Earnings Inequality in Spain: Evidence from Social Security Data*

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Abstract

We use detailed information on labor earnings and employment from social security records to document the evolution of earnings inequality in Spain from 1988 to 2010. Earnings distributions experienced substantial fluctuations over the period, with inequality following a marked countercyclical pattern. The economic expansion of the early 2000s was associated with decreasing gaps between skill and age groups, and narrowing earnings differences between permanent and temporary workers. That period was also characterized by a sharp increase in the share of the construction sector in the labor force, and by earnings increases in that sector. Together, these findings suggest that the fall in inequality was partly due to sustained demand for a particular type of labor. However, the Spanish expansion was fragile: the recession starting in 2008 has already seen a sharp increase in earnings inequality, in addition to the surge in unemployment.

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1 Introduction

The increase in earnings inequality in the United States during the 1980s and 1990s is the subject of a large and growing literature. Similar increases in inequality have been reported for other Anglo-Saxon countries.[1] In contrast, most countries in Continental Europe show much smaller increases in inequality in the 1980s or no increases at all, with the exception of (West) Germany.[2] To date, however, the evidence on the evolution of earnings inequality in Spain is rather incomplete. The first goal of this paper is to document this evolution over the last two decades, using a recently released dataset.

The Spanish experience during the 1988-2010 period shows several remarkable features. As one can see from Figure 1, that period has been characterized by two severe recessions (at the beginning of the 1990s, and after 2007) and a ten-year expansion from 1998 to 2007. The unemployment rate has been very high by European standards, and has shown large variation with the business cycle. In particular, the recent recession has seen a surge in unemployment from 8% in 2007 to more than 20% in 2010. In addition, the period has been characterized by a continued increase in the share of college graduates in the economy, and in the proportion of working women. The large immigrant inflows starting in the early 2000s, and the marked duality of the labor market with two main types of contracts ("temporary" and "permanent") are also part of the picture. All these factors could have contributed to the evolution of earnings inequality. The second goal of this paper is to identify the factors that are mostly responsible for the evolution that we document.

Documenting the evolution of the Spanish earnings inequality has proven challenging, mainly because of data limitations. Evidence from survey data suggests that inequality decreased from the mid 1990s until 2006 in parallel with a decrease in the college premium, while inequality increased at the beginning of the 1990s (Pijoan-Mas and Sánchez-Marcos, 2010).[3] However, wage or earnings surveys have often a far from complete coverage of the working population, rendering comparisons over time difficult. In addition, comparisons across surveys are sometimes inconsistent.

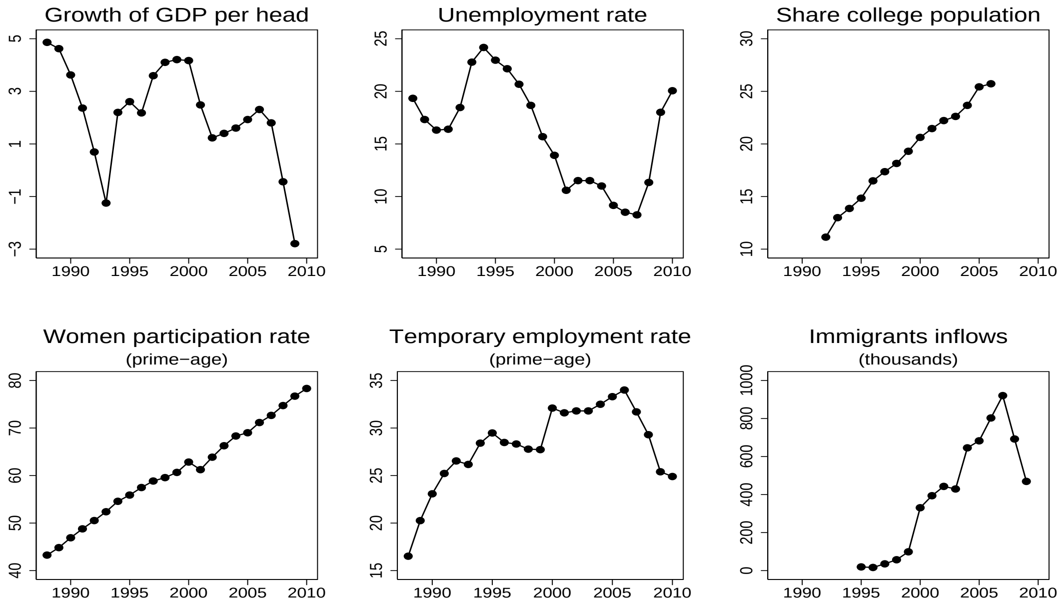
In this paper we use recently released social security data to characterize the evolution

[1] Among the many references for the US are Bound and Johnson (1992), Katz and Murphy (1992), Levy and Murnane (1992), Acemoglu (2002), or more recently Autor *et al.* (2008). See also Gosling *et al.* (2000) for the the UK, and Boudarbat *et al.* (2006) for Canada.

[2] See for example Freeman and Katz (1995), or Guvenen *et al.* (2009). For West Germany, Dustmann *et al.* (2009) find that wage inequality increased in the 1980s and 1990s.

[3] Most of the previous evidence on the Spanish wage inequality is based on three datasets: the Spanish wage structure survey, the European Community household panel, and the consumption survey. For example, using the latter Hidalgo (2008) documents a slight increase in inequality between 1990 and 2000. See also Simón (2009), Carrasco *et al.* (2011), and Izquierdo and Lacuesta (2012). For evidence before 1990, see for example Del Río and Ruiz-Castillo (2001), Abadie (1997), or Bover *et al.* (2002).

Figure 1. A few facts on the Spanish labor market (1988-2010)



Notes: Source OECD. Data on education comes from the Spanish section of the European Community Labour Force Survey.

of earnings inequality in Spain, from 1988 to 2010. Social security records have several advantages compared to the cross-sectional and panel datasets that have been previously used to document the evolution of inequality. These include large sample sizes, complete coverage of the part of the population that is covered by social security (more than 80% of the Spanish working population), and accurate earnings measurements. Overall, these data represent a unique source of consistent data for a period of more than twenty years. In Spain, there is no other dataset that reports information on labor income over such a long period.[4] In a recent study, Dustmann *et al.* (2009) use social security data to provide an accurate description of the German earnings structure. Here we use individual earnings records to provide the first description of Spanish inequality over a long period of time.[5]

Although the social security dataset that we use is well-suited for the study of earnings inequality, it has also several drawbacks. First, the social security dataset has a proper longitudinal design from 2005 to 2010 only, whereas before 2004 the information is retrospective.

[4]The longest running household survey is the Spanish labor force survey (EPA, in Spanish), which started in 1976. However, EPA does not contain any information on earnings.

[5]Felgueroso *et al.* (2010) use the same administrative source as we do, with the aim of documenting the driving forces behind the evolution of the earnings skill premium in Spain from 1988 to 2008. Ours is the first paper to use these data for the purpose of documenting earnings inequality.

This means that earnings data come from the records of individuals who were in the social security system some time between 2005 and 2010, either working, unemployed or retired. Comparison with the Spanish Labor Force Survey and other data sources suggests that, despite this retrospective design, past cross-sectional distributions of male earnings remain representative up to the late 1980s. In contrast, results for females could be subject to more severe biases. For this reason, we shall split our analysis by gender and mostly focus on males when commenting the results.

A second difficulty is that, as is commonly the case with administrative records, our measure of (daily) labor earnings is top- (and bottom-) coded. This represents a challenge for our analysis of earnings inequality, as the 90/10 percentile ratio, for example, is censored. To correct for censoring, we compare two approaches, based on quantile regressions and cell-by-cell tobit regressions, respectively. To assess the accuracy of these methods, we make use of the tax files available in the most recent years for the same individuals as in the social security dataset. Tax records are not subject to censoring, making them suitable to perform a validation check. Our out-of sample prediction exercise unambiguously favors the tobit-based approach over the quantile regression method. This motivates relying on predicted earnings using the cell-by-cell tobit method. We will focus on the 90/10 percentile earnings ratio, but also on the 80/20 ratio, which is much less censored over the period.

Our results show that earnings inequality has experienced a marked countercyclical pattern for the last two decades.[6] For males, the 90/10 percentile ratio experienced a sharp increase around the recession of the early 1990s, followed by a marked decrease until 2007. During the recent recession after 2008, inequality started to increase again. Moreover, these fluctuations are substantial. The magnitude of the yearly increases and decreases in inequality that we find are comparable with that of the yearly inequality increases in the United States (Autor *et al.*, 2008) or Germany (Dustmann *et al.*, 2009). This shows that, contrary to a widespread view (e.g., Carrasco *et al.*, 2011), the Spanish earnings distribution has experienced large changes in the recent period. In addition, we find that most of the inequality increase in the early 1990s occurred in the upper half of the distribution, while the subsequent decrease and recent increase affected the two halves of the distribution in similar ways.

We then explore several factors that could have contributed to this evolution. We start by performing a conventional decomposition of the change in inequality. Following the approach of Autor *et al.* (2005), we separate the effects of changes in labor force composition and

[6]Countercyclical patterns of inequality have been documented for other countries. Using CPS data for the US, Heathcote *et al.* (2010) find that household earnings inequality tends to increase in recessions, and to remain relatively stable in expansions. Using Labor Force Survey data for France, Bonhomme and Robin (2009) find that individual earnings inequality tended to widen following the recession of the early 1990s.

changes in skill prices.[7] As our main proxy for workers' skills we use occupation groups, which we complement using the education level as our second proxy.[8] We also include age as a control, in order to proxy for experience. We find that composition effects explain a large part of the inequality increase during the recent reversal of economic activity. In addition we find that the increase in inequality in the early 1990s is associated with an increase in the skill premium, while the decrease from 1997 to 2006 is well explained by a fall in the skill premium (in particular a fall in the college premium), and a fall in the return to experience.

These patterns are not easily reconciled with standard explanations given to the evolution of US inequality, notably the skill-biased technical change explanation (e.g., Goldin and Katz, 1998). To explain the evolution of inequality in Spain, one needs to search for idiosyncratic, country-specific factors. One particular factor is the role of the construction sector in the economy. We see in our data that the share of construction in male employment increased from 14% to more than 20% between 1997 and 2006. In the same period, construction workers' earnings moved from the 30th percentile to the 40th percentile of the aggregate distribution. Since 2007 the employment share has dropped to 13%, less than its 1990 level, while median earnings have remained flat. These findings point to a very special role of the construction sector in the Spanish economy since the end of the 1990s, and suggest that a period of high demand for construction workers was followed by a sharp drop in demand during the recent recession.

The role of construction in the Spanish expansion of the early 2000s has been acknowledged by the recent literature. Between 1998 and 2008, the house price index per square meter more than doubled in real terms (Garriga, 2010). The causes of this recent housing boom are still a matter of debate, candidate explanations being low interest rates, the softening of lending standards in the mortgage market, the prevalence of homeowner tax deductions, and the large migration inflows or the existence of overseas property buyers, all of which may have boosted the demand for housing.[9] Our findings suggest that the boom and subsequent housing bust have been important drivers of the evolution of male inequality in Spain.

To further explore the sources of the evolution of inequality we consider three additional factors. First we use that, starting in 1997, our dataset records the type of contract, which may be interpreted as a measure of labor protection in the highly dual Spanish economy (Dolado *et al.*, 2002). We show that the earnings gap between permanent and temporary

[7] See also DiNardo *et al.* (1996) and Lemieux (2008) for closely related decomposition techniques.

[8] Education is not well measured in the social security data as it is taken from the municipal register form, and thus only infrequently updated. This means that higher education levels tend to be understated.

[9] See for example García-Montalvo (2007), Ayuso and Restoy (2007), or González and Ortega (2009). In turn, the housing boom may have had implications for education decisions (Aparicio, 2010, Lacuesta *et al.*, 2012).

workers experienced a pronounced decrease in the period 1998-2006, before starting to increase in the recent recession. Given the high share of temporary contracts in construction, this pattern may partly reflect the demand boom for construction workers.

The minimum wage is another candidate explanation. We argue that, unlike in the US, the minimum wage is unlikely to explain the evolution of inequality in Spain. Indeed, most of the 1998-2006 period of fall in inequality was characterized by a slight decrease in the real minimum wage, while the minimum wage increased during the recent recession as inequality was rising. A third potentially important factor is the large immigration inflows of the early 2000s. The evidence we find using the social security data suggests that immigration had little effect on the evolution of Spanish earnings inequality.

Lastly, one limitation of most earnings inequality studies is that they focus on employed workers only. This is a particular source of concern in Spain given the very large variation in unemployment rates and duration of unemployment spells, and the fact that earnings inequality has tended to evolve in parallel with unemployment. In the last part of the paper we try to combine earnings and employment inequality into a single measure, and to document the evolution of this measure of overall inequality, by comparing two approaches for imputing income values to the unemployed.

Accounting for the role of unemployment in the evolution of earnings inequality does not change the overall qualitative pattern. Both imputation methods yield an evolution of overall inequality that is almost the exact mirror image of the unemployment rate over the period. However, taking unemployed individuals into account in the analysis increases the level of inequality substantially, and has a strong quantitative impact on its evolution. We view this exercise as suggesting that, in Spain, the combined effect of unemployment and earnings inequality should be taken into account in order to assess the welfare consequences of inequality.

The rest of the paper is organized as follows. We start by describing the data in Section 2. Section 3 describes our censoring correction strategy. Section 4 shows the results on the evolution of earnings inequality in Spain, whereas Section 5 describes the roles of skills and age in that evolution. Section 6 focuses more specifically on the period of fall and subsequent increase in male inequality starting in the late 1990s, and Section 7 studies the role of unemployment. Lastly, Section 8 concludes.

2 The Social security dataset

Our main data source comes from the Continuous Sample of Working Histories (*Muestra Continua de Vidas Laborales*, MCVL, in Spanish). The MCVL is a micro-level dataset built upon Spanish administrative records. It is a representative sample of the population registered with the social security administration in the reference year (so far, from 2004 to 2010). The MCVL also has a longitudinal design. From 2005 to 2010, an individual who is present in a wave and subsequently remains registered with the social security administration stays as a sample member. In addition, the sample is refreshed with new sample members so it remains representative of the population in each wave. Finally, the MCVL tries to reconstruct the market labor histories of the individuals in the sample back to 1967, earnings data being available since 1980. In addition to the MCVL, we will use tax files that have been matched to the social security sample. These will be useful to address censoring issues, as we shall argue in the next section.

2.1 Sample selection

The population of reference of the MCVL consists of individuals registered with the social security administration at any time in the reference year, including pension earners, recipients of unemployment benefits, employed workers and self-employed workers, but excluding those registered only as medical care recipients, or those with a different social assistance system (part of the public sector, such as the armed forces or the judicial power). The raw data represent a 4 per cent non-stratified random sample of this reference population. It consists of nearly 1.1 million individuals each year.

We use data from a subsample that represents a 10 per cent random selection of individuals from the MCVL original samples from 2005 to 2010.[10] We keep prime-age individuals enrolled in the general regime, that is, regular workers aged 25-54.[11] To ensure that we only consider income from wage sources, we also exclude all individuals enrolled in the self-employment regime. Then, we reconstruct the market labor histories of the individuals in the sample back to 1980. Finally, we obtain a panel of 93,132 individuals (52,878 men and 40,254 women) and more than 12 million monthly observations for the period 1988-2010. We present descriptive statistics in sample composition and demographics by gender in Appendix A.[12]

Representativeness. The MCVL dataset represents a unique source of consistent data for a period of more than twenty years. However, given the particular sampling design of the

[10]This selection was done in order to reduce the size of the dataset. Taking another 10% random sample made almost no difference to the results.

[11]In Spain, more than 80 per cent of workers are enrolled in the general scheme of the social security administration. Separate schemes exist for some civil servants, workers in fishing, mining and agricultural activities, and the self employed. This means that these categories are not considered in this study.

[12]The reason for starting in 1988 instead of 1980 is that sample representativeness tends to become less accurate as one goes back in time, as we document below.

MCVL, using the retrospective information for the study of population aggregates may be problematic in terms of representativeness. Here we consider three issues in turn.

A first concern with the data is that, by construction, individuals who were working at some point in the period but died before 2004 are not part of our sample. So, the earnings distributions that we construct may be non-representative of the working population, especially for earlier years. To address this concern, we computed mortality rates by gender and age using individual data provided by the Spanish statistics institute (*INE*). Table B.1. in Appendix B reports yearly mortality rates over the period 1988-2004. We see that, for the age categories that we consider, mortality rates are low. Indeed the *cumulative* probabilities of death between 25 and 54 years old are 4.2% for males and 3.4% for females, respectively. Weighted inequality estimates that correct for attrition due to mortality are very similar to the unweighted ones.[13]

A second concern with the data is the fact that some workers may have migrated out of the country. Given the way the data are recorded, migrants who did not come back to Spain before 2004 are not in the MCVL dataset. This concern is alleviated by the fact that during this period Spain became a host country for immigrants, as shown in Figure B.1. and Table B.2 in Appendix B. The data show that, between 1990 and 2000 the stock of emigrants leaving Spain has decreased.[14] Given these numbers, we consider that mobility out of the country does not represent an important source of attrition in our sample.

Finally, attrition due to long periods of inactivity is a serious source of concern for women. Individuals who were in the labor force before 2004 and receive a retirement pension at some point in the period 2005-2010 are part of our sample. However, individuals who stopped working at a young age will typically not be in our sample. In fact, data for the Spanish section of the Survey of Health, Aging and Retirement in Europe (SHARE) show that a large number of Spanish women stopped working early in their careers (see Figure B.2. in Appendix B).[15] For this reason, caution will be needed when interpreting the results we obtain for women as one moves back in time. See García-Pérez (2008), for a related point.[16]

[13]We also computed mortality rates by occupation (available for men), and we found small differences in the age groups that we consider (workers aged 25-54).

[14]A striking fact from Figure B.1. is the large inflows of immigrants in the later period. We will focus on immigration in Section 6.

[15]Data in Figure B.2. correspond to individuals who ever worked and who were between 34 and 53 years old in 1988. Thus, they are on average 6 years older than individuals in our sample. Although female labor participation has clearly increased for younger cohorts, we think that those early-career interruptions may still be relevant to our analysis.

[16]Figure B.3. in Appendix B shows a comparison of average age between the MCVL and the Spanish labor force survey (EPA). One possibility to improve representativeness is to re-weight the data, using age-specific weights calculated from the EPA. Felgueroso *et al.* (2010) use this method and find small differences for men, and larger differences for women.

Figure 2. Quantiles of uncapped daily Earnings

Notes: Source Social Security data. Solid lines are observed daily earnings. Dark and light crosses are the real value of the maximum and minimum caps, respectively.

2.2 Social security earnings

As it is often the case in administrative sources, the Spanish social security does not keep track of uncapped earnings. The MCVL only provides information on censored earnings, the so-called "contribution base". The contribution base captures monthly labor earnings plus 1/12 of year bonuses,[17] taking into account maximum and minimum caps according to a category classification based on skills. The caps are adjusted each year with the evolution of the minimum wage and the inflation rate, as described in Figure C.1. in Appendix C, and in Table C.1 for the most recent years.

In most of the analysis, we use *daily earnings* as our main earnings measure, computed as the ratio between the monthly contribution base and the days worked in that particular month. Earnings are deflated using the 2006 general price index. Unfortunately, the social security data do not record hours of work, so we cannot compute an hourly wage measure.[18] Figure 2 shows the 1988-2010 evolution of several percentiles of observed real daily earnings. The crosses in the graph represent the real value of the legal maximum and minimum caps.[19]

As a preliminary observation, we can see that real earnings have generally increased over

[17]Important exceptions are extra hours, travel and other expenses, and death or dismissal compensations.
[18]The data contain measures of part-time and full-time work. Re-weighting daily earnings using these measures makes little difference for males, although it does somewhat affect the results for females, especially at the bottom of the earnings distribution.
[19]On the figure, the cap is calculated as an average of the legal caps across skill groups, weighted using the relative shares of each group every year.

the period. For example, for males median daily earnings increased from 46.5 Euros in 1988 to 54 Euros in 2010. This represents an increase of 15.5% over the period. In comparison for women the increase has been of 7.6%. This suggests that, with the caveat mentioned above concerning the results for women, the median gender gap has *increased* over the twenty year period. As shown in the figure, however, the proportion of top-coded observations is substantial. For example, for men the 80th percentile (q80) is observed from 1998 to 2010, and the q90 is never observed. For women instead, the 90th percentile is observed in 1998 and from 2000 to 2006. At the opposite end, we also see that the the 10th percentile of the female earnings distribution is capped during the whole period (except in 1988).

The presence of censoring complicates the analysis of earnings inequality. For example, the 90/10 gap, which is a commonly used index of inequality, is censored during the whole period, for both men and women. To address this issue and draw a complete picture of the recent evolution of earnings inequality in Spain, we now compare two alternative methods to correct for censoring.

3 Censoring corrections

Censoring due to top and bottom-coding is a serious issue in the social security data that we use. Our aim is to recover, at each point in time, the cross-sectional distribution of uncensored earnings, so as to document the level and evolution of earnings inequality. For this, we compare two models of (uncensored) earnings: the first is based on a linear quantile model, while the second method relies on distributional assumptions. The two methods are based on very different assumptions to extrapolate and recover the earnings in the top and bottom-coded regions. We start by describing the methods in some detail. In the second part of this section, we will compare their out-of sample predictions using the tax files data.

3.1 Two correction methods

The two models are conditional on individual covariates. Given the individual determinants available in the data, it is convenient to construct *cells, c*, within which individual observations are treated similarly. The cells incorporate three sources of heterogeneity, $c = (\text{skill}_c, \text{age}_c, \text{time}_c)$: broad occupation, or "skill", dummies, with 10 categories (such as "engineers, college", "manual workers", ...);[20] age dummies, from 25 to 54 years; and time dummies, which contain 23 yearly dummies (from 1988 to 2010) and 12 monthly dummies

[20] See notes in Table C.1. in Appendix C for a definition of the 10 categories.

(from January to December).[21]

This yields a total of 82,800 cells. The use of the 10 occupation groups as a proxy for skills is motivated by the fact that education data are rather imperfect in our sample. As we pointed out in the introduction, education is taken from the municipal register form, and is only infrequently updated. Nevertheless, as a complement we will also present results using education dummies (4 categories) as a proxy for skills.[22] For the same reason, we use age as a proxy for experience, instead of a measure of general experience net of the number of years of schooling.

We now describe the two censoring correction methods.

Method 1: quantile regression. Let w_c^q denote the qth conditional quantile of earnings in cell c, where the percentile level q is a number in $(0, 1)$. The conditional quantile satisfies:

$$\Pr\left(\text{wage}_i \leq w_c^q \middle| \text{cell}_i = c\right) = q.$$

We model the logarithm of w_c^q (or alternatively the conditional quantiles of log-earnings)[23] as:

$$\log\left(w_c^q\right) = \gamma_s^q \text{skill}_c + \gamma_a^q \text{age}_c + \gamma_t^q \text{time}_c, \tag{1}$$

where γ_s^q, γ_a^q, and γ_t^q are q-specific parameters to be estimated. Linear quantile models such as (1) are widely used in applied work, since Koenker and Bassett (1978). See Gosling *et al.* (2000) for an application to earnings inequality.

When, as in our application, covariates are grouped into cells, Chamberlain (1991) notes that the parameters may be consistently estimated using a simple two-step approach. In the first step, we estimate w_c^q in each cell c, and for all q belonging to a finite grid of values. We will take $q \in \{.01, .02, ..., .99\}$, and compute sample quantiles $\widehat{w}_c^q$. Note that some quantiles are censored, so $\widehat{w}_c^q$ will be missing for some (c, q) pairs.

Then, in the second step, and for each q value in the grid, we pool all cells together and regress $\log\left(w_c^q\right)$ on skill_c, age_c, and time_c. In this regression, the cell is the unit of observation. Following Chamberlain (1991), we weight each observation by (the square root of) the sample size of the cell. The parameter estimates are denoted as $\widehat{\gamma}_s^q$, $\widehat{\gamma}_a^q$ and $\widehat{\gamma}_t^q$. Lastly, once the parameters have been estimated we predict daily earnings using:

$$w_c^{q,QR} = \exp\left(\widehat{\gamma}_s^q \text{skill}_c + \widehat{\gamma}_a^q \text{age}_c + \widehat{\gamma}_t^q \text{time}_c\right). \tag{2}$$

[21] Note that, in this way, birth cohorts are mechanically taken into account, as they are a linear combination of age and calendar time.

[22] The four education categories are: less than elementary school, high school dropout, high school graduate, and college.

[23] Indeed, it follows from a well-known property of quantiles that: $\log\left(w_c^q\right) = \left(\log w\right)_c^q$.

Importantly, $w_c^{q,QR}$ is always well-defined even if, because of censoring, the sample quantile $\widehat{w}_c^q$ is missing. The extrapolation relies on the assumption that conditional quantiles are linear in skill_c, age_c and time_c. For example, this model rules out skill/time interaction effects. If linearity is violated in the data, the predicted quantiles may poorly approximate the true quantiles of uncensored earnings.

Method 2: normal censored regression. In the second method, we parametrically model log-earnings in a cell. Specifically we suppose that, within cell c, log-earnings follow a distribution with density f_c that is fully characterized by a cell-specific parameter θ_c. We impose no restrictions on f_c or θ_c across cells.

Parameters θ_c can be estimated using a cell-by-cell maximum likelihood approach. Given the double censoring, the likelihood function has three parts in general. Let $\overline{w}_c$ and $\underline{w}_c$ denote the upper and lower caps on earnings in cell c, respectively. Let cens_i be a discrete variable that takes three values: 1 when wage_i is top-coded, -1 when it is bottom-coded, and 0 when the wage is uncensored. The likelihood function in cell c is, restricting i to belong to that cell:

$$\sum_{\text{cens}_i=-1} \log \Pr\left(\log \text{wage}_i \leq \log \underline{w}_c\right) + \sum_{\text{cens}_i=0} \log f_c\left(\log \text{wage}_i\right) + \sum_{\text{cens}_i=1} \log \Pr\left(\log \text{wage}_i \geq \log \overline{w}_c\right).$$

The parameter θ_c is estimated by maximizing this function.

Let F_c denote the cumulative distribution function (cdf) of log-earnings (that is, the integral of f_c), and let $\widehat{F}_c$ denote its value at the maximum likelihood estimate of θ_c. Conditional quantiles of earnings are predicted as:

$$w_c^{q,ML} = \exp\left(\widehat{F}_c^{-1}(q)\right). \tag{3}$$

The nature of the extrapolation here is very different from the quantile regression approach. The validity of the latter relies on between-cells restrictions, which take the form of linearity assumptions on the conditional quantile functions. Here, in contrast, the validity of (3) relies on within-cells restrictions, according to which the parametric distribution f_c must be correctly specified. In the next section we will see that this second method performs clearly better than the first one in terms of out-of-sample prediction.

The choice of the parametric distribution f_c is important. Consistently with a large literature that finds that log-normality provides a reasonable approximation to empirical earnings distributions, we specify f_c to be Gaussian with cell-specific means and variances μ_c and σ_c^2, respectively. Denoting as Φ the standard normal cdf, the cell-specific likelihood function takes the familiar form (up to an additive constant):

$$\sum_{\text{cens}_i=-1} \log \Phi\left(\frac{\log \underline{w}_c - \mu_c}{\sigma_c}\right) + \sum_{\text{cens}_i=0}\left[-\frac{1}{2}\log\sigma_c^2 - \frac{1}{2\sigma_c^2}(\log \text{wage}_i - \mu_c)^2\right] + \sum_{\text{cens}_i=1} \log\left(1 - \Phi\left(\frac{\log \overline{w}_c - \mu_c}{\sigma_c}\right)\right).$$

Moreover, in the log-normal case, conditional earnings quantiles are predicted using:

$$w_c^{q,NCR} = \exp\left(\widehat{\mu}_c + \widehat{\sigma}_c \Phi^{-1}(q)\right), \tag{4}$$

where $(\widehat{\mu}_c, \widehat{\sigma}_c)$ is the maximum likelihood estimate of (μ_c, σ_c).[24]

Recovering unconditional quantiles. After estimating the model, we simulate earnings for every cell using the model for the conditional quantiles, w_c^q. This is immediate in method 2, as the earnings distribution is known within cells. In the quantile regression approach (method 1) we simulate earnings as follows: (i) we draw u_i, uniformly on $(0,1)$; and (ii) we compute the simulated earnings in cell c as $w_c^{u_i,QR}$, where $w_c^{q,QR}$ is given by (2). Unconditional earnings quantiles, for a given year, are then computed as the sample quantiles of the simulated data (as in Machado and Mata, 2005).[25]

3.2 A validation exercise

To overcome the top and bottom-coding issue, we take advantage of the fact that from 2004 to 2010 the MCVL was matched to individual income tax data. For those seven years, information on uncensored annual earnings is thus available from the income tax system, which tracks individual income at the firm level. We now present a comparison exercise between the social security contributions (taken from the MCVL) and the matched individual annual labor income (obtained from the tax data). We start by showing that social security contributions are strongly correlated with the taxable labor income for the uncapped observations. Next, we use the tax files to evaluate the predictive power of the two censoring correction methods.

[24]Similarly, Dustmann *et al.* (2009) impute censored earnings under the assumption that the error term in the log-earnings regression is normally distributed, with different variances for each education and each age group. Then, as we do, for each year they impute censored earnings as the sum of the predicted earnings and a random component, drawn from a normal distribution with mean zero and the cell-specific variance. This approach differs from the one in Boldrin *et al.* (2004) and Felgueroso *et al.* (2010), who simulate earnings only for the workers whose original earnings were censored.

[25]Given the very large sample sizes, this approach will deliver very similar results to the ones obtained using exact analytical formulas (Melly, 2006).

Social security contributions vs. taxable labor income. To conduct the comparison exercise, we focus on individuals with positive taxable labor income during the period 2004-2010. Table 1 reports sample correlations between the annual contributions for uncapped observations and the annual labor income obtained from the tax data.

Table 1. MCVL matched with Tax data: Sample correlations

Group	Levels	Growth
Engineers, College	0.77	0.81
Technicians	0.90	0.80
Administrative Managers	0.90	0.81
Assistants	0.93	0.84
Administrative workers	0.93	0.86
Manual workers	0.94	0.85

Note: for uncapped observations in two consecutive years.

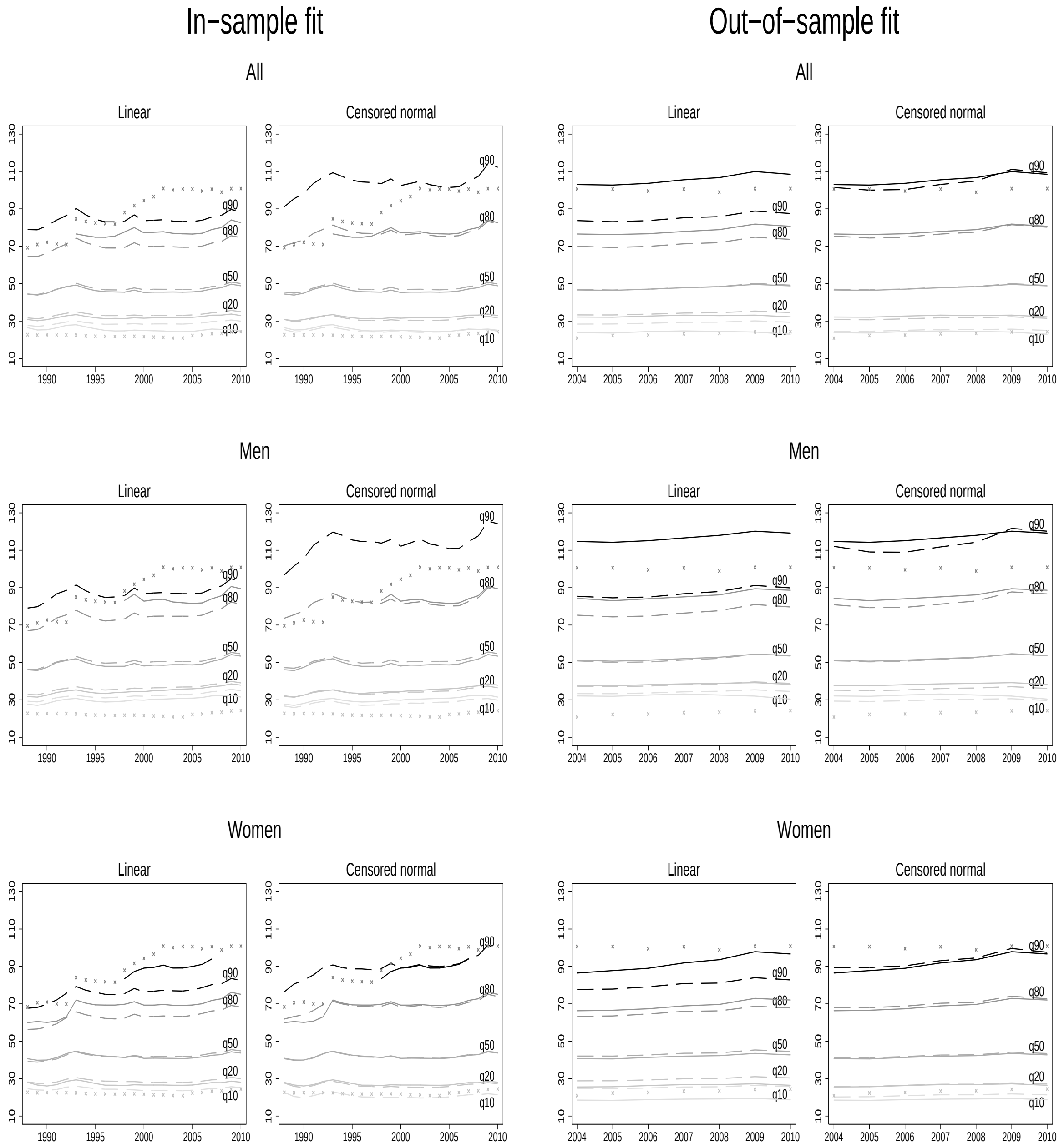
The high correlations in levels indicate that the two income concepts are related, although they are not identical. For example, social security contributions exclude extra hours, travel and other expenses, and dismissal compensations. These differences seem more relevant for high skilled workers, as the correlation in levels between contributions and taxable labor income is lower for group 1 (77%) than for other groups (over 90%). The second column in the table shows that year-to-year growth rates are also strongly correlated between the two datasets, although correlations are slightly lower than in levels.[26]

Predictive power of the censoring corrections. In the remainder of this section we evaluate the predictive power of the two censoring correction methods. We shall compare the estimated unconditional earnings quantiles using either of the two methods, with the earnings quantiles from the social security data (in-sample prediction), and with the earnings quantiles from the tax data (out-of-sample prediction). The results of these two exercises are shown in the left and right panels of Figure 3, respectively.

The left panel of Figure 3 shows the observed earnings quantiles in the social security dataset (solid lines), and the estimated quantiles (dashed lines). In the first column, the unconditional quantiles are estimated using the linear quantile regression method, while in the second column quantiles are estimated using the normal censored regression method. As in Figure 2, the real value of the maximum and minimum caps are represented by crosses in

[26] As an additional piece of evidence, Figure D.1. in Appendix D shows the distributions of the social security contributions (solid lines) and the taxable labor income (dashed lines). We can see that the uncensored parts of the distributions are rather similar.

Figure 3. Prediction performance of the two censoring correction methods



Notes: Sources Social Security data and Income Tax data. Dark and light crosses represent the real value of the maximum and minimum caps, respectively. In the left panel, solid lines are observed earnings quantiles in the social security dataset, and dashed lines are the estimated quantiles. In the right panel, solid lines are observed earnings quantiles in the tax data, and dashed lines are the estimated quantiles.

the graph. Results show that the censored regression method outperforms quantile regression in terms of fitting the observed data. The difference is particularly noticeable in the upper-part of the earnings distribution. Moreover, while normal censored regression rightly predicts earnings above or below the caps when the data are censored, the 90th percentile predicted by the quantile regression method is often *below* the cap. This provides a first evidence of the superiority of the normal censored regression method.

Next, the right panel of Figure 3 shows the observed earnings quantiles in the tax data (solid lines), and the estimated quantiles using either of the two correction methods (dashed lines). The linear quantile regression method is shown in the first column, and the normal censored regression in the second. The comparison exercise clearly favors the normal censored regression approach. For this method, the overall 90th and 10th percentiles are reasonably well reproduced, especially if we recall that the estimates are predicted using social security earnings that are subject to censoring. In contrast, the fit of the quantile regression method is quite poor. For example, for males the 90th earnings percentile is predicted to lie *below* the value of the cap.[27]

In what follows we will use the normal censored regression estimates to assess the recent evolution of earnings inequality in Spain. When interpreting the results, it will be important to keep in mind that the censoring correction is not perfect. Although the comparison with the tax data suggests that it does a relatively good job for the more recent period, the accuracy of the extrapolation may be poorer in the first part of the sample, where the amount of censoring is larger (see Figure C.1 in Appendix C). In order to alleviate concerns related to the extrapolation, we shall document the evolution of the 20th and 80th percentiles, as a complement to the more commonly studied 10th and 90th percentiles.

4 Overall evolution of earnings inequality

In this section we start by describing the evolution of earnings inequality in Spain from 1988 to 2010. Then we compare our results with recent papers that have documented the evolution of Spanish inequality using different data sources.

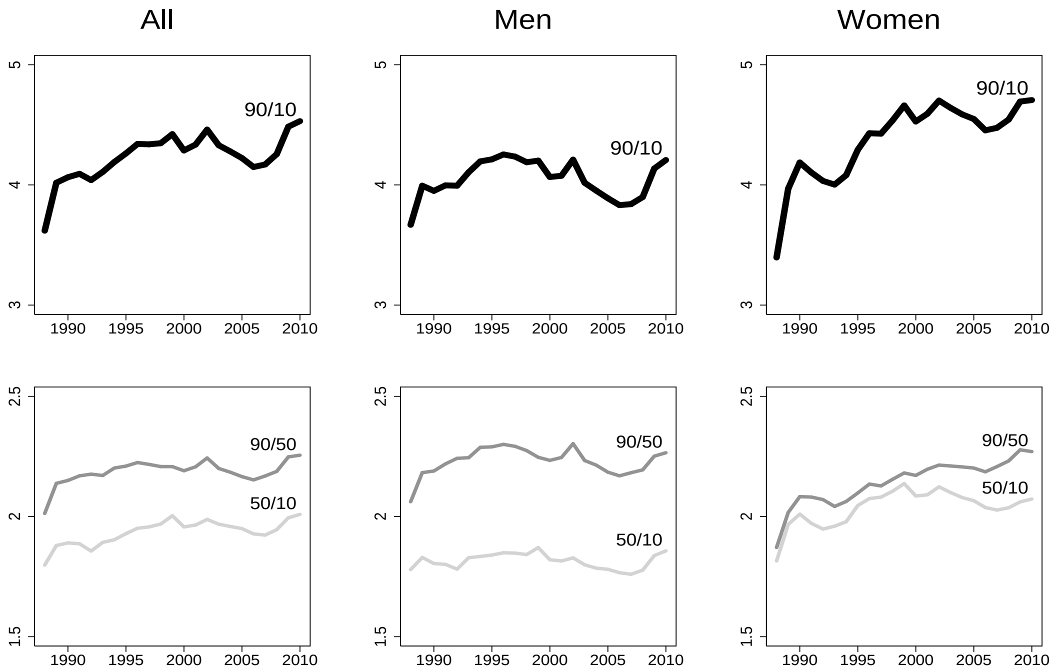
4.1 Patterns of inequality

Figure 4 shows the evolution of several inequality measures over the period: the ratio of the 90th to 10th earnings percentiles (90/10), the ratio of the 90th to 50th (90/50), and the ratio

[27] Using education instead of occupation categories as a proxy for skills yields comparable picture, though the out-of sample fit using the censored normal regression method is slightly worse for men (not reported).

of the 50th to 10th (50/10). Table 2 reports the numerical values of the 10, 50, and 90th percentiles, and the corresponding ratios, for some particular years.

Figure 4. Inequality Ratios: 90/10, 90/50, and 50/10



Notes: Source Social Security data. Solid lines are ratios of estimated unconditional quantiles of daily earnings.

In Figure 4 we can see that earnings inequality has experienced a marked hump-shaped pattern, followed by a sharp increase at the end of the period. The fluctuations in inequality are inversely related to the business cycle. According to Table 2, for men the 90/10 earnings ratio increased by 16% between 1988 and 1996, then decreased by 9.5% between 1997 and 2006, after which inequality increased again by 9.5%.[28] In addition, the table shows that the inequality increase in the earlier period was essentially concentrated in the upper part of the earnings distributions, as the 90/50 earnings ratio increased by 11.6% while the 50/10 earnings ratio increased by 3.9%. In contrast, the decrease during the 1997-2006 period and the subsequent increase affected the two halves of the distribution similarly. The results for women follow a qualitatively similar pattern, although the fall in inequality seems to

[28]Note that the median and 90th earnings percentile levels increased more during the two recessions than during the expansion. This may partly reflect changes in employment composition, the employed population being a selected subset of the total population. We will return to the link between unemployment and inequality in Section 7.

have started later for them (early 2000s) and to have been less pronounced. There is also evidence of an inequality increase in the recent recession for women, as the 90/10 earnings ratio increased by 5.2% between 2007 and 2010.

Table 2. Estimated Quantiles of Daily Earnings and Inequality Ratios

		1988	1997	2007	2010	1988-1996 (%)	1997-2006 (%)	2007-2010 (%)
(A) Estimated Quantiles of Daily Earnings								
All	w^{10}	25.5	24.2	25.5	25.0	-4.96	2.73	-1.71
	w^{50}	45.8	47.3	49.0	50.3	3.14	1.20	2.69
	w^{90}	92.3	104.9	106.2	113.4	14.00	-1.74	6.79
Men	w^{10}	26.8	27.2	30.1	29.8	1.24	7.32	-1.01
	w^{50}	47.6	50.3	53.0	55.3	5.23	2.59	4.47
	w^{90}	98.2	115.4	115.6	125.4	17.41	-2.90	8.45
Women	w^{10}	22.6	20.1	21.3	21.3	-10.74	3.39	0.19
	w^{50}	41.0	41.8	43.2	44.2	2.03	1.24	2.46
	w^{90}	76.8	88.9	95.3	100.5	16.42	4.04	5.36
(B) Ratios from Estimated Quantiles								
All	w^{90}/w^{10}	3.62	4.34	4.17	4.53	19.95	-4.35	8.65
	w^{90}/w^{50}	2.01	2.22	2.17	2.25	10.52	-2.91	3.99
	w^{50}/w^{10}	1.80	1.96	1.92	2.01	8.53	-1.49	4.48
Men	w^{90}/w^{10}	3.67	4.23	3.84	4.21	15.97	-9.53	9.55
	w^{90}/w^{50}	2.06	2.29	2.18	2.26	11.57	-5.35	3.81
	w^{50}/w^{10}	1.78	1.85	1.76	1.86	3.94	-4.41	5.53
Women	w^{90}/w^{10}	3.40	4.43	4.47	4.71	30.44	0.63	5.16
	w^{90}/w^{50}	1.87	2.13	2.21	2.27	14.11	2.77	2.82
	w^{50}/w^{10}	1.81	2.08	2.03	2.07	14.31	-2.09	2.27

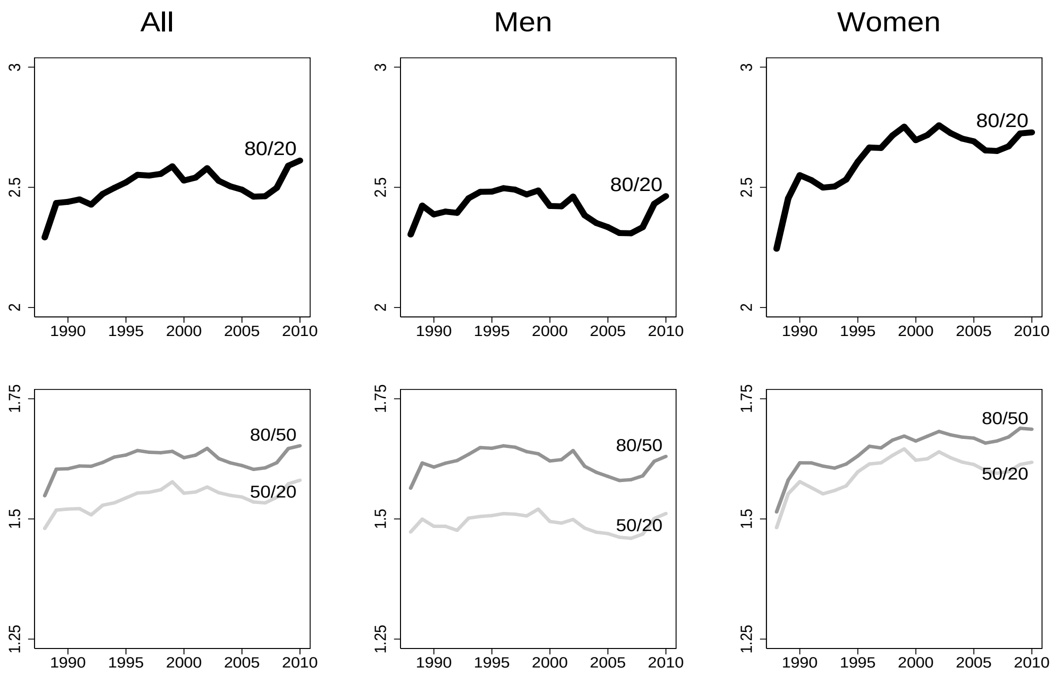
Note: Unconditional quantiles estimated from Social Security data.

One concern with the 90/10 ratio is that it is sensitive to the chosen censoring method.[29] Less subject to censoring are the 80/20, 80/50, and 50/20 earnings inequality ratios which we show in Figure 5. The picture of inequality is very similar to Figure 4, with a marked countercyclical pattern. Quantitatively, the changes are of a slightly smaller magnitude. For example, for men the 80/20 ratio increased by 11.3% between 1988 and 1996, decreased by 3.4% between 1997 and 2006, and increased by 6.0% between 2007 and 2010.[30]

[29] We also computed inequality measures using the 2004-2010 tax files, which are not subject to censoring. We found that the 90/10 ratio increased by 11% between 2007 and 2010. Although the tax and social security data differ in several respects, this provides additional evidence of a strong inequality increase in the recent recession.

[30] As an additional robustness check, we computed the evolution of inequality as in Figure 4 using education dummies instead of occupation groups to predict earnings, finding similar results. We also computed weighted unconditional quantiles, taking into account mortality rates by gender and group age over the entire period, again finding very similar results.

Figure 5. Inequality Ratios: 80/20, 80/50, and 80/20



Notes: Source Social Security data. Solid lines are ratios of estimated unconditional quantiles of daily earnings.

These fluctuations of inequality are substantial by international standards. To see this, consider the well documented case of the United States. According to Autor *et al.* (2008), and as reproduced in Table 3, male inequality measured by the 90/10 percentile ratio increased by 18% between 1973 and 1989.[31] This corresponds to a yearly increase of 1%. A slightly lower yearly rate of increase in inequality was found by Dustmann *et al.* (2009) for Germany. In comparison, in Spain between 1997 and 2006 the 90/10 ratio *decreased* at a 1% rate per year. And between 2007 and 2010 it *increased* at a 2.4% rate per year. These results thus show a high variability of earnings inequality, which tends to go in parallel with pronounced variations in unemployment.

4.2 Comparison with previous studies

Here we briefly compare our results with recent papers on earnings distributions in Spain. Pijoan-Mas and Sánchez-Marcos (2010) combine two different data sets: the longitudinal

[31] A slight difference between the results in Autor *et al.* (2008) and ours is that they compute changes in log-percentile ratios, while we compute percentage changes in percentile ratios. Using changes in log-percentile ratios instead gives very similar results to the ones reported in Table 3.

Table 3. Changes in Overall Inequality Ratios (%)

	United States*		Spain**			Germany***	
	1973-1989	1989-2005	1988-1996	1997-2006	2007-2010	1980-1990	1990-2000
	90/10		90/10			85/15	
Men	18.3	16.4	15.97	-9.53	9.55	8.3	10.7
Women	25.7	12.7	30.44	0.63	5.16		
	90/50		90/50			85/50	
Men	10.2	14.2	11.57	-5.35	3.81	5.8	5.1
Women	11.3	9.8	14.11	2.77	2.82		
	50/10		50/10			50/15	
Men	8.1	2.1	3.94	-4.41	5.53	2.5	5.6
Women	14.4	2.8	14.31	-2.09	2.27		

Notes: * Overall Hourly Inequality Measures from Autor *et al.* (2008). ** Ratios of quantiles estimated from Spanish Social Security data. *** Overall Daily Inequality Measures from Dustmann *et al.* (2009)

consumption survey (ECPF), which was run between 1985 to 1996, and the Spanish section of the European household panel, which covers 1994 to 2001. Their main outcome is the hourly wage, in a sample of workers aged 25 to 60 who supply a positive number of hours. Given that there is no available data for hours in the ECPF, they can only build series of hourly wages for the period 1994 to 2001. According to their results, wage inequality increased between 1994 and 1997 and decreased afterwards. Moreover, they find that the fall in inequality after 1997 was driven by compression at both ends of the wage distribution. Although our data differ both in terms of the earnings measure (daily instead of hourly wages) and sample selection (prime-age employees in our case), we obtain comparable results on the period they study.

Using data from the Wage Structure Survey, of which three waves (1995, 2002 and 2006) are available, Carrasco *et al.* (2011) and Izquierdo and Lacuesta (2012) find that inequality decreased slightly between 1995 and 2006. This survey consists of a random sample of workers from firms of at least 10 employees in the manufacturing, construction and services sectors. In 2002 the coverage of the survey was extended to some non-market services (educational, health, and social services sectors) which were not included in the 1995 wave. Table E.1. in Appendix E compares inequality ratios from the social security records and the wage structure survey in years 1995, 2002 and 2006. Although the levels of those ratios differs, especially for women, the evolution is qualitatively similar. For men, Carrasco *et al.* (2011) find a decrease of 1.3% in 1995-2002 (or 4.2%, depending on the sample), and of 7.1% in 2002-2006, whereas we find decreases of 0.1% in 1995-2002 and 9% in 2002-2006. For women, Carrasco *et al.* (2011) find a decrease of 14.4% in 2002-2006 using the wage structure survey, while with the social security records the decrease is only 5.3%.

Compared to previous work on earnings inequality in Spain, the evidence presented in this section offers two main new insights. First, a long-period view shows that Spanish inequality has experienced a marked countercyclical pattern, the (expansion) period of fall in inequality being surrounded by two (recession) periods where inequality has increased sharply. Second, the magnitude of these changes is large by international standards, challenging the common view that the Spanish earnings distribution has been stable over time. In the next sections we study several factors that may have explained this idiosyncratic evolution.

5 The role of labor force composition and prices

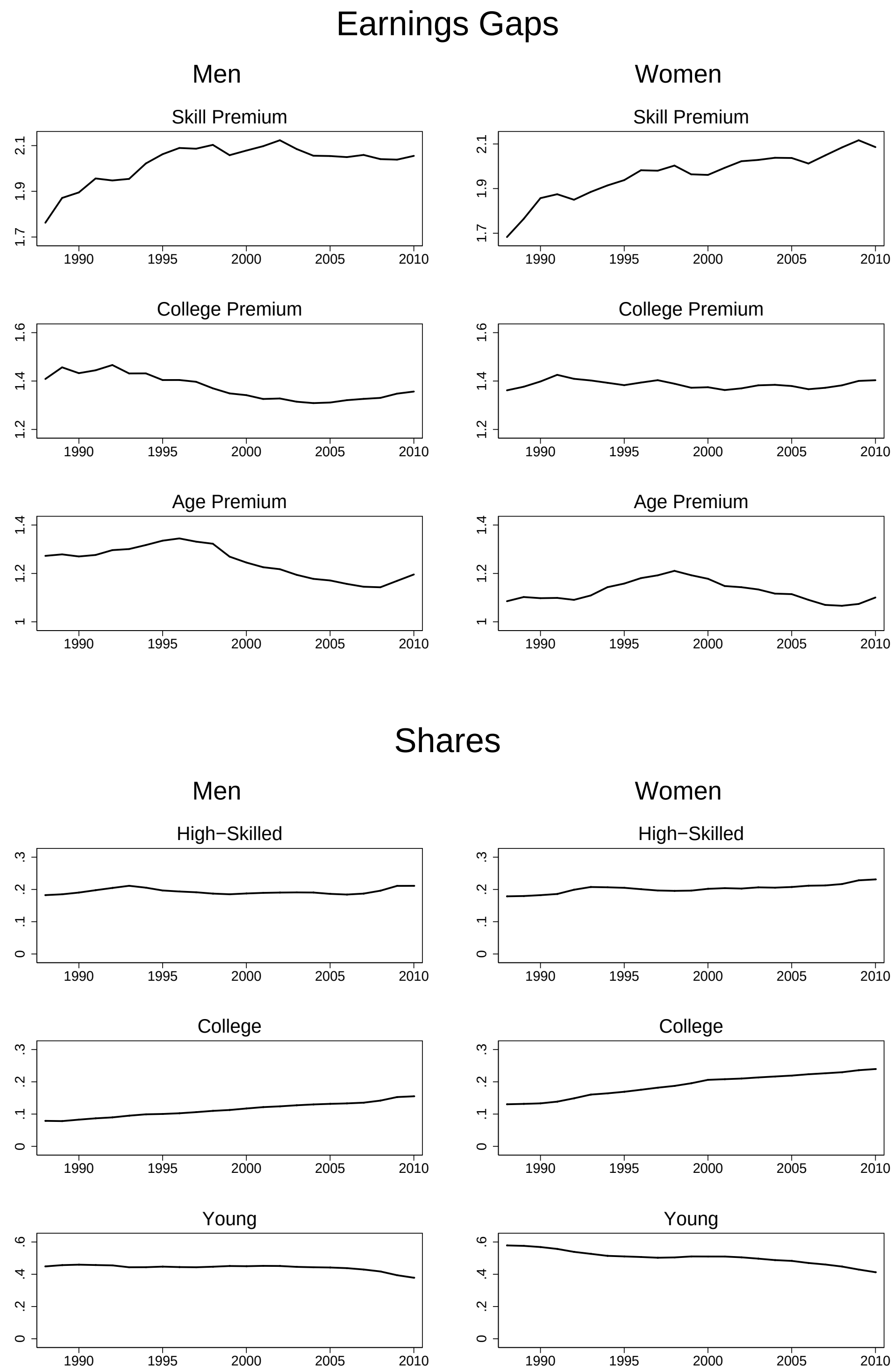
In this section we focus on the role of labor force characteristics (skills and experience) in the evolution of inequality. We start by documenting the evolution of earnings gaps by occupation, education, and age groups. We then perform a decomposition exercise to assess the role of changing labor force composition (in terms of occupation/education and age categories) and returns, or "prices", in the evolution of Spanish earnings inequality.

5.1 Earnings gaps

Figure 6 shows median daily earnings by occupation groups (our main proxy for skills) and age groups (our proxy for experience). We also show results by education groups (college and non-college). The bottom graphs show the weight of these groups in the Spanish working population.

Let us focus on men first, on the left column of Figure 6. On the top graphs we see that the ratio of median daily earnings between high-skilled (occupation groups 1-3) and low-skilled workers (groups 4-10) increased during the recession of the early 1990s and tended to stabilize afterwards. Interestingly, the second row shows the ratio between the median daily earnings of college graduates and those of non-college graduates (the "college premium"). We see that the college premium increased slightly in the early 1990s, and then decreased substantially until 2004, by roughly 10%. This evidence of a decline in the college premium in Spain has been documented before (e.g, Pijoan-Mas and Sánchez-Marcos, 2010, Felgueroso *et al.*, 2010). We shall see below that it has partly contributed to the decline in inequality during the Spanish expansion. In addition, we see on the bottom graphs that, while the share of high-occupation groups has remained relatively constant over the period, the share of college graduates has increased sharply (see also Figure 1). Lastly, note also that since 2006 the college premium has increased slightly.

Figure 6. Skill, education, and age groups: median earnings gaps and employment shares



Notes: Source Social Security data. The "premia" refer to ratios of median daily earnings between i) occupation groups 1-3 and groups 4-10 ("skill premium"), ii) college and non-college workers ("college premium"), and iii) workers aged more than 35 years and those aged 35 or less ("age premium").

The third row in Figure 6 shows the ratio of median daily earnings of older workers (older than 35 years old) and young workers. We see that, like the occupation and education premia, this "age premium" increased in the early 1990s. Moreover, we observe a sizable reduction in this gap from 1997 to 2006, and a slight increase at the end of the period. Also, on the bottom graph we notice a decrease in the proportion of young workers in the recession of the late 2000s. Results for women (right column) are qualitatively similar, one noticeable difference being that the college premium remained stable over the period.

5.2 A decomposition exercise

In order to quantitatively assess the influence of skills and experience on inequality we next perform a decomposition exercise. The decomposition is a simple extension of the Machado and Mata (2005) method, and has been applied by Autor *et al.* (2005) to study US inequality.[32]

Methodology. We decompose the change in inequality between two periods, say t and t' - being $t' > t$, into three components: change in composition, change in between-group prices, and change in within-group prices.

The first part corresponds to the evolution of inequality that would have prevailed if the skill/experience composition had remained constant from t to t'. Following Machado and Mata (2005), this is simply obtained by re-weighting the time-t conditional quantiles by the proportions of skill and experience groups at time t'.[33]

In the context of our simple cell-by-cell normal model, the between-group and within-group price effects are easily computed as follows. Recall that, by (4) the qth conditional earnings quantile in skill/experience cell c at time t is given by:

$$w_{c,t}^{q} = \exp\left(\widehat{\mu}_{c,t} + \widehat{\sigma}_{c,t}\Phi^{-1}(q)\right),$$

where we have isolated the time subscript for clarity. Adapting the method proposed in Autor *et al.* (2005) to our model we compute the between-group and within-group price effects by moving $\widehat{\mu}_{c,t}$ and $\widehat{\sigma}_{c,t}$ one at a time. That is, the between-group price change in inequality is obtained by first computing the following counterfactual conditional quantiles:

$$w_{c,t}^{q,BG} = \exp\left(\widehat{\mu}_{c,t'} + \widehat{\sigma}_{c,t}\Phi^{-1}(q)\right),$$

[32] As noticed by Autor *et al.* (2005), this exercise is closely related to Juhn, Murphy and Pierce (1993), and is conceptually similar to DiNardo *et al.* (1996) and Lemieux (2006).

[33] Note that this choice amounts to taking the final period, t', as the reference period. Note also that this type of decomposition relies on a partial equilibrium assumption according to which quantities of skill/experience do not affect prices.

and then re-weighting these conditional quantiles by the proportions of skill and experience groups at time t'. Difference between inequality (e.g., the 90/10 ratio) obtained using these counterfactual quantiles, and inequality obtained under the scenario that composition has remained constant over the period, is the between-group price effect. Difference with actual inequality in period t' is the within-group price effect.

Note that the results will depend on the order of the decomposition: composition effect, between-group price effect, and within-group price effect, in this order. We checked that the qualitative results remain when changing the order of the decomposition.

Results. Figure 7 shows the results of this decomposition exercise, taking occupation groups as a proxy for skills. Let us consider first the top left graph, which shows the 90/10 earnings percentile ratio for men. The dark bar shows that, according to this measure, inequality increased by 16% between 1988 and 1996. The gray bar shows that inequality would have increased by 12%, if the labor force composition in terms of occupation and age groups had been constant to its 1996 level. The light bar shows that there would have been no increase at all if in addition the cell-specific means had remained constant over the period. This means that, out of the 16% total increase in inequality between 1988 and 1996, 4% were due to composition effects, 11% to between-group price effects, and almost nothing to within-group price effects. Table E.2. in Appendix E shows the numbers.

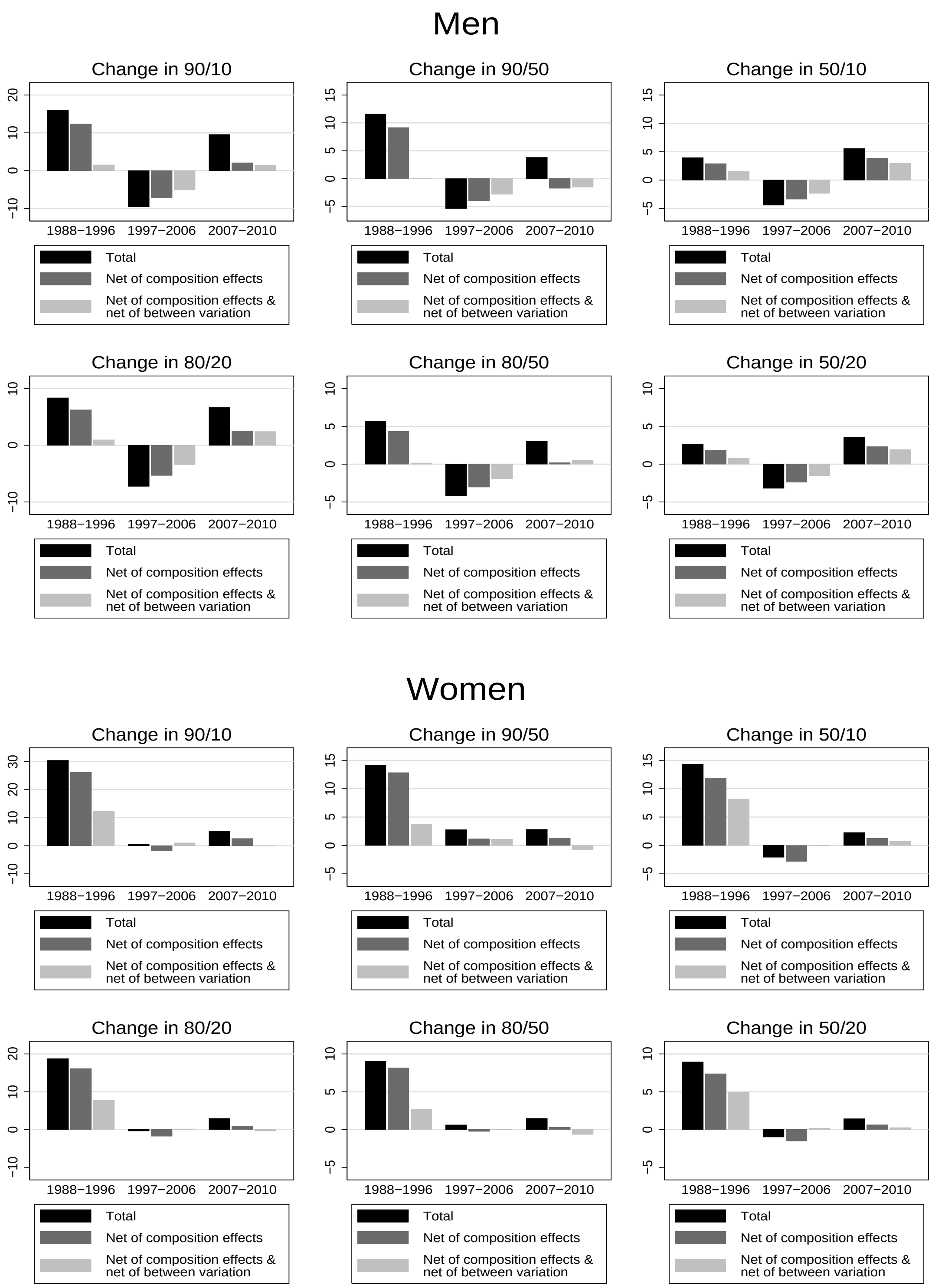
Between 1997 and 2006, Figure 7 shows that composition effects explain roughly 25% of the fall in the 90/10 percentile ratio. Between and within-group price effects, due to the fall in skill and experience premia documented above, thus explain most of the fall in inequality. In contrast, price effects appear to be small during the 2007-2010 period and most of the inequality increase is explained by changes in labor force composition, namely the increased unemployment rates for the young and the low-skilled (see Figure 6).[34] Interestingly, for this last period the 90/50 and 50/10 results show that, while price effects were small and even negative for upper tail inequality (90/50), they explain a substantial share of the increase in lower-tail inequality (50/10).

For women (lower panel in Figure 7), inequality from 1997 to 2010 has been more stable than for males. One interesting finding is that the fall in lower-tail inequality (50/10 ratio) between 1997 and 2006 appears due to price effects, while composition effects seem to have played in the other direction.

Lastly, the results using education instead of occupation as a proxy for skills are qualitatively similar, as shown in Figure E.1. in Appendix E. One interesting difference is that,

[34]In addition, re-weighting age and skill separately shows that skill composition– rather than age composition– is mostly driving the composition effects (unreported).

Figure 7. Age and occupation groups: decomposition



Notes: Source Social Security data.

while the fall in inequality between 1997 and 2006 is partly explained by composition effects when considering occupation as a measure of skills, composition effects seem to play little role when using education instead, so the fall is in an important part attributable to a decline in the education premium.

Overall, this section suggests that composition and price effects had different impacts on inequality in the three subperiods. In particular, the fall in male inequality during the 1997-2006 expansion is partly explained by a decrease in returns to skills and experience. In the next section we explore several factors that could have driven the recent evolution of male earnings inequality.

6 Spain is different: sectoral composition and labor market duality

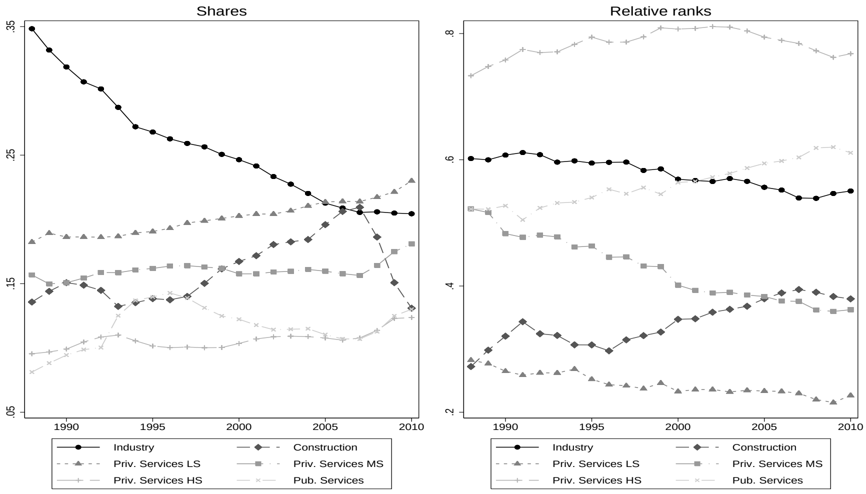
The above results on the effects of skill/experience quantities and prices are difficult to reconcile with existing theories of skill-biased technical change and demand for skills. Here we start by exploring the sectoral composition of earnings inequality, which we argue may be interpreted in light of the housing boom that started in the late 1990s. Then, we study other possible driving forces: labor market duality, immigration, and the minimum wage. The focus on males is motivated by the fact that the evolution of inequality has been more stable for women during the two subperiods 1997-2006 and 2007-2010. A more precise assessment of the factors that have driven the evolution of female earnings inequality is out of the scope of this paper.

6.1 A sectoral view: boom and bust

The left graph in Figure 8 shows the evolution of employment shares by sector. To facilitate interpretation we have aggregated sectors into 6 broad categories: industry (other than construction), construction, private services: low, medium, and high-skilled, and public services.[35] This graph shows two striking facts. The first one is the steady decline of industry in Spanish employment. The second fact is the sharp increase in the share of construction during the expansion: between 1997 and 2007 the employment share of construction increased from 14% to 21%. Interestingly, that share decreased to 13% in 2010, less than its 1990 level. This remarkable evolution points to a special role of the construction sector in the Spanish economy. By comparison, the private service sectors experienced a steady but more moderate

[35] See Table E.3. in Appendix E for a detailed definition of the sectors. Recall that in our dataset public employees refer to those belonging to the general regime of the social security administration. Hence, some government employees, such as the armed forces or the judicial power, are not included.

Figure 8. Employment shares and median earnings, by sector (men)



Notes: Source Social Security data. The left graph shows employment shares, by sector. The right graph shows median daily earnings, by sector, expressed as ranks in the aggregate distribution of daily earnings.

increase during the whole period.

Remarkably, the results for earnings shown on the right panel indicate that earnings in the construction sector increased substantially during the expansion. In 1996, the median earnings in the construction sector were at the percentile 30 of the aggregate earnings distribution. In 2007, they were at the percentile 40. Comparing these results with the sector shares suggests that demand for construction workers was very high during the boom, and dropped very sharply from 2007. Indeed, despite the large employment loss shown on the left panel, relative earnings of construction workers fell slightly during 2007-2010.

Overall, Figure 8 provides support to the idea that the construction sector is key to the understanding of the recent Spanish expansion and recession, and of the evolution of earnings inequality. Like the well-documented experience of the United States, Spain seems to have experienced a long period of high demand for a special type of workers. However, unlike the US this was a demand for low or medium-skilled workers, which went in parallel with a fall in the college premium. In addition, unlike the US, that period ended by a brutal recession where the sector that had benefited the most from the boom suffered severe employment losses.

To assess the quantitative role of sectoral changes in the evolution of inequality, we perform two different exercises. First, we take out the construction sector and compute inequality measures in an economy without construction. Figure 9 shows the results. We see that the fall

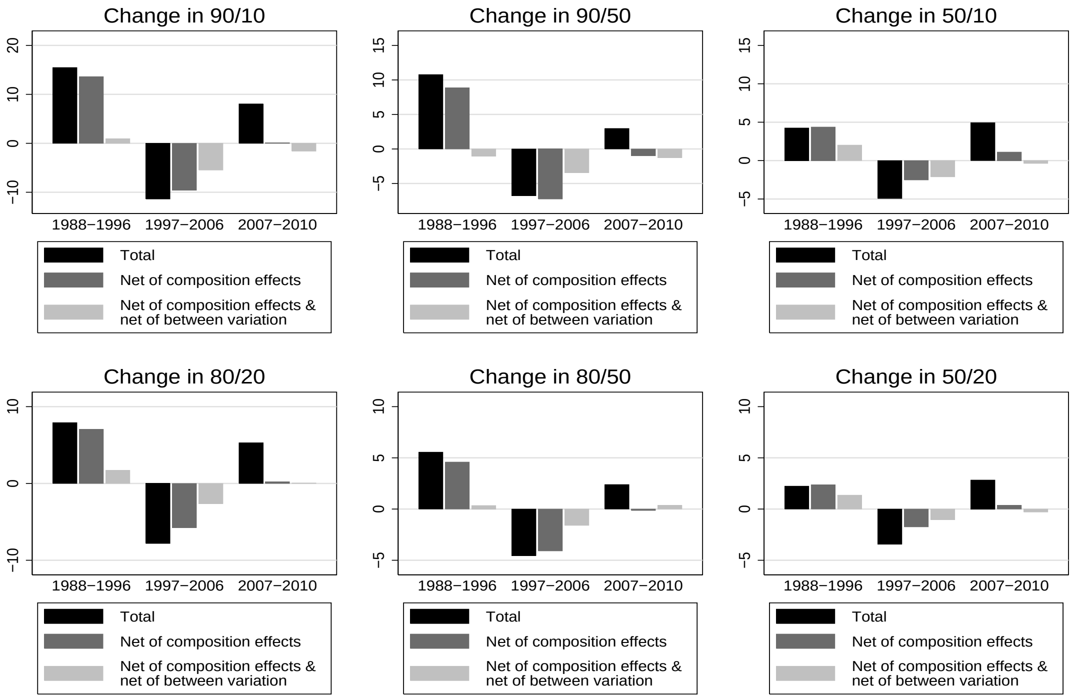
Figure 9. Inequality (men), with and without the construction sector

Notes: Source Social Security data. Solid lines are ratios of estimated unconditional quantiles of daily earnings, dashed lines are ratios of estimated unconditional quantiles of daily earnings in a sample without the construction sector.

in inequality during the Spanish expansion, and the increase during the recession of the late 2000s, are much less pronounced when taking out the construction sector. The 90/10 ratio decreases by 5.7% between 1997 and 2006, as opposed to 9.5% when including construction (see Table 2), while it increases by 4.2% in the sample without construction between 2007 and 2010, as opposed to 9.5% in the original sample. Similarly, the 80/20 ratio decreases by 5.0% as opposed to 7.2%, and then increases by 3.2% instead of 6.7%. This simple exercise suggests that a substantial part of the movements in the male earnings distribution over the past 15 years has been driven by the construction sector.

As a second exercise, we conduct the same decomposition analysis as in the previous section, but now also including sector dummies and interactions in addition to skills and age. Results are shown in Figure 10, and in Table E.4. in Appendix E. Comparing with Figure 7, we see interesting differences at the bottom of the earnings distribution. While price effects seemed to partly explain the increase in the 50/10 ratio between 2007 and 2010 when allowing for occupation and age dummies alone, the increase is mostly explained by composition effects when also allowing for sectoral composition. Similarly, composition effects now explain approximately half of the fall in 50/10 inequality between 1997 and 2006. This provides additional evidence that changes in sectoral composition, and in particular changes in the construction sector pictured in Figure 8, explain a large part of the recent evolution

Figure 10. Age, occupation groups, and sectors: decomposition (men)



Notes: Source Social Security data.

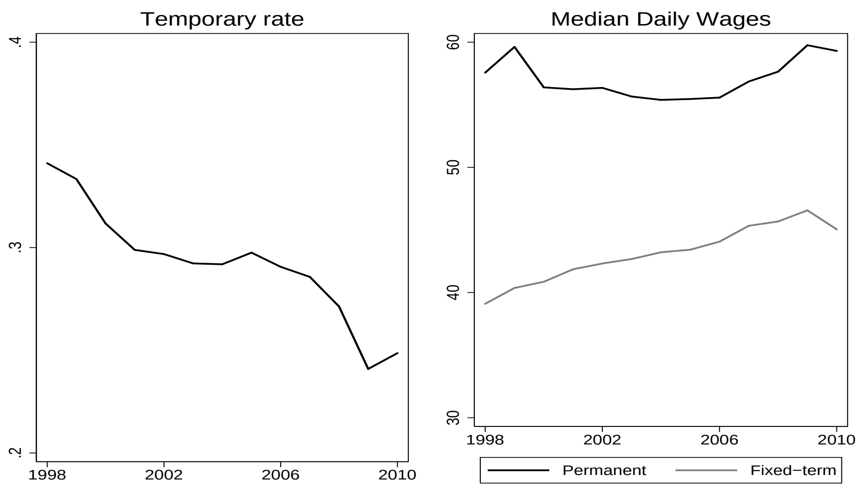
of inequality in Spain.

6.2 Labor market duality, minimum wage, and immigration

In this subsection we study three other factors that may have contributed to the evolution of male inequality: the duality of the labor market, the evolution of the minimum wage, and immigration.

Labor market duality. In Spain, around one third of employees are in temporary jobs. After the introduction of these contracts in 1984, they grew rapidly up to approximately 33% by the early 1990s. The proportion has remained relatively stable since then until the current crisis (see the left panel of Figure 11), and represents the largest share in Europe. Most of the literature has focused on the determinants of the duration and conversion rates of temporary contracts into permanent positions (Amuedo-Dorantes, 2000, Güell and Petrongolo, 2007, García-Pérez and Muñoz-Bullón, 2010), or the effects of having a dual employment protection on productivity (Dolado *et al.*, 2011). Remarkably less is known about the effect of

Figure 11. Type of contract: temporary rates and median earnings (men)



Notes: Source Social Security data. The left graph shows the share of temporary (or fixed-term) contracts in employment. The right graph shows median earnings by type of contract.

temporary contracts on earnings over time.

In our administrative data, information regarding the type of contract - permanent *versus* fixed term - is available only since 1997, thus we restrict this analysis to the subperiod 1998-2010. As showed in Figure E.2. in Appendix E, temporary contracts are highly concentrated among the young, immigrants, and low-skilled workers. By sector, temporary contracts are disproportionately high in construction (63% on average over the period, and 67% from 1998 to 2006).

The right panel of Figure 11 shows the evolution of median earnings of permanent and temporary workers. We see that the relative difference between the two types of contract decreased substantially between 1998 and 2007, with the relative ratio between permanent and temporary median earnings falling by almost 20%. This ratio increased from 2007 to 2010, by about 7%. The evolution of between-type-of-contract inequality is consistent with the evolution of overall earnings inequality between 1998 and 2010. In addition, given the high share of temporary contracts in the construction sector documented in Figure E.2., this may partly reflect the surge and subsequent fall in demand for constuction workers.

Minimum wage. Another candidate to explain the evolution of inequality is the minimum wage. In the US, several studies have argued that the decline in the Federal minimum wage partly explains the increase in earnings inequality in the 1980s (see e.g. DiNardo *et al.*, 1996, Lee, 1999). Changes in the Spanish minimum wage are a potential source of concern for our analysis, as the minimum wage is always capped throughout the period. The minimum wage is unlikely to have played a major role in the evolution of Spanish earnings inequality, however. Figure E.3. in Appendix E shows the evolution of the real value of the minimum wage between 1988 and 2010. We see that most of the 1998-2006 period was characterized by a slight decrease in the real minimum wage, while the end of the 2000s saw a marked increase between 2004 and 2009. This timing is unable to explain the patterns of overall and lower-tail inequality that we have described.

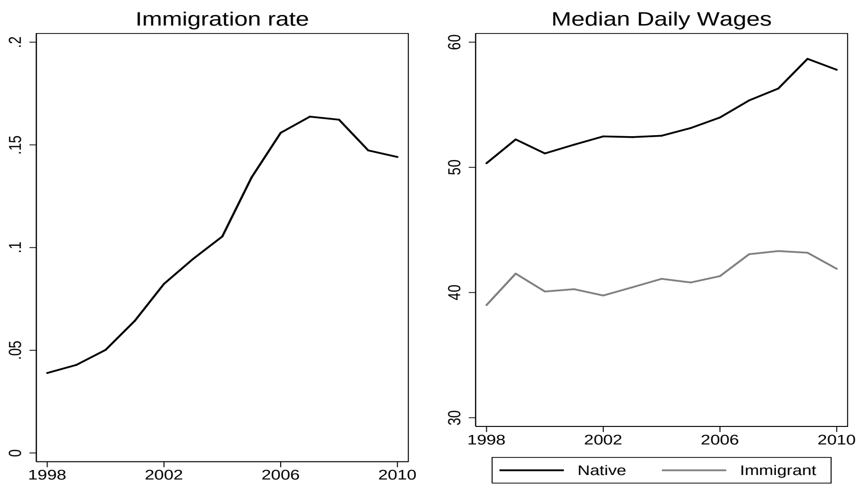
Immigration. During the last decade the inflows of immigrants in Spain increased sharply. Available data sources (population census, administrative registers of residence and work permits, labor force survey, ...) do not always coincide in the measurement of the stock of foreign population in Spain, due to illegal immigration. Similarly, our dataset only contains those immigrants registered with the social security administration. As shown on the left panel of Figure 12, the proportion among male employees of foreign-born workers increased from 5% in 2000 to 16.4% in 2007, and then decreased to 14.4% in 2010. So, according to our data the period of fall in inequality was associated with increased immigration, while the recent period of inequality increase is associated with decreasing immigration. This pattern could in part reflect the demand shocks related to the housing boom and bust of the 2000s. In addition, the right panel of Figure 12 shows that, during the same period the native-immigrant earnings gap experienced only minor changes until 2007, while it seems to have increased in the recent recession.

As a crude way of assessing the effect of immigration of inequality, Figure E.4. in Appendix E shows the evolution of the inequality ratios in a sample without immigrants. We see that inequality figures are very similar to the ones in the full sample. This suggests that immigration has had little effect on overall earnings inequality. One limitation of the exercise is that immigration could have had an effect on earnings of non-immigrants, for example by reducing the wages of native workers working in similar occupations. The evidence we have presented does not seem to support this hypothesis, however, as for example earnings in the construction sector (where the share of male immigrants is highest) increased in relative terms until 2007.[36]

The evidence presented in this section is consistent with the evolution of male earnings inequality reflecting the special nature of Spanish growth between 1998 and 2007. As a

[36]See Figure E.5. in Appendix E for shares of foreign-born workers in employment, by sector. A recent paper of Carrasco *et al.* (2008) does not find significant effects of immigration on either the employment rates or the wages of native workers during the second half of the 1990s.

Figure 12. Immigration: immigration rates and median earnings (men)



Notes: Source Social Security data. The "immigration rate" is computed as the share of foreign-born workers among employees.

response to the high demand for construction workers driven by the housing boom, the share of the construction sector in the economy increased, and relative earnings of construction workers increased as well. New jobs were partly in the form of fixed-term contracts, causing a decrease in the earnings gap between permanent and temporary workers. Immigration and the minimum wage had at most small effects on the evolution of inequality, which fell substantially until 2007 while unemployment reached historically low levels. With the 2008 recession, however, the housing bust has played in the opposite direction, generating an increase in unemployment and earnings inequality. In the last section of this paper we try to integrate these two dimensions of labor market inequality.

7 The role of unemployment

Employment is another dimension of labor market inequality. In this final section our aim is to take the level and duration of unemployment into account in order to compute unemployment-adjusted inequality measures.

7.1 Earnings distributions adjusted for unemployment

We will compare and contrast two different approaches to impute earnings values to the unemployed.

Table 4. Unemployment benefits

Months of unemployment	1-6	6-24	25-48	49-72	73-96	97-120	>120
% of prev. earnings	0.7	0.6	0.5	0.4	0.3	0.2	0.1

Approach 1: Potential earnings. The first approach is based on a neoclassical Mincer model where potential earnings are equal to the marginal productivity of labor. As in Heckman (1979), individuals decide whether or not to work by comparing their potential earnings with their reservation wage. Several methods have been proposed to account for non-random selection into employment in this framework (see Neal, 2004, or Blundell *et al.*, 2007 for recent examples).

We follow Olivetti and Petrongolo (2008) and make use of the panel dimension of our data. For those not in work, we recover the daily earnings observation from the nearest wave in which the same individual is working. Hence, when unemployment spells are followed by another employment relationship, the imputed earnings follow a step function with a jump in the middle of the spell.[37]

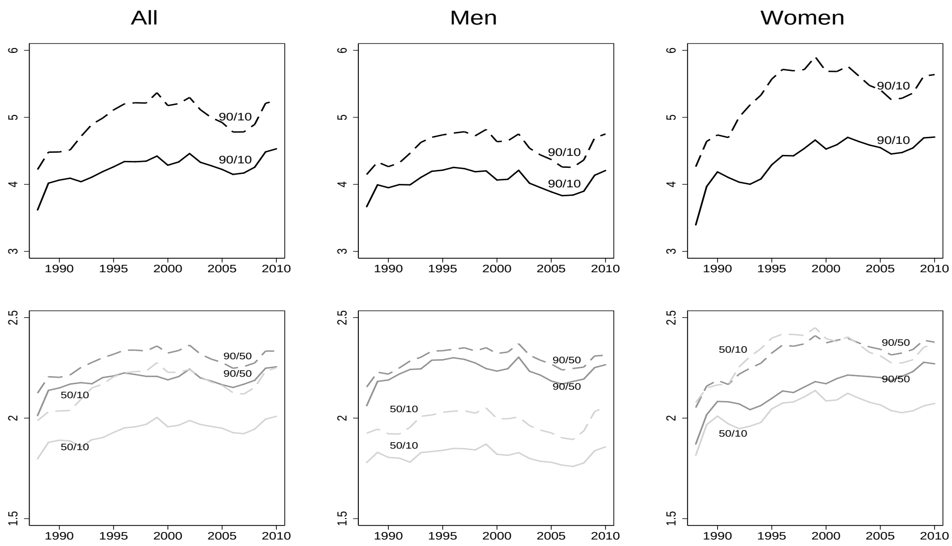
The underlying assumption is that, for a given individual, the latent earnings position with respect to her predicted quantile when she is unemployed can be proxied by her earnings in the nearest wave in which she is employed. As the position with respect to the quantile is determined using alternative information on earnings, as opposed to measured characteristics, this method is effectively allowing for selection on unobservables.

Approach 2: Unemployment benefits. One limitation of the previous approach is that it is not directly related to the benefits individuals actually perceive when unemployed. As a complement we will use a second approach that uses unemployment benefits to impute labor income to the unemployed. This second approach depends on the benefits rules. We use a simple approximation that mimics the rules of the Spanish system over the period, as reported in Table 4.[38] For this second approach we also use the panel structure of the data to compute the duration of the unemployment spell. Our measure of previous earnings is the last (predicted) earnings that the individual had when she was working. An attractive feature of this approach is that benefits decrease with the duration of unemployment, possibly reflecting some productivity loss or human capital depreciation.

[37]Notice that some of the imputed earnings are censored. We then apply the normal censored regression method to imputed earnings.

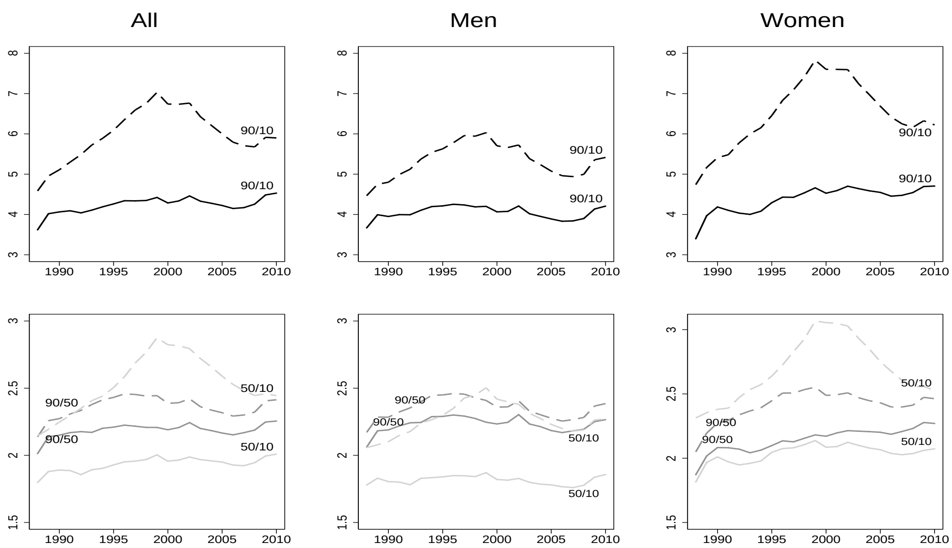
[38]As a simplification, we assume that the rule is stationary over the whole period.

Figure 13. Inequality Ratios for Earnings and Potential Earnings



Notes: Source Social Security data. Solid lines are ratios of estimated daily earnings conditional on employment. Dashed lines are ratios of estimated potential earnings.

Figure 14. Inequality Ratios for Earnings and Labor Income



Notes: Source Social Security data. Solid lines are ratios of estimated daily earnings conditional on employment. Dashed lines are ratios of estimated labor income, based on imputed unemployment benefits.

7.2 Evidence on labor market inequality

We start by commenting the evolution of inequality in potential earnings, as shown in Figure 13.[39] We see that the level of inequality in potential earnings is higher than that of observed earnings inequality (conditional on employment). This reflects the fact that there is positive selection in employment. However, the overall qualitative pattern of evolution is preserved. For males, the percentage changes in the 90/10 inequality ratio are comparable to those reported in Table 2. For women, our results suggest that inequality in potential earnings increased more strongly during the recession of the early 1990s.

We next turn to the second method to impute income values to the unemployed, based on the benefits rule. By construction, this approach takes into account the duration of unemployment. Figure E.6. in Appendix E shows that Spain presents high cyclical variation of employment and high incidence of long-term unemployment. Figure 14 shows that the level of inequality is substantially higher than when using the potential earnings method.[40] In terms of evolution, the 2008-2010 recession seems to have had a smaller effect relative to the recession of the early 1990s. This could be due to the fact that these numbers partly reflect the duration of unemployment spells, so the effect of a recession on overall inequality may take some time to appear.

Overall, Figures 14 and 15 show that the level and evolution of inequality is quantitatively different when considering our combined measures of earnings and employment inequality. In particular, the evidence presented in this section shows large differences along the business cycle. This suggests that the welfare costs of a recession may be much higher than the ones captured using conventional earnings inequality measures.

8 Conclusions

In this paper we have used administrative data from the Social Security to characterize the evolution of earnings inequality in Spain from 1988 to 2010. The evidence that we document suggests that the dispersion of the earnings distribution has experienced substantial changes over the past two decades. The pattern of male inequality shows a fall during the expansion, and sharp increases in recessions. The magnitude of these changes is large by international standards.

Our search for factors that have driven this evolution suggests that the construction sector has played a very special role. The Spanish boom of the late 1990s and early 2000s was in

[39]Figure E.7. in in Appendix E shows the quantile levels, and Table E.5. gives the numbers.
[40]Table E.6. in Appendix E gives the numbers.

part a housing boom. We find evidence that sectoral composition explains a large share of the fall in inequality. High demand for construction workers resulted in increasing employment shares for the construction sector and higher relative earnings. Partly as a result, earnings of temporary workers also increased relative to those of permanent workers, and the college premium decreased.

The recent Spanish experience thus illustrates a situation where low or middle-earnings workers are in high demand, and where inequality falls. However, the Spanish expansion was fragile: the recent recession shows that inequality can increase sharply together with unemployment as the economy reverses. The housing bust then results in steep increases in earnings and employment inequality.

The social security sample that we use in this study has important limitations. Due to the retrospective design, results for women should be interpreted with caution. In addition, the severe censoring in the earlier period makes the results for the early 1990s less accurate. However, these data offer a unique opportunity to follow workers over long periods of time.

One possibility would be to estimate a micro panel data model with unobserved heterogeneity to also account for composition changes in terms of unobservable characteristics, combined with macro indicators to measure the vulnerability of different individuals to the business cycle. This type of framework would allow us to extend the analysis of inequality to earnings mobility as well. We view this as an interesting avenue for future research.

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APPENDIX

A Sample composition

Table A.1. Sample composition and Descriptive Statistics by gender

	Whole sample											
	Total				Men		%		Women		%	
Individuals	93,132				52,878		56.78		40,254		43.22	
Observations	12,670,734				7,375,381		58.21		5,295,353		41.79	
	1988	1997	2007	2010	1988	1997	2007	2010	1988	1997	2007	2010
Average Age	36.27	37.22	37.92	38.72	37.02	37.86	38.16	38.95	34.48	36.28	37.64	38.46
	(8.08)	(8.17)	(8.11)	(8.05)	(8.20)	(8.35)	(8.14)	(8.02)	(7.48)	(7.81)	(8.07)	(8.07)
Immigrants (%)	1.69	3.78	15.09	15.89	1.54	3.95	16.85	17.43	2.04	3.52	12.98	14.08
Engineers-College	6.60	6.46	7.23	7.80	7.34	7.37	7.33	7.70	4.84	5.11	7.12	7.91
Technicians	4.73	4.82	5.89	6.16	3.50	3.72	4.50	4.64	7.70	6.47	7.55	7.93
Adm. managers	5.00	4.53	4.26	4.22	5.82	5.72	5.25	5.07	3.06	2.75	3.07	3.22
Assistants	3.68	3.38	3.20	3.30	4.42	4.25	3.63	3.63	1.93	2.08	2.68	2.92
Adm. workers	24.75	27.44	28.71	29.59	18.77	19.53	18.97	20.00	39.07	39.27	40.31	40.82
Manual workers	55.22	53.36	50.71	48.92	60.16	59.41	60.31	58.95	43.39	44.31	39.26	37.19
Annual workdays=0	17.10	28.74	15.55	18.18	14.41	25.25	14.51	19.18	23.42	33.93	16.79	17.01
	Working individuals											
	Total				Men		%		Women		%	
Individuals	92,579				52,599		56.82		39,980		43.18	
Observations	8,526,953				5,185,955		60.82		3,340,998		39.18	
	1988	1997	2007	2010	1988	1997	2007	2010	1988	1997	2007	2010
Average Age	36.90	37.39	37.82	38.69	37.52	37.92	38.12	38.96	35.18	36.44	37.43	38.38
	(8.12)	(8.23)	(8.11)	(8.05)	(8.21)	(8.33)	(8.14)	(8.02)	(7.60)	(7.96)	(8.06)	(8.07)
Immigrants (%)	1.69	3.51	14.79	13.41	1.57	3.62	16.53	14.54	2.02	3.31	12.54	12.12
Engineers-College	7.01	7.26	8.22	9.55	7.70	7.79	8.04	9.53	5.09	6.34	8.47	9.57
Technicians	5.26	6.29	6.81	7.62	3.95	4.53	5.00	5.74	8.89	9.39	9.17	9.77
Adm. managers	5.87	5.77	4.77	4.88	6.58	6.81	5.67	5.85	3.89	3.94	3.60	3.76
Assistants	4.38	4.31	3.56	3.81	5.12	5.26	4.07	4.32	2.30	2.64	2.90	3.22
Adm. workers	26.25	30.43	30.20	32.38	20.06	21.86	19.59	22.18	43.48	45.54	43.97	44.06
Manual workers	51.23	45.93	46.43	41.77	56.58	53.74	57.63	52.38	36.35	32.15	31.90	29.61
Top-coded	24.02	17.84	13.57	14.82	27.10	21.48	16.07	17.98	15.44	11.41	10.33	11.21
Bottom-coded	4.45	7.18	7.32	9.22	3.01	4.00	3.37	4.96	8.46	12.80	12.44	14.10
Median daily earnings	44.81	45.84	47.44	49.09	46.54	48.36	50.93	53.76	40.78	41.84	42.66	43.87
	(19.5)	(23.5)	(24.4)	(25.2)	(19.8)	(23.6)	(23.9)	(24.7)	(17.9)	(22.5)	(24.3)	(24.9)
Temporary (%)	-	33.21	28.15	25.54	-	32.17	28.57	24.86	-	35.05	27.60	26.32

Note: Standard deviations of non-binary variables in parentheses.

B Sample representativeness

Table B.1. Mortality rates by gender and group age (deaths per 1000 individuals)

	Men						Women					
	25-29	30-34	35-39	40-44	45-49	50-54	25-29	30-34	35-39	40-44	45-49	50-54
1988	0.83	0.76	0.89	1.31	1.93	3.57	0.57	0.56	0.74	1.19	1.69	0.310
1989	0.97	0.86	0.91	1.35	2.01	3.27	0.59	0.58	0.69	1.19	1.70	0.280
1990	1.01	0.96	0.92	1.36	2.00	3.17	0.59	0.63	0.75	1.10	1.65	0.270
1991	1.10	1.07	0.99	1.32	2.08	2.96	0.60	0.64	0.75	1.16	1.76	0.259
1992	1.06	1.15	1.01	1.33	2.06	2.80	0.62	0.65	0.71	1.07	1.72	0.231
1993	0.97	1.16	1.03	1.30	2.15	2.77	0.62	0.69	0.74	1.10	1.69	0.230
1994	0.94	1.22	1.10	1.28	2.14	2.81	0.59	0.76	0.77	1.06	1.79	0.232
1995	0.90	1.28	1.18	1.28	2.09	2.84	0.54	0.76	0.89	1.09	1.65	0.232
1996	0.79	1.22	1.21	1.31	1.98	2.92	0.55	0.80	0.83	1.13	1.56	0.227
1997	0.64	0.93	1.03	1.23	1.96	2.88	0.40	0.63	0.76	1.02	1.57	0.225
1998	0.58	0.78	0.95	1.24	1.82	2.81	0.38	0.50	0.71	1.07	1.53	0.226
1999	0.55	0.73	0.95	1.26	1.86	2.79	0.33	0.51	0.70	1.08	1.58	0.220
2000	0.54	0.66	0.92	1.28	1.83	2.74	0.32	0.48	0.70	1.10	1.53	0.214
2001	0.46	0.64	0.89	1.17	1.78	2.72	0.33	0.48	0.70	1.02	1.57	0.217
2002	0.45	0.60	0.83	1.19	1.80	2.68	0.30	0.43	0.68	0.99	1.56	0.216
2003	0.43	0.59	0.78	1.20	1.75	2.61	0.29	0.41	0.68	1.04	1.64	0.214
2004	0.41	0.51	0.79	1.08	1.78	2.63	0.28	0.40	0.60	0.99	1.52	0.212
Average (1988-2004)	0.74	0.89	0.96	1.26	1.94	2.88	0.47	0.58	0.73	1.08	1.63	2.36

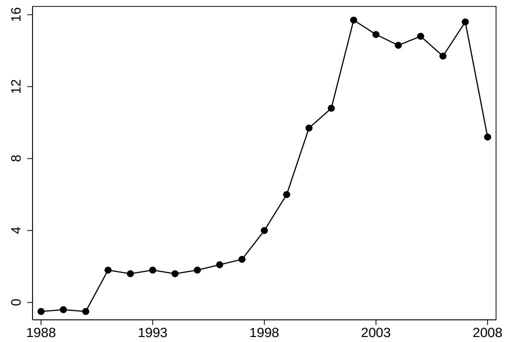
Source: National Statistics Institute.

Table B.2. Stock of emigrants over total population by educational attainment (%)

	1990			2000		
	Total	College	Non-college	Total	College	Non-college
Abroad	2.07	2.12	2.06	1.83	1.91	1.80
Europe	1.69	0.93	1.78	1.48	1.17	1.56
America	0.34	1.11	0.25	0.31	0.69	0.21
Asia and Oceania	0.03	0.08	0.03	0.03	0.05	0.03

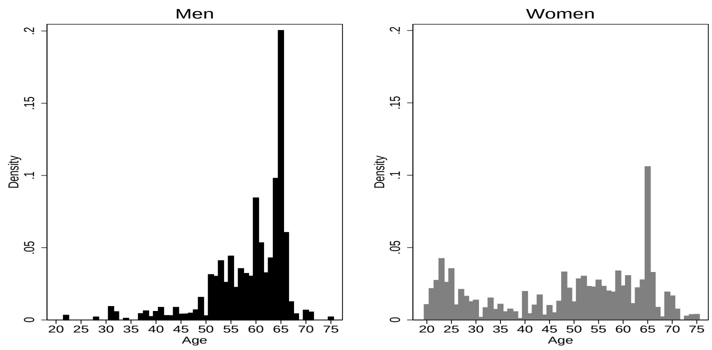
Source: International Migration by Educational Attainment (2005, Release 1.1).

Figure B.1. Spanish crude rate of net migration in % (1988-2008)



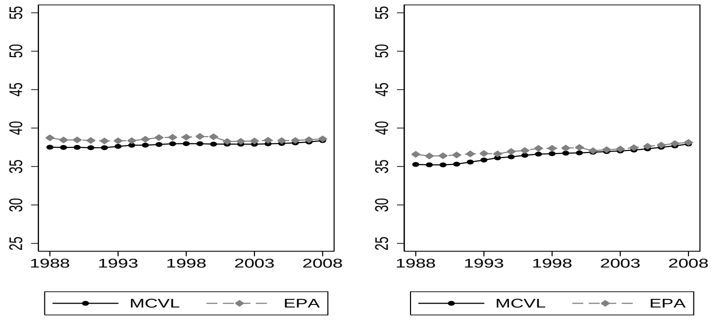
Notes: Source EUROSTAT. The indicator is defined as the ratio of net migration plus adjustment during the year to the average population in that year, expressed per 1,000 inhabitants. The net migration plus adjustment is the difference between the total change and the natural change of the population.

Figure B.2. Age when stopped working (Spain)



Notes: Source SHARE. Individuals who ever worked and were aged between 34 and 53 years in 1988.

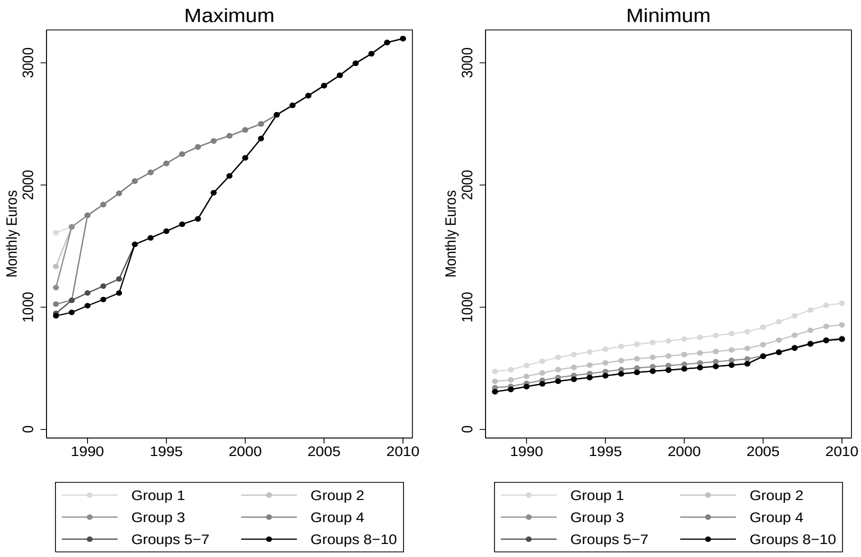
Figure B.3. Average age (Spain)



Notes: Sources MCVL = Continuous Sample of Working Histories; EPA = Spanish Labor Force Survey.

C Legal caps in the Social Security System

Figure C.1. Caps in the General Regime



Notes: Monthly quantities in nominal EUR. See notes in Table C.1. for a definition of the groups.

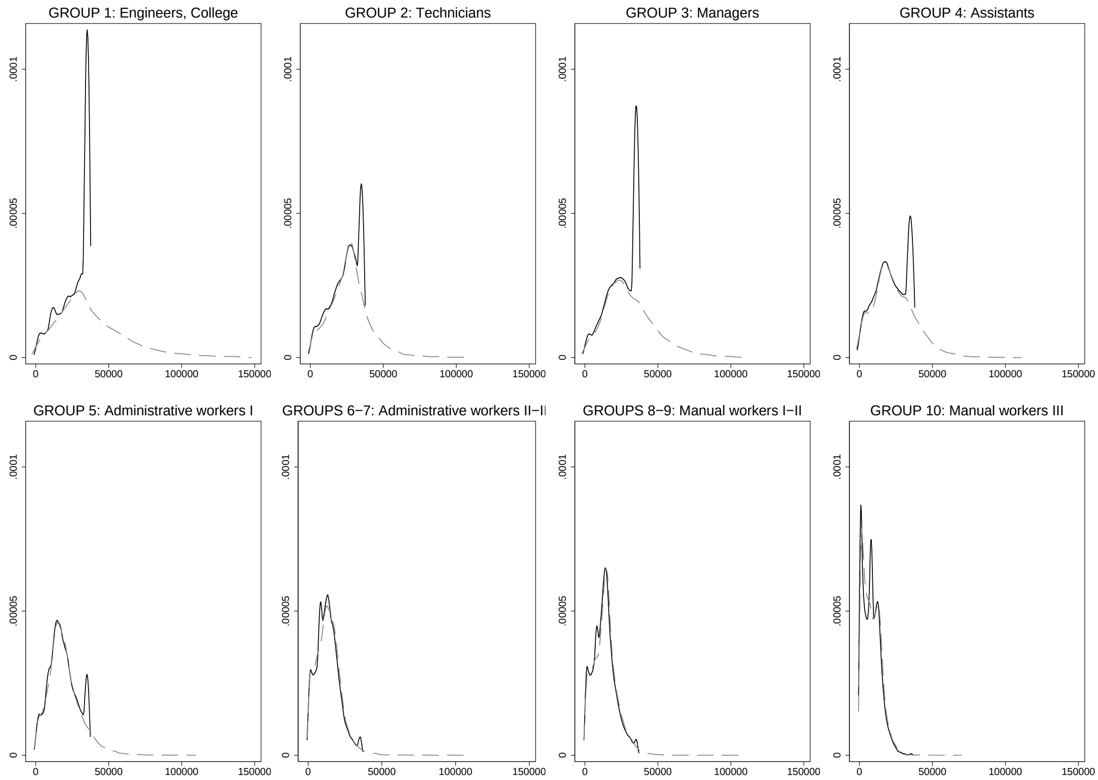
Table C.1. Caps in the General Regime

Groups	2002	2003	2004	2005	2006	2007	2008	2009	2010
Maximum									
1-4	2574.9	2652.0	2731.5	2813.4	2897.7	2996.1	3074.1	3166.2	3198.0
5-7	2574.9	2652.0	2731.5	2813.4	2897.7	2996.1	3074.1	3166.2	3198.0
8-10	85.83	88.4	91.05	93.78	96.59	99.87	102.47	105.54	106.60
Minimum									
1	768.9	784.2	799.8	836.1	881.1	929.7	977.4	1016.4	1031.7
2	637.9	650.7	663.6	693.6	731.1	771.3	810.9	843.3	855.9
3	554.4	565.5	576.9	603.0	635.7	670.8	705.3	733.1	744.6
4-7	516.0	526.5	537.3	598.5	631.2	665.7	699.9	728.1	738.9
8-10	17.2	17.55	17.91	19.95	21.04	22.19	23.33	24.27	24.63
Minimum Wage	442.2	451.2	460.5	513.0	540.9	570.6	600.0	624.0	633.3

Notes: Quantities in nominal EUR. Monthly for groups 1-7 and daily for 8-11. Group 1: Engineers, College. Group 2: Technicians. Group 3: Administrative managers. Group 4: Assistants. Groups 5-7: Administrative workers. Groups 8-10: Manual workers.

D Distributions of the social security contributions and the taxable labor income

Figure D.1. MCVL matched with Tax data: Kernel densities



Notes: Sources Social Security data and Income Tax data. Solid lines are observed annual earnings from Social Security data. Dashed lines are observed annual earnings from Income Tax data. To draw the graphs we have dropped individuals with earnings over 3 times their corresponding top-cap (4 times for Group 1: Engineers, College graduates), which amounts to dropping 0.2% of the observations.

E Additional Results

Table E.1. Overall Inequality Ratios

		1995	2002*	2002	2006
(A) Ratios from the Wage Structure Survey**					
Men	w^{90}/w^{10}	3.64	3.48	3.59	3.33
	w^{90}/w^{50}	2.08	2.22	2.23	2.15
	w^{50}/w^{10}	1.75	1.57	1.61	1.55
Women	w^{90}/w^{10}	3.23	3.02	3.50	3.00
	w^{90}/w^{50}	2.08	2.06	2.27	2.03
	w^{50}/w^{10}	1.55	1.46	1.54	1.48
(B) Ratios from Social Security data***					
Men	w^{90}/w^{10}	4.21		4.21	3.83
	w^{90}/w^{50}	2.29		2.30	2.17
	w^{50}/w^{10}	1.84		1.83	1.77
Women	w^{90}/w^{10}	4.29		4.70	4.45
	w^{90}/w^{50}	2.10		2.21	2.19
	w^{50}/w^{10}	2.04		2.12	2.04

Notes: * Figures exclude some non-market sectors (education, health, and social services) to obtain comparable figures with those for 1995. ** Ratios of percentiles of Hourly Wages.
** Ratios of estimated quantiles of Daily Earnings.

Table E.2. Age and skill (occupation) groups: decomposition

	1988	1997	2007	2010	1988-1996 (%)	1997-2006 (%)	2007-2010 (%)	1988-1996 (%)	1997-2006 (%)	2007-2010 (%)
I. MEN										
Ratios of estimated quantiles					(A) Change in ratios					
90/10	3.67	4.23	3.84	4.21	15.97	-9.53	9.55			
90/50	2.06	2.29	2.18	2.26	11.57	-5.35	3.81			
50/10	1.78	1.85	1.76	1.86	3.94	-4.41	5.53			
80/20	2.30	2.49	2.31	2.46	8.36	-7.25	6.69			
80/50	1.56	1.65	1.58	1.63	5.63	-4.20	3.06			
50/20	1.47	1.50	1.46	1.51	2.59	-3.18	3.53			
Composition constant					(B) Price effects			Composition effects: (A)-(B)		
90/10 w.	3.79	4.13	4.12	4.21	12.32	-7.23	2.07	3.65	-2.30	7.48
90/50 w.	2.11	2.26	2.30	2.26	9.16	-4.01	-1.73	2.41	-1.34	5.54
50/10 w.	1.80	1.83	1.79	1.86	2.89	-3.36	3.87	1.05	-1.05	1.66
80/20 w.	2.35	2.44	2.40	2.46	6.25	-5.33	2.50	2.11	-1.92	4.19
80/50 w.	1.58	1.63	1.63	1.63	4.33	-3.03	0.17	1.30	-1.17	2.89
50/20 w.	1.48	1.50	1.48	1.51	1.84	-2.37	2.32	0.75	-0.81	1.21
Composition and mu constant					(C) Within variation			Between variation: (B)-(C)		
90/10 w.	4.19	4.04	4.15	4.21	1.52	-5.09	1.44	10.80	-2.14	0.63
90/50 w.	2.30	2.23	2.30	2.26	-0.01	-2.81	-1.54	9.17	-1.20	-0.19
50/10 w.	1.82	1.81	1.80	1.86	1.53	-2.35	3.02	1.36	-1.01	0.85
80/20 w.	2.47	2.39	2.40	2.46	0.96	-3.42	2.42	5.29	-1.91	0.08
80/50 w.	1.65	1.61	1.62	1.63	0.16	-1.91	0.48	4.17	-1.12	-0.31
50/20 w.	1.50	1.48	1.48	1.51	0.79	-1.53	1.94	1.05	-0.84	0.38
II. WOMEN										
Ratios of estimated quantiles					(A) Change in ratios					
90/10	3.40	4.43	4.47	4.71	30.44	0.63	5.16			
90/50	1.87	2.13	2.21	2.27	14.11	2.77	2.82			
50/10	1.81	2.08	2.03	2.07	14.31	-2.09	2.27			
80/20	2.24	2.66	2.62	2.73	18.76	-0.38	2.92			
80/50	1.51	1.65	1.66	1.69	9.02	0.61	1.47			
50/20	1.48	1.62	1.59	1.62	8.94	-0.99	1.43			
Composition constant					(B) Price effects			Composition effects: (A)-(B)		
90/10 w.	3.51	4.53	4.59	4.71	26.22	-1.71	2.57	4.22	2.34	2.59
90/50 w.	1.89	2.16	2.24	2.27	12.83	1.15	1.31	1.28	1.62	1.51
50/10 w.	1.85	2.04	2.05	2.07	11.87	-2.83	1.23	2.44	0.74	1.04
80/20 w.	2.29	2.70	2.70	2.73	16.13	-1.76	0.93	2.63	-1.38	1.99
80/50 w.	1.53	1.66	1.68	1.69	8.15	-0.25	0.31	0.87	0.86	1.16
50/20 w.	1.50	1.62	1.61	1.62	7.37	-1.52	0.62	1.57	0.53	0.81
Composition and mu constant					(C) Within variation			Between variation: (B)-(C)		
90/10 w.	3.95	4.41	4.71	4.71	12.24	1.02	-0.11	13.98	-0.69	2.68
90/50 w.	2.06	2.16	2.29	2.27	3.74	1.09	-0.82	9.09	0.06	2.13
50/10 w.	1.92	2.04	2.06	2.07	8.18	-0.07	0.72	3.69	-2.76	0.51
80/20 w.	2.47	2.65	2.74	2.73	7.74	0.16	-0.41	8.39	-1.60	1.34
80/50 w.	1.61	1.66	1.70	1.69	2.69	-0.02	-0.66	5.46	-0.23	0.97
50/20 w.	1.54	1.60	1.61	1.62	4.92	0.18	0.25	2.45	-1.34	0.37

Notes: Ratios of estimated daily earnings from Social Security data. w=re-weighted.

Table E.3. Sectors definitions

Industry:	Agriculture, mining, food and tobacco industry, clothing and footwear industry, metal industry, paper industry, timber industry, plastics industry, chemical industry, machinery and car industry, furniture industry and manufacturing.
Construction:	All general building works, installation systems and extensions (electrical system, painting, plumbing and tiling, carpentry, flooring, plastering), civil engineering works, renting of the building equipment.
Services:	Sales, hotels, storing, transport, telecommunications and energy, financial services, corporate services, personal services, administration, education, health, social activities. **Public services:** When the employer is any local, regional or national government institution. **Private services:** Otherwise. **High-skilled** (HS): Skill groups 1-3. **Mid-skilled** (MS): Skill groups 4-7. **Low-skilled** (LS): Skill groups 8-10.

Table E.4. Age, occupation groups, and sectors: decomposition (men)

	1988	1997	2007	2010	1988-1996 (%)	1997-2006 (%)	2007-2010 (%)	1988-1996 (%)	1997-2006 (%)	2007-2010 (%)
Ratios of estimated quantiles					(A) Change in ratios					
90/10	3.66	4.21	3.73	4.03	15.47	-11.37	8.05			
90/50	2.07	2.29	2.14	2.20	10.77	-6.78	2.97			
50/10	1.77	1.84	1.74	1.83	4.25	-4.93	4.94			
80/20	2.31	2.48	2.29	2.41	7.92	-7.81	5.29			
80/50	1.57	1.65	1.58	1.62	5.56	-4.55	2.39			
50/20	1.47	1.50	1.45	1.49	2.24	-3.42	2.83			
Composition constant					(B) Price effects			Composition effects: (A)-(B)		
90/10 w.	3.72	4.13	4.02	4.03	13.61	-9.58	0.11	1.86	-1.79	7.94
90/50 w.	2.11	2.30	2.22	2.20	8.86	-7.25	-0.98	1.91	0.47	3.95
50/10 w.	1.76	1.80	1.81	1.83	4.37	-2.52	1.11	-0.12	-2.41	3.83
80/20 w.	2.33	2.43	2.40	2.41	7.05	-5.76	0.22	0.87	-2.05	5.07
80/50 w.	1.58	1.65	1.62	1.62	4.59	-4.09	-0.14	0.97	-0.46	2.53
50/20 w.	1.47	1.47	1.48	1.49	2.36	-1.74	0.36	-0.12	-1.68	2.47
Composition and mu constant					(C) Within variation			Between variation: (B)-(C)		
90/10 w.	4.19	3.95	4.10	4.03	0.95	-5.47	-1.61	12.66	-4.11	1.72
90/50 w.	2.32	2.21	2.23	2.20	-1.05	-3.43	-1.24	9.91	-3.82	0.26
50/10 w.	1.80	1.79	1.84	1.83	2.02	-2.11	-0.37	2.35	-0.41	1.48
80/20 w.	2.45	2.35	2.41	2.41	1.71	-2.62	0.06	5.34	-3.14	0.16
80/50 w.	1.65	1.60	1.61	1.62	0.34	-1.59	0.36	4.25	-2.50	-0.50
50/20 w.	1.48	1.46	1.49	1.49	1.36	-1.04	-0.29	1.00	-0.70	0.65

Notes: Ratios of estimated daily earnings from Social Security data. w=re-weighted.

Table E.5. Estimated Unconditional Quantiles of Potential Earnings (pe^q)

		1988	1997	2007	2010	1988-1996 (%)	1997-2006 (%)	2007-2010 (%)
All	pe^{10}	21.19	18.95	21.79	21.74	-9.92	11.39	-0.21
	pe^{50}	42.11	42.29	46.19	48.94	0.82	6.17	5.95
	pe^{90}	89.46	98.89	104.22	114.21	10.96	2.08	9.56
Men	pe^{10}	22.95	22.59	26.76	26.32	-1.43	14.76	-1.65
	pe^{50}	44.18	46.01	50.68	54.09	4.18	7.18	6.74
	pe^{90}	95.21	108.11	113.86	125.09	13.23	2.15	9.86
Women	pe^{10}	17.88	15.08	17.72	18.02	-15.19	13.85	1.72
	pe^{50}	37.14	36.44	40.29	42.73	-1.30	7.22	6.04
	pe^{90}	76.23	85.91	93.64	101.60	13.66	5.26	8.51

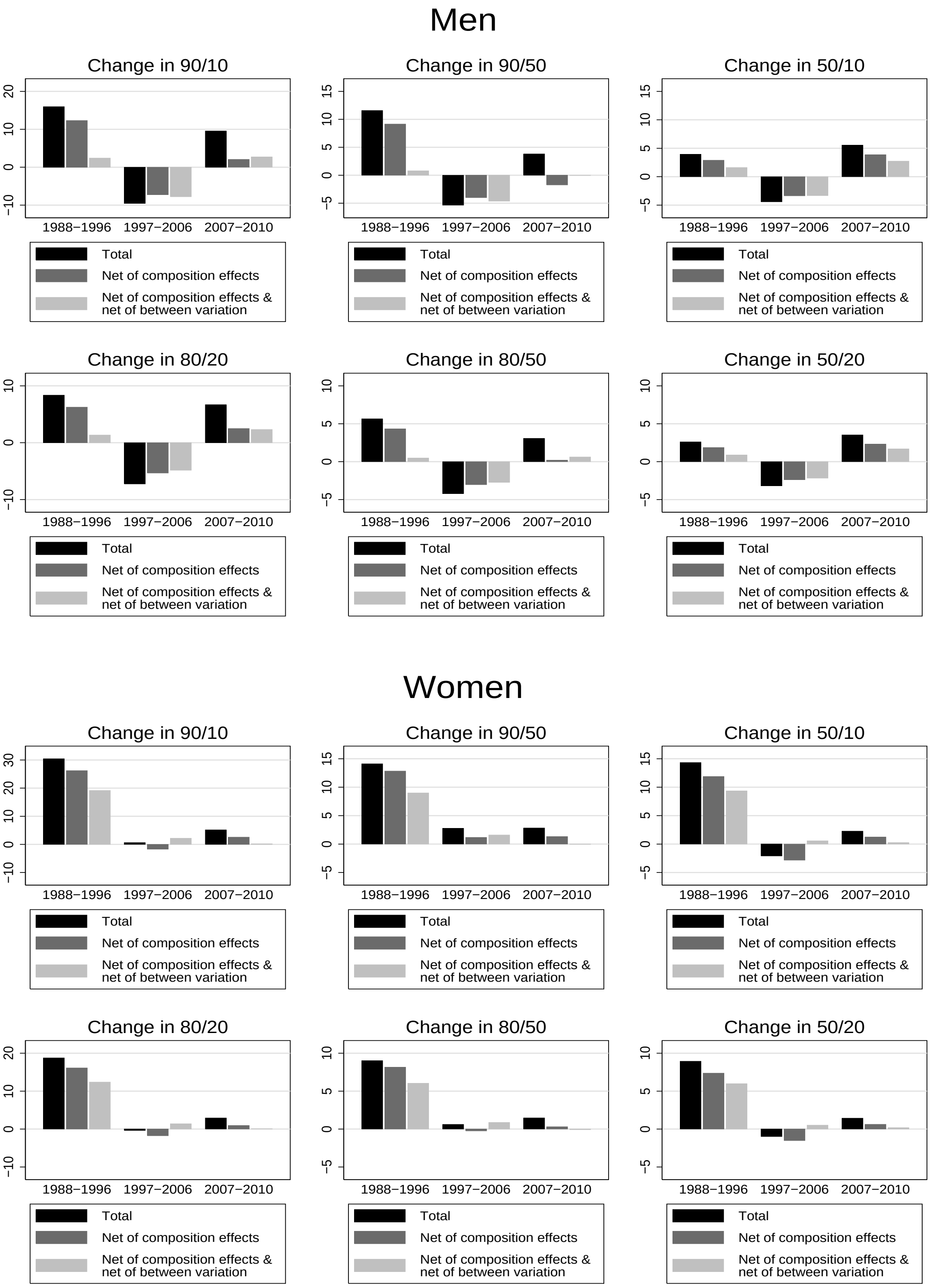
Notes: Unconditional quantiles estimated from Social Security data.

Table E.6. Estimated Unconditional Quantiles of Daily Income (i^q)

		1988	1997	2007	2010	1988-1996 (%)	1997-2006 (%)	2007-2010 (%)
All	i^{10}	18.61	13.64	16.96	16.94	-23.78	18.49	-0.10
	i^{50}	39.91	36.67	42.08	41.41	-8.15	11.44	-1.59
	i^{90}	85.30	89.96	96.80	99.96	5.61	4.13	3.26
Men	i^{10}	20.46	16.77	21.51	20.12	-15.78	23.57	-6.44
	i^{50}	42.10	40.71	46.90	45.69	-3.77	12.03	-2.56
	i^{90}	90.41	99.96	106.26	108.99	9.06	2.89	2.57
Women	i^{10}	14.99	10.69	13.77	14.40	-25.71	21.13	4.53
	i^{50}	34.67	30.25	35.89	36.38	-12.47	14.58	1.36
	i^{90}	71.05	75.84	86.08	89.59	7.07	9.63	4.09

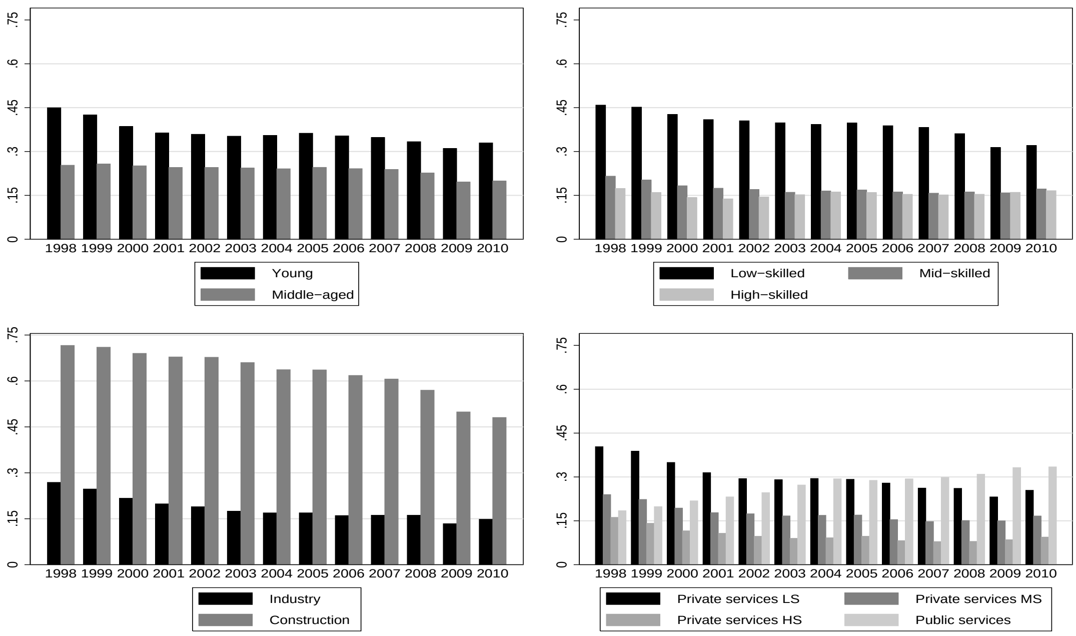
Notes: Unconditional quantiles estimated from Social Security data.

Figure E.1. Age and education groups: decomposition



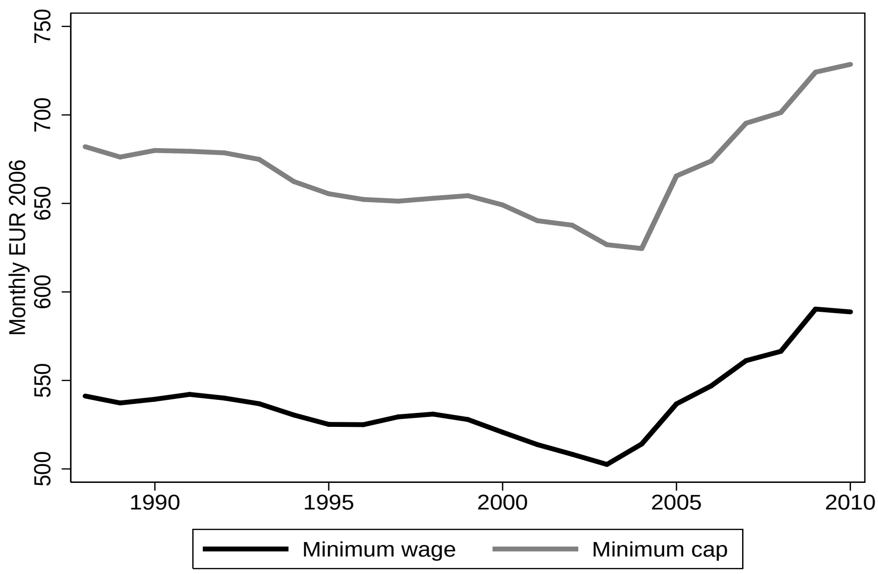
Notes: Source Social Security data.

Figure E.2. Temporary rates (men)



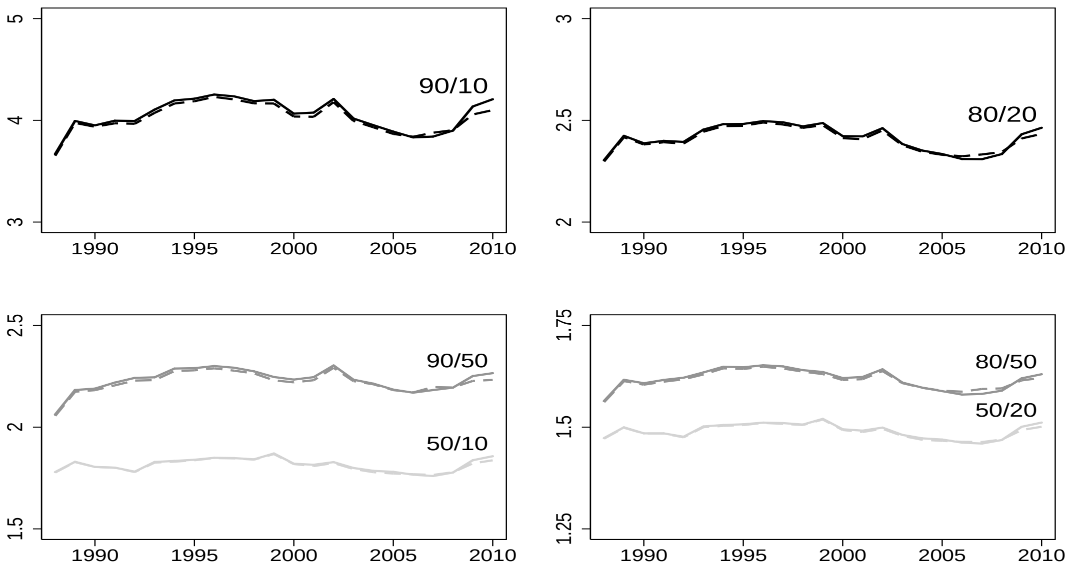
Notes: Source Social Security data. "Young" are less than 35 years old, "low-skilled" are occupation groups 8-10, "high-skilled" are occupation groups 1-3.

Figure E.3. Real value of the minimum wage in Spain



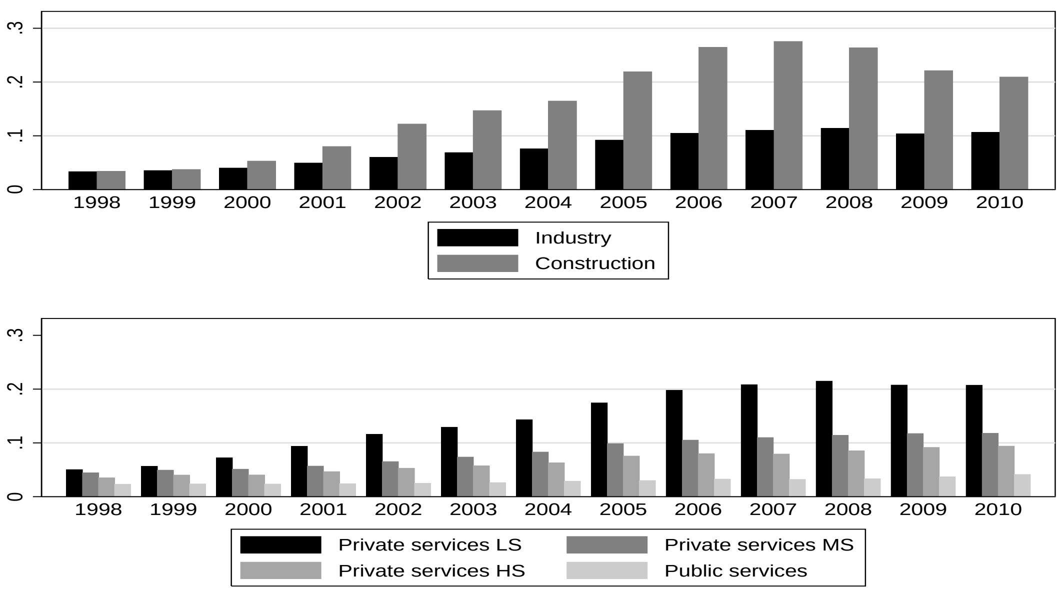
Notes: Source Social Security data (for minimum caps).

Figure E.4. Inequality (men): 90/10, 90/50, and 50/10; 80/20, 80/50, and 50/20



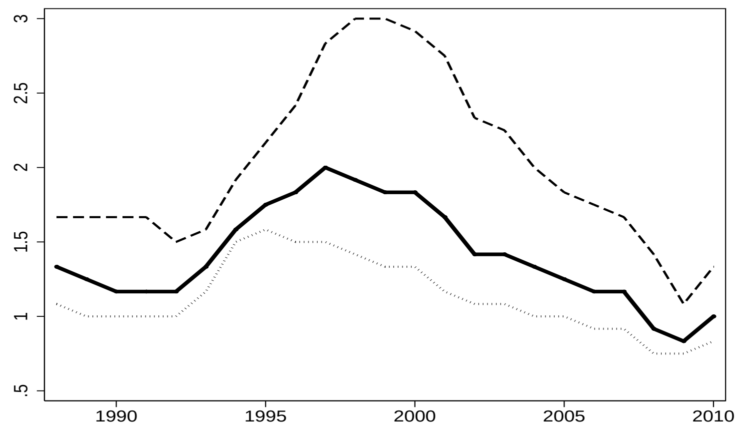
Notes: Source Social Security data. Solid lines are ratios of estimated unconditional quantiles of daily earnings, dashed lines are ratios of estimated unconditional quantiles of daily earnings in a sample of native workers only.

Figure E.5. Shares of foreign-born workers by sector (men)



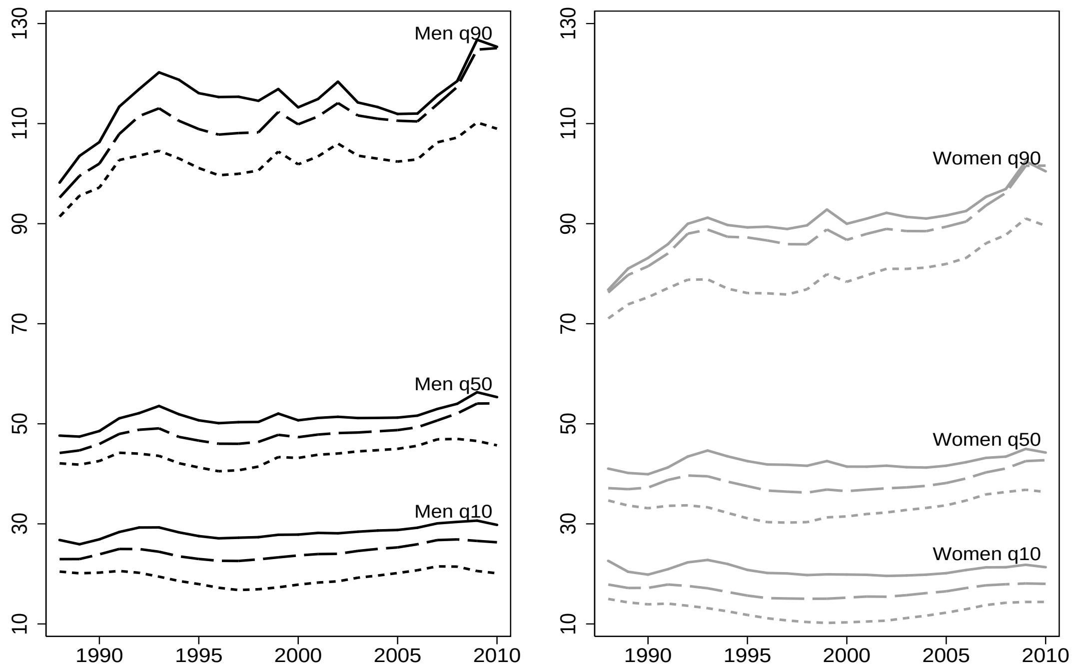
Notes: Source Social Security data.

Figure E.6. Median unemployment duration (in years)



Notes: Source Social Security data. The solid line is median unemployment duration for all non-employed, the dashed line for those older than 40, and the dotted line for those under 40.

Figure E.7. Unemployment-adjusted Unconditional Quantiles of Daily Earnings



Notes: Source Social Security data. Solid lines are estimated daily earnings conditional on employment. Long-dashed lines are estimated potential earnings. Short-dashed lines are estimated labor income, based on imputed unemployment benefits.