likely *prefer* or *choose* to work in a public sector (see e.g. Maloney, 2004; Saavedra Chong, 1999)). Given

[1]See for example Borjas (2002) for United States, Panizza and Qiang (2005) — Latin American countries, Damiani, Pompei and Ricci (2016)— Italy, de Castro et al. (2013) — European countries, Anghel et al. (2011) — OECD countries, and Gracia-Perez & Jimeno (2007) — Spain. See also Gregory and Borland (1999) for extensive review in European countries. Campus et al (2017) and Lausev (2014) also provides review of recent literature examining transition economies

[2]This so-called public sector premium has also been attributed to inefficient public sector wage management. In developed countries however, the existence of wage premium has been as a result of stronger labour union participation and noncompetitve wage settlement in the public sector (Giordano et al., 2011; de Castro et al., 2013; Finan et al, 2015)

that workers with higher education are more likely to experience better labor market outcomes such as wages and productivity, an estimation strategies that depend on assessing the average wage between these workers without controlling for both observed and unobserved characteristics of workers in these sectors will be bias. To overcome this most of the literature in Africa [3] have employed variant version of the conical Oaxaca-Blinder (1973) decomposition to decompose the public-private sector wage inequality into explained portion (for example, education and experience) and unexplained portion (discrimination). That notwithstanding, there are two key limitation to this decomposition technique that also serve as a motivation for this study. First, the presence of unobservable characteristics of workers both at the wage level and the selection into a particular sector. Second, this technique focus on mean estimates which may be misleading if there is heterogeneity in the wage gaps across the distribution of earnings.

In this paper, I examined wage policy impact on the public-private sector wage differentials, taking cue of the the above econometric challenges in assessing the exogeneity of the policy. Specifically, I take advantage of the the Single Spine Pay Policy (SSPP) in Ghana as a natural experiment to examine the private and public sector wage gap and its effect on earnings and productivity – the case of developing countries. My aims are to both provide a clear scientific measure to ascertain the effectiveness of the SSPP as a wage policy in reducing the private-public wage inequality and also explore the impact on workers productivity. I consider the endogeneity of the government decision to implement SSPP, a choice that may depend on factors that influence earnings and productivity. Using the public sector as a treatment group, I follow the work of Ampofo and Tchatoka (2018) [4] by employing a quantile treatment effect (QTE) approach based on a difference-in-difference (DID) estimation. That is, I show the impact of SSPP on the public-private sector wage gap across the entire distribution of earnings in Ghana. By assuming that the policy is as good as random, conditional on time and individual fixed effect, the DID becomes more appropriate. This means that by using the DID strategy I am able to estimate the policy effect, while accounting for unobserved variables that are assumed to remained constant over time. Since the mean effect of the policy may be completely misleading if the the gap varies significantly along the earnings and effort distribution, I use the quantile estimates to assess the policy impact of workers on the entire distribution of wage and effort. Such heterogeneity may imply that the policy has different effect especially at the tails of the earnings and effort distribution function.

[3] See for example Younger & Osei-Assibey, (2017) and Kwenda& Ntuli, (2018)

[4] To the best of my knowledge this is the only scientific paper using the SSPP as a natural experiment in Ghana. The authors examine the impact of SSPP at cohort level. This study however deviate from the work of Ampofo and Tchatoka (2018) by looking at the effect on individual level. Secondly, this study take advantage of an updated data from the Ghana Living Standard Survey.

Three major findings stands out in this study. First, I find that SSPP improves the public sector wages on average. However, when the impact is spread across the distribution of earnings, I uncover little evidence that SSPP improved the wages of workers at the lower tail of the earning distribution. It is only the workers at the 25th quantile and above that experience significant positive effect. This suggests that the policy was ineffective in bridging the wage disparities for lowest income earners. Secondly, by allowing for gender-effect, I find that the SSPP has a substantial effect on the earnings of female workers compared to male workers. This was also true in both health and education subsectors in the public sector. I therefore argue that SSPP was effective in bridging the gender wage gap, especially in health and education subsectors. Lastly, I find that the policy lead to a fall in productivity of workers in effort distribution (measured by weekly hours of work). Productivity is particularly low for females beyond the 25th quantile of the effort distribution. This suggest a backward bending nature of the female labor supply curve in the public sector. To some extent, my findings are in sync with Ampofo and Tchatoka (2018) who use similar data and context and also Damiani, Pompei and Ricci (2016) who find positive policy impact across the quantiles of earnings and productivity in Italy. Although I cannot explicitly pin down the exact mechanism that give rise to these effects, I rationalize my findings by drawing on theoretical literature on efficiency wage theory, labour supply and economics of vocation. This study therefore fill the lacuna in the existing literature in a unique way - in terms of study area and method.

The remainder of this paper is structured as follows: Section 2 discusses the context of the study with respect to the objective of the SSPP. This is followed by a brief discussion of the theories underlying this research in Section 3. The empirical strategy is described in section 4. Section 5 describes the data that I use for investigating my question of interest empirically. Section 6 and 7 presents the results and robustness checks to the findings respectively while section 8 concludes.

2 Context: The SSPP in Ghana

Over the last decade, the Ghanaian economy, just like many emerging countries has seen an improved economic growth, fueled by vibrant private sector. Although the expansion in the private sector has led to improved earnings of workers, the public sector is yet to experience same (Ampofo & Tchatoka, 2018). Prior to the year 2010, the government of Ghana embarked on series of wage policies geared towards bridging the private-public pay differential and improving productivity in the public sector. However, the wage structure has proven to be unsatisfactory to many public-sector workers, especially the lowest income earners.

Baah and Reilly (2009) estimates that prior to 2010, the public-private wage gap was high hovering around 15% and 20%. In fact a noticeable decline in the real wages in the public sector wages lead to many Ghanaian professionals leaving the country for greener pastures abroad (Debrah, 2010). This lead to a lot of wage negotiation causing prolonged strike, industrial unrest and reduction in productivity in the country (Ampofo Tchatoka, 2018). Specifically, Baah and Reilly (2009) find that between 1980 and 2004, while the private sector lost about 3.3 days of work per year, the public sector lost an average of 5.8 days of work per year due to strikes. This strike been costly to productivity (see Figure 1). It is against this backdrop that the government of Ghana implemented the Single Spine Pay Policy (SSPP) in 2010. The ultimate purpose is not only to reduce strike but also to ensure equity, fairness and transparency in salary administration while improving worker performance and productivity (Ghana White Paper, 2010).

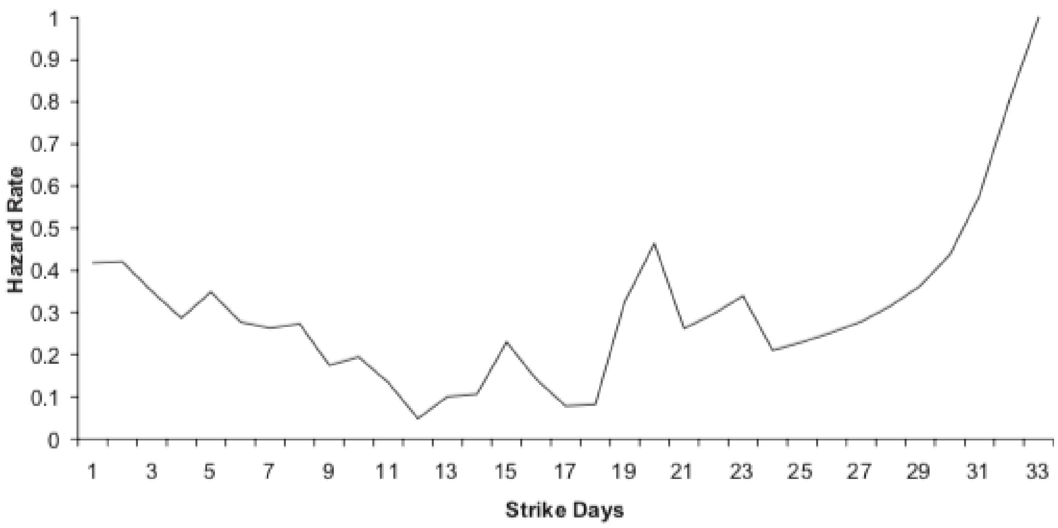


Figure 1: Hazard Rate of Strike. Source: Baah and Reilley (2009)

The SSPP entails "series of incremental pay points in which progression is based on service" (Oppong, Dickson & Asumeng, 2015. p.84). Public servants who are listed under the 1992 constitution of the Republic of Ghana, Article 190 are covered by the policy. In this pay administration, compensations are given to workers with comparable skills, qualification and experiences. Armstrong (2009) maintain that this policy is easy to manage, however, there is little room for linking the pay to on-job performance due to difficulty in measuring performance and the cost associated with staff drifting up the spine. I offer some insight into this argument by expanding the analysis of the policy impact on effort or productivity in the public sector.

3 Theory

Introducing the SSPP to influence the public-private wage disparities may have substantial consequences. Adamchik and Bedi (2000) argue that changing the economic position of different groups of people may cause resentment, and political disillusionment. Lower public sector wages may cripple public sector's ability to retain and attract workers, as well as induce the rate of moonlighting among workers which adversely affect public sector efficiency. For these reasons, the efficiency wage theory postulates that the implementation of such wage policy is positively linked to increased effort and productivity.

According to Shapiro and Stiglitz (1984) the relationship is such that increased wages induces high opportunity cost of shirking and hence workers tend to be highly productive. Akerlof (1984) adds that workers show appreciation for high wages by increasing effort and hence resulting in higher productivity. Even more importantly, if workers believe that a given wage is fair, there is a high probability of increasing effort in the workplace (Ampofo & Tchatoka 2018; Akerlof & Yellen, 1990). Thus, per the efficiency wage theory workers operate more efficiently and become more productive if their wages are above the equilibrium level. On the other hand, the literature on economics of vocation explains that workers effort may not increase even with an increase in wages. The basic idea is that when workers perceive their job as vocation, they respond less to external motivation such as salary (Frey, 1993). This means that increased wages will have less impact on workers' effort compared to intrinsic motivation.

In the models of employment and wage decisions in the public sector, Jackam et al. (1992), and Blanchard (1997) notes that there is a trade-off between employment and wages. That is, lower wages in the public sector is the result of trying to maintain large employment. Private sector on the other hand, may set wages above equlibrium level to reduce turnover costs and, thus, to increase the efficiency of the firm (Salop, 1979) and also reduce shirking (Shapiro & Stiglitz, 1984). Therefore, a higher wage in the private sector may include elements of efficiency wages while public sector wages may simply reflect compensation for job security and lower non-wage benefits (Damiani et al., 2016). Accordingly, implementing the SSPP to improve wages of the public sector is thus expected to also improve productivity.

4 Empirical Strategy

Despite the intuitiveness of these theories, the empirical investigation of wage policy is faced with challenges. The main problem with identifying the effect of SSPP on wage differential and sector productivity is that earnings and efforts can be explained by series of observed and unobserved factors and that correlate with the policy. A second source of concern is that being in the treatment group or choice of sector may be influenced by the wage differential in the first place. Workers decides to work in a specific sector if the wage is already high. Higher wage in a specific sector may therefore draw completely different set of workers. This is a classic problem of self-selection.

In this paper, I use the Difference in Difference (DID) estimation strategy to tackle this problem. The basic idea of the DID is to observe the (self-selected) treatment group and a (self-selected) comparison group before and after the policy. The implicit assumption of the DID approach is that this selection bias relates to fixed characteristics of individuals. That is, the magnitude of the selection bias is not changing over time. In addition, using the DID setup, I implicitly assume that the time trend of wages and effort are the same for both public sector workers and private sector workers in the absence of the policy. These two necessary conditions are referred to as the common or parallel trend assumption. If this assumption is satisfied, then I can estimate the true unbiased effect of the wage policy which does not depend on time periods or individuals characteristics. For example if workers are selected in such a manner that highly skilled and educated are employed in public sector as compared to the private sector, and that this level of selection bias is assumed to not change before and after the policy, then finding the difference between pre-treatment and post-treatment periods across the treatment and comparison group eliminates the bias.

Despite the prominence of applying the DID methods, there is little empirical work in the literature exploiting the access to repeated observations over time to study the distributional effect of a treatment or policy impact (Callaway & Li, 2017). To understand distributional impact of the policy, this study estimates the quantile treatment effect (QTE). The basic idea behind the QTE is that the effect of the SSPP differs between relatively high wage earners, and relatively low wage earners. Thus, the government may not be interested in the average effect but in whether the wage policy is able to move low income earners to a higher trajectory of earning profile. It is important to remark that the assumptions needed to identify the QTE under the distributional DID are analogous to the ones invoked under the commonly used mean DID (Callaway & Li, 2017). Specifically, under the QTE it is assumed that ”the distribution of the change in potential untreated outcomes does not depend on whether or not the individual belongs to the treatment or the control group” (Callaway & Li, 2017, p.6). This simply generalized the idea of the common trend assumption holding on average for the entire distribution.

Intuitively, consider, a random variable X, where the τ-quantile of X is given as follows.

$$x_\tau = G_X^{-1}(\tau) \equiv \inf\{x : F_X(x) \geq \tau\} \tag{1}$$

where F_X is the distribution of X. One might be interested in the policy impact over a particular quantile such as the median earners 0.5-quantile or the top earners of 0.99-quantile or low earners such as 0.25-quantile. If $\mathrm{F}_{Y_{1i}}(y)$ and $F_{Y_{0i}}(y)$ represents distribution of our potential outcome in the treated and untreated state Y_{1i} and Y_{0i} respectively, then the QTE is defined as[5]

$$\mathrm{QTE}(\tau) = F_{Y_{1i}}^{-1}(\tau) - F_{Y_{0i}}^{-1}(\tau) \tag{2}$$

Similar to the way we identify the average treatment effect (ATE), the QTE is not directly identified because one cannot observe simultaneously the treated state Y_{1i} and untreated state and Y_{0i} for any individual. One can only recover the QTE if the treatment is randomized. In the event of no randomize trails, this study uses a quasi-experimental analysis to recover the QTE using DiD.

More formally, my empirical strategy consider the QTE model by Powell (2016)[6] as:

$$Outcome_{it} = (PUB \times POL)'\beta_1(\epsilon_{it}) + X_{it}'\beta_2(\epsilon_{it}) + \lambda_t(\epsilon_{it}) + \omega_i(\epsilon_{it}) \tag{3}$$

$$\epsilon_{it} = f(\mu_i, \nu_{it}) \tag{4}$$

where $\mathrm{Outcome_{it}}$ is the average outcome variables - log of monthly wages and log of weekly hours of work of individual at survey year t. I use the log of weekly hours of individuals to measure the effort variable [7]. The interaction term of PUB (public sector) and POL (post SSPP) is the variable of interest. The study seeks to provide an unbiased and consistent estimate of β_1 that meaure the treatment effect of the wage policy on monthly earnings and efforts. I include a vector of covariates $\mathrm{X_{it}}$ - years of education, age, presence of labor union, marital status, household size, gender and formally employed household head. β_2 therefore reflects the effect of a change in the covariates on the outcome variables.

To (partially) overcome any potential endogeneity in β_1 due to unobserved time-

[5] For more on the econometric intution, see Callaway & Li (2017)

[6] The DID is estimated by using the Generalized Method of Moments (GMM). Powell (2016) uses two key moment conditions which is derived and explained in Appendix A

[7] The argument is that productivity is difficult to measure, however studies have shown that effort is positively related to productivity levels (Ampofo & Tchatoka, 2018). In Ghana though workers are required to work 40hours a week, public sector hours has been fairly low partly due to prolong strike. Since the SSPP is intended to link pay to productivity, and government believe that workers will work within the stipulated working hours, measuring effort and for that matter productivity as hours of work is very reasonable.

invariant and time variant characteristics that can affect earnings and efforts rather than the policy, I further include year fixed effect and industry-specific fixed effect. More specifically, the year fixed effect helps to capture the variation of the earnings that is attributed by political and economic changes over time in the country. It is possible that the difference in wages may be due to political and economic shock rather than the SSPP. Also, the type of industry in the public and private sector may be a source of time-invariant confounding to the policy. Therefore failure to account for these impact may impair the identification of the policy effect.

As rightly noted by Ampofo and Tchatoka (2018), Ghana experienced economic challenges with huge debt prior to the implementation of SSPP in 2010. However, the economy benefited immensely from the production of crude oil in commercial quantities which spurred economic growth, with an annual GDP growth moving from 5 percent to 14 percent between 2010 and 2011. Therefore the SSPP may be endogenous by this economic shock. Adding year fixed effect and industry specific fixed effect [8] thus helps address this problem, especially by disentangling the time-variant and time-invariant characteristics to the SSPP. Finally, ϵ_{it} represents the composite error term consisting of the fixed effect reflecting the time-invariant individual characteristics and is the random noise or idiosyncratic shocks.

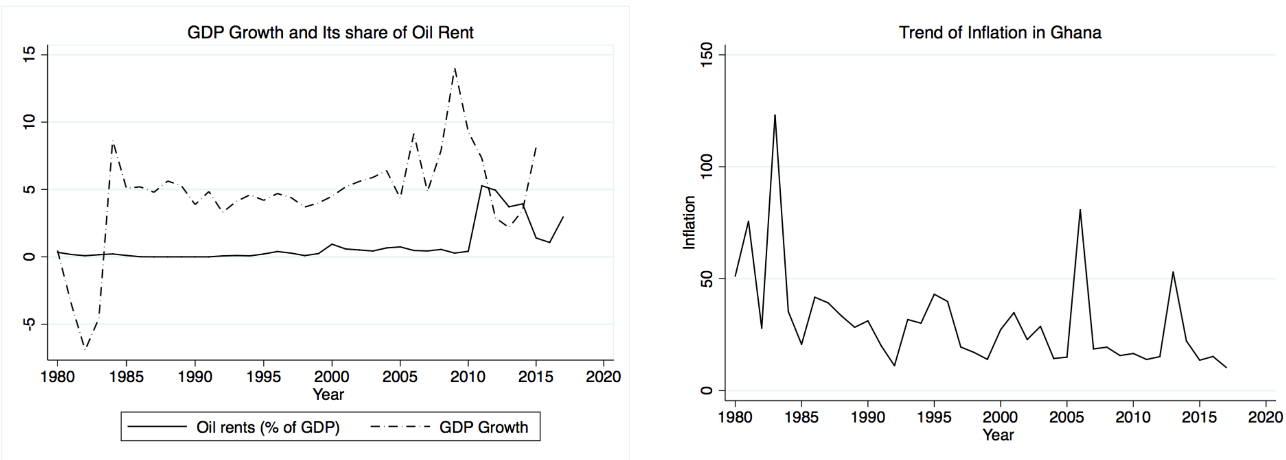


Figure 2: Macroeconomic Indicators

In line with the above, two key assumptions behind my identification strategy are worth noting. That is the SSPP was as good as random, conditional on the controls included and that there is no time-variant individual specific unobservables or the common support assumption holds. First of all, conditioned on the covariates, the composite error should have a zero τ quantile. This identification strategy relies on the assumption that change in wages for different groups of workers in the public

[8]This specifically help to alienate the time invariant factors caused by different features of each industry in these sectors.

sector can be taken as exogenous. Formally, $\epsilon_{it}|$PUB x POL, X_{it} has a zero τ quantile (Ampofo & Tchatoka 2018; Powel, 2016). However, this identification may fail if the government of Ghana improved the earnings of group of workers based on the characteristics that are correlated with the error term or attrition in the data. It is therefore important to control for demographic and job characteristics in the data. Studies have shown that factors such as education and years of experience significantly affect earnings (see e.g Mincer, 1974; Gleww, 1991). Thus failing to condition on these covariates may lead to model mispecification and bias the estimate of the coefficient of interest. Since I conditioned the policy on these covariates, the source of variation in wage and productivity can be mainly be attributed to the implementation of the policy.

Secondly, it is crucial to note that if workers in public sector finds that their effort is not linked to the pay they receive, they may consider moving to the private sector. In the same vein, if private sector workers consider the public sector as a great option to earn more, then the resulting impact on earnings and effort my not be solely attributed to the policy. This, therefore, poses a threat to the identification strategy. However, according to the Fair Wages and Salary Commission [FWSC] (2009), there is the fear that government may lose its workers to the private-sector and not the other way round (Ampofo & Tchatoka, 2018). In addition, distribution of workers in both sectors before and after the intervention remain stable before and after the policy. Thus using the private sector as a comparison group is very appropriate to disentangle the policy impact.

5 Data and Sample Selection

The data for the empirical analysis stems from the Ghana Living Standard Survey (GLSS) wave 4, 5, 6 ans 7 conducted in 1998/99, 2005/06 , 2012/2013 and 2016/2017 respectively. GLSS is a nationally representative repeated cross-section data that sampled households and household members in about 1,200 enumeration areas in Ghana. The survey provides a wide range information of economic activity, employment, workers earnings, time use and working condition, their sector of employment, as well as other demographic characteristics such as education, gender, age and marital status. The data is hierarchical in nature with variables being measure at the individual, household and community levels and hence facilitate unit-specific to aggregate level analysis. The sampling is based on stratified selection process. This selection procedure ensures household has an equal probability of being selected. Each sample in each survey are therefore selected randomly.

In the survey, respondents were asked to report their earnings from both the main and secondary jobs. Due to a lot of missing values in the secondary jobs, I only use earnings from the main jobs. Also, it is only the earnings of main job that this study seeks to investigate. I restrict my attention to individuals aged 15 and 64 who are full-time workers and pay taxes on their employment income.[9] Workers with missing wages are excluded from the sample. All workers are therefore labor who receive positive monthly wages.

In the GLSS data, the private sector are grouped into informal private-sector and formal private sector. To reasonably compare public sector workers and private sector workers, only formally employed workers in the private sector are used as a control group. This create two groups of comparable skills, education, and experience. Given the survey periods and the year of SSPP intervention, this study obtains two pre-policy and two post-policy data points.

It is important to acknowledge that the GLSS follows a survey structure applied in an unequal year intervals. Therefore, there are certain biases that arise due to household changes, non-response, migration or attrition. In addition since the GLSS is a repeated cross-section data, it is difficult to track all respondents overtime. Ideally, one can tackle this problem by constructing a pseudo panel proposed by Deaton (1985). This method basically group respondent into a cohorts according to the same time invariant characteristics that identify them. The mean values of the continuous time varying variables are then computed for each cohorts across each survey as observations. According to Ampofo and Tchatoka (2018), this approach allow to infer individuals' behavior with similar characteristics and also increase the sample size used. In effect a pseudo panel setting increases the statistical power of the DID analysis. However, in the absence of the pseudo panel, I used a pooled data from four periods of repeated survey. This is because, I find the sector group composition to be stable (see e.g. Meyer, 1995 ; Abadie, 2005) and nonresponse rate is low at about 8% (Ghana Statistical Service, 2017). In fact, as explained by Callaway and Li (2017), the typical setup of in most DID application require at least two periods of repeated cross-section data. Earlier works that identify quantile treatment has also maintained similar setup (see. e.g Fan & Fu, 2012).

5.1 Descriptive Statistics

Table 1 shows the differences in the average monthly earnings, weekly hours of work and other covariates for both public and private sectors, prior to the implementation of the SSPP. The absolute value of difference in means are reported as well as their significance. First, it appears that the workers in public sector tends to be more educated and have more experience than those in the private sector. This is, statistically significant implying huge self selection problem between the treatment and control group. Aside employed mother that did not differ significantly, other characteristics

[9] I use this sample because by the International Labour Law, working at age below 15 years is defined as child labor.The statutory age for retirement in Ghana is 64 years. Thus I use sample of only legally employed workers.

such as age, household size, gender, marital status, and employed father show major differences. It is interesting to note that, there is no such significant difference at the lower tail and top tail of the distribution in these covariates. In particular the difference in education is almost the same for top earners in the private and public sector.

Table 1: Descriptive Statistics Prior SSPP

VARIABLES	(1) Total	(2) Public Sector	(3) Private Sector	(4) Diff (Pub-Priv)	(5) p value
ln(wage)	2.117***	2.724***	2.855***	-0.131***	0.000
	(0.025)	(0.034)	(0.027)	(0.054)	
ln(hours of work)	3.795***	3.746***	3.808***	-0.062***	0.001
	(0.007)	(.0121)	(0.008)	(0.016)	
Education	2.432**	3.086***	2.217***	0.868***	0.000
	(0.012)	(0.025)	(.011)	(0.024)	
Age	36.217***	41.856***	34.662***	7.193***	0.000
	(0.138)	(0.268)	(0.153)	(0.324)	
Household Size	4.043***	4.531***	3.876***	0.656***	0.000
	(0.038)	(0.080)	(0.042)	(0.086)	
Gender	0.526***	0.709**	0.476***	0.234**	0.034
	(0.006)	(0.012)	(0.007)	(0.015)	
Marital Status	0.672**	0.801***	0.636***	0.165***	0.000
	(0.006)	(0.010)	(0.006)	(0.014)	
Employed Father	0.345**	0.426***	0.322***	0.1036	0.000
	(0.006)	(0.013)	(0.007)	(0.015)	
Employed Mother	0.504***	0.508***	0.503***	0.005	0.744
	(0.007)	(0.013)	(0.007)	(0.015)	
Observations	2,512	1,400	1,112		

* Note: All figures are averages prior to the implementation of SSPP. Only monthly wages are reported since most workers in Ghana are paid every month. I measure education by level of of formal education completed. The reference point is no education, followed by primary, secondary and post education. Age is measured in years. In some specification I include the square of age and education level for flexibility. The household size refers to the number of members in a particular household. Gender is a dummy variable taking the value of 1 if the respondent is a female worker and 0 for male workers. I also include a dummy for household head (mother and/or father), who is either employed or not. This takes the value of 1 if employed and 0 otherwise. The p values of the t-test are reported and standard errors are in parenthesis.

Therefore we see that in the Ghanaian labor market, the average worker with higher level of education and experience may self-select into the public sector. However, this self-selection is not huge at certain part of the earnings and effort distribution. Nonetheless, it is this level of selection bias that I assume to be constant over time by employing the DiD estimation strategy. The individual bias is basically eliminated if it is constant over time and hence allow to estimate only the effect that is related to the policy. This assumption seems tenable, when we look at composition of public and private sector before and after the policy. The descriptive statistics in Table 6 and Table 7 in appendix show that the composition of public and private sector in terms of education, age, household size, gender marital status and employment share remain the same over time. Under section 7, I further show that the common trend assumption is reasonably met.

A cursory look at the average earning and hours of work (effort) of workers across these sectors gives interesting insight. Before the wage policy, earnings and efforts in private sector appears to be higher than in the public sector. While earning increased after the policy, public sector effort decreased.

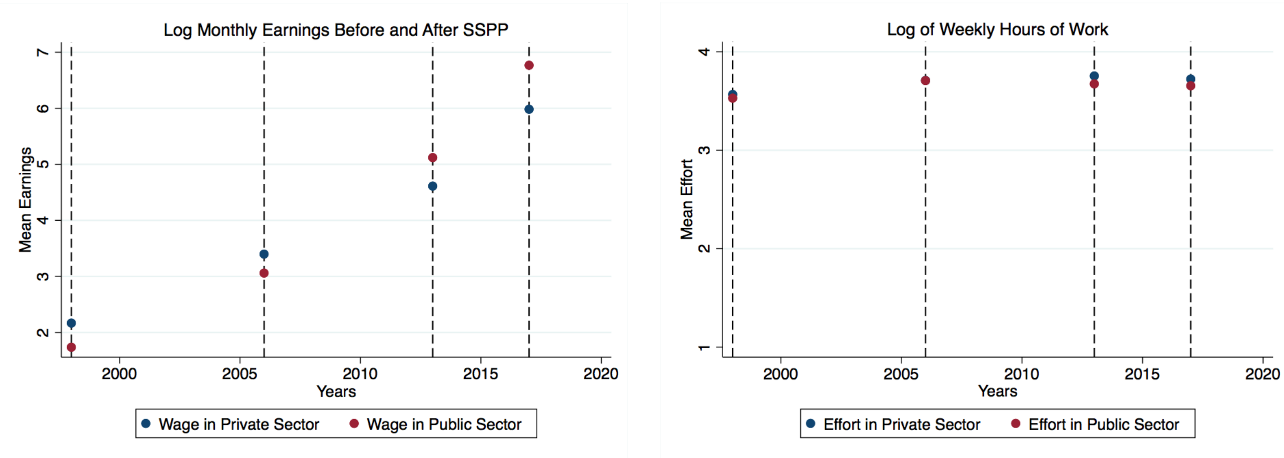


Figure 3: Mean Earnings and Effort Pre and Post Policy

However the mean can be a misleading measure of central tendency given that the distribution of earning and effort is skewed. The kernel density distribution in figure 4 and 5 show the pattern of wages and weekly hours of before and after policy periods respectively. By disaggregating earnings by public and private sector, the distribution shows that prior to the policy, public sector workers earn relatively more than formally employed workers in the private sector at the lower tail of distribution. Although there exist an overlap in the earning distribution , the distribution in the private sector dominate at higher earnings. After the policy, monthly earnings of lower earners in the public sector seems to improve significantly, while private sector workers at the top tail enjoy higher wages compared the private sector. In terms of effort, there seems to be higher median effort by private sector workers, while more efforts are exerted by public sector workers at the top tail of the distribution before the implementation of the policy. This pattern looks the same after the implementation of the policy. Though this shows that there are still gaps between the public and private sector and hence the SSPP is yet to reduce the wage gap, or link pay to productivity, it is premature to infer that these effects are causal. In the analysis that follows, I show that the earnings are more concentrated around the mean indicating homogeneity in monthly wages in the public sector. Similar story occurs when we look at effort distribution. I use the quantile treatment effect along with a DID identified above to establish heterogeneous causal effect. I check the validity of the results by conducting some robustness checks.

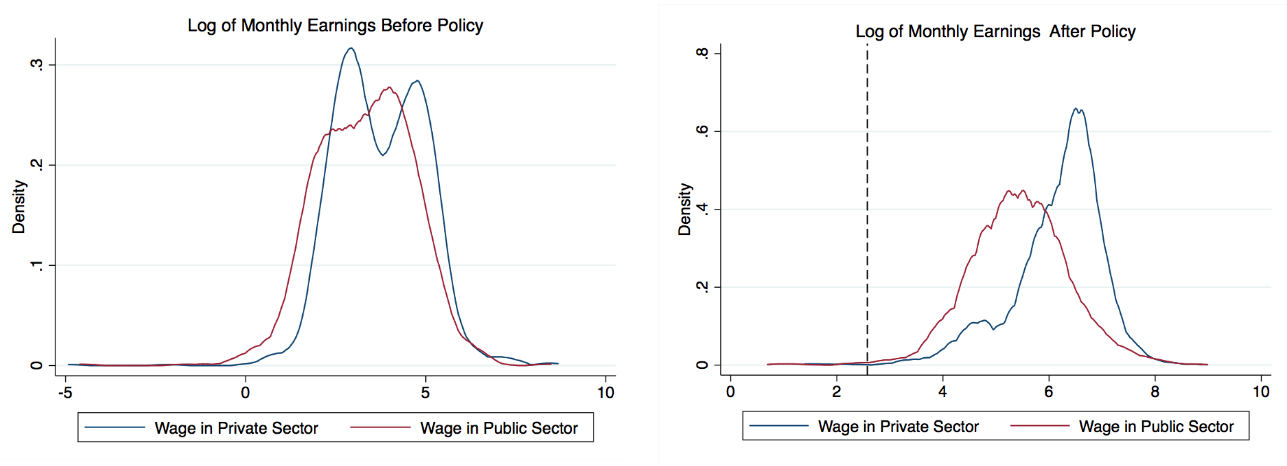


Figure 4: Distribution of Earnings

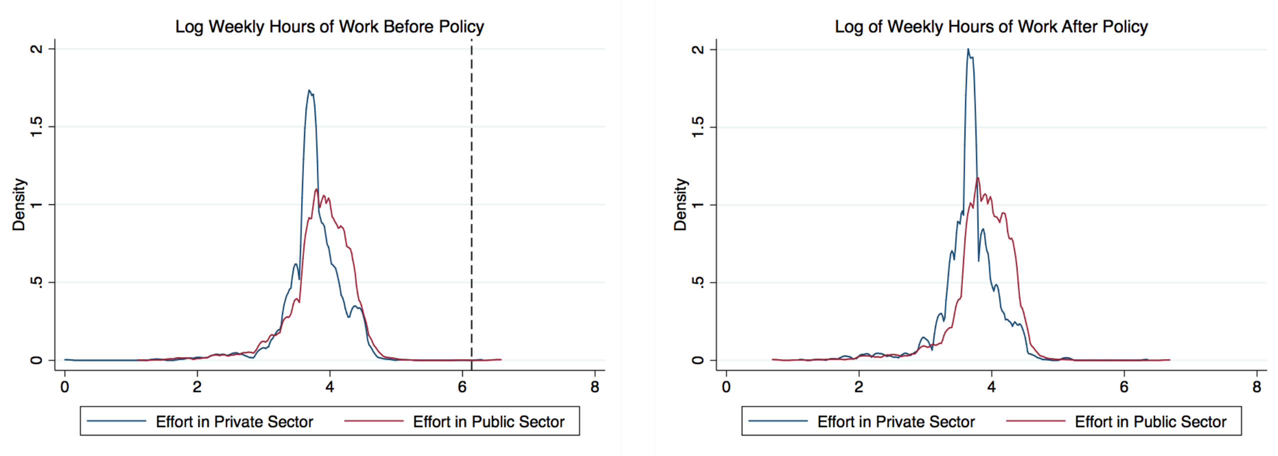


Figure 5: Distribution of Efforts

6 Results

In this section, I present the results of the policy effect of the wages and efforts at the mean (OLS), 10th, 25th, 50th and 90th quantiles. Results are presented for the full sample of respondents, and further disaggregated by gender (Male and Female) and the Health and Education subsectors. The disaggregation of the sample into different sectors helps to analyse the extent of the wage differentials within the gender dimension and sub-sectors. This is important as there are wide differences in the characteristics of employment, wages and effort by gender and other sub-sectors in the labour market.

6.1 Main Effects

I begin by presenting the main empirical results. I show OLS (mean) estimates as well as the quantile treatment effect of the earnings and efforts in Table 2. I control for worker's age, years of education, household head's employment status, gender and household size. Without including the controls, I find that the impact is rather small across all quantiles, suggesting a downward bias.

First of all, looking at the log of monthly earnings in Panel A, the results show largest impact of SSPP at the 25th quantile of the earning distribution. As the quantile increases, we see a gradual reduction in the impact of the SSPP, indicating a heterogenous nature of the wage policy in the public sector. Interestingly, the results show a significant positive average impact while below the 25th quantile the result is insignificant. This means that the SSPP did not significantly move the lowest income earners in the public sector to a higher trajectory of earning profile.

Table 2: DID Estimate of SSPP Effect on Earnings and Effort

VARIABLES	(1) OLS	(2) 0.1 Q	(3) 0.25 Q	(4) 0.5 Q	(5) 0.75 Q	(6) 0.9 Q
			Panel A - Monthly Earnings			
Public Sector	0.321***	0.887***	0.305***	0.0264	-0.0769	-0.0689
	(0.0715)	(0.288)	(0.112)	(0.106)	(0.0822)	(0.0933)
Policy Effect	0.400***	0.592	0.661***	0.572***	0.433***	0.260**
	(0.0764)	(0.391)	(0.147)	(0.120)	(0.0815)	(0.125)
Individual Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Specific FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6,780	6,780	6,780	6,780	6,780	6,780
			Panel B - Effort			
Public Sector	-0.137***	-0.130	-0.133***	-0.169***	-0.163***	-0.0966**
	(0.0236)	(0.0880)	(0.0401)	(0.0304)	(0.0432)	(0.0400)
Policy Effect	0.0863***	0.335***	0.0431	0.0670*	-0.00503	-0.0202
	(0.0293)	(0.075)	(0.0534)	(0.0384)	(0.0632)	(0.0578)
Individual Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Specific FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6,754	6,754	6,754	6,754	6,754	6,754

* Note: *,**,***denotes significant at the 10% , 5% and 1% level respectively. Standard errors using Marcov chain Monte Carlo (MCMC) numerical optimization are reported in parenthesis for the quantile estimates while robust standard errors are presented in parenthesis for the OLS estimate. Also included in the individual controls are the presence of trade union and age-squared.

In particular, while SSPP improved the log of monthly earnings by 0.433 and 0.260 beyond the median quantile for public workers, such earnings was about 0.59 and insignificant. Thus, though the wage policy has a positive impact, its goal of bridging the earnings-gap for low income earners was not materialized. This result at the 10th and 90th quantile is line with Damiani, Pompei and Ricci (2016) but in contrast to the findings by Ampofo and Tchatoka (2018) who find significant positive results for the lower quantile and negative impact for the top 90th quantile. The key difference here may be due to the fact that Ampofo and Tchatoka (2018) examined the impact at cohort-levels. Therefore, according to the authors, cohorts with same year of birth, gender ethnicity and also find themselves in the 90th quantile of the earning distribution experience a reduction in wage [10].

In connection with the efficiency wage theory, the results in Panel B of Table 2 show that workers exerts high effort on average as a result of the wage policy. Apparently, this is driven by workers at the lower tail of the effort distribution. Weekly hours of work by public sector workers increases at the 10th quantile. Beyond the this quantile, effort however, reduces significantly. Thus, the efficiency wage theory seems to work well at the lowest tail of the distribution as against workers at the higher tail of the effort distribution. This, once again shows that there is heterogeneity of the impact of wage policy on the earnings and effort of workers. I find little evidence that the SSPP improves workers productivity across the entire distribution of effort. These effects suggest that estimates based on the mean may be misleading and a quantile estimation is more appropriate. Figure 6 lends a verisimilitude to the above discussion.

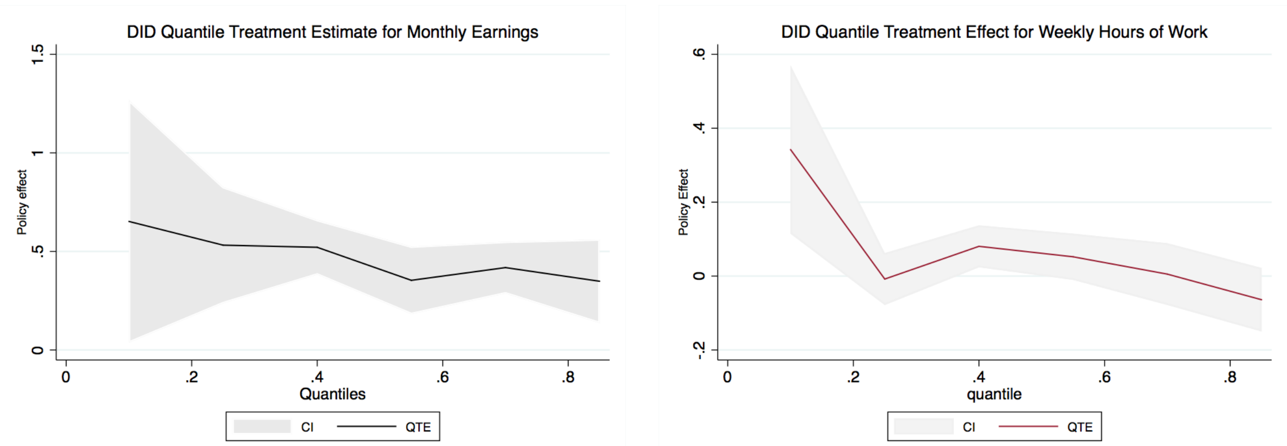


Figure 6: DID Quantile Treatment Effect on Earnings and Effort

[10] A limitation of cohort studies is that the wages are averaged out among cohorts, and hence it is possible that key individual information may be missing. Also the estimates may be a potential source of bias if attrition via migration or death of respondents affect composition and sizes of the cohorts (see Antman & McKenzie, 2007). More importantly, attrition is known to occur more with groups at the tail ends of the distribution (Yee & Niemeier, 1996) and hence likely to lead to bias estimates at these ends.

6.2 Allowing for Gender and Sub-Sector Effects

The quantile estimates can also be used to show rich evidence of heterogenous effects along gender and subsector dimension in the distribution of earnings and efforts. In Table 3 and Table 4, I find that the positive result at the higher tail of the earning distribution is driven by female workers in the public sector. The policy impact on female public sector workers are positive and significant across the entire distribution of earning while the male counterparts experience insignificant policy effect at the 25th and 90th quantile.

Table 3: Effect of SSPP on Earnings and Effort for Males

VARIABLES	(1) OLS	(2) 0.1 Q	(3) 0.25 Q	(4) 0.5 Q	(5) 0.75 Q	(6) 0.9 Q
		Panel A - Monthly Earnings				
Public Sector	0.333***	1.187***	0.191	-0.0180	-0.164	-0.0652
	(0.0776)	(0.269)	(0.126)	(0.138)	(0.113)	(0.123)
Policy Effect	0.323***	0.431	0.798***	0.478**	0.547***	0.253
	(0.0837)	(0.298)	(0.158)	(0.190)	(0.134)	(0.270)
Individual Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Specific FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5,203	5,203	5,203	5,203	5,203	5,203
		Panel B - Effort				
Public Sector	0.333***	-0.205*	-0.104**	-0.169***	-0.151***	-0.0343
	(0.0776)	(0.105)	(0.0456)	(0.0457)	(0.0413)	(0.0458)
Policy Effect	0.323***	0.0632***	-0.0326	0.0451	-0.0212	-0.102
	(0.0837)	(0.008)	(0.0659)	(0.0502)	(0.0565)	(0.0649)
Individual Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Specific FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5,203	5,231	5,231	5,231	5,231	5,231

* Note: *,**,***denotes significant at the 10% , 5% and 1% level respectively. Standard errors using Marcov chain Monte Carlo (MCMC) numerical optimization are reported in parenthesis for the quantile estimates while robust standard errors are presented in parenthesis for the OLS estimate. Also included in the individual controls are the presence of trade union and age-squared.

Moreover, I find the policy impact to be higher across the entire distribution of the female earning distribution compared to male workers in the public sector. The result suggests that the gender wage-gap has improved after the implementation of the policy. Interestingly, the result also suggest that the most disadvantage group are males who find themselves at the lowest quantile of the earning distribution. There is no significant wage-premium for male earners at the lowest quantile as a result of the policy, however, they are the only group in the male effort distribution that exerts significant higher effort.

Table 4: Effect of SSPP on Earnings and Effort for Females

VARIABLES	(1) OLS	(2) 0.1 Q	(3) 0.25 Q	(4) 0.5 Q	(5) 0.75 Q	(6) 0.9 Q
Panel A - Monthly Earnings						
Public Sector	-0.343*	-1.121**	-0.902***	-0.329**	-0.152	-0.0203
	(0.179)	(0.422)	(0.254)	(0.183)	(0.328)	(0.421)
Policy Effect	0.522***	1.621***	1.532***	0.484**	0.444**	0.032***
	(0.185)	(0.021)	(0.502)	(0.329)	(0.196)	(0.007)
Observations	1,577	1,577	1,577	1,577	1,577	1,577
Individual Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Specific FE	Yes	Yes	Yes	Yes	Yes	Yes
Panel B - Effort						
Public Sector	0.031	-0.355***	-0.138***	0.014***	0.102	0.253***
	(0.041)	(0.129)	(0.005)	(0.001)	(0.120)	(0.013)
Policy Effect	-0.038	0.034**	0.343*	-0.203	-0.266**	-0.522***
	(0.035)	(0.022)	(0.179)	(0.566)	(0.127)	(0.185)
Individual Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Specific FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,577	1,523	1,523	1,523	1,523	1,523

[*] Note: *,**,***denotes significant at the 10% , 5% and 1% level respectively. Standard errors using Marcov chain Monte Carlo (MCMC) numerical optimization are reported in parenthesis for the quantile estimates while robust standard errors are presented in parenthesis for the OLS estimate. Also included in the individual controls are the presence of trade union and age-squared.

Along the female effort distribution, the quantile estimates in Table 4 Panel B reveals a backward bending female labor supply curve above the 25th quantile. Female effort (hours of work) is reduced compared to male after the implementation of the policy beyond the 25th quantile. This is situation is an indicative that beyond this quantile, many of the female workers in the public sector are married and have children (see e.g Angrist & Evans, 1998). Also, the labor supply elasticity for female workers in the public sector is inelastic. Thus, an increase in wage, do not significantly translate into effort. This result though contrary to the theory of efficiency is in line with the literature on economics of vocation which argue that that workers effort may not increase even with an increase in wages. Interestingly, effort exerted by the lowest quantile male workers is high and significant. I equally ascribed this to theory of vocation.

Moreover, I zoom into results by disaggregating the public and private sector into sub-sectors. Particularly, I look at the health and education sector[11]. Under this sector, I estimate the effect for both males and females. Table 9 and Table 10 give interesting results. The findings point to the fact that earnings in education and health subsector increased marginally for public sectors at the lower quantile but a reduction for workers at the higher quantiles. In sum, however, the policy leads to higher average effect driven by female workers in these subsectors. Though the results indicate that gender wage-gap seems to be reduced, male workers however benefit more from the SSPP. In terms of effort, the policy induces positive impact across the distribution of effort for male workers compared to female workers in the health and education sector. These heterogeneous pattern allow to make the conclusion that the wage policy is yet to improve overall productivity in Ghana.

7 Robustness Checks

The credibility of the results crucially relies on the common trend assumption. This assumption is fundamentally untestable. However, one can visually inspect to see if wages or effort were on the same trajectory before the implementation of the policy. Figure 3 in section 5 suggest that the ”averagely” common trend assumption is fairly met. Also the composition of public and private sector did not change over time per the descriptive statistics and hence can conclude that the selection bias did not grow over time. This suggest that conditioned on the covariates the SSPP is exogenous.

Another insightful way to test the assumption that only SSPP explains these findings rather than other confounding factors (such as presence of trade unions) by using a falsification strategy or conducting a placebo test. This is a very useful diagnostic check which basically says that we expect no policy effect in the multiple pre-policy periods and we should (only) find results in the multiple post-policy periods (if the policy has an effect). If the pattern of results and non-results is as expected, we can be more confident in our identifying assumptions (especially the ”parallel trends” assumption). To do this, I used 2006 as pseudo year where the was implemented and interacted this pseudo year with the treatment group (public sector). Table 5 shows the results of the estimated impact of the pseudo policy. I find no sign of significant policy impact across the earning and effort distribution and hence conclude that the assumption is met.

[11]Due to insufficient data in other sub-sectors

Table 5: Placebo Test

VARIABLES	(1) OLS	(2) 0.1 Q	(3) 0.25 Q	(4) 0.5 Q	(5) 0.75 Q	(6) 0.9 Q
Panel A - Monthly Earnings						
Public Sector	0.147**	0.0853	0.310	0.180	-0.303	-0.145
	(0.0587)	(0.152)	(0.255)	(0.203)	(0.277)	(0.206)
PseudoPolicy Effect	-0.117	0.0899	-0.340	-0.340	0.257	0.108
	(0.0811)	(0.167)	(0.256)	(0.269)	(0.315)	(0.170)
Individual Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Specific FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,515	1,515	1,515	1,515	1,515	1,515
Panel B - Effort						
Public Sector	-0.0897**	-0.0639	-0.0942	-0.0497	0.0759	1.393
	(0.0358)	(0.173)	(0.0784)	(0.145)	(0.121)	(2.585)
PseudoPolicy Effect	-0.0761	-0.128	0.136	-0.111	-0.130	-1.172
	(0.0475)	(0.160)	(0.169)	(0.178)	(0.248)	(1.894)
Individual Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Specific FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,451	1,451	1,451	1,451	1,451	1,451

[*] Note: *,**,***denotes significant at the 10% , 5% and 1% level respectively. Standard errors using Marcov chain Monte Carlo (MCMC) numerical optimization are reported in parenthesis for the quantile estimates while robust standard errors are presented in parenthesis for the OLS estimate. Also included in the individual controls are the presence of trade union and age-squared.

8 Conclusion

In this paper, I have examined the impact of wage-policies in brigding the public-private pay differential and its impact on productivity. I use the SSPP as a natural experiment and employ the quantile treatment effect based on DID to show that the policy has heterogeneous effect on wage-gap. The analysis is highly relevant due to its strong internal validity. From a methodological perspective, the study innovate the previous literature on heterogeneous examination of policy effect on wages and effort. The quantile estimate is more appropriate to unravel the policy effect rather than average estimates. The findings are supported by a number of robustness checks.

In terms of results, I find that the SSPP was successful in improving the earnings of public sector workers except at the lower tail of the earning distribution. However, these findings mask some marked heterogeneity along the gender and subsector dimension. I find that positive impact on earnings is particularly large for female workers. In fact, the study shows that the policy has a trickle down effect in bridging the gender pay gap in the education and health sectors across the entire distribution of earnings. The results on effort suggests that female workers tend to reduce effort beyond the 25th quantile after the implementation of the SSPP. This is attributed to the backward bending labor supply curve of females in the public sector as well as responding less (negatively) to higher wages.

Has the implementation of the SSPP reduced wage inequality in the public and private sector? Maybe too soon to admit. It is important to mention that, the findings should not be taking in isolation. Other political and macroeconomic factors (such as inflation, depreciation of the Ghana Cedis, political appointments, unemployment etc.) might have crippled the desired policy impact. Furthermore, this study gives a hint that there are some variation of the policy impact within the public sector. However, such intra-public sector examination was not rigorously examined. It is possible that the policy affect the wage differential within the public sector itself (e.g. between a manager and a section head in the same industry). I leave this for future research. Lastly, time has elapsed since the policy measure took place, and yet there is no available data following workers who benefit directly from the policy over time. A better data is therefore needed to give better descriptors of the policy. That, notwithstanding, this study provides a good ground for insightful wage policy intervention geared towards bridging the public-private wage gap and linking pay to productivity.

References

Abadie, A. (2005). Semiparametric difference-in-differences estimators. *The Review of Economic Studies*, 72(1), 1-19.

Adamchik, V. A., & Bedi, A. S. (2000). Wage differentials between the public and the private sectors: Evidence from an economy in transition. *Labour Economics*, 7(2), 203-224.

Akerlof, G. A. (1982). Labor contracts as partial gift exchange. *The Quarterly Journal of Economics*, 97(4), 543-56

Akerlof, G. A.,& Yellen, J. L. (1990). The fair wage-effort hypothesis and unemployment. *The Quarterly Journal of Economics*, 105(2), 255-283

Ampofo, A., & Doko Tchatoka, F. (2018). Reducing Public–Private Sector Pay Differentials: The Single Spine Pay Policy As A Natural Experiment In Ghana. *Economic Inquiry*, 57(1), 283-315.

Anghel, B., S. de la Rica, & J. Dolado (2011) .The Eect of Public Sector Employment on Womens Labour Martket Outcomes., FEDEA Working Paper No. 2011-08.

Angrist, J. D., Evans, W. N. (1996). Children and their parents' labor supply: Evidence from exogenous variation in family size (No. w5778). *National bureau of economic research*.

Antman, F. & McKenzie, D. (2007): Earnings Mobility and Measurement Error: A Pseudo-Panel Approach. *Economic Development and Cultural Change*, vol. 56(1), pp. 125- 161.

Armstrong, M. (2009). Armstrongs Handbook of Human Resource Management Practice (11th ed.). London: Kogan Page Limited.

Baah, A. Y., & Reilly, B. (2009). An Empirical Analysis of Strike Durations in Ghana from 1980 to 2004. *Labour*, 23(3), 459-479

Blanchard, O. (1997). The economics of post-communist transition. Oxford: Clarendon press.

Borjas, G. (2002) .The Wage Structure and the Sorting of Workers into the Public Sector., NBER Working Paper No. 9313.

Bregn, K. (2013). Detrimental effects of performance-related pay in the public sector? On the need for a broader theoretical perspective. *Public Organization Review*, 13(1), 21-35.

Callaway, B., & Li, T. (2017). Quantile Treatment Effects in Difference in Differences Models with Panel Data. Available at SSRN 3013341.

Campos, M. M., Depalo, D., Papapetrou, E., Prez, J. J., & Ramos, R. (2017). Understanding the public sector pay gap. *IZA Journal of Labor Policy*, 6(1), 7.

Damiani, M., F. Pompei, & Ricci, A . (2016). Performance Related Pay, Productivity and Wages in Italy: A Quantile Regression Approach. *International Journal of Manpower*, 37(2), 34471

de Castro, F., Salto, M., & Steiner, H. (2013). The gap between public and private wages: new evidence for the EU (No. 508). Directorate General Economic and Financial Affairs (DG ECFIN), European Commission.

Fan, Y., & Yu, Z. (2012). Partial identification of distributional and quantile treatment effects in difference-in-differences models. *Economics Letters*, 115(3), 511-515.

Finan, F., Olken, B. A., & Pande, R. (2015). The personnel economics of the state (No. w21825). *National Bureau of Economic Research*.

Freeman, R., & Schettkat, R. (2001). Skill compression, wage differentials, and employment: Germany vs the US. *Oxford Economic Papers*, 53(3), 582-603.

Frey, B. S. (1993). Shirking or work morale?: The impact of regulating. *European Economic Review*, 37(8), 1523-1532.

Ghana Statisical Service (2017) Ghana - Living Standards Survey (With Labour Force Module) 2012-2013, Sixth Round. Accessed Online: `https://www.ilo.org/surveydata/index.php/catalog/466/sampling`

Ghinetti, P. (2007). The publicprivate job satisfaction differential in Italy.Labour, 21(2), pp 361-388.

Glewwe, P. (1991). Schooling, Skills, and the Returns to Government Investment in Education: An Exploration Using Data from Ghana Living Standards Measurement Study, Working Paper No. 76. The World Bank, Publications Department, 1818 H St., NW, Washington, DC 20433

Government White Paper on the Single Spine Pay Policy November (2009), Retrieved Online: `WP.No.1/2009-fairwages.gov.gh/files/GovernmentWhitepaper.pdf`

GarPerez, J. I., Jimeno, J. F. (2007). Public sector wage gaps in Spanish regions. The Manchester School, 75(4), 501-531.

Gregory, R. & Boland, J. (1999) Recent development in public sector labour markets. In A. Ashenfelter and D. Card (eds.) Handbook of Labor Economics, 3(C) 3573-3630. New York, Elsevier Science, North Holland

International Labour Organisation (2002) Decent Work and the Informal Economy. Retrieved Online: `https://www.ilo.org/wcmsp5/groups/public/---ed_emp/---emp_policy/documents/publication/wcms_210442.pdf`

Jackman, R., & Pauna, C. (1997). Labour market policy and the reallocation of labour across sectors. In Lessons from the Economic Transition (pp. 373-392). Springer, Dordrecht.

Jacobs, M. (2016). Public-private sector wage differentials and household poverty among Black South Africans (Doctoral dissertation, University of the Witwatersrand, Faculty of Commerce, Law and Management, School of Economic and Business Sciences).

Khalid, M. (n.d) The Gender Wage Gap in Ghana: Empirical Evidence from the Formal and Informal Sectors. Retrieved online: `http://home.cc.umanitoba.ca/~khalidm/Wage_Gap.pdf`

Kwenda, P., & Ntuli, M. (2018). A detailed decomposition analysis of the public-private sector wage gap in South Africa. Development Southern Africa, 35(6), 815-838.

Maloney, W. F. (2004). Informality revisited. World Development, 32(7), 11591178.

Meyer, B. D. (1995). Natural and quasi-experiments in economics. *Journal of business economic statistics*, 13(2), 151-161.

Oppong, S., Dickson, E., & Asumeng, M. (2015). Implementation Of Single Spine Pay Policy In Public Sector Of Ghana: Analysis And Recommendations From Organizational Development Perspective. Business Excellence, 9(2), 83.

Panizza, U. & C. Qiang (2005) .Public.private wage dierential and gender gap in Latin America: Spoiled bureaucrats and exploited women?. , The Journal of Socio-Economics, vol. 34, pp. 810-833.

Powell, D. (2016). Quantile regression with nonadditive fixed effects. Quantile Treatment Effects, 1-28.

Saavedra, J. & A. C. (1999). Structural reforms, institutions and earnings: evidence from the formal and informal sectors in urban Peru. Journal of Development Studies, 35(4), 95116.

Shapiro, C., & Stiglitz, J. E. (1984). Equilibrium unemployment as a worker discipline device. The American Economic Review, 74(3), 433-444.

Yee, J. L., & Niemeier, D. (1996). Advantages and disadvantages: Longitudinal vs. repeated cross-section surveys.

Younger, S. D., & Osei-Assibey, E. (2017). Are Ghanas Public-Sector employees overpaid?: Understanding the public/private wage gap and its effect on the government deficit (Vol. 1691). Intl Food Policy Res Inst.

Appendix A

Powell (2016) proposed a quantile treatment estimator that is more flexible to additional controls and can be applied on pooled cross-section data. Crucial aspect of the estimator is that it uses a generalized method of moment (GMM) approach that allows to uncover the treatment effect between the treatment variable and the outcome distribution, conditional on additional covariates. This means that in general, Powell (2016) provides a powerful tool to estimate treatment effect of endogenous or exogenous policy variables conditional on workers characteristics even without additive fixed effects. According to Powell (2016) this requires two major moment conditions. Firstly, within-individual variation is used as identification. Secondly, the expected probability of each individual is equal to the quantile function. This is formally shown as:

$$E\left[\frac{1}{T}\sum_{t=1}^{T}\left(Z_{it}-\overline{Z}_i\right)\left[1\left(\overline{Y}_{it}\leq q\left(D_{it},\tau\right)\right)\right]\right]=0 \tag{5}$$

$$E\left[1\left(\overline{Y}_{it}\leq q\left(D_{it},\tau\right)\right)-\tau\right]=0 \tag{6}$$

where $\overline{Z}_i=\frac{1}{T}\sum_{t=1}^{T}Z_{it}$ is the GMM estimator of β_1 and β_2 in equation (1). Powell (2016) uses the generalized method of moment (GMM) to solve the optimization problem as:

$$\widehat{\boldsymbol{\beta}(\tau)}=\arg\min_{\mathbf{b}}\hat{h}(\mathbf{b})'\hat{W}\hat{h}(\mathbf{b}) \tag{7}$$

where $\hat{W}$ is the weighing matrix and $\hat{h}(\mathbf{b})$ is a sample moment defined as:

$$\hat{h}(\mathbf{b})=\frac{1}{N}\sum_{i=1}^{N}h_i(\mathbf{b}) \quad \text{with} \quad h_i(\mathbf{b})\equiv\begin{bmatrix}\frac{1}{T}\sum_{t=1}^{T}\left(\mathbf{Z}_{it}-\overline{\mathbf{Z}}_i\right)\left[\mathbf{1}\left(Y_{it}\leq\mathbf{D}'_{it}\mathbf{b}\right)\right]\\ \frac{1}{T}\sum_{t=1}^{T}\left[\mathbf{1}\left(Y_{it}\leq\mathbf{D}'_{u}\mathbf{b}\right)\right]-\tau\end{bmatrix} \tag{8}$$

The parameters are restricted to $\mathcal{B}$ such that the condition $Y_{it}\leq\mathbf{D}'_{it}\mathbf{b}$ holds for (approximately) 100τ% of the observations in each time period

$$\mathcal{B}\equiv\left\{\mathbf{b}\quad|\tau-\frac{1}{N}<\frac{1}{N}\sum_{i=1}^{N}\mathbf{1}\left(Y_{it}\leq\mathbf{D}'_{it}\mathbf{b}\right)\leq\tau\quad\text{for all }t\right\} \tag{9}$$

As estimation can be numerically challenging, and recovering standard errors (SEs) difficult, Powell (2016) provides a number of alternative estimation methods. One can estimate via grid search, Markov chain Monte Carlo (MCMC), or Nelder-Mead numerical optimization. This study adopts the MCMC algorithm to recover the SEs.

Appendix B

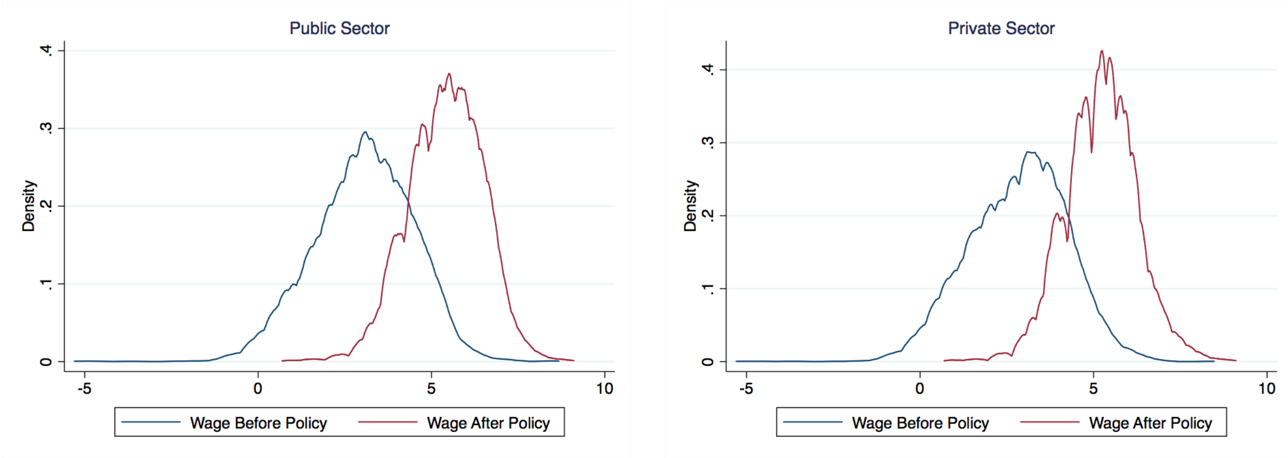


Figure 7: Distribution of Log of Monthly Earnings

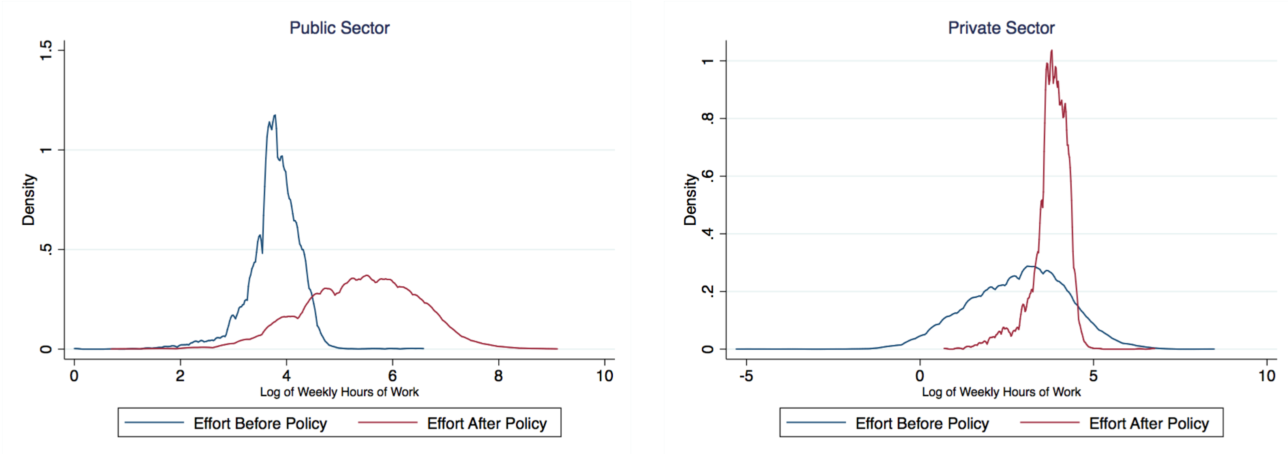
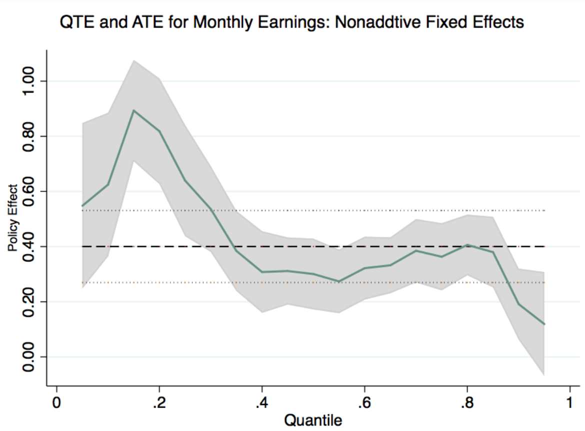
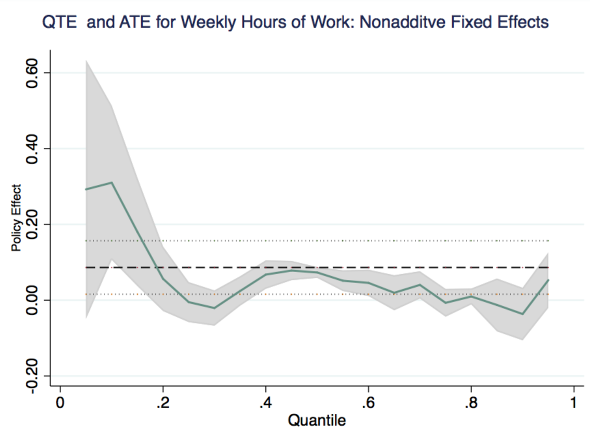


Figure 8: Distribution of Log of Weekly Hours of Work



(a) Monthly Earnings



(b) Weekly Hours of Work

Table 6: Descriptive Statistics for Survey year 1998 and 2006

VARIABLES	(1) Total	(2) Public	(3) Private	(4) Total	(5) Public	(6) Private
	1998			*2006*		
Wage	25.41	26.51	28.85	130.4	145.2	157.8
	(221.9)	(309.3)	(28.14)	(221.5)	(204.6)	(243.5)
Hours of Work	49.40	46.36	52.80	48.28	45.74	52.16
	(27.28)	(18.35)	(34.33)	(30.00)	(25.84)	(35.10)
Education	2.762	2.961	2.535	2.952	3.191	2.571
	(0.845)	(0.895)	(0.722)	(0.979)	(0.956)	(0.892)
Age	38.43	42.23	34.49	39.6	41.54	36.66
	(10.93)	(9.351)	(11.06)	(11.08)	(10.59)	(11.18)
Household Size	4.296	4.855	3.642	4.090	4.246	3.826
	(2.535)	(2.607)	(2.283)	(2.653)	(2.677)	(2.594)
Gender	0.745	0.717	0.775	0.720	0.703	0.745
	(0.436)	(0.451)	(0.418)	(0.449)	(0.457)	(0.436)
Marital Status	0.732	0.861	0.598	0.700	0.752	0.620
	(0.443)	(0.347)	(0.491)	(0.459)	(0.432)	(0.486)
Employed Father	0.336	0.363	0.306	0.502	0.481	0.536
	(0.472)	(0.481)	(0.461)	(0.500)	(0.500)	(0.499)
Employed Mother	0.461	0.514	0.401	0.553	0.504	0.632
	(0.499)	(0.500)	(0.491)	(0.497)	(0.500)	(0.483)
Employment share	100	50.88	49.12	100	60.59	39.41
Observations	1,256	639	617	1,256	761	495

[*] Note: All figures are averages except employment share which is in percentage. It shows the sectorial share of wage employment for each survey year. Standard deviations are in parenthesis.

Table 7: Descriptive Statistics for Survey year 2013 and 2017

VARIABLES	(1) Total	(2) Public	(3) Private	(4) Total	(5) Public	(6) Private
	2013			*2017*		
Wage	566.2	647.7	456.8	582.4	996.1	417.3
	(808.3)	(708.7)	(914.3)	(1,061)	(772.1)	(1,115)
Hours of Work	47.46	43.47	53.07	41.90	38.09	43.50
	(80.23)	(29.46)	(119.2)	(53.46)	(55.90)	(52.33)
Education	3.393	3.551	3.165	3.161	3.632	2.989
	(0.651)	(0.603)	(0.650)	(0.624)	(0.547)	(0.558)
Age	36.94	38.62	(34.59)	33.16	38.29	31.43
	(11.33)	(10.95)	(11.43)	(11.25)	(10.84)	(10.86)
Household Size	3.613	3.755	3.396	4.390	4.229	4.444
	(2.351)	(2.452)	(2.173)	(2.985)	(2.634)	(3.093)
Gender	0.649	0.615	0.697	0.654	0.625	0.664
	(0.477)	(0.487)	(0.460)	(0.476)	(0.484)	(0.472)
Marital Status	0.638	0.703	0.547	0.526	0.688	0.471
	(0.481)	(0.457)	(0.498)	(0.499)	(0.463)	(0.499)
Employed Father	0.537	0.525	0.556	0.477	0.546	0.451
	(0.499)	(0.500)	(0.497)	(0.500)	(0.498)	(0.498)
Employed Mother	0.590	0.557	0.639	0.569	0.589	0.561
	(0.492)	(0.497)	(0.480)	(0.495)	(0.492)	(0.496)
Employment share	100	58.35	41.65	100	74.73	25.27
Observations	2,977	1,737	1,240	5,735	4,286	1,449

* Note: All figures are averages except employment share which is in percentage. It shows the sectorial share of wage employment for each survey year. Standard deviations are in parenthesis.

Table 8: DID Estimate of SSPP Effect on Earnings and Effort: Without Controls

VARIABLES	(1) OLS	(2) 0.1 Q	(3) 0.25 Q	(4) 0.5 Q	(5) 0.75 Q	(6) 0.9 Q
	Panel A - Monthly Earnings					
Public Sector	1.008***	1.864***	1.015***	0.532***	0.209*	0.0310
	(0.0660)	(0.179)	(0.122)	(0.0871)	(0.114)	(0.138)
Policy Effect	0.231***	0.223	0.452**	0.537***	0.557***	0.409**
	(0.0721)	(0.378)	(0.186)	(0.125)	(0.129)	(0.169)
Individual Controls	No	No	No	No	No	No
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Specific FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	9,652	9,652	9,652	9,652	9,652	9,652
	Panel B - Effort					
Public Sector	-0.121***	-0.162	-0.0738*	-0.160***	-0.220***	-0.0706
	(0.0187)	(0.0999)	(0.0430)	(0.0617)	(0.0572)	(0.0663)
Policy Effect	0.0678***	0.137	-0.00670	-0.0606	0.00214	-0.0976
	(0.0243)	(0.163)	(0.0526)	(0.0696)	(0.0651)	(0.114)
Individual Controls	No	No	No	No	No	No
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Specific FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	9,715	9,715	9,715	9,715	9,715	9,715

[*] Note: *,**,***denotes significant at the 10% , 5% and 1% level respectively. Standard errors using Marcov chain Monte Carlo (MCMC) numerical optimization are reported in parenthesis for the quantile estimates while robust standard errors are presented in parenthesis for the OLS estimate. Also included in the individual controls are the presence of trade union and age-squared.

Table 9: Effect of SSPP on Earnings in Education and Health Subsector

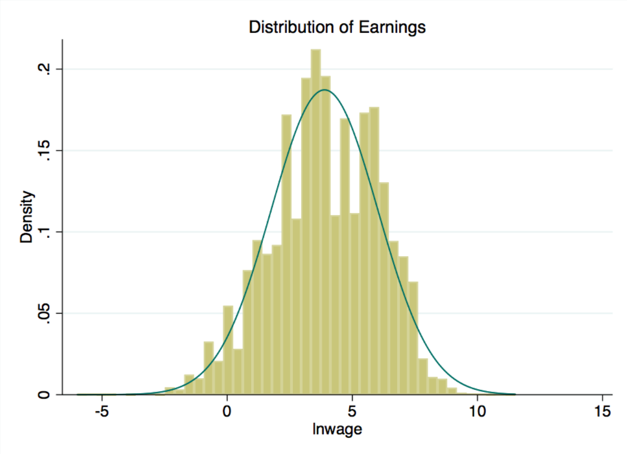
VARIABLES	(1) OLS	(2) 0.1 Q	(3) 0.25 Q	(4) 0.5 Q	(5) 0.75 Q	(6) 0.9 Q
			Full sample			
Public Sector	0.312	1.033***	1.035***	0.392	0.284**	-0.021
	(0.436)	(0.242)	(0.223)	(0.281)	(0.084)	(0.661)
Policy Effect	-0.992***	0.439***	-0.246***	-0.128	-0.012	-0.024***
	(0.072)	(0.022)	(0.068)	(0.129)	(0.035)	(0.005)
Observations	892	892	892	892	892	892
			Male			
Public Sector	-0.005	-0.054***	0.016*	-0.029	-0.017	-0.010***
	(0.031)	(0.018)	(0.011)	(0.240)	(0.201)	(0.001)
Policy Effect	-0.0064	-0.187***	-0.224	0.173***	-0.141	-0.0122***
	(0.065)	(0.039)	(0.231)	(0.002)	(0.132)	(0.004)
Observations	561	561	561	561	561	561
			Female			
Public Sector	0.831	0.162**	-0.135***	0.149	0.183	-0.171**
	(0.537)	(0.042)	(0.024)	(0.139)	(0.111)	(0.061)
Policy Effect	-0.351	0.223***	-0.214***	-0.095	-0.008	-0.136
	(0.271)	(0.020)	(0.068)	(0.129)	(0.033)	(0.116)
Observations	331	331	331	331	331	331
Individual Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Specific FE	Yes	Yes	Yes	Yes	Yes	Yes

[*] Note: *,**,***denotes significant at the 10% , 5% and 1% level respectively. Standard errors using Marcov chain Monte Carlo (MCMC) numerical optimization are reported in parenthesis for the quantile estimates while robust standard errors are presented in parenthesis for the OLS estimate. Also included in the individual controls are the presence of trade union and age-squared.

Table 10: Effect of SSPP on Effort in Education and Health Subsector

VARIABLES	(1) OLS	(2) 0.1 Q	(3) 0.25 Q	(4) 0.5 Q	(5) 0.75 Q	(6) 0.9 Q
		Full sample				
Public Sector	0.0034	0.103**	0.035*	0.099	0.019***	0.052
	(0.061)	(0.011)	(0.004)	(0.132)	(0.002)	(0.183)
Public Effect	-0.187	-1.002***	-0.982***	-0.595***	0.345*	-0.060
	(0.472)	(0.007)	(0.009)	(0.102)	(0.212)	(0.036)
Observations	892	892	892	892	892	892
		Male				
Public Sector	0.082	0.040***	0.032***	0.441	0.012	0.068
	(0.121)	(0.006)	(0.001)	(0.605)	(0.220)	(0.222)
Policy Effect	-0.0250	0.762***	-0.985	0.865*	-0.254	-0.143***
	(0.555)	(0.134)	(0.731)	(0.433)	(0.132)	(0.034)
Observations	561	561	561	561	561	561
		Female				
Public Sector	0.115	1.165**	0.631***	0.343	-0.382	-0.675
	(0.236)	(0.932)	(0.024)	(0.181)	(0.514)	(0.633)
Policy Effect	-0.0543	-1.302***	-1.114**	0.085	-0.108	-0.313***
	(0.472)	(0.020)	(0.568)	(0.129)	(0.133)	(0.016)
Observations	331	331	331	331	331	331
Individual Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Specific FE	Yes	Yes	Yes	Yes	Yes	Yes

* Note: *,**,***denotes significant at the 10% , 5% and 1% level respectively. Standard errors using Marcov chain Monte Carlo (MCMC) numerical optimization are reported in parenthesis for the quantile estimates while robust standard errors are presented in parenthesis for the OLS estimate. Also included in the individual controls are the presence of trade union and age-squared.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.2
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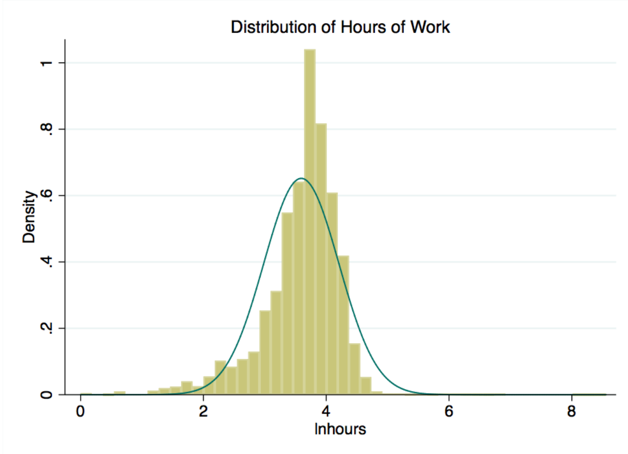
5
10
15
lnwage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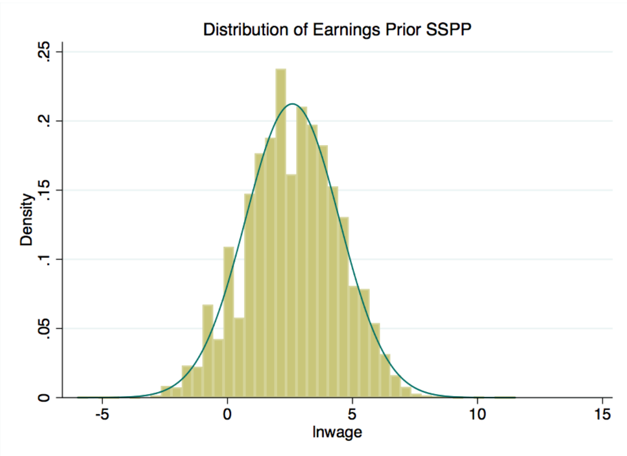
1
0
2
4
6
8
lnhours


Distribution of Earnings Prior SSPP
Density
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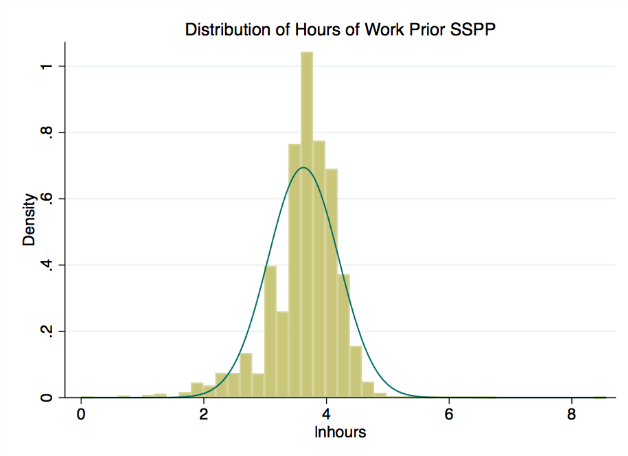
.25
-5
0
5
10
15
lnwage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1
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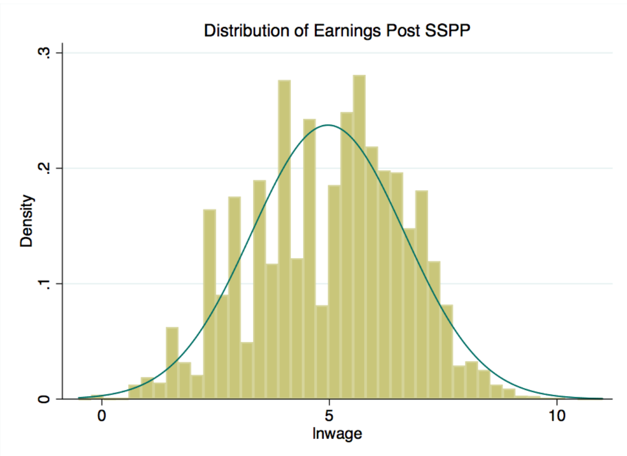
2
4
6
8
lnhours


Distribution of Earnings Post SSPP
Density
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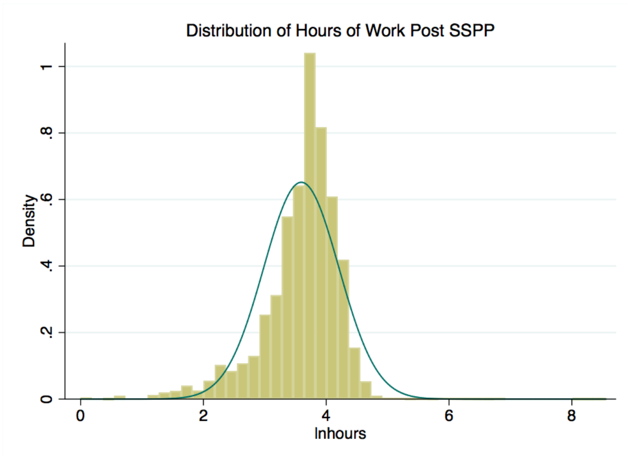
0
5
10
lnwage


Distribution of Hours of Work Post SSPP
Density
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1
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2
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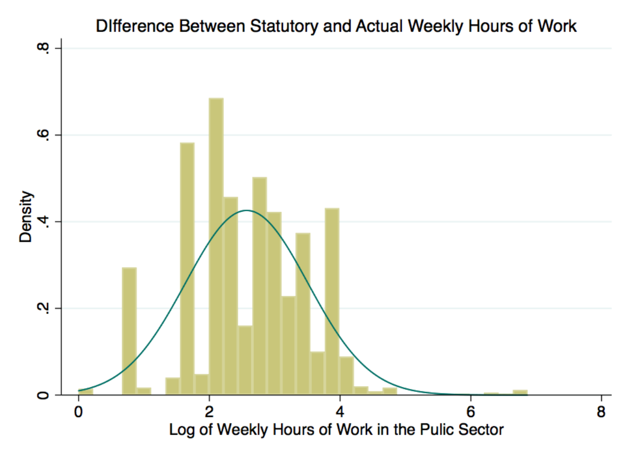
lnhours


DIfference Between Statutory and Actual Weekly Hours of Work
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.8
0
2
4
6
8
Log of Weekly Hours of Work in the Pulic Sector