Mind the Wage Gap by Internet[1]

Filipe Lage de Sousa

UFF and BNDES

Maurício Canêdo Pinheiro

UERJ and FGV/EPGE

Gabriel Richter de Almeida

FGV/EPGE

Abstract

Literature on labor economics shows the existence of wage gap between internet users and non-users. Moreover, wage gap is wider in developing countries than developed world. This paper investigates whether internet users in Brazil present higher wages compared to those outside this global network. Our results show that wage premium due to internet use in Brazil is much more like developed world than previous evidence. Gap is wider between those older and higher wages in recent years, but gender gap become irrelevant. However, unexplained factors have increased importance over the years.

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Keywords: Wage Premium; Internet; Labor Market

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1. Introduction

Use of Information and Communication Technology (ICT) has spread across individuals worldwide and its impact on wages has been investigated by the labor literature. Krueger (1993), for instance, estimated that wage premium for computer users in the US is between 10% to 15%, Bell (1996) found 13% in the UK, Oosterbeek (1997) 12% in the Netherlands and Miller and Mulvey (1997) from 12 to 16% in Australia. As observed, wage premium due to computer use is over 10% in developed countries.

On internet use, Goss and Phillips (2002) estimate an average gain of 13.5% for US workers on-the-job internet usage after controlling for selectivity bias. For developing countries, Navarro (2010) analyzed the impact of internet use on individual earnings in six Latin American countries.[2] Aside Paraguay, his findings suggest wage premium in all other five countries ranging from 18% in Mexico to around 30% in Brazil and Honduras. Focusing on Brazilian data yet using more years, Ambrozio, Machado and Reis (2011) found that wage premium for internet use at work is over 40%.[3]

As observed, wage premium of internet use is greater in developing countries compared to developed ones, as suggested in Navarro (2010). There are different factors explaining it, but we advocate that two shortcomings are the main ones. First, internet use in developing world lacks behind advanced economies, therefore incremental gains are higher in lower levels of use. Second, both papers mentioned investigating internet use in developing countries rely on cross-section data estimation procedures; therefore, they do not fully control for individual's characteristics, including some non-observable which are correlated to internet use. As a result, findings might be biased.

The objective of the paper is to provide a more accurate estimation of the wage premium derived from internet use in a relevant developing country: Brazil. This country presents an opportunity to investigate this phenomenon because it has a recent and cross-section microdata at individual level for different years available, which enables the research to overcome these two main shortcomings mentioned previously.[4] As internet use in Brazil has increased substantially in recent years, it enables, for example, to investigate whether wage premiums due to internet use reduces as prevalence of internet among individuals increases. Although microdata is not constructed in a panel format, but rather different cross-sections from distinct years, econometric techniques, such as pseudo panel data, are able to address some issues of unobserved time-invariant characteristics.

Our findings suggest that wage premium regarding internet use is lower than previous papers have found. Moreover, we found that the gap between internet users and non-users have reduced over the years, which corroborates the fact that expansion of internet use among workers have made them more

[2] Brazil, Chile, Costa Rica, Honduras, Mexico and Paraguay.

[3] Discrepancies on Brazilian findings reside on different empirical strategies implemented in both papers. Moreover, Navarro (2010) uses only one year for each country (including Brazil) while Ambrozio et al. (2011) uses two years.

[4] Survey is constructed by a random selection of individuals over the years. Therefore, it consists of different cross-sections for each year (not a panel).

similar. However, decomposing the gap between explained and unexplained factors, our findings show that unexplained factors have increased their share over the years.

In order to present these arguments, this paper is structured as follows. Section 2 describes our dataset and show descriptive statistics between internet users and non-users. Our empirical strategy is presented in Section 3. Our main results are shown in Section 4. Our final remarks conclude this investigation.

2. Data Description and Some Statistics

The National Household Sample Survey (*Pesquisa Nacional por Amostra de Domicilios* – PNAD, acronym in Portuguese) is a representative survey of the Brazilian population. It investigates annually general characteristics of the population, regarding education, labor, income and housing, besides others, according to type of information needed, including ICT use. PNAD investigated the Internet access and ownership of mobile phones for personal use as a supplementary theme in four years: 2005, 2008, 2009, 2011, 2013, 2014 and 2015.

The use of internet has increased steadily over the years among Brazilian residents, as observed in Figure 1. Numbers show that percentage of people using internet has more than the double in 11 years. While only 21% of Brazilian have used internet in 2005, in 2015 58% have made use of internet. These figures show a dramatically increase over this short period raising the question on whether it might have impacted the Brazilian labor market.

Figure 1: Percentage of Internet Users in the Brazilian Population

<INSERT FIGURE 1 HERE>

Source: PNAD 2005, 2008, 2009, 2011, 2013, 2014 and 2015.

Regarding internet use, there was a change in the survey's questionnaire over the years. For the first two years (2005 and 2008), individuals were asked not only whether they have accessed internet recently but also where this access has taken place. Options include home and work, for instance. For those two years, it is possible to assess whether internet use at work is associated with wage's gap between users and non-users. However, information on where individuals have accessed internet is not available in the last years of this survey (2009, 2011, 2013, 2014 and 2015). Although, it is not feasible to know whether individuals' access to internet was at their workplace, we are able to restrict the sample to only those which were working when they were interviewed. Therefore, our analysis will consider access to internet at work for the first two years as well as access to internet regardless where for all years of information (2005/08/09/11/13/14/15). In order to perform this investigation, our restricted sample is limited to only working age individuals (from 21 years to 65 years) and excluded all those

which were working less than 10 hours per week (including those not working – zero hours worked).[5] Moreover, we have also eliminated domestic workers' and their relatives as well as any retiree. Nevertheless, our restricted sample contains more than 100 thousand individuals for each year.

Figure 2: Percentage of Internet Users in the Brazilian Working Age Population

<INSERT FIGURE 2 HERE>

Source: PNAD 2005, 2008, 2009, 2011, 2013, 2014 and 2015.

Among occupied workers, percentage of individuals using internet increases over the period similarly to the total shown in Figure 1, but numbers are slightly higher for each year. For instance, percentage of working individuals reached 2/3 in 2015 while considering all surveyed individuals is still below 60% (see Figure 2). It is also shown that increase is much more accentuated in accessing at home (11 p.p.) rather than at work (4 p.p.).[6] Considering this information, we might infer that all increase was originated by working occupied people in accessing internet at home. This reduces the importance of investigating only those accessing internet at work, since most of the increase accessing anywhere is explained by the increase of internet at home.

Figure 3 shows evolution of wage premium, which is the wage ratio of internet users over non-users, as well as their real wages per hour over the surveyed years.[7] Wage premium shrinks by 1.05 from 2005 to 2015 mainly due to a reduction of internet users' wages, since their wage per hour reduced from 10.5 to 7.7 over the investigated period, while wage per hour from non-internet wages increase slightly from 3.3 to 3.7. A possible explanation might be related to the increase of working force with lower skills and educational achievement among internet users.

Figure 3: Nominal Wages per Hour in R$ and Wage Premium (Internet Users / Non-Internet Users)

<INSERT FIGURE 3 HERE>

Source: PNAD 2005, 2008, 2009, 2011, 2013, 2014 and 2015.

Wage gap is not only present at the average, but also in the whole distribution of internet users versus non-internet users. Figure 4 shows the relative wage kernel distribution of these two groups.[8] As observed, internet users show higher wages compared to non-internet users in the whole distribution. For instance, wage from a non-internet user on its 20 percentile is equivalent to an internet user lower than 10 percentile (see Figure 4).

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[5] It is important to highlight that we are not eliminating those in informal jobs, yet only those which working is not the main activity.

[6] According to the surveys from 2005 and 2008, home and work are the main places where people access internet, therefore we restricted our descriptive analysis to these two locations only.

[7] Real wages are calculated using the official price index (INPC-IBGE). Full descriptive statistics are available in Appendix A.

[8] A curve below the 45 line shows that internet users have higher wages compared to non-internet users in the whole distribution, while any point above the 45 line shows the opposite.

Figure 4: Relative Wage Kernel Distribution

<INSERT FIGURE 4 HERE>

Source: PNAD 2005, 2008, 2009, 2011, 2013, 2014 and 2015.

Regarding education, Figure 5 shows the number of years of schooling from internet users and non-users. As expected, internet users are more educated than non-users, but difference is double. Nevertheless, gap has slightly decreased from 2005 to 2011. Two interpretations emerge from these numbers. First, expansion of the working force in Brazil during this period was towards less educated people. Second, reduction of wage premium from 3.23 in 2005 to 2.45 in 2011 might be partially explained by educational gap decrease.

Figure 5: Years of Schooling

<INSERT FIGURE 5 HERE>

Source: PNAD 2005, 2008, 2009, 2011, 2013, 2014 and 2015.

3. Empirical Strategy

3.1 Basic Approach

As mentioned previously, PNAD microdata consist of repeated cross-sectional data and those with internet use information are available in seven years: 2005, 2008, 2009, 2011, 2013, 2014 and 2015. Therefore, standard panel data cannot be implemented since individuals are not tracked over time. In the investigation proposed in this paper, this data shortcoming creates a potential problem which is the impossibility of controlling for unobservable characteristics that might be correlated to the investigated phenomenon (internet use).[9] For instance, internet use might be a consequence of an unobservable person's tendency to use new technologies which is intrinsic to an individual.[10] However, absence of panel data structure does not impinge on being able to control for these factors, since existence of alternative econometric approaches, such as pseudo panel, enables to address this issue, as pointed out in Verbeek (2007). Nevertheless, other techniques, like Propensity Score Matching, might be able to overcome other potential problems, such as differences in observable characteristics. Educational level is one example, since educated individuals are more inclined to use internet. In summary, our empirical strategy will be able to consider different techniques to tackle most of the existent shortcomings in investigating this issue. Our basic econometric specification is represented in formula (1).

$$ln\,(wage_{it}) = \alpha + \vartheta I_{it} + \beta\, X_{it} + \varepsilon_{it} \qquad (1)$$

[9] Although panel data resolves issues like time-invariant unobservable characteristics, it presents other problems such as attrition and non-response that other methods might be able to address.

[10] We define unobservable characteristics as issues which are not covered by survey's questionnaire.

where $wage_{it}$ is the wage per hour of an individual i in year t; I_{it} is a dummy indicating whether an individual i has accessed internet in year t; X_{it} represents all variables affecting wage of an individual i at time t (for example, education, gender and others) and ε_{it} is the error term. All other terms are parameters to be estimated. As the place of accessing internet is only available in the first two years, our initial approach is to estimate equation 1 by OLS using two definitions for internet access dummy: either accessing it anywhere; or accessing it at work. Comparing the result, we may be able to establish similarities and differences of using these two measures. If they perform similarly, there is no issue on estimating the real effect using access to internet regardless where it takes place.

One way to further investigate this issue consists of considering not only these two locations (work and home) in the same regression, but also if individuals access internet in both places. In the IBGE publication, percentage for individuals using in either place is increasing over time at a higher rate than either of them isolated. Therefore, our econometric specification might shift to incorporate these three possibilities as represented in equation 2.

$$ln\ (wage_{it}) = \alpha + \vartheta IW_{it} + \lambda IH_{it} + \phi IW_{it} * IH_{it} + \beta\ X_{it} + \varepsilon_{it} \quad (2)$$

where IW represents accessing internet at work and IH, at home. Parameter ϕ represents whether interaction between home and work is superior to the contribution of each place isolated. If not, we may restrict our investigation on just isolated effects.

In order to reduce potential bias related in time-invariant unobservable characteristics, we introduce cohorts in our econometric specification (see equation 3).

$$ln\ (wage_{it}) = \alpha + \vartheta I_{it} + \beta\ X_{it} + \mu\ C_i + \varepsilon_{it} \quad (3)$$

Variable C_{it} is a dummy variable for whether an individual i belongs to a specific cohort. In this approach, we utilize individuals' age group as our initial criteria to define our cohort. However, one part of the literature uses other measures jointly with age's group when constructing their cohort, such as in Propper, Rees and Green (2001). As we know that individual's access to internet differs substantially in distinct measures, we will consider two other measures in the construction of our cohort. First, geographical locations play a significant role for internet use, since some regions present better infrastructure to access internet than others. Second, individuals have distinct abilities to adapt to new technologies, since some people might be more reluctant to (or interested in) new technologies than others. As both are time-invariant characteristics yet considering location and individual attributes, we include them when constructing our cohort groups in order to control for unobservable time-invariant characteristics correlated to our investigated variable (internet use) and the error term. In this approach, age's group are divided into 9 categories of 5-year period, regions are classified into 5 groups defined by the Brazilian Statistical Institute (North, Northeast, Southeast, South and Middle-West) jointly with whether a person has a mobile or not (technological tendency). As a result, cohorts are split into 90 groups (9 age's group x 5 regions x 2 technological tendency).

Access to internet can be also correlated to observable characteristics leading to biased estimated values of β. In order to tackle this issue, we consider using Propensity Score Matching to construct

similar groups of individuals and then estimating the impact of internet on wages by using these similar groups. In order to construct our similar groups, we estimate the probability of an individual to access internet anywhere.[11] Control groups are defined by the nearest neighbor without replacement. After matching, we estimate equation (1) and (3) to measure the effect of internet on individual's wages.

Not all unobservable time-invariant characteristics might be eliminated by the methods proposed, since some individuals living in the same region, having same age and using mobile phone might have completely different abilities which cannot be captured by those measures. In order to address this issue, we construct a pseudo panel defined by individual's cohorts. Equation 4 shows our pseudo panel in an econometric specification.

$$ln\,(wage_{ct}) = \alpha + \vartheta I_{ct} + \Upsilon C_c + \beta X_{ct} + \varepsilon_{ct} \qquad (4)$$

where $wage_{ct}$ is the wage's mean of individuals belonging to cohort c in year t; I_{ct} is the average of internet users of cohort c in time t; C_c is a dummy for cohort c, X_{ct} represents all controls' averages for cohort c at time t and ε_{ct} is the error term. In this approach, we consider a different cohort definition as it is not credible to rely on estimates of 90 observations per year. In order to spam our cohort observation number, we consider three other geographical information: State level (27 units); metropolitan area (two groups); and urban or rural area (two groups). In total, cohort units raises to 1,944 observations per year considering mobile and age groups jointly with these geographical information.[12]

3.2 Heterogenous Effect: Quantiles, Age and Gender

Different approaches can be developed after these basic empirical findings. For instance, different categories, such as gender and age might have different patterns. In the labor market literature, wage differentials persist in these two categories, therefore it is relevant to assess how internet use might affect these differences. Moreover, distinct income levels might be present different wage gaps. Therefore, it is relevant to assess whether heterogeneity wage gap due to internet exist between different groups.

For age, we classified workers according to their career stage, which is dividing them into three groups: entering in the labor market (21 to 29); maturation stage (30 to 44); last stage (over 45). Using those entering in the market as our base, we will be able to evaluate whether wage premium is larger for the other two groups. Our strategy is to estimate our basic models with the interaction of age group with internet dummy.

Regarding gender, we use a different approach. In the labor literature, the most common method of investigating wage gap between man and woman is by using Heckman selection model. In order to estimate it by Heckman selection model, we need some further information on whether woman has a child and their marital status. This information is only available after 2009, therefore our estimation should be based only on the use of internet regardless where it took place.

[11] Internet access at work relies much more on firms' attributes than individuals' characteristics. Since information of firms' characteristics is not available, we consider only the probability of having access to internet as a whole for this investigation.

[12] Kernel Distribution from internet users across these cohort's mean are available in the Appendix.

We also perform quantile regressions in order to evaluate whether wage gap between internet users and non-users differ according to the individual wage level.

Last, but not least, although observable characteristics distinguishes internet users to non-users, it is relevant to assess how much can be explained by observable factors and non-observable factors. Blinder-Oaxaca Decomposition is proper way to address this issue and we perform to evaluate how much cannot be explained by observable characteristics.

4. Empirical Results

Before analyzing econometric results, it is relevant to emphasize that all estimations and procedures (including averaging variables for pseudo panel) are performed using individuals' weights. OLS results from equation 1 are shown in Table 2.

<INSERT TABLE 2 HERE>

Although we use some additional controls, results are very similar to what was found in Ambrozio et al (2011).[13] On average, worker's wage premium for using internet is 48.9% using at work and 41.8% using anywhere considering the years of availability of both information (2005 and 2008). Although levels of internet wage premium are extremely similar in 2005 for both (anywhere and at work), worker's wage premium for using anywhere shrinks 11.9 p.p. and for using internet at work presents a slight decline from 50.7% in 2005 to 48.1% in 2008. Considering all years (column 9), our findings suggest that internet users earned on average 31.3% more, but this gap shrinks over the period reaching only 23.2% in 2015. These results confirm the tendency of decline of wage gaps between workers due to internet use, yet it remains relevant even after their expansion among individuals.

Individuals might use internet at home and at work, which means that we need to address whether accessing it in both places present higher gap compared to those using in a single location. Table 3 shows results when estimating at work and at home considering these issues as proposed in Equation 2.

<INSERT TABLE 3 HERE>

As observed, wages are 9.3% higher when individuals use internet at home and at work and with tendency to increase over the period. Nevertheless, their individual contributions from home and work use to wage premium are still higher although declining over time in both places (home and work), which permit us to assume that assessing it wherever it occurs remains relevant.

As discussed in the empirical strategy, our outcomes might be biased as there might be inherent characteristics correlated to the error term. One way to overcome this issue is by using cohorts. Table 4 presents results of equation 2 using age-region-mobile cohort dummies. Results are very similar to what is shown in previous tables, yet internet impact on wages is higher using cohorts in all years considered. For example, wage gap of the entire year using cohorts is 1.2 percentage points superior to when cohort

[13] Ambrozio et al (2011) does not include dummies for mobile use, urban area and metropolitan region.

is neglected. This indicates that bias of omitting these time-invariant unobservable characteristics is downward. A possible explanation might be that most of the internet users are younger which means that wage gap is wider when controlling for their age-group. Nevertheless, internet use impact on wages remains shrinking over the years, like our previous results without cohort dummies.

<INSERT TABLE 4 HERE>

Controlling for observable characteristics, Table 5 shows the results of regression after performing propensity score matching nearest neighbor within caliper.[14] Outcomes suggest that impact of internet on wages are much lower than previous findings. Now, wage premium for using internet anywhere is only 21.8% (compared to 31.3% from Table 2) and at work, 16.9% (compared to 48.9% from Table 2). This indicate that observable factors can reduce the estimates bias substantially. Nevertheless, effect of internet anywhere remains decaying over the period. While wage premium was 13.7% in 2005, it reaches 7.5% in 2015. This is further corroborated when estimating using all years (column 8), since the interaction of internet use with years present negative value for all parameters estimated.

<INSERT TABLE 5 HERE>

At work, it has remained reasonably stable over the years comparable to accessing internet anywhere. While the former shrank 3.7 percentage points from 2005 to 2008, the latter reduced only 1.6 percentage points during the same period. Furthermore, this decline when using internet at work is not statistically significant when considering the period 2005/08 and using the interaction between internet use at work and 2008 year-dummy. In other words, wage gap for those using internet at work has not reduced after three years.

Combining Cohort with PSM enables us to control for both unobservable factors which might be disturbing the effects of internet use on wages. Table 6 presents results of this combination which are very similar to Table 5. This indicates that estimating internet effect on wages based on individuals with similar observable characteristics might be eliminating any time-invariant unobservable characteristics of individuals as well. In other words, our cohorts have a null effect on reducing the bias after matching internet users with non-users. However, our results contrast to outcomes found in Navarro (2010), which shows a wage premium around 30%, while our findings suggest a wage premium nearly 10 percentage points lower (21.9% in column 8 from Table 6).

<INSERT TABLE 6 HERE>

Another approach is estimating equation 4 with cohorts fixed effects in order to evaluate whether these results remain valid after averaging individuals in the same cohorts (see Table 7 for outcomes). Wage premium for those using internet at work are substantially higher using this approach. It is nearly the double comparing with those using internet anywhere, while at work it is 68.8%, anywhere is only 39.3%.

[14] Probit estimates are available in the Appendix and value for maximum distance of controls is 0.01. Moreover, differences of groups after matching are statistically close to zero (available upon request).

<INSERT TABLE 7 HERE>

5. Heterogeneous Effects in terms of Age, Gender and Wage as well as Gap Decomposition

As results on matching without cohort dummies seem to show more accurate estimates of wage premium, our investigation on age and gender will show only outcomes on estimating wage premium using this approach.

As discussed in Section 3, we classified workers in three groups: entering in the labor market (21 to 29); maturation stage (30 to 44); last stage (over 45). Table 8 shows the results by using the interaction of those dummies with internet use.

<INSERT TABLE 8 HERE>

Compare to young workers, wage premium is larger for the other two age groups (either from 30 to 44 or over 45). On average, wage premium for those between 30 to 44 years was 4.7 percentage points higher than young workers regardless where they have accessed the internet, when using all years available (column 8). However, wage premium is nearly 10 percentage points higher for those over 45 accessing internet at work, but 6.1 percentage points above for those using internet anywhere. Over time, there is not a clear message for those from 30 to 44 years, but a tendency to increase the gap with those older (over 45 years) exists as well as a reduction on those younger (below 30 years). For instance, in the last years (2014 and 2015), wage gap between internet users and non-users in the age group of young workers (under 30 years) is not statistically significant. In 2005, for example, there was no difference in wage gap between young and older workers (column 1).

Using Heckman selection model for gender issue, results suggest that wage premium does not exist between women and man when considering all years as shown in columns 6 and 12 from Table 9. However, when looking at the evolution over time, wage premium for women reduces nearly 2 percentage points from 2009 until 2015 while for man it was only half. Therefore, while women tended to have higher wage gap due the use of internet, they have closed the gap quicker than men over the investigated period.

<INSERT TABLE 9 HERE>

As for different wage levels, Table 10 show the outcomes using quantile regressions.[15] One interesting fact is that while lower levels of wage present higher levels of gap compared to those at the top of the wage distribution when looking at internet use at work, wage gap is higher on those with higher levels of wage when using internet anywhere. In other words, those earning more tend to benefit more when using internet anywhere compared to those with lower wages, yet gap is wider for those with lower

[15] Full results are available in Tables A.4 and A.5 in the Appendix.

earnings when considering the use of internet at work. However, the difference between those using internet at work is less than one percentage point and it ranges from 2 to 3 percentage points for those using internet anywhere. This indicates that difference might be only relevant when considering the use of internet anywhere.

<INSERT TABLE 10 HERE>

Last, but not least, we estimate Blinder-Oaxaca decomposition in order to evaluate how much is still unexplained after controlling for observable characteristics. First, unexplained factors account for nearly 40% of the difference between internet users and non-users, regardless where the use has taken place (at work or anywhere). Another crucial fact lies on the fact that unexplained factors increases over the years at work and anywhere, but more in the former. However, when considering a longer period, we can detect a decrease of the percentage of unexplained factors, which reduced 2.6 percentage points from 2005 until 2015. Despite this reduction, more than a third of the total differences are not explained by the observable factors which consists of an area for further research, especially qualitative.

<INSERT TABLE 11 HERE>

6. Final Remarks

In this paper, we have investigated what is the effect of internet use on worker's wage in Brazil. Our results back up previous studies (Ambrozio et al (2011) and Navarro (2010)) showing that wage premium for internet users are initially higher than what is observed in developed countries, because our naive estimates show that worker's wages from internet users are over 40% than those non-users. However, results reduced by half after controlling for observable characteristics while using matching. Moreover, our most sophisticated methods show a reduction of the gap after the expansion of internet use among working occupied individuals over the years. In terms of age, older people tend to have higher wage premium for internet use compare to those at the begging of their careers for recent years. Regarding gender, wage premium gap is wider for women than for men initially, but this gap narrows over the years and become not relevant. Nevertheless, nearly 40% of the wage premium difference regarding internet use is still unexplained, as evidenced by Blinder-Oaxaca decomposition. Therefore, our results suggest that the spread of internet use in Brazil has reduced the wage premium of internet users and it has impacted differently people according to their age and gender, yet these differences have becoming much more unexplained than before.

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Annex

<INSERT TABLE A.1 HERE>

Source: PNAD 2005, 2008, 2009, 2011, 2013, 2014 and 2015

<INSERT TABLE A.2 HERE>

Source: PNAD 2005, 2008, 2009, 2011, 2013, 2014 and 2015.

<INSERT TABLE A.3 HERE>

<INSERT TABLE A.4 HERE>

<INSERT TABLE A.5 HERE>