Inequality in Pension Contribution Gaps [1]

by

Salvador Valdés-Prieto[2] and Samuel Leyton[3]

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Abstract

Gaps in pension contribution histories reduce contributory pensions and have other negative impacts. We use a 14-year survey panel and a 35-year administrative panel from Chile. Considering all types of gaps together, their frequency falls from 91% for the lowest decile of relative earnings to about 35% for the highest decile. Analyzing separately the gaps exhibited by earners, we find that low-wage workers and women bear disproportionately larger cuts to their contributory pensions. For low-wage women, an increase in wages to the third decile or more is expected to reduce their gaps significantly. For low-wage men, the same increase in wages is predicted to be about half as effective in reducing gaps. Unobserved characteristics that raise the persistence of gaps among men keep their gaps higher even if their wages rise. Earner gap levels estimated from cross-sections are found to be downward biased by about a third. We show that vesting requirements like those in the U.S.A. and Spain lead to underestimating gaps if data from pensioners is used alone. A puzzle that remains is that although many gaps occur among earners who could pay, politicians invest little in reducing statutory exemptions and raising enforcement.

Keywords: labor market, old-age pensions, informality, inequality, enforcement, exemptions.

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[2] Senior Fellow at Universidad Adolfo Ibáñez (UAI) in Santiago, Chile, salvador.valdes.p@uai.cl Both authors started an initial draft of this work while at the Catholic University of Chile.
[3] Institute of Economics, Academia Sinica (IEAS), Taipei 11529, Taiwan. sleytonswinburn@gmail.com.

1. Introduction

Gaps in contribution histories are a leading cause of insufficient contributory old-age pensions in emerging economies. These gaps are defined as interruptions in the sequence of contributions towards a set of pension plans with shared portability, or to a single national plan. To illustrate the massive impact gaps may have on pension amounts, let us define the "excess gap" for a given country as the difference between the average gap in that country and the average gap reported by pensioners in Spain. We find that the excess gap in our HPA sample from Chile reduced the sufficiency of contributory pensions for men by twice the reductions created by 30 years of increases in life expectancy.[4] In many emerging economies, the impact of excess gaps on contributory pension amounts is even larger (Bosch et al, 2013). In advanced economies, platform and gig work growth portends larger contribution gaps and inadequate pension sufficiency for old age (OECD 2018, Katz and Krueger 2019, Bieber and Moggia 2021). The inequality in gap frequency reported here implies that low earners and women bear disproportionately larger cuts to their contributory old-age pensions.[5] [6]

Gaps also have immediate detrimental effects, while in the active ages. Gaps reduce access to short-term social insurance benefits.[7] Gaps reduce lenders' ability to verify earnings, so access to consumer and housing credit falls. Frequent gaps may also signal a confinement to jobs with both a lower rate of human capital accumulation and a reduced return on existing human capital, as in informal employment. Gaps do have short-term benefits for individuals: since gaps conceal earnings, they may allow more access to targeted social benefits, such as poverty supplements or earned income tax credits.

Our focus is on full-time earners' gaps, i.e. those gaps that coexist with earnings, as in statutorily exempt jobs and informal jobs. We find that earner gap frequency is dramatically higher in the two lowest wage deciles, for both men and women, so they bear disproportionately larger cuts to their contributory pensions. For low-wage women, an increase in wages that leaves them at the third decile or higher is expected to reduce their gaps significantly. For low-wage men, the same increase in wages is predicted to be about half as

[4] Details and assumptions are available in Appendix 2.

[5] However, replacement rates from formal pensions alone are an inadequate indicator of consumption smoothing. In intervals when contribution gaps coexist with earnings (from exempt and informal jobs), many individuals save voluntarily for old age (mostly outside the financial sector, as in housing and other durables), not necessarily at sufficient rates. Because of this other saving, strong inequality in formal pension replacement rates can coexist with moderate inequality in consumption smoothing.

[6] This paper does not measure the impact of gaps on the amounts of contributory pensions. The reason is that these amounts (and replacement rates) depend on three other factors in addition to contribution gaps: (1) on the varying growth rates of taxable earnings; (2) in DC and fully-funded schemes, on the sequence of financial rates of return achieved by the progression of portfolios chosen; and (3) on the realized annuity conversion coefficients, which combine the long-term interest rate at the conversion date, with idiosyncratic features including the pension modality chosen (Castro, Torche and Valdés-Prieto, 2009).

[7] Such as insurance for salary losses due to short-term sickness and unemployment insurance.

effective in reducing gaps. Unobserved characteristics that raise the persistence of gaps among men keep their gaps higher at most wage levels. Cross-section surveys are more widely available in developing countries than our panels, so we ask how good a substitute they are. We find that earner gap levels estimated from cross-sections suffer from downward bias, part of which is due to the underreporting of gaps in surveys. When broadening the analysis to all types of gaps, we find that vesting requirements like those in the U.S.A. and Spain lead to underestimation of gaps if data from pensioners is used alone, without adding data from participants that did not vest. The paper also reviews explanations for the puzzle that few politicians invest in reducing contribution gaps by earners, say by reducing statutory exemptions and raising enforcement budgets.

We classify gaps into two types that differ in their access to earnings observations that allow the assignment of each observation to a wage or earnings decile. Gaps of individuals with no current earnings (type-1) cannot be assigned to a wage or earnings decile. Earner gaps (type-2) can be assigned to a wage or earning decile if they declare earnings to a survey. In many countries, statutes provide exemptions from the mandate to contribute to large segments of the self-employed, employers, operatives of non-standard work such as platform and gig work, and to specific jobs or sectors (common exempt sectors include sailors, miners, truck drivers, etc.). Stints in these jobs create gaps in full compliance with the law. In contrast, informality is defined as incomplete or no compliance with labor and social insurance laws (Almeida and Carneiro, 2012) and is associated with weak enforcement. Underreporting of earnings is important but as it does not create gaps, it is not studied here. We do adjust for underreporting of gaps, which we find is considerable.

The distinction between types of gaps is also important for public policy: type-1 gaps can be reduced by policies that raise the employment rate. In contrast, reducing type-2 gaps requires replacing exemptions with mandates based on presumptive earnings and applying larger enforcement budgets.

This distinction also drives our use of datasets. The HPA dataset is the only one that offers the long contribution histories needed to draw on earnings reported far in the past to assign individuals undergoing type-1 gaps to an earnings decile. This dataset is also appropriate for measuring the impact of vesting requirements. However, the HPA lacks most labor market information different from contributions, so it cannot apply controls. In contrast, the 14-year EPS panels have earnings declared by respondents undergoing type-2 gaps, allowing assignment to an earnings decile when not contributing. The EPS also provides data on important controls, such as appropriate labor market information, and is matched to the HPA dataset.

The descriptive statistics obtained from our panels are novel. First, in the HPA administrative panel, which is 34.67 years long with monthly data, we consider subsamples for men and women of 20 annual cohorts whose ages are close to the pension ages. We compute overall gap frequencies averaged over the last 6, 12, 20, and 34.67 years, counting backward from the first age of easy pension access. Individuals are assigned to deciles of relative monthly earnings. Section 2.1 finds that the overall gap frequency for a 34.67-year averaging period for men is 91% at the lowest earnings decile and 34% at the highest decile. For women, overall gap frequencies for the same averaging period are 91% and 36% at the same deciles. Contribution gap inequality is pervasive.

To focus on type-2 gaps alone (statutory exemptions and informality, or earner gaps), we use EPS panels restricted to individuals who report private-sector earnings and hours of work in at least one month per calendar year and order them in deciles of hourly wages. Additionally, we limit our analysis to individuals working full-time, defined as 35 or more hours per week. Matching with the HPA finds that underreporting of gaps in the EPS survey is 18.5% for men and 15.5% for women. Section 2.2 develops a procedure to correct this underreport. After correction, the annual frequency of type-2 gaps for men is 86% for the lowest decile of hourly wages, as opposed to 20% for the highest decile. For women, the analogous descriptive numbers are 83% for the lowest decile of wages and 12% for the highest decile.[8]

This paper adds to the literature in three further ways. Section 3 uses our 14-year EPS panels, adjusted for gap underreporting, to determine if the relationship between wages and type-2 contribution gaps becomes a constant for all wage deciles after controls. How much earner gap inequality survives? If little survives, then a simple exogenous increase in wages that moves the individual to higher wage deciles will have a minor impact on type-2 gap frequencies. Which are the main mechanisms?

Our controls are individual fixed effects, the employment rate, allowing persistence of gap frequency, and others such as region and sector of employment. Endogenous variables are instrumented using lags. To identify the sources of change, section 3 compares three models: OLS, FE and FE-IV.

A major finding is that for men, these controls cut in half the difference in type-2 gap frequency between the two lowest wage deciles and the average of the next 8 deciles, as compared to the same difference seen in the descriptive statistics, in the long run. We also find that the main barrier to a larger reduction in gaps is unobserved characteristics that increase persistence and are absorbed by fixed effects. We interpret that a man who holds those characteristics persists in his current level of type-2 gaps for long years even if his wages improve to higher deciles. Policies that identify those characteristics and mitigate them, especially among men, are likely to be effective in reducing their type-2 gaps.

[8] The large gap frequencies in high-earning deciles appear to be idiosyncratic to the Chilean institutional setting.

For women, the outcome and the causes are different. If an exogenous increase in wages moves a woman from wage deciles 1 and 2, to wage deciles 3 to 10, her type-2 gap frequency will fall by almost 100% of the amount predicted by the descriptive statistics, which is a lot. Thus an average woman has the flexibility to reduce her current level of type-2 gaps if her wages improve to decile 3 or higher. That said, the level of women's gap frequency – in any wage decile – is not due only to the wage decile, since a certain number of type-2 gaps is due to unobserved characteristics and to the endogeneity of some control variables.

Summing up the results of section 3, low-wage workers and women bear disproportionately larger cuts to their contributory pensions. For low-wage women, an increase in wages to the third decile or more will reduce their type-2 gaps significantly. For low-wage men, the same increase in wages is predicted to be about half as effective in reducing type-2 gaps. Unobserved characteristics that raise the persistence of gaps among men keep their type-2 gaps relatively high at most wage levels.

Section 4 contributes a set of comparisons with other measurement methods that yield lessons on how *not* to measure gap frequency. Can contribution gaps be accurately measured with cross-section surveys? This instrument is much more widely available than our long panels. Cross-sections ask whether the respondent contributed in a recent single month, such as the month before the survey was taken. However, respondents out of employment do not report wages or earnings. This missing data excludes type-1 gaps from the sample and prevents cross-sections from exploring the link between wages and overall gaps. Of course, cross-sections can still be used to measure the link between type-2 gaps and wages. This section aims to diagnose potential biases in this use of cross-sections, as compared to our panels. The gold standard is given by the gaps measured with panel data like the one used in section 3. Two intermediate reference panels are introduced to help determine the relative importance of several sources of bias, if any. These intermediate reference panels are modified versions of Section 3's panels that exclude annual observations with positive type-1 gaps (non-employment) within the calendar year. This modification mimics cross-section data, which is naturally limited to individuals who report earnings and hours of work.

The results are grouped around two outcomes: the level of gap frequency by wage decile, and the marginal effect on gap frequency of belonging to a certain wage decile, relative to belonging to decile 1. The comparison of levels shows that the cross-section underestimates the average gap for all deciles together by about a third, for both men and women. About half of this total comes from underreporting of gaps in our cross-section. Underreporting cannot be repaired without matching with administrative data. The ratio of gap levels in wage deciles 1 and 4 is exaggerated in cross-section results, relative to the true results, because the cross-section yields a downwardly biased value for the denominator of this ratio. Regarding the marginal effects on the estimated gap frequency of joining each wage decile, relative to belonging to decile 1, cross-sections also create biases, especially for men.

The administrative dataset (HPA) allows a novel assessment of the impact on pension data of vesting requirements, such as 10 years of "work credits" in the U.S.A. and 15 years of contribution in Spain. Section 4 finds that overall gap inequality becomes fully hidden from the Chilean HPA samples if 15-year vesting is applied. For 10-year vesting, as in the U.S.A., some inequality in overall gaps remains in Chilean data, although significantly muted as compared to what is revealed by the direct data from contributions. One lesson is that overall gap inequality should not be measured with data from pensioners alone when vesting requirements are present, because vesting truncates the distribution of gaps above. A solution is to add data from participants that did not vest.

Section 5 measures with the HPA the individual risk of *future* overall gaps, and finds it is a major source of uncertainty about future pension amounts. Future overall gaps are also associated with detrimental impacts while in future active ages. We consider young participants looking forward from 1995. How large was the actual dispersion in their gap frequencies observed over the next two decades (until 2015)? How does dispersion differ among groups ordered by average relative earnings in the previous period (1986 to 1995)? To our knowledge, this type of uncertainty has not been quantified previously. Using the HPA, we find that the 20-year-ahead dispersion in future contribution gaps is significantly larger for those who started in the middle earnings (quintiles 3 and 4 of relative earnings in 1986-95).

This section also explores the communication standard recommended by the 66 countries that have signed ILO Convention No. 102: the requirement to officially label a contributory old-age benefit as "pension" (rather than "reduced pension"), is 30 years of contribution. This standard communicates the importance of keeping gaps at a modest level. Section 5.2 finds that in Chile the 30-year standard is met by less than 20% of the members of the two lower-earning quintiles in our HPA samples, who are close to the pension age. Some impacts of officially adopting and communicating this standard may be to persuade more workers to limit their contribution gaps, to drive the political system to design and apply policies to reduce gaps and to pare down expectations on contributory pension amounts entertained by individuals with frequent contribution gaps. Such diminished expectations may also help safeguard fiscal sustainability from widespread disappointment with pension amounts, which may force politicians to engage in massive expansions of non-contributory pension expenditure.

Section 6 explores the fact that earners with gaps have the resources to pay contributions, but the size and persistence over decades of substantial earner gaps (type-2 gaps), suggest that most policymakers around the world have not invested enough in reducing those gaps. This fact raises a puzzle that must be solved to understand contribution gaps thoroughly. As a preliminary step, section 6 summarizes mechanisms and evidence in the literature that may help explain this puzzle. Three traditional explanations of policy inaction to reduce earner gaps are found to be insufficient. Then Section 6 presents the view that “gaps are good” for low earners and the opposite view that gaps are bad for them. This section also summarizes a recent literature in political science that appears to explain satisfactorily this puzzle through the public perception, shared by voters, that gaps are good for low earners. This would make the persistence of earner gaps a stable political equilibrium. Until economists establish the degree to which this perception is correct or not, contribution gaps by earners will not be adequately understood.

In the related literature, the oldest branch targets type-1 gaps alone, i.e. gaps from non-employment, and ignores type-2 gaps (earner gaps). Several of the seminal papers targeted female employment, as in Mincer and Polachek (1974) and Light and Ureta (1995). Another literature established long ago that in emerging economies a plurality of labor markets exhibits high levels of informality (Jenkins 1993; Ginneken 2003). This was confirmed by La Porta and Shleifer (2014) and Ulyssea (2020). However, statutory exemptions were ignored in these and other papers, despite their impact on gaps, and therefore on contributory old-age pensions and the contemporaneous impacts while in active ages. A third literature on gap frequency was based on cross-section data, which as explained in section 4.3, measures short-term instability of contributions and type-2 gaps. Examples are the probits by Arenas et al (2004) and Gill et al (2005). Only Behrman et al (2012) and CIEDESS (2018) use panel data, from Chile as well, but do not investigate inequality in contribution gaps.

Section 2 develops novel descriptive statistics. Section 3 determines how much of earner gap inequality by wages survives a battery of controls. Section 4 contributes a set of comparisons with other measurement methods. It explores whether earner gaps can be accurately measured with simple cross-section surveys. Section 5 presents two unique uses of the 34-year-long HPA panel. Section 6 presents the puzzle of modest efforts by politicians to reduce earner gaps and summarizes an explanation: the perception, shared by voters, that gaps are good for low earners.

2. Descriptive statistics on contribution gaps

This section presents two sets of descriptive statistics on how individual contribution frequency is correlated with relative earnings.

We classify gaps into two groups. The first type considers gaps due to labor market inactivity and unemployment. The second group targets gaps observed among individuals who earn at least some labor income. These gaps are mostly due to statutory exemptions from the mandate to contribute and to informality. The first part of this section reports on both types of gaps combined. The second part offers descriptive results for the second type of gap alone.

Some drawbacks of this section’s descriptive approach are overcome by the econometric work in Section 3, which targets the second type of gap alone.

2.1 Descriptive statistics for the HPA samples

The variables in this section are taken from the "Pension History of Participants" (HPA in Spanish) database, an administrative panel on the money amount contributed each month by each individual from May 1981 to December 2015. Throughout this period, the contribution rate for old age pensions remained constant at 10% and fully charged to the worker.[9] The contribution gaps measured by the HPA report all types of gaps together, combining stints out of the labor force and in unemployment (type-1, where no contemporaneous earnings exist), with the gaps in exempt and informal employment (type-2). The HPA measure of total gaps is the most appropriate to help predict future contributory pensions because these are based on histories that consider both types of gaps.[10]

We use a sample of the HPA restricted to a 20-year cohort of older men (born from 1939 to 1958, both years included) and older women (born from 1944 to 1963). These cohorts were chosen because a large proportion of these individuals have very long or completed contribution histories and reached the pension access ages[11] by the end of our sample, and gaps and earnings are important determinants of pension sufficiency. At the end of this sample, women were 53 to 72 years old (both ages included) and men were 58 to 77 years old. These HPA samples are used again in Sections 4 and 5.

To make this sample representative of these 20 cohorts of the adult Chilean population who participate in the unified pension scheme introduced in 1981, we use expansion factors from the Chilean "Social Protection Survey"[12] (acronym in Spanish: EPS) in its 2015 round.[13] We chose to use the expansion factors from the 2015 round of the EPS for consistency with the analysis in Section 4.2, which compares with results from a cross-section taken in 2015 (CASEN 2015). The HPA does not have data on individuals who never contributed up to December 2015. The EPS panels presented in Section 2.2 have and use data on some of those individuals, as explained there.

[9] For each month with a positive contribution, taxable earnings are obtained as the amount of money in the contribution divided by 0.1. Other charges, such as the premium for disability and survivorship (death) insurance, and administrative charges, are shown separately to workers.
[10] If a contribution is paid late, the HPA credits that contribution to the month when it accrued and not to the date of the delayed payment. Thus, the gaps reported by the HPA are accrued gaps.
[11] In Chile during the sample period, the first birthdays with full access to contributory old-age pensions were 60 and 65 (women/men).
[12] All waves are available at the webpage of the government office *Subsecretaría de Previsión Social* upon request.
[13] The EPS is a random and longitudinal survey representative at the national level. For this section, we use the 2015 cross-sectional expansion factors from EPS observations matched to the HPA. Since the HPA contains contribution records, using the EPS expansion factors ensures that the resulting sample is representative only of those cohorts, among participants in the pension scheme in 2015.

2.1.1 Definition of overall gap frequency and earning deciles

The aim is to compute overall gap frequencies (which add type-1 and type-2 gaps), for several given averaging periods (AP). Averaging periods are defined to be the *last* AP years of history up to the pension access age. Thus, we use backloaded APs. Combining type-1 and type-2 gaps, the "overall gap frequency" (GF_i^{AP}) for individual i is:

$$GF_i^{AP} \equiv 1 - \frac{N_i^{AP}}{Effective\ AP_i} \qquad (1)$$

where N_i^{AP} is the number of months within the effective averaging period in which individual i registered a positive contribution.[14] [15]

$$N_i^{AP} \equiv \sum_{t=F_i}^{t=T_i} \{1\ if\ YD_{it} > 0; 0\ if\ not\} \qquad \forall i\ \in \Omega(\text{AP}) \qquad (2)$$

where YD_{it} is the taxable earning that individual i's employer or the individual herself declared to the social security institutions for month t, and Ω(AP) is the set of individuals that have a positive N_i^{AP} for the given AP. The first month included in (2) for individual i is designated as F_i.[16] Similarly, T_i is the latest month included in (2).[17]

Going back to (1), the denominator is the effective averaging period, defined as:[18]

$$Effective\ AP_i\ \equiv \min(AP\ ; T_i - F_i(AP) + 1) \qquad [months] \qquad (3)$$

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[14] A limitation of the N_i^{AP} variable is that it assumes that each worker's compliance in any given month is binary: she is fully covered or fully uncovered (an extensive margin). However, a given worker-employer pair may agree on the regular payment of both a covered salary and an uncovered supplement, an evasion practice known as partial underreporting. Another limitation of N_i^{AP} is that it does not recognize cases where the worker holds two jobs simultaneously, some of which are not reported.

[15] If $YD_{it} > 0$, a 1 is added to the sum regardless of whether the individual worked part-time in covered jobs or worked only a part of the month in covered jobs.

[16] F_i is the latest among three dates: the date where the HPA begins (May 1981), the calendar month in which i turned 20 years of age, denoted $B_i(20)$, and the calendar month in which i first met the pension access age minus the averaging period AP. Since women's pension access started at birthday 60 and for men at birthday 65 in this sample, the calendar month as of i's pension age is denoted $A_i(65, 60)$. Thus, $F_i(AP) \equiv$ max (max $\{May\ 1981;\ B_i(20)\}$; $A_i(65, 60) - AP$).

[17] T_i is the smaller between the calendar month in which i reaches the pension access age (further contributions are voluntary) and the end of the sample (December 2015). However, if i dies before reaching the pension access age, the date of death applies (D_i).
Thus: $T_i \equiv \min(\,min\{\,A_i(65, 60)\ ; December\ 2015\}; D_i)$. Note that T_i does not depend on the AP.

[18] Many individuals in the sample have a shorter *Effective AP* than the *AP*. To illustrate, women aged 52, 53 and 54 in December 2015 do not have observations in the 6 years prior to their pension access birthday (60), so they are omitted from the sample for AP = 6 years. Likewise, women aged 55 to 59 in December 2015 have less than 6 years of observations, so they have an $Effective\ AP$ shorter than their AP. Among individuals in the sample who have at least 1 month of observations, 46% have less than 6 years of observations for AP = 6 years. For the same reason, $Effective\ AP$ is shorter than the respective AP for 54% of the sample in the 12-year averaging period, for 55% in the 20-year AP and for more than 95% of the sample in the 34.67- year AP.

These definitions imply that $Effective\ AP_i \geq N_i^{AP}$ and that each gap frequency (GF_i^{AP}) is a number in [0,1].

The chosen averaging periods are $AP = 6, 12, 20\ and\ 34.67$ years. Looking forward to Sections 2.2 and 3, which use $AP = 1$ year, it may appear attractive to extend results here to the case $AP = 1$ as well. However, comparability between results from the HPA (here) and our EPS panels (Sections 2.2 and 3) suffers from a major structural difference: gaps in the HPA combine both types of gap (those where contemporaneous earnings do not exist and those where they do), whereas our EPS panels are built to target the second type of gap alone.[19]

Next, define average relative earnings. The HPA provides data on monthly contributions to individual savings accounts, and we know the history of contribution rates to those accounts.[20] In the sample, this rate was always 10% of taxable earnings, The ratios of money contribution to contribution rate yield histories of taxable earnings. Note a limitation of the HPA: it does not have data on hours worked for many months in our samples. In our samples, the statutory ceiling on monthly taxable earnings (not on hourly wages) always falls inside the tenth earnings decile.

In Chile, average real earnings rose 96% from 1981 to 2015 (HPA sample).[21] In the presence of economic growth at that pace, descriptive statistics that attempt to capture labor market segments are likely to be more informative when defined by earnings *relative* to the month's national average, than when defined in absolute (real) terms.[22] The measure of relative taxable earnings used here is constructed in two steps. First, compute the current month's relative earnings from the amount declared by i's employer or by the individual herself, for calendar month t, as:

$$re_{it} \equiv \frac{YD_{it}}{Nat.Aver.Rem_t} \qquad (4)$$

where YD_{it} is declared absolute earnings for month t from the HPA registry and is zero for a month with a gap.

The second step computes average relative earnings (ARE_i^{AP}) as a time-average of the monthly re_{it}, for a given averaging period, where gaps are removed by counting only those months within the effective averaging period in which i registered a positive contribution. Using the N_i^{AP} defined in (2) and noting that re_{it} is zero in a month with a gap:

[19] Further, the last year before the first pension access age is particularly less representative of the working life, so results for an $AP = 1$ year would be farthest from helping estimate future contributory pension amounts. The literature shows that the labor market changes substantially near the end of the working life.

[20] Contribution rates to pay disability and death insurance, and administration fees, were separate and changed over time within the sample.

[21] Estimated from the Central Bank of Chile's database on average earnings and the consumer price index.

[22] Several authors define segments in the labor market by relative earnings. For example, Meghir et al. (2015). This segmentation is compatible with substantial job mobility between covered and uncovered jobs.

$$ARE_i^{AP} \equiv \frac{1}{N_i^{AP}} \cdot \sum_{t=F_i}^{t=T_i} re_{it} \qquad \forall i \in \Omega(\text{AP}) \qquad (5)$$

Consider earnings histories with large fluctuations in relative earnings. Definition (5) smooths them by taking the average over time, which is more representative of permanent income. With longer APs those averages become less sensitive to recent values of relative earnings and are more representative of the individual's experience of declared relative earnings over a longer stretch of the working life. Note that a given individual has different values of ARE_i^{AP} for different APs.

Another feature of this metric is that a higher AP expands the set Ω of individuals that have at least one positive YD_{it}, and this raises sample size. Thus, the identity of any grouping of individuals based on the ARE_i^{AP} (deciles, bins, etc.) must change when the AP changes.

Finally, we build deciles for the ARE_i^{AP}, separately for each averaging period. We choose to group individuals in deciles – rather than in bins with fixed values - to facilitate comparison with the econometric results of Sections 3 and 4.[23] We build the deciles after pooling ARE_i^{AP} values for men and women, to allow comparisons across genders.

Table 1 presents descriptive statistics for the longest averaging period (34.67 years). Rather than presenting the gap frequency averaged within each decile, it reports the number of monthly contributions averaged within each earnings decile and divided by 12. The overall average number of years of contribution is 16.9 for men and 11.2 for women, confirming other estimates for Chile that show large gaps. Dividing by 34.67 years, Table 1 says that overall gap frequency for men is 91% at the lowest earnings decile and 34% at the highest earnings decile. For women, overall gap frequencies are 91% and 36% at the same deciles.

Table 1: Contribution years by earnings decile in the HPA

Decile ARE [a]	HPA subsample of men.			HPA subsample of women.			Population (with exp. factors)		
	Contribution Yrs. (mean)	ARE (mean)	Obs.	Contribution Yrs. (mean)	ARE (mean)	Obs.	Men	Women	Total
1	3.0	0.178	49	3.2	0.180	243	40,357	165,359	205,716
2	6.2	0.283	76	6.3	0.278	223	59,705	145,120	204,825
3	11.7	0.339	107	7.7	0.337	203	72,498	132,629	205,127
4	12.8	0.389	113	9.2	0.390	204	79,221	125,777	204,998
5	13.9	0.461	154	9.9	0.458	165	102,843	102,781	205,624
6	17.8	0.553	189	12.8	0.554	140	120,784	83,800	204,584
7	19.3	0.701	204	17.4	0.697	119	130,941	74,041	204,982
8	20.2	0.909	191	20.8	0.905	107	140,271	65,404	205,675
9	20.6	1.330	161	23.1	1.363	143	117,840	86,743	204,583

[23] If the ARE_i^{AP} are ordered in bins with fixed values, frequency spikes in the bin that collects ARE_i^{AP} values between 2 and 3, compared to adjacent bins, due to the statutory maximum for taxable earnings.

10	23.0	2.631	162	22.1	2.356	61	148,097	56,786	204,884

Note a: Deciles are built from the pool of men and women, weighting them with the expansion factors (only use of these expansion factors).

Table 1. Reports descriptive statistics for our 20-cohort subsamples from the HPA. The first column from the left indicates deciles in the distribution of average relative earnings (ARE) of the pooled sample of men and women. These deciles are built for an averaging period (AP) of 34.67 years. The second column is the mean of years of contribution within each decile. The third column is the mean of the average of relative earnings (ARE) within each decile. Values are below 1.0 for most observations because the denominator, $Nat.Aver.Rem_t$, is for full-time workers during complete months, while the numerator is any positive YD_{it} regardless of hours worked. The three columns on the right show the impact of expansion factors, used to build the pooled deciles.

2.1.2 Link between gap frequency and relative earnings deciles in HPA

This section reports, for each given APs, values for the associated gap frequency (GF_i^{AP}) in each decile of average relative earnings (ARE_i^{AP}). All types of gaps are counted in the GF_i^{AP}. These descriptive results are reported separately for men and women, for AP values of 6 years, 12 years, 20 years, and the maximum AP allowed by this HPA sample, which is 416 months (34.67 years, abridged to 34 years in Figure 1).[24]

Figure 1: Average gap frequencies by relative earnings decile (HPA)

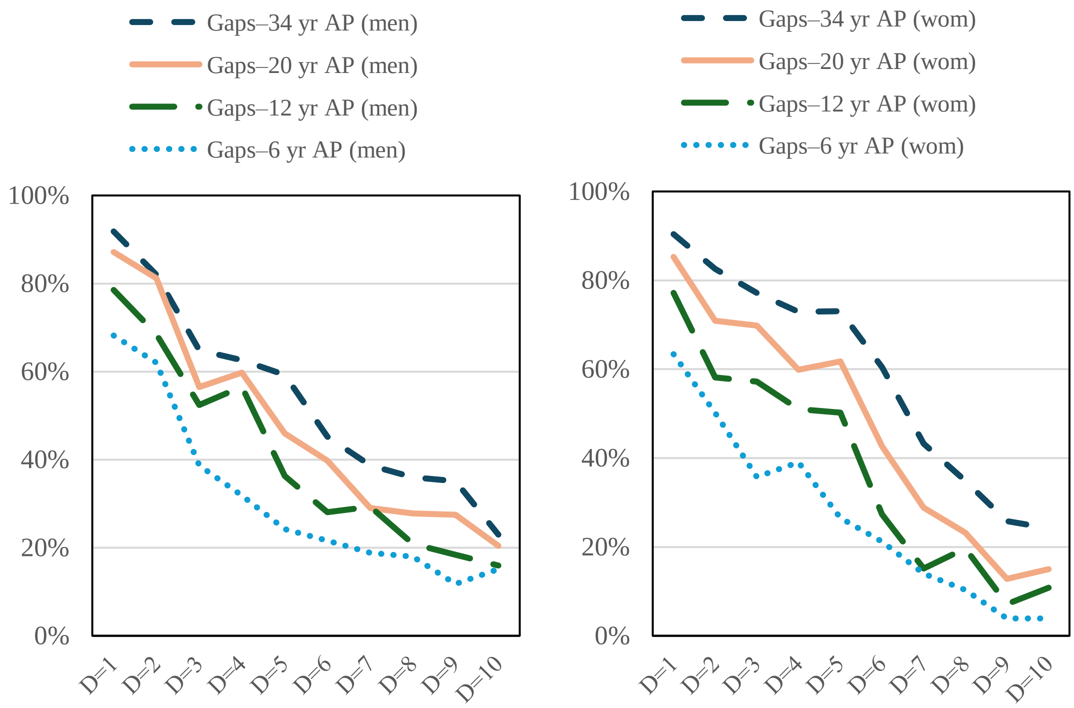

Figure 1. The left panel is for males and the right panel is for females. The horizontal axis is the decile of average relative earnings, defined on the pool of the ARE_i^{AP} for men and women for each given AP separately. Decile 1 collects the lowest monthly earnings. The vertical axis shows average gap frequencies along the distribution of average relative earnings, for given APs. A higher AP provides more representative average relative earnings and increases the sample size.

[24] The sample starts in May 1981 and ends in December 2015.

For men, and in the case of the longest averaging period, the fall is from an average gap of 92 in decile 1 (lowest monthly earnings) to 23% at decile 10 (highest monthly earnings). We provide below a formal test for thresholds in the rate of change in gap frequency as deciles rise.

For women, gap frequency starts in decile 1 at a similarly high level as for men, but initially falls more slowly than for men. Gap frequency remains at a higher level (relative to men) until decile 5. Women present a concave threshold in decile 5, because for higher relative earning deciles gap frequencies fall more rapidly. There is a secondary threshold in decile 9, which is convex.

A result that seems idiosyncratic for Chile is that individuals in the upper 2 deciles of relative earnings gap frequencies for the longest averaging period (34.67 years) specifically 29% for men and 25% for women that are surprisingly high relative to gaps in advanced countries. Indeed, the average contribution gap for male pensioners in Spain with some higher education and completed work histories was only 15.1%.[25]

To assess the non-linearities more precisely, we identify thresholds with Wald tests. The null hypothesis is that from one decile pair to the adjacent pair, the slope at which average gap frequency changes does not have a statistically significant change. For this purpose, an OLS regression was run for each averaging period, with relative earning decile dummies as explanatory variables. Striving for a stronger test, we add 5-year birth cohort controls to this regression. Cohort controls can make test results differ from what a visual inspection of Figure 1 may suggest. Expansion factors were used to weigh the observations in these regressions.

Table 2 confirms the previous description of Figure 1: we find a globally important threshold for women in decile 5 that is statistically significant, and its curvature is concave. This finding suggests that Chilean women's behavior regarding paid work and care provision was stratified into two main regimes, as of our sample period. Men do not exhibit globally important thresholds.

Table 2: P-values for Wald tests for the hypothesis that the slope changes in HPA
(only p-values below 0.05 are shown; blanks indicate larger p-values)

Earnings Decile (k)	Men, different *AP*s (years)				Women, different *AP*s (years)			
	34.67	20	12	6	34.67	20	12	6
2						0.031*	0.021*	
3	0.043*	0.005*	0.045*					
4		0.043	0.003					
5					0.026	0.004	0.011	
6								

[25] Source: Sánchez (2017) reports the average number of years of contribution of Spanish men with completed histories. For those with some higher education, this average was 38.2 years. For a 45-year career, a simple proportion yields a gap of 15.1%. The data from Spain is discussed further in Section 4.1.

7		0.039*
8		
9		0.016*

Table2. The tests included in the table are H0: $(\beta_k^{AP} - \beta_{k-1}^{AP}) = (\beta_{k+1}^{AP} - \beta_k^{AP})$, where β_k^{AP} is the estimate of the average gap among individuals in decile k, for averaging period AP. Only interior deciles are tested $(k = 2, \ldots 9)$. Since β_1^{AP} (for decile 1) is the OLS regression's constant, the test of this hypothesis on the estimated coefficients takes a slightly different form for decile 2 $(k = 2)$ than for other deciles. This OLS regression includes 5-year birth cohort controls. An asterisk * marks kinks that are convex. Kinks without an asterisk are concave.

Another feature of Figure 1 is that as the averaging period rises, the average gap frequencies always rises. This applies to all pairs of similar deciles of relative earnings. Figure 2 explores this further and shows that in all decile pairs the impact of raising the averaging period is to increase the frequency of gaps, because both lines are clearly above zero.[26]

Figure 2: Positive differences in Gap Frequency between 34.67-year and 6-year AP

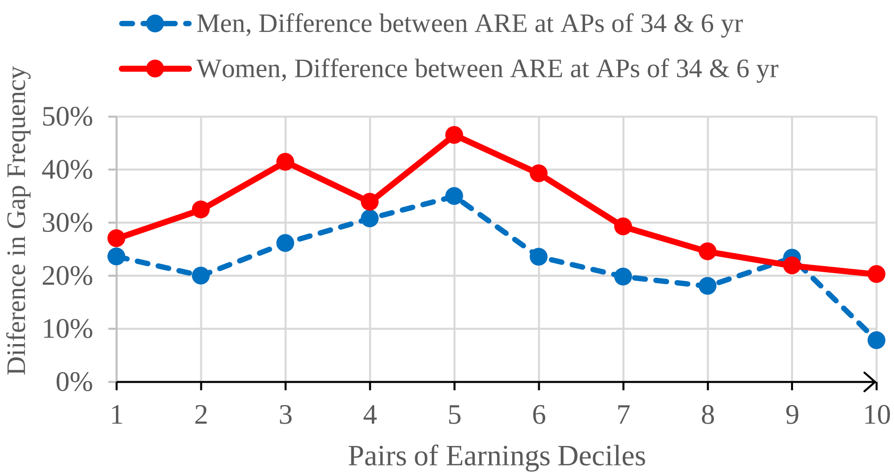

Figure 2. The horizontal axis indicates a pair of similar deciles of average relative earnings, where the ARE_i^{AP} pool men and women. The vertical axis is the difference between average gap frequencies in pairs of similar deciles of average relative earnings, separately for men and women. Controls for 5-year birth cohort are not present.

One interpretation is that some longer spells spent away from jobs that contribute to social insurance can only be detected by a longer averaging period. Low-frequency shocks to contribution frequency that *persist* beyond the shortest averaging period (here, 6 years), rather than withering to zero within the averaging period, are likely to be present. Those shocks would be overlooked by data limited to a short averaging period (here, 6 years) unless a lagged dependent variable is allowed for. This observation is used in Section 3.

Figure 2 also suggests that persistence is stronger for women, so childcare comes to mind.

[26] The language of "decile pairs" intends to convey that comparisons of average gap frequencies across different APs are limited by the fact that the deciles themselves change when the AP changes.

However, this and other interpretations are hobbled by the HPA samples' lack of matched controls for economically important explanatory variables, such as participation in gainful employment, some measure of the persistency of gaps, controls for region where the main job is located, branch of economic activity, calendar year, and corrections for endogeneity. These controls are applied in Section 3, but to a different sample, one that targets gaps of the second type.

2.2 Construction of EPS panels and its descriptive statistics

The variables in this section are taken mainly from the "Social Protection Survey" (EPS in Spanish). The panels discussed here are built with a specific aim: to begin the exploration of type-2 contribution gaps. This type of gap appears among those who have earnings from which contributions could have been financed in the same month.[27] Policies that might reduce these gaps differ substantially from the policies that could reduce type-1 gaps, where no contemporaneous earnings are available. Only the EPS can be used to explore type-2 gaps because the HPA does not separate type-1 from type-2 gaps.

We select EPS panels limited to individuals who report at least one month of earnings (with or without contribution) within the calendar year.[28] These panels exclude longer type-1 gaps (those with no earnings within the calendar year), associated with longer stints in labor inactivity or in unemployment. This design permits a focus on type-2 gaps while also allowing some controls for attachment to paid employment, likely to vary by wage decile. Those controls are applied in Section 3, not here.

Matching HPA and EPS observations also allows us to measure and correct for underreporting. We compare the total gaps reported by a given individual to the EPS with her administrative record of contributions. Total gaps in our EPS panel (adding type-1 and type-2 gaps) are considerably underreported on average: 18.5% for men and 15.5% for women. This prevalence is large enough to warrant the development of an adjustment procedure that prioritizes the gap data from the HPA (administrative data). Our procedure is presented in this section.

Our EPS panels are limited to observations on individual-years with positive earnings and at least 35 hours of work per week in the private sector. Only individuals whose age was between 20 and less than 65/60 years for men/women are included. The hourly wage for a given month is defined as monthly earnings divided by hours, which are self-reported to the EPS. Deciles of

[27] Partial statutory exemptions are not counted as gaps here. For example, the contribution rate may be set below the standard rate for certain calendar years, or the basis for contribution can be reduced. We are not aware of cases like those in the sample period, but they become present later, starting in 2019.
[28] An individual is not required to appear in all 14 calendar years of our EPS panels. However, it is required that she is interviewed in all rounds.

hourly wages are built from the pooled sample of men and women, for each calendar year separately.[29]

Our EPS panel is limited to respondents from the 2004 wave (reporting employment information from 2002 onward) who were interviewed in every subsequent wave through 2015. The EPS provides panel expansion factors to adjust for sample attrition between the 2004 and 2015 waves. These factors are calculated using a two-stage procedure that controls for individual characteristics potentially correlated with panel attrition. We apply these expansion factors consistently throughout our analysis of the 2002–2015 EPS panel.[30]

Individuals who never contributed before the end of our EPS panels (December 2015) are included if they report earnings in at least one month within the 2002-15 period, both in Sections 2.2 and 3. Some EPS panels introduced in Section 4.2 are different because inclusion is restricted to individual-years who report earnings for all 12 months.

2.2.1 Correcting for underreporting of gaps in the EPS

As explained above, total gaps in our EPS panel are considerably underreported on average. This section develops an adjustment procedure that prioritizes the gap data from the HPA (administrative data). We do not seek explanations for this considerable underreporting. Several mechanisms may act simultaneously, ranging from optimism bias to respondent attempts to project a better image on EPS interviewers. Mechanisms of employer evasion without worker knowledge are limited to activities with specific characteristics.[31]

The procedure is as follows. For individual i in calendar year a, let $GT(i,a)$ be the number of total monthly gaps reported by the administrative data (HPA) and let $gt(i,a)$ be the number of total monthly gaps self-reported to the EPS. Let $type1\ g(i,a)$ and $type2\ g(i,a)$ be the numbers of monthly gaps originally reported to the EPS according to type, before any adjustment is performed.

Let us classify observations into four groups according to the original values taken by $GT(i,a)$ and $gt(i,a)$. Group 1 consists of observations where both $gt > 0$ and $GT > 0$. In this group, our adjustment procedure multiplies type-1 and type-2 gaps reported to the EPS by the factor GT/gt. Specifically, we define:

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[29] This separation is necessary to accommodate the growth of average real earnings in 2002-2015. The amount of that cumulative growth was 35.4%.
[30] The detailed procedure is described in the EPS methodological documents, available online.
[31] Contributions for pensions are bundled with contributions for the short-term branches of social insurance. Since losses covered by the latter branches emerge frequently, lack of access to the associated benefits allows workers to notice evasion and become informed quickly. This restricts this mechanism to environments where the employer folds or closes after a few months, which is feasible in seasonal work.

$$adjtype\varphi\, g(i,a) = type\varphi\, g(i,a) \cdot \left(\frac{GT(i,a)}{gt(i,a)}\right) \;,\;\; \varphi = 1{,}2 \qquad (6)$$

These adjustments are not restricted to cases of gap underreporting (i.e. where $gt < GT$). If a respondent over-reports gaps to the EPS, the adjustment will be downward.[32]

Group 2 collects observations where $GT = 0$ and the original $gt \geq 0$. In this case GT takes precedence, so we define that $adjtype\varphi\, g(i,a) = 0$ $(\varphi = 1{,}2)$.

Group 3 consists of observations where $gt = 0$ and $GT > 0$. The individual self-reports zero gaps but the administrative record belies her. This group must be further divided into two subcategories, 3(a) and 3(b). Let $L(a,i)$ be the number of *other* calendar years for which $gt > 0$ for the same individual i, different from the year a where $gt(i,a) = 0$. Subcategory (a) consists of observations for which $L(i,a) > 0$. In this subcategory, the gaps of each type declared to the EPS are replaced by the average of the gaps of the same type in years other than year a, as follows:

$$adjtype\varphi\, g(i,a) \equiv \frac{1}{L(i,a)} \cdot \sum_{k \in \{a/gt(i,a)>0\}} type\varphi\, g(i,k) \quad if\ gt(i,a) = 0,\ \ \varphi = 1{,}2 \qquad (7)$$

where k indexes calendar years. In this procedure total average gaps are allocated between types 1 and 2 according to the prevalence of each type among the observations that participate in that average. This adjustment does not use information from $GT > 0$.

Category (b) within Group 3 consists of observations for which $L(i,a) = 0$. Although we know the total true gaps $GT(i,a)$, we lack information to allocate underreporting across the two types of gaps, and this precludes determination of the frequency of gainful employment. For this reason, observations in Group 3(b) are excluded from our EPS panels.

Group 4 concerns observations where $GT = 1 \wedge type1\, g(i,a) = gt(i,a) \in (0{,}1)$. The individual tells the EPS survey that 100% of her gaps are due to non-employment, implying that no earnings existed in the year. However, our EPS panel is limited to observations that report at least one month of earnings within the calendar year. If our procedure gave credit to this aspect of the individual's declaration in this case, it would create an observation that does not comply with this foundational definition. We exclude observations in Group 4 from our EPS panels to respect this criterion.

These two exclusions (Groups 3b and 4) combined involve 4.6% of the crude observations for men and 4.5% of those for women.

As shown by the columns labeled "Gap Deficit" in Part 1 of Table 3, most of the deficit due to underreporting remains after dropping the observations indicated in step B, so that step is not critical. The largest contribution to eliminating the discrepancy between self-reported and

[32] This may happen, for example, when the worker knew that her employer delayed the payment of a certain monthly contribution (perhaps due to a liquidity squeeze), but she was not informed when her employer paid the pending contribution a few months later.

administratively confirmed gaps is made by the adjustments in Group 3(a), included in row C. The combination of adjustments and exclusions in this procedure raises the proportion of gaps slightly above the proportion in the original panels, partly explained by the exclusion of some observations.

Table 3: Adjustments in EPS panels for underreported total gaps, and other data

	Men			Women		
1. Total Gaps and underreporting	Mean	Stand. Dev.	Gap deficit	Mean	Stand. Dev.	Gap deficit
A. Unadjusted gaps		(33,023 obs.)			(23,529 obs.)	
Total Gaps in admin. record (GT)	0.3791	0.4373		0.3985	0.4469	
Total Gaps self-reported EPS (gt)	0.3089	0.4420	-18.5%	0.3368	0.4464	-15.5%
B. After dropping *Group 3b*		(31,644 obs.)			(22,780 obs.)	
Total Gaps admin. record (GT)	0.3789	0.4414		0.3995	0.4501	
Total Gaps self-reported EPS (gt)	0.3223	0.4467	-14.9%	0.3479	0.4494	-12.9%
C. After all adjustments (in Groups 1, 2, 3a) and exclusion of Group 4.		(31.476 obs.)			(22,468 obs.)	
Total Gaps self-reported EPS (gt)	0.3939	0.4396		0.4028	0.4417	

2. Type 2 Gaps				
Type 2 gaps in original EPS panels [a]	0.2756	0.4321	0.2631	0.4212
Type 1 gaps in original EPS panels [a]	0.0333	0.1295	0.0737	0.1955
Type 2, after all adjust. and exclusions [b]	0.3383	0.4354	0.3015	0.4246
Type 1, after all adjust.and exclusions [b]	0.0555	0.1518	0.1013	0.2118

3. Description of other variables	Men: 31,644 obs.			Women: 22,780 obs.		
			Range			Range
Hourly Wages (UF/hour) [c]	0.0945	0.0868	0.004 - 3.07	0.0839	0.0777	0.004 - 2.77
Monthly Earnings (UF/month) [c]	16.95	12.38	1.16 - 96.1	13.60	10.76	1.16 - 94.8
Age (years)	44.84	10.61	20-64	42.44	9.424	20-59
Schooling (years)	11.45	3.551	0-18	12.34	3.402	0-18

Note *a*: as a share of all obs. in the original panel, including months not in gainful employment; Note *b*: as a proportion of months in Gainful Employment only; Note *c*: variables measured in "UF" units are measured in inflation-adjusted (real) terms. UF names an index that adapts changes in the CPI to a daily frequency. As of July 1, 2024, 1 UF = 39.8 USD.

Table 3. Part 1 summarizes the procedure used to correct the underreporting of gaps in the EPS self-reports, which draws on administrative data (from the HPA). Part 2 uses the richer questionnaire from the EPS to identify type 2 gaps, those where contemporaneous gainful earnings exist (as reported). Part 3 provides descriptive statistics on other variables of interest. The sample sizes shown here are somewhat larger than in Section 3 because of a few missing observations in some controls used there, such as sector-industry dummies.

Part 2 of Table 3 shows statistics for the proportion of type-2 gaps before and after adjustment for underreporting. First, it presents some results for the crude panels, before adjustment.[33] Second, it presents descriptive statistics for the following variable, to be analyzed econometrically in Section 3:

$$Frequency\ type2\ g(i,a) \equiv \frac{adjtype2\ g(i,a)}{[12 - \ adjtype1\ g(i,a)]} \equiv GF2_{ia} \qquad for\ calendar\ year\ a \qquad (8)$$

where the denominator is the number of months in gainful employment self-reported to the EPS by individual i in calendar year a. This denominator subtracts type-1 gaps because there are no earnings while in unemployment or labor market inactivity. By construction, all observations in our EPS panels have at least one month of positive earnings in each calendar year, i.e. at most 11 months of gaps, ensuring a positive denominator in (8). Descriptive statistics for these ratios are obtained from the adjusted panels, not the raw panels.

Table 3 reports that the average proportions of type-2 gaps are substantial: between 30% and 34% of all months in gainful employment, depending on gender. Moreover, these gaps are 3.7 percentage points higher for men on average, while the analogous proportion of type-1 gaps is 4.6 points larger for women.

Part 3 of Table 3 shows that mean hourly wages for women are 11% lower than for men (self-reports). By dividing mean monthly earnings by mean hourly wage we find that men report gainful work of 179 hours per month while women report 162 hours, 10% less. On the other hand, responding women completed 0.9 more years of schooling than men.

2.2.2 The link between type-2 gap frequency and wage deciles in EPS panels

This subsection targets the main purpose of our EPS panels: measuring inequality in type-2 pension contribution gaps. For this purpose, Table 4 reports for each hourly wage decile the average wage and the mean proportion of type-2 gaps, as a proportion of the number of months in gainful employment in the same calendar year (definition (8)). These means are averages over the calendar years and all individuals in the panels and are adjusted for underreporting.

Table 4: Type-2 gap frequency by wage decile, after correcting for underreports

	Adjusted panels (men)				Adjusted panels (women)			
Wage Decile, standard decilization [a]	Standard decilization			Other decilization	Standard decilization			Other decilization
	Aver. Wage	T-2 Gaps (% # mo. employ.)	% T-1 Gaps in sample	Aver. Wage	Aver. Wage	T-2 Gaps (% # mo. employ.)	% T-1 Gaps in sample	Aver. Wage

[33] This denominator includes months not in gainful employment, such as those in type-1 gaps.

1	0.0240	85.5%	4.7%	0.0240	0.0244	82.9%	10.5%	0.0244
2	0.0406	66.2%	5.0%	0.0406	0.0407	54.9%	10.6%	0.0408
3	0.0498	42.2%	4.5%	0.0501	0.0504	30.1%	10.3%	0.0505
4	0.0551	28.9%	3.8%	0.0553	0.0565	22.0%	9.5%	0.0566
5	0.0627	31.2%	3.1%	0.0630	0.0621	24.5%	7.0%	0.0625
6	0.0719	30.1%	2.9%	0.0724	0.0729	23.7%	5.5%	0.0736
7	0.0855	25.3%	2.8%	0.0862	0.0853	21.7%	5.3%	0.0864
8	0.1036	23.2%	2.6%	0.1049	0.1058	17.6%	3.2%	0.1066
9	0.1393	19.5%	2.4%	0.1406	0.1417	14.5%	3.0%	0.1431
10	0.2668	20.0%	1.9%	0.2691	0.2581	12.2%	2.7%	0.2596

Note *a*: The "standard decilization" of hourly wage deciles is defined to be the one built from the pooled panels for men and women before adjustment for underreporting. To check whether this makes a material difference, the robustness exercises in the third and sixth columns show average wages for an alternative decilization based on the panels after adjustment. They report similar wages for all deciles and both genders.

Table 4. The table reports the average hourly wage by decile of hourly wages (the unit is UF/hours). The second and sixth columns present the proportion of type-2 gaps, according to definition (8), for men and women. In these two columns, the denominator is the number of months of gainful employment. The third and seventh columns show the proportion of observations in these panels that are type-1 gaps, i.e. due to non-employment.

A major message from Table 4 is that gap inequality also appears to be substantial for type-2 gaps taken alone. The gap inequality reported in Section 2.1 (from HPA data) is far from being limited to type-1 gaps, which are those related to non-participation and unemployment.

Table 4 also answers a question that will be raised in Section 3: How much type-2 gap frequency falls if an exogenous shift in wages shifts a representative individual from an average of the two lowest-wage deciles to an average that represents the remaining wage deciles (3 to 10). According to Table 4, the drops in type-2 gap frequencies would be 48.3 percentage points (pp) for men and 48.1 pp for women.[34]

The portion of type-1 gaps that remains in our EPS panels is shown by the third and seventh columns (the percentage shown is the average of $adjtype1\ g(i,a)/12$ for the decile). As expected, these columns capture the standard positive correlation between wages and participation in gainful employment. The proportion of type-1 gaps is higher for women.

Another important message is that type-2 gaps appear to fall non-linearly with the wage decile, with convex thresholds at decile 4 for men and at decile 3 for women. For type-2 gaps, the major nonlinearity for men suggested by Table 4 contrasts with what was suggested for both gaps together in Section 2.1.2 (see Figure 1).

The concave threshold for women revealed by the administrative data in Section 2.1 (HPA) is absent here, suggesting that it is driven by type-1 gaps alone. Instead, women present a convex threshold in type-2 gaps taken alone. These findings are investigated further in Section 3.

[34] From Table 4, the average rates of type-2 gaps in the two lowest wage deciles are 75.9% for men and 68.9% for women. The average rates of gaps in wage deciles 3 to 10 are 27.6% for men and 20.8% for women. The difference is in the main text.

3. Estimation of gaps controlling for non-wage causes

The descriptive statistics in section 2 are insufficient to establish the actual relationship between hourly wages and type-2 contribution gaps. This relationship might become a constant for all wage deciles after controlling for unobserved individual characteristics that remain fixed over time, for the employment rate, for the persistence of contribution gaps, among other potential controls. To determine whether this is so, this section uses the variables described in section 2.2, plus some others, and finds how much of this relationship survives controls.

3.1 Construction of the Main Variables

Several variables were introduced in section 2.2. For example, the frequency of type-2 gaps for calendar year a is $GF2_{ia}$ and its definition was given in equation (8). In the denominator in (8) $adjtype1\ g(i,a)$ is the number of months individual i is outside employment in calendar year a.[35] Individuals who do not report earnings in any month of the calendar year are fully outside our EPS panels. If the individual does not contribute at all in this calendar year but reports some earnings (say in statutorily exempt jobs or informality), the observation remains in the panel and the value of $GF2_{ia}$ is 1. As in section 2.2, observations are annual, not monthly, so averaging periods do not overlap.

The next variable is hourly wages. They are obtained for each calendar year by dividing earnings from gainful employment, by the number of hours worked, both declared to the EPS. Earnings reported to the EPS are take-home amounts, net of social insurance contributions and personal income taxes, unless the worker is exempt or evades. In case the worker reports a contribution, the declared earning is transformed into a figure comparable to those reported by non-contributing workers by dividing it by 0.8. This coefficient takes into account that workers who contribute to one branch of social insurance must do so for the other branches as well.[36]

Deciles of hourly wages are built from the pooled sample of men and women, separately for each calendar year in the panel. The assignment of deciles to observations is done before adjusting gaps for underreporting. In this semiparametric approach, the decile dummy D_{ia}^{x} is assigned to individual i in year a according to the hourly wage that is contemporaneous to the dependent variable $GF2_{ia}$.

[35] This number can be positive because of labor inactivity or unemployment, because the individual reached the pension access age or died in the midst of the calendar year or because she joined the sample at some intermediate date of the calendar year.
[36] Of course, workers with social insurance may attach value to the benefits obtained in exchange for contributions, provided the amount of the benefit is significantly linked to the respective contribution.

The next control is Participation in Gainful Employment by individual i in year a (PGE_{ia}). This variable controls for the standard supply-side relationship that predicts less attachment to paid employment when hourly wages are lower. Lower wages would reduce the likelihood of contributing to social insurance.[37] We cannot control for labor force participation because the EPS does not have data on job search efforts by workers and vacancy-filling efforts by employers. The definition of Participation in Gainful Employment is:

$$PGE_{ia} \equiv adjtype1\ g(i,a)/12 \qquad a = 2002, \dots 2015. \qquad (9)$$

Descriptive data on PGE_{ia} (Table 4, columns 3rd and 7th) show how it changes across wage deciles and gender. Adjusted type-1 gaps are higher for women than men and are also higher for lower wage deciles, as expected. This suggests that the marginal impact of participation in gainful employment may change across individuals in different wage deciles. Since this variation may be important for public policy, our third variable of interest is a set of interactions between each wage decile dummy and contemporaneous participation in gainful employment, $D_{ia}^{x} \cdot PGE_{ia}$.

Another important control is the lagged dependent variable, $GF2_{ia-1}$. The portion of section 2.1 that compares gaps for different averaging periods shows that contribution gaps are higher for longer averaging periods. This suggests the importance of controlling for the persistence of shocks to contribution gaps. The lagged dependent variable, used as an explanatory variable, captures persistence. We explored the possibility that persistence could vary across wage deciles, but the results favored a uniform degree of persistence across deciles.

3.2 The three models that are estimated

The three specifications estimated here are OLS as an introduction, an individual fixed effects model (FE), and the fixed-effects model plus instrumentation of certain variables (FE-IV). The omitted category is wage decile 1 when we report marginal effects. Section 3.5 re-estimates using decile 10 as the omitted category and uses the results to simulate gap levels by wage decile. The estimated coefficients for each specification are provided in Appendix 1.

The dependent variable is always the frequency of type-2 gaps in the calendar year, $GF2_{ia}$. The four explanatory variables of interest were discussed already. One is a set of wage decile dummies D_{ia}^{x}, whose coefficients measure average differences in contribution gaps with individuals in a reference decile. The second is participation in gainful employment, PGE_{ia}. This captures the standard correlation between earnings and participation in gainful employment,

[37] Implicitly, participation in gainful employment may control for the presence of children in the household and gender, because caring for children reduces labor force participation according to other evidence.

reported in Table 4. The third is an interaction that recognizes that the influence of PGE_{ia} varies by wage decile. The fourth is the lagged dependent variable, which measures the persistence of type-2 gaps over time.

In the OLS regressions, the controls included but whose coefficients are not presented in the table are schooling (in line with Lagakos et al., 2018, we consider schooling up to a maximum of 18 years); dummies for administrative region;[38] dummies for the sector of the economy;[39] quinquennial birth-year dummies[40] and calendar year dummies.

The OLS model is the following:

$$GF2_{ia} = \sum_{x \in X} \mu_x D_{ia}^x + \lambda GF2_{ia-1} + \gamma PGE_{ia} + \sum_{x \in X} \nu_x \cdot (D_{ia}^x PGE_{ia}) + \beta X_{ia} + \varepsilon_{ia} \qquad (10)$$

where X_{ia} is the vector of controls for the OLS model and ε_{ia} are random errors.

Next, in regressions with individual fixed effects (FE), the latter capture both observed and unobserved variables that influence contribution gaps, provided they remain constant over time within the sample. The controls of the OLS regression that are subsumed in the individual fixed effect are schooling and birth years. The other controls change over time for at least part of the sample, so they are retained in the FE model as the Z_{ia} vector. The FE model is:

$$GF2_{ia} = \sum_{x \in X} \phi_x D_{ia}^x + \lambda' GF2_{ia-1} + \gamma' PGE_{ia} + \sum_{x \in X} \eta_x \cdot (D_{ia}^x PGE_{ia}) + \delta c_i + \beta' Z_{ia} + \nu_{ia} \qquad (11)$$

where c_i are the individual fixed effects and ν_{ia} are random errors.

The third model is like (11) combined with the use of IV for endogenous variables. Wages may be endogenous to participation in gainful employment (simultaneity bias), which may affect the fact of belonging or not to a certain wage decile. The instruments for the wage decile dummies are the wage decile dummies in the previous 2 years, for the same individual (D_{ia-1}^x and D_{ia-2}^x). For the same reason, it is necessary to instrument the interaction terms ($D_{ia}^x \cdot PGE_{ia}$).

In fixed-effects models the coefficient of the lagged dependent variable is biased. In a standard case the size of the bias is of the order T^{-1} (Nickell 1981). Since this sample has 14 independent annual observations in the time dimension and our averaging period is one calendar year, this bias might be important. This bias can be corrected with instrumental variables. A

[38] We use the administrative region numbering as of 2006, which was changed in 2007. The model includes dummies for 13 regions, with an additional category for individuals who worked abroad or did not report their region (these two groups combined account for 2.3% of observations).
[39] A total of 10 dummies are generated, including one category for individuals who did not report their industry.
[40] A total of 12 cohort dummies is generated.

commonly recommended instrument is the dependent variable lagged twice (Wooldridge 2010, p. 255 and p. 302-3). Thus, the instruments for $GF2_{ia-1}$ are $GF2_{ia-2}$ and $GF2_{ia-3}$ for the same individual. The instrumented FE model is designated as the FE-IV model.

3.3 Multicollinearity and the Variance Inflation Factor

A common issue is the degree of multicollinearity between explanatory variables. If high, coefficients are estimated imprecisely even if the collinear variables together have substantial explanatory power. An accepted diagnostic is the variance inflation factor (VIF). If the VIF is larger than 10, or even if larger than 5 according to some authors, the recommendation is to drop some explanatory variables, or to change the model in some other way, until the VIF becomes low enough (Kutner et al 2005, p. 406-9). For each explanatory variable j, the VIF is obtained by regressing variable j on the remaining explanatory variables in the model, recouping the coefficient of multiple determination R_j^2, and calculating $(VIF)_j \equiv (1 - R_j^2)^{-1}$.

Table 5: Variance Inflation Factors for the explanatory variables in (10 and (11)

Before dropping wage decile dummies			After dropping wage decile dummies		
Expl. variable	VIF (men)	VIF (women)	Expl. variable	VIF (men)	VIF (women)
D=2	75.3	25.2			
D=3	74.1	25.1			
D=4	68.8	22.6			
D=5	77.7	27.9			
D=6	87.8	30.1			
D=7	94.1	31.6			
D=8	106.2	37.3			
D=9	119.3	47.7			
D=10	120.5	47.5			
D=2·PGE	74.4	24.7	D=2·PGE	2.0	1.7
D=3·PGE	72.5	24.4	D=3·PGE	2.0	1.7
D=4·PGE	66.1	21.9	D=4·PGE	2.1	1.7
D=5·PGE	75.0	27.9	D=5·PGE	2.3	1.8
D=6·PGE	84.9	30.0	D=6·PGE	2.6	1.9
D=7·PGE	91.5	32.0	D=7·PGE	2.7	2.0
D=8·PGE	104.2	38.2	D=8·PGE	3.0	2.0
D=9·PGE	118.8	49.1	D=9·PGE	3.2	2.3
D=10·PGE	120.6	49.0	D=10·PGE	3.3	2.6
PGE	17.7	8.3	PGE	1.6	1.9

Gap Freq. 2 (a-1)	1.2	1.3	Gap Freq. 2 (a-1)	1.2	1.3

Table 5. The variance inflation factor (VIF)s obtained from regressing variable j on the remaining explanatory variables in the model, using the following controls, whose VIFs are not shown: calendar year, birth cohort, industry, region, years of schooling. Regressions are run separately for men and women. Deciles are constructed with hourly wages; the omitted wage decile is D=1.

For our explanatory variables we find that when both wage decile dummies and their interactions with employment are present, the VIFs for most of these variables are higher than 10, as shown in Table 5. Confronted with the need to drop some subset of the highly multicollinear variables, we give precedence to the literature that finds that employment is correlated with the wage. This is supported by the evidence in Table 4, which confirms that it applies to our panels. For these reasons we retain the interaction terms $(D_{ia}^{x} \cdot PGE_{ia})$ and drop the wage decile dummies D_{ia}^{x}. Next, we check that after dropping these variables, the variance inflation factors for the remaining explanatory variables comply with the maximum bounds recommended by the literature. This is indeed the case, as shown by Table 5. Thus, the adjusted models estimated are:

$$GF2_{ia} = \lambda GF2_{ia-1} + \gamma PGE_{ia} + \sum_{x \in X} \nu_x \cdot (D_{ia}^{x} PGE_{ia}) + \beta X_{ia} + \varepsilon_{ia} \qquad (12a)$$

$$GF2_{ia} = \lambda' GF2_{ia-1} + \gamma' PGE_{ia} + \sum_{x \in X} \eta_x \cdot (D_{ia}^{x} PGE_{ia}) + \delta c_i + \beta' Z_{ia} + \nu_{ia} \qquad (12b)$$

for the OLS and FE specifications, respectively. The FE-IV model instruments $GF2_{ia-1}$ with contribution gap lags numbers 2 and 3, and instruments $(D_{ia}^{x} PGE_{ia})$ with lags 1 and 2.

3.4 Results of the estimation

Table 6: The empirical link between wage deciles and contribution gaps

(the omitted wage decile is the first- the lower wages; entries report both the coefficient estimate and its standard error, which is clustered in the panels)

	Men				Women		
Explan. Var.	OLS	FE	FE-IV	Explan. Var.	OLS	FE	FE-IV
Gap Freq.(a-1)	0.7012***	0.2350***	0.1511***	Gap Freq.(a-1)	0.6377***	0.1824***	0.0648*
	(0.009)	(0.013)	(0.025)		(0.012)	(0.014)	(0.027)
PGE	0.2113***	0.0705*	0.0895*	PGE	0.2365***	0.1339***	0.2145***
	(0.025)	(0.032)	(0.039)		(0.025)	(0.025)	(0.036)
D=2·PGE	-0.0477***	-0.0426*	-0.0711	D=2·PGE	-0.1335***	-0.1105***	-0.2099***
	(0.014)	(0.017)	(0.036)		(0.013)	(0.015)	(0.039)
D=3·PGE	-0.1333***	-0.0867***	-0.1242**	D=3·PGE	-0.2704***	-0.1980***	-0.3152***

	(0.014)	(0.019)	(0.039)
D=4·PGE	-0.1942***	-0.1130***	-0.1246**
	(0.015)	(0.020)	(0.039)
D=5·PGE	-0.1893***	-0.1201***	-0.1402***
	(0.014)	(0.019)	(0.036)
D=6·PGE	-0.1868***	-0.1364***	-0.1153**
	(0.015)	(0.021)	(0.038)
D=7·PGE	-0.2137***	-0.1528***	-0.1988***
	(0.015)	(0.020)	(0.035)
D=8·PGE	-0.2246***	-0.1630***	-0.1787***
	(0.015)	(0.020)	(0.033)
D=9·PGE	-0.2306***	-0.1690***	-0.2010***
	(0.015)	(0.021)	(0.037)
D=10·PGE	-0.2244***	-0.1664***	-0.1783***
	(0.017)	(0.025)	(0.041)
Constant	0.2478***		
	(0.059)		
Obs	31,125	31,080	30,766
R2(adj/wth/ctr)	0.62	0.12	0.10
F	567	12	5

Stand. errors in parentheses; in panels they are clustered

* p<0.05, ** p<0.01, *** p<0.001

	(0.014)	(0.018)	(0.044)
D=4·PGE	-0.2933***	-0.2141***	-0.3214***
	(0.015)	(0.018)	(0.048)
D=5·PGE	-0.2947***	-0.2165***	-0.3125***
	(0.017)	(0.020)	(0.042)
D=6·PGE	-0.2839***	-0.2152***	-0.2657***
	(0.015)	(0.021)	(0.045)
D=7·PGE	-0.2906***	-0.2313***	-0.3504***
	(0.017)	(0.022)	(0.052)
D=8·PGE	-0.3068***	-0.2494***	-0.3293***
	(0.016)	(0.019)	(0.040)
D=9·PGE	-0.3259***	-0.2590***	-0.3709***
	(0.016)	(0.020)	(0.048)
D=10·PGE	-0.3315***	-0.2553***	-0.3412***
	(0.017)	(0.021)	(0.049)
Constant	0.3946***		
	(0.076)		
Obs	22,330	22,199	22,009
R2(adj/wth/ctr)	0.62	0.13	0.10
F	543	12	5

Stand. errors in parentheses; in panels they are clustered

* p<0.05, ** p<0.01, *** p<0.001

Table 6. Coefficients of interest for EPS panels, equations (12a) and (12b). In the FE-IV case, the lagged dependent variable is instrumented with contribution gap lags numbers 2 and 3, and the interaction between the decile of earnings with employment gaps is instrumented with lags 1 and 2 of itself. Longitudinal expansion factors (2004-2015) are used for all the regressions.

One of the goals of Table 6 is to help determine how much of the higher frequency of type-2 gaps for the two lowest wage deciles, reported in descriptive statistics survives after the controls imposed in this section. To measure this, we calculate from the coefficients in Table 6 how much lower is the average of the wage decile coefficients for deciles 3 to 10 than the average of wage coefficients for deciles 1 and 2. This drop measures how much type-2 gap frequency falls in the short run if an exogenous shift in wages shifts a representative individual from the 2 lowest-wage deciles to some of the higher deciles. Table 7 presents this drop.

One finding is that for men, this short-run drop is similar for the three models (their values are -17.6 percentage points (pp) for OLS, -16.0 pp for plain FE, and -19.3 pp for FE-IV). This similarity implies that the unobserved variables controlled by the fixed effects introduced by the FE models, and which are absent from the OLS model, do not substantially influence how much type-2 gap frequency falls in the short run. This finding applies only to men.[41]

Now consider long-run falls in the same exercise, that take into account the estimated persistence of gaps over time. In equations (12), long-run drops are the previous short-run drops

[41] In the case of schooling and quinquennial birth cohort this result is expected, because these 2 controls are present in all models: explicitly in the OLS model and embedded in the fixed effects in the FE models.

divided by $\left(1-\hat{\lambda}\right)$, where $\hat{\lambda}$ is the estimated coefficient of lagged gaps. Long-run drops are radically different for the men's panel, depending on the presence or absence of individual fixed effects. For men, the long-run drops diminish from 48.3 pp for the descriptive statistics (Table 4, section 2.2), to 20.9 and 22.8 pp for the two fixed effect models.[42] Thus the long-run drop is cut in half relative to the descriptive statistics. Since this drop does not occur in the OLS estimate, this considerable reduction of long-run effects of the wage decile on type-2 gaps must be attributed to the fact that the fixed effects absorb most of the persistence parameter.

This is a second interesting finding, only for men: the reason for the contribution gap inequality reported by descriptive statistics are unobserved but fixed individual characteristics that increase persistence. We interpret that a man who holds those characteristics persists in his current level of type-2 gaps for long years even if his wages change. This finding has a policy implication: policies that identify those characteristics and mitigate them among men are likely to be particularly effective in reducing their type-2 gaps and also gap inequality.

For women, the controls fail to reduce the difference in frequency of type-2 gaps for wage deciles 3 to 10, as compared to wage deciles 1 and 2. Indeed, Table 7 shows that for women, the long-run drop in the frequency of type-2 gaps for those wage deciles is as large for the FE-IV model as for the descriptive statistics (obtained from Table 4 in section 2.2). Although controls do reduce the level of type-2 gaps for women, they do so uniformly for most wage deciles.

Table 7: Impacts on the difference in type-2 gaps between low-wage deciles and other deciles
(all coefficients are negative because the omitted decile is D1, which has the highest average gap)

	Men			
	OLS	FE	FE-IV	Drop in descript. statistics (Table 4)
Short-run coefficients:				
Aver. coeff. D3*PGE to D10*PGE	-0.200	-0.138	-0.158	
Drop w/r to the aver D1*PGE & D2*PGE	-0.176	-0.160	-0.193	
Long run:				
L. run drop = Short-run drop /(1- lambda)	-0.588	-0.209	-0.228	-0.483
Difference with drop in descript. stats.:	-0.588	-0.209	-0.228	

	Women			
	OLS	FE	FE-IV	Drop in descript. statistics (Table 4)
Short-run coefficients:				
Aver. coeff. D3*PGE to D10*PGE	-0.300	-0.230	-0.326	
Drop w/r to the aver D1*PGE & D2*PGE	-0.233	-0.285	-0.431	
Long run:				
L. run drop = Short-run drop /(1- lambda)	-0.643	-0.349	-0.461	-0.481
Difference with drop in descript. stats.:	-0.643	-0.349	-0.461	

[42] Instrumental variables do not make a large difference for men.

Table 7. The average of the coefficients from D3*PGE to D10*PGE is obtained directly from the estimated coefficients available in Table 6. The average of the coefficients for D1*PGE and D2*PGE takes into account that D1*PGE is the omitted decile in Table 6, so its coefficient is zero. For the "long-run" numbers, lambda is the coefficient of the lagged dependent variable GF2(i, a-1) in Table 6. The "Short-run drop" is the value in the line called "Drop relative to the average of D1*PGE and D2*PGE".

The reduction in the average level of type-2 gaps for women in all wage deciles is relevant, and must be attributed to the correction for endogeneity achieved by the instrumental variables and to unobserved fixed effects. Importantly, the small difference between short-run and long-run drops for the FE-IV model indicates that fixed effects capture little of the persistence for women, contrary to what happens in the case of men.[43]

3.5 Simulation of the marginal effects of wages on type-2 gaps

This subsection presents a complementary perspective on the previous findings, that shows graphically how consequential are the controls introduced by models (12). The focus here is on the marginal effect of belonging to each wage decile. Each marginal effect is defined as the difference in the dependent variable (type-2 gap frequency) between the value obtained by setting each decile's dummy to 1, and the value obtained by setting that dummy to 0.

The steps followed here are the following. First, re-estimate equation (12) with the tenth wage decile as the omitted decile. Second, determine the marginal effect for each individual in the first nine wage deciles. Of course, this effect is zero for individuals in the tenth wage decile. Third, add to the previous estimate a constant equal to the average of gaps for individuals in decile 10, obtained from the dependent variable. Fourth, construct the FE-IV curves in the figures below by averaging the marginal effects for those individuals in each wage decile. Acting as a reference, those figures also include a curve with the average of the dependent variable in each wage decile (descriptive statistics). The estimated coefficients used in this simulation are in Appendix 1.

The resulting figures do not include adjustments for the difference between short-run and long-run marginal effects, because the focus here is on the size of the short-run effects. In any case, the difference between those effects is not large for the FE-IV estimates, because the coefficients for the lagged dependent variable are 0.1536 (men) and 0.0676 (women). They imply long-run multipliers of 1.181 and 1.073, both not far from 1.

Figure 3: Marginal Effects of Belonging to different wage deciles on type-2 contribution gaps

[43] The causes must be different from schooling and birth cohort, because these are present in all 3 models.

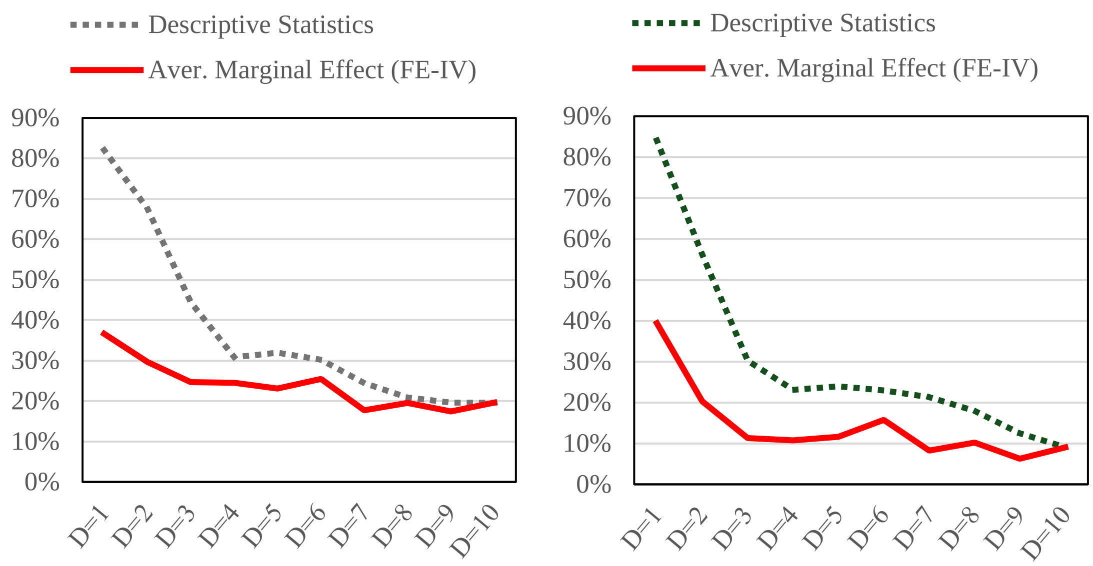

Figure 3. The left panel is for men and the right panel for women. The marginal effect is defined as the difference in the dependent variable (type-2 gap frequency) between the value obtained by setting each decile's dummy to 1, and the value obtained by setting that dummy to 0, plus a constant equal to the average of gaps for individuals in decile 10, obtained from the dependent variable. The FE-IV curves in the figures average marginal effects across individuals in each wage decile. The "Descriptive Statistics" curve shows the average of the dependent variable in each wage decile.

Figure 3 shows that the controls introduced in this section are consequential because they cut by slightly more than half the type-2 gap rate that can be attributed to belonging to the lower two wage deciles (in decile 2, the cut is 38 pp for men and 36 pp for women; in decile 1, the cut is 45 pp for both), as compared to the descriptive statistics.

Belonging to a low-wage decile still influences type-2 gaps significantly. Low-wage workers bear disproportionately larger cuts to their contributory pensions. However, the presence of other factors implies that a simple exogenous increase in wages that moves the individual to higher wage deciles will have a more modest impact than what could be surmised by comparing type-2 gaps from descriptive data.

Other findings from Figure 3 are some differences between genders: women at wage deciles 4 and higher have lower type-2 gaps than men, both in the descriptive data and after the controls introduced in this section. In addition, the average cut introduced by the controls in deciles 4 to 9 is 10 pp for women but only 5 pp for men.

4. Biases in measuring gap inequality with other data

This section explores other methods to measure contribution gap frequencies and their link to earnings or wages. Some of the findings yield lessons on how *not* to measure gap frequency. The first part uses the HPA samples to assess gap frequencies obtained from contribution histories of pensioners, in pension plans with commonplace vesting requirements.

Cross-section surveys are more widely available than the long panels used in this paper. The second part of this section investigates if the link between type-2 contribution gaps and wages can be accurately measured with cross-sections. Results are compared with those from our EPS panels to assess the size and sources of biases.

4.1 The contribution histories of pensioners are a truncated sample

This section shows that average gaps and gap inequality can be dramatically masked when data on contribution histories comes from pension beneficiaries alone, provided that the pension scheme has vesting requirements. Consider the following example. Sanchez (2017) reports that for Spanish men born in the 1920s who got a contributory pension from the *Régimen General*, the average number of years of contribution was 37.9 for those with primary education and 38.2 for those with some higher education, i.e. these two groups had almost the same moderate level of gaps. A casual observer might conclude that old-age benefits in Spain are not stratified by schooling (and are not strongly correlated with earnings). However, Spain's *Régimen General* has a vesting requirement ("minimum contribution period") of 15 years (5475 days) of contributions (Sánchez, 2017).[44] The old-age retirement pension for those who do not comply is zero.[45]

In general, vesting conditions imply that contribution data obtained from pension beneficiaries is truncated when compared to data that includes contributors who did not vest.[46] Figure 4 shows the impact that Spain's vesting requirement would have had on gap inequality when applied to our HPA samples (from Chile). It almost erases the inequality by earning deciles reported in Section 2.1, for both men and women.

Figure 4: Average gap frequencies by relative earnings decile (HPA) after vesting requirement in Spain.

[44] A further requirement is having two years (730 days) of contribution among the last 15 calendar years before starting the retirement pension. We do not impose this requirement. https://www.seg-social.es/wps/portal/wss/internet/Trabajadores/PrestacionesPensionesTrabajadores/10963/28393/28396/28472#6157 The Spanish *Régimen General* excludes the self-employed, who have a separate old-age system.
[45] Zero pension applies both in Spain and the U.S.A. Both countries have separate non-contributory support programs for the old who do not meet the vesting condition, where access requires means tests.
[46] The HPA datasets allow measuring this bias because of a feature that is unique in comparative perspective: by 2015 the datasets were long enough to approximate complete gap and contribution histories.

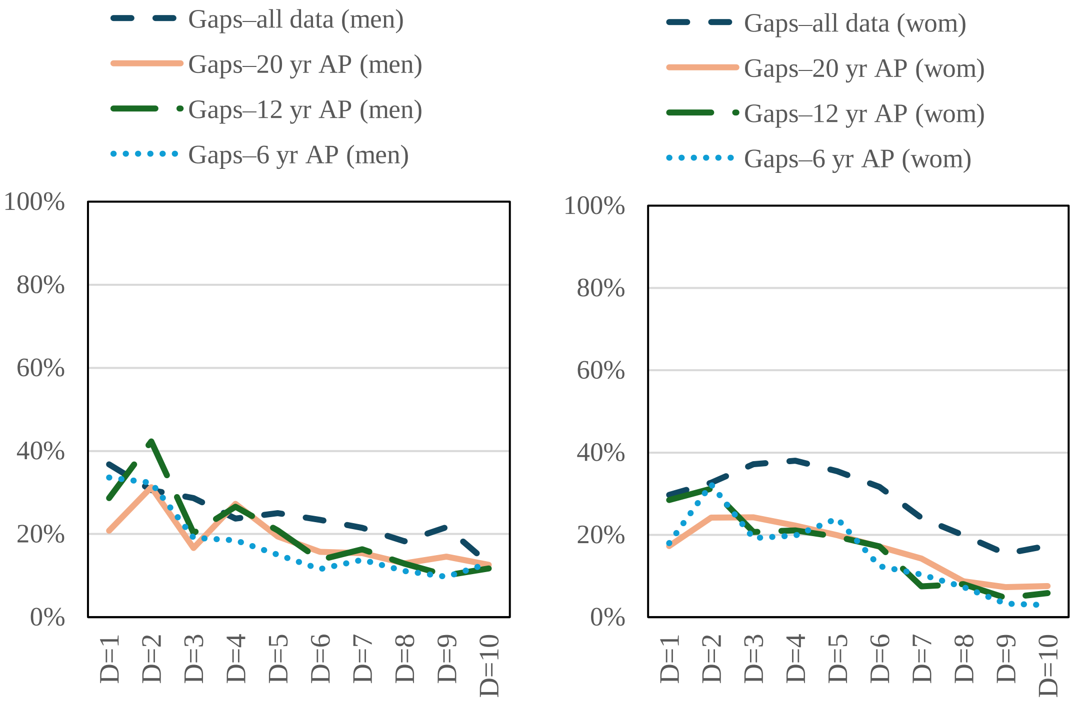

Figure 4. Vesting requirement in Spain (15 years) applied to our HPA sample. The left panel is for males and the right panel is for females. The horizontal axis is the decile of average relative earnings, defined by pooling the ARE_i^{AP} for men and women as in Section 2.1. The vertical axis reports average gap frequencies after eliminating observations that do not comply with the 15-year vesting condition in Spain's *Régimen General*. All four averaging periods are shown: 6, 12, 20, and 34.67 years.

To be clear, one mechanical result of this truncation is to reduce the average gap frequency in any given earnings decile. What is not mechanical is that the size of this fall is significantly larger for low-earnings deciles than for high-earnings deciles. The proportion of excluded low-earning individuals is larger in the low-earning deciles, even though the working poor who hold covered jobs for extended periods (low gaps) remain in the sample after truncation.

Another case is the U.S.A.'s Social Security. The main vesting condition to obtain non-zero retirement benefits from Social Security is the completion of a minimum of 40 "work credits".[47] However, only up to four work credits can be earned in each calendar year. Thus, this requirement implies a vesting period of 10 years.[48] Imposing a 10-year vesting requirement on our HPA samples allows some gap inequality to survive, as shown by Figure 5. Still, the surviving gap inequality is substantially less than with the full sample (shown in Section 2.1) because the reduction in average gaps is concentrated in the low-earning deciles.

[47] Source: https://www.ssa.gov/pubs/EN-05-10072.pdf

[48] A further requirement on work credits is meeting a minimum amount for taxable earnings, indexed to an average national wage index. In 2024 the minimum amount of work credits was USD 1,730. However, work credits are computed for each calendar year separately. For example, taxable earnings of $800 per month from November to January, whose sum exceed the minimum amount, yield zero credits if no other earnings occur in those two years. Neither year qualifies for a work credit. Source: https://www.ssa.gov/OACT/COLA/QC.html There are special rules for some jobs.

Figure 5: Average gap frequencies by relative earnings decile (HPA) after vesting requirement in the U.S.A.

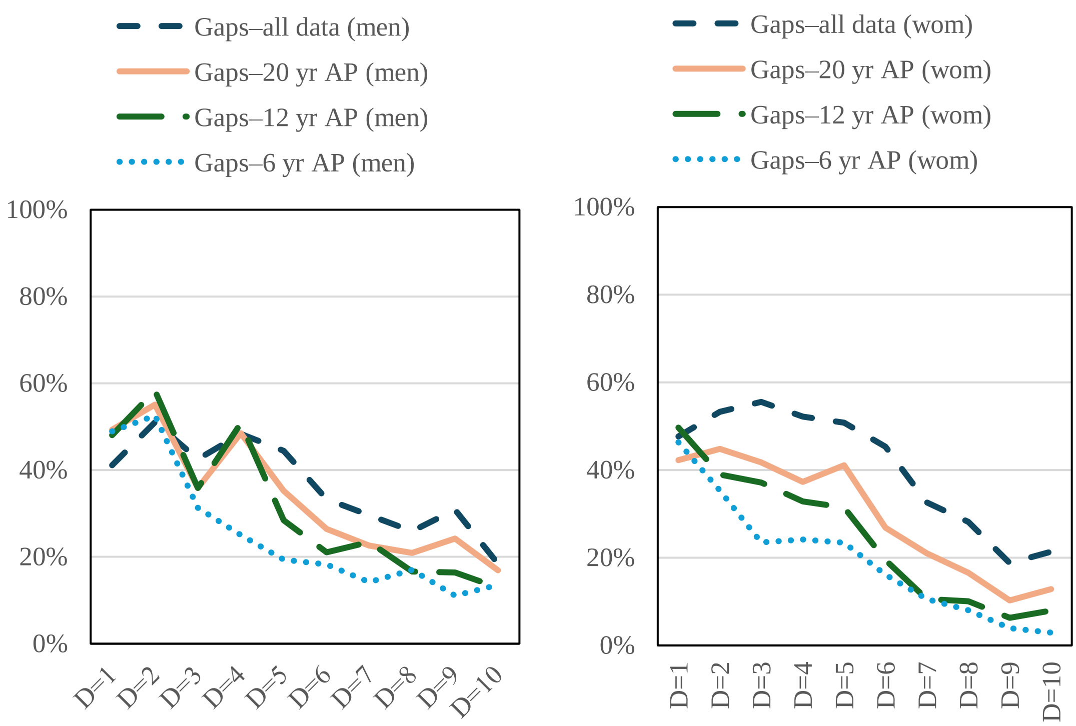

Figure 5. Vesting conditions in the U.S.A.'s Social Security applied to our HPA sample. The left panel is for males and the right panel is for females. The horizontal axis is the decile of average relative earnings, defined by pooling the ARE_i^{AP} for men and women. The vertical axis measures average gap frequencies after eliminating observations that do not comply with the 10-year vesting condition in the U.S.A.'s Social Security. All four averaging periods are shown: 6, 12, 20 and 34.67 years.

The lesson is general: vesting requirements introduce a downward bias that is larger for lower earnings deciles. If someone used data on the contribution histories of pensioners in the U.S.A. or Spain, gap levels and gap inequality would be hidden. Researchers can avoid this bias by expanding their dataset on contribution gaps to a representative sample of individuals who were refused contributory pensions because they failed to meet the vesting requirement.[49]

Note that our EPS panels cannot be used for this section's purpose because they are shorter in the time dimension (14 years) than Spain's vesting period.

4.2 Biases in gaps estimated from cross-section data

[49] Those who deem it unlikely to meet the vesting requirement, perceive that most of the current month's contribution for old-age benefits is a pure tax. This high tax rate may induce some of those workers to shorten stints in covered jobs. In contrast, those who believe are close to meeting the requirement perceive a high incentive to reduce contribution gaps in the near future. They may even simulate a covered job for this purpose.

Many countries have cross-section data and do not have long panel panels such as those presented in 2.2 and used in Section 3. This section asks if cross-section results are biased when measuring type-2 gaps, and if so, to what extent and which are the main causes?

Cross-sections are special because they always exclude type-1 gaps (caused by stints out of employment). Since those observations do not report wages, type-1 gaps create missing data if the cross-section attempts to explore the link between gaps and wages. This prevents comparison with gaps in administrative panels that include type-1 gaps in some way. Cross-sections might still be appropriate to investigate type-2 gaps, i.e. those derived from statutory exemptions from the mandate and informality, if they avoid serious biases.

A basic requirement for a cross-section to fulfill this role is that its questions include "Did you contribute last month?" If it also asks about earnings and hours in that month to respondents who are statutorily exempt from contributing and to those in informal jobs, then responses provide some measure of the relationship between type-2 gaps and wage deciles.

Consider how to design reference panels to assess potential biases. The gold standard is the gaps measured with panel data like the one used in Section 3. It is also desirable to decompose the difference to determine the main sources of the observed biases, if any. The following potential sources of bias can have an influence:

(1) The wider dataset in a panel (2002-15) versus a cross-section (2015 alone). This difference is moderated by adding dummies for calendar years to all panels;
(2) Unobserved heterogeneity, controlled by individual fixed effect in reference panels;
(3) Persistence of gaps, which is measured in panels with a lagged dependent variable. In contrast, a cross-section asks only about a single gap in a recent month. Its dispersion measures "short-term contribution instability", not autocorrelation;
(4) Endogeneity in some explanatory variables can be corrected in panels using lags of those explanatory variables as instruments;
(5) Underreporting of gaps may affect cross-sections. Although a cross-section could be corrected for underreporting if matched with administrative data, this is not the case for our cross-section data;
(6) Gainful employment. A panel can provide an explanatory variable that represents these decisions by individuals, allowing controls for them, but a cross-section cannot.

The panel data used in Section 3 includes these six additional controls and operates as a gold standard or best reference. Two intermediate reference panels are introduced to help determine the relative importance of several sources of bias. The difference between the cross-section results and the first intermediate reference panel collects the combined impact of sources of bias numbered as (1), (2), (3) and (4). The difference between outcomes of the first and second reference panel measures the marginal impact of source (5), underreporting of gaps. The difference between the second reference panel and the final (gold standard) reference panel measures the marginal impact of source (6).

The intermediate reference panels must exclude source (6). To achieve this, these intermediate reference panels are modified to exclude annual observations with positive type-1 gaps (non-employment) within the calendar year.[50] This modification mimics cross-section data, which is naturally limited to individuals who report earnings and hours of work.

4.2.1 The cross-section equation and equations for intermediate references

The CASEN (the *Encuesta de Caracterización Socioeconómica Nacional*) is a well-established cross-section survey in Chile. Since it asks about a recent contribution gap, it is used here to compare with the gold standard, estimated in Section 3.[51] We restrict the data in the 2015 CASEN so that the earnings observations come from a month in which the individual declared positive earnings and at least 35 hours of work per week in the private sector.[52] Only individuals with ages after birthday 20 and before birthdays 65/60 (men/women) are included in our CASEN samples.[53]

We estimate a logit model for the response to the question on a recent contribution gap, designated here as Y_i, with values 1 for a gap and 0 for a contribution. Hourly wages are constructed from answers to the labor market and income modules in CASEN. Earnings include earnings from self-employment, work as an employer, and informal work.[54] Wages are determined as earnings divided by hours devoted to gainful employment. Wage deciles are built from the pooled sample of men and women. Dummy variables are used to capture the link between gaps and wages. The following equation is estimated separately for men and women:

$$Pr\left[Y_i = 1 \,|WD_i^k, X_i'\right] = \Lambda\left(\sum_k \theta_k \cdot WD_i^k + \pi \cdot X_i'\right) \tag{13}$$

where $\Lambda(\cdot) \equiv \exp(\cdot)/[1 + \exp(\cdot)]$ is the logistic distribution, the WD_i^k are dummy variables for the cross-section that take value 1 for the wage decile k $(k = 1, \dots 10)$ to which individual's i hourly wage belongs (zero otherwise). The omitted decile is the one for the lowest hourly wages $(k = 1)$. The X_i' are the following controls: dummies for industry of employment, dummies for residence in each administrative region, quinquennial birth year dummies and years of schooling.[55] The θ_k and π are coefficients to be estimated. CASEN expansion factors are used.

[50] An individual may appear in the modified panels in some but not all 14 years. In the calendar years in which she appears, the observation will report earnings in all 12 months of that year.
[51] This question is numbered as o.29 in the 2015 survey. See Ministry of Social Development (2018).
[52] Public sector employees and members of the armed forces and the police are excluded from the sample.
[53] The introduction in 1981 of a new unified contributory mandatory pension plan had transition rules that implied that some respondents remained in the "old" system. Our cross-section is also limited to respondents who report participating in the unified scheme introduced in 1981.
[54] The earnings datum is the amount of earnings before tax from the individual's main occupation in the month before the 2015 survey. These earnings are self-reported.
[55] These two last controls are introduced because the panel estimates have individual fixed effects, which

Now we discuss the standards for comparison. The gold standard is given by equation (12b) estimated in Section 3 in the sample defined there. The two intermediate standards estimate equations similar and are estimated on modified EPS panels, which as described in the previous subsection, exclude observations that report earnings in 11 or less months of each calendar year. In each standard for comparison, wage deciles are built from the pooled sample of men and women, separately for each calendar year.

For the two intermediate standards, the estimated model uses as dependent variable the type-2 gap frequency in months with employment (definition (8) in 2.2, the same as in Section 3). The difference between these two intermediate standards is that, in the first, the dependent variable (gap frequency) is not adjusted for underreporting, whereas in the second, it is adjusted as described in Section 2.2.1. The following equation is estimated separately for men and women:

$$GF_{it} = \sum_{x \in X} \phi_x D_{it}^x + \lambda GF_{it-1} + \delta c_i + \beta Z_{it} + \nu_{it} \qquad (14)$$

The explanatory variables include wage decile dummies (D_{it}^x), the lagged dependent variable, and individual fixed effects (c_i). The omitted decile is the one for the lowest hourly wages ($k = 1$). Other controls, labeled Z_{it}, are dummies for industry of employment, dummies for administrative region and dummies for calendar years. The ϕ_x, λ, δ and β are coefficients to be estimated. As in Section 3, endogenous variables are instrumented with lags of themselves. The estimation uses the longitudinal expansion factors for 2004-2015 obtained from the EPS.

The difference with the model in Section 3 (the gold standard, eq. (12b)) concerns participation in gainful employment (PGE_{it}), defined in Section 3. Recall that the modified EPS panels built for the two intermediate standards require employment for all 12 months in each calendar year, replicating the CASEN sample. Comparing to Section 3, this implies that $PGE_{it} = 1\ \forall i, t$. Therefore, the impact of PGE_{it} is subsumed in the fixed effects in the modified panels. This implies also that the coefficients of the interactions between PGE_{it} and the wage decile dummies are subsumed in equation (14) in the coefficients of the wage decile dummies.

4.2.2 Results: biases in our cross-section and their sources

This section compares two outcomes: the level of gap frequency by wage decile (simple averages of the dependent variable, weighted by expansion factors), and the marginal effect on gap frequency of belonging to a certain wage decile, relative to belonging to decile 1.

The comparison of the level of average gap frequency in each wage decile is presented

control for them implicitly, together with other individual attributes that remain constant in 2002-15.

in Figure 6, separately for men and women, with three standards of comparison. Comparing first levels with the gold standard reference (FE-IV as in Section 3), it shows that the cross-section underestimates the average gap for all deciles together by about a third, for both men and women (for men, by 12 percentage points, 25% as compared to 37% in the gold standard; for women, by 11 percentage points, 19% as compared to 30% in the gold standard). The shares in this total bias of the six sources are about half for underreporting of gaps (53% for men, 49% for women) and almost half for the combined impact or sources (1) to (4). The share of source (6) in the combined impact of the six sources is the smallest: about a tenth for women and almost zero for men.[56]

The cross-section also overreports gap inequality, measured by the ratio between average gap frequency in decile 1 and average gap frequency in decile 4 (this is the threshold decile observed here; using gap frequency in decile 8 in the denominator does not affect conclusions). In the cross-section, this inequality index is 4.9 times for men and 9.0 times for women. However, in the gold standard reference, this index is only 2.7 for men and 3.6 for women. The main cause resides in the higher wage deciles: they underreport gaps to a higher degree, as revealed by the gold standard, and this cross-section does not correct for it.

Figure 6A: Biases in cross-sections: average gap frequency in each wage decile, Men

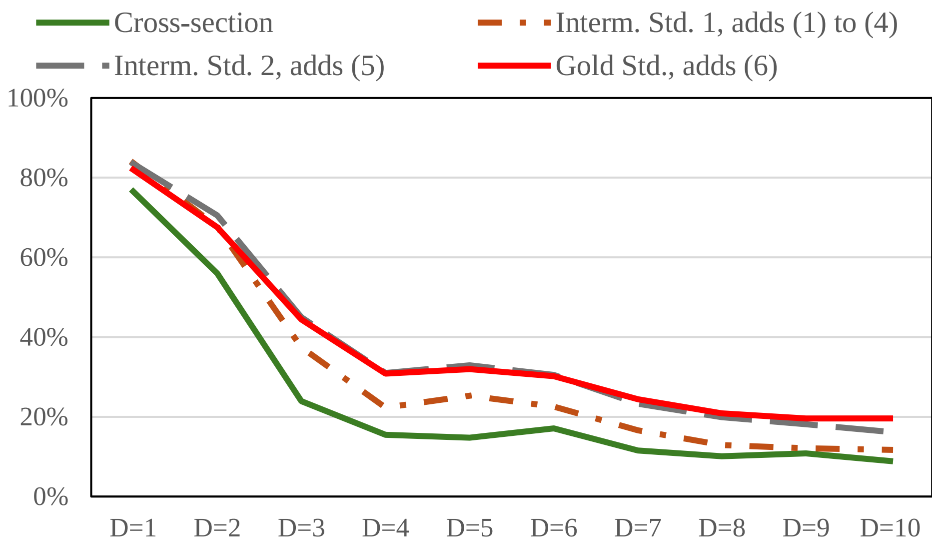

Figure 6B: Biases in cross sections: average gap frequency in each wage decile, Women

[56] The small impact of source (6) may be due in part to the 35 hours of work per week requirement.

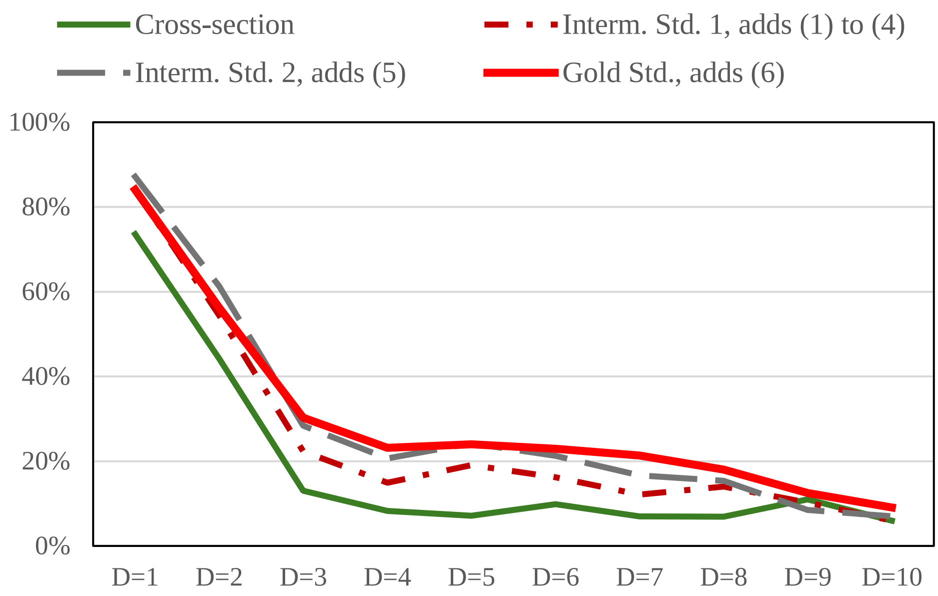

Figure 6. Biases in measuring type-2 gap inequality with a cross-section. The horizontal axis is the decile of relative wage (earnings per hour) and the vertical axis is the type-2 contribution gap averaged for each decile. Panel A is for men and Panel B for women. Each gap value is the average gap frequency for the observations in the decile. Deciles come from pooling data for men and women. The gaps in the cross-section are the lower green continuous lines, which underestimate type-2 gaps relative to the gold standard (the upper continuous line), for both men and women. The sources of the bias are classified (1) to (6) as presented in the text.

The intermediate standards shown in Figure 6 allow the identification of the sources of bias, which vary across the wage distribution. For the three lower-wage deciles, the main source of underestimation of gaps is the combination of sources (1) to (4), for both men and women. In contrast, for higher wage deciles the main source of underestimation is the inability of this cross-section to correct for gap underreporting. Interestingly, in the two highest wage deciles, the bias from the cross-section is negligible for women, but underreporting remains unabated for men.

Next, we present the marginal effects on the estimated gap frequency of joining each wage decile, relative to belonging to decile 1, in Tables 8A (men) and 8B (women). Again, three standards of comparison are used. Marginal effects differ from the average of the dependent variables shown in Figures 6A and 6B for several reasons. One is that the averages of the dependent variable include the averages of the individual fixed effects.

Table 8A: Biases in cross sections: Marginal effects in each wage decile, Men
(dependent variable: contribution gap frequency in year t for individual i)

Explanatory variable	Cross-section (CASEN 2015)	Interm. Std. 1, adds (1) to (4)	Interm. Std. 2, adds (5)	Gold Std., adds (6) [a]
Gap Freq.(t-1)		0.2449***	0.1881***	0.1511***
		(-0.017)	(-0.025)	(-0.025)
PGE				0.0895*
				(0.039)
D=2	-0.1256***	-0.0039	-0.0625	-0.0711
	(0.008)	(0.039)	(0.036)	(0.036)
D=3	-0.3198***	-0.1315**	-0.1408***	-0.1242**
	(0.008)	(0.042)	(0.039)	(0.039)
D=4	-0.3917***	-0.1938***	-0.1623***	-0.1246**
	(0.009)	(0.040)	(0.036)	(0.039)
D=5	-0.3982***	-0.1455***	-0.1065**	-0.1402***
	(0.010)	(0.036)	(0.033)	(0.036)
D=6	-0.3774***	-0.1219**	-0.1137**	-0.1153**
	(0.010)	(0.040)	(0.036)	(0.038)
D=7	-0.4417***	-0.2182***	-0.1780***	-0.1988***
	(0.011)	(0.035)	(0.032)	(0.035)
D=8	-0.4572***	-0.2090***	-0.1694***	-0.1787***
	(0.012)	(0.038)	(0.032)	(0.033)
D=9	-0.4513***	-0.1994***	-0.2009***	-0.2010***
	(0.013)	(0.038)	(0.035)	(0.037)
D=10	-0.486***	-0.2248***	-0.1675***	-0.1783***
	(0.014)	(0.042)	(0.039)	(0.041)
Obs	46,542	29,465	25,032	30,766
R2	0.22	0.25	0.14	0.10
F	–	13	5	5

Stand. errors in parentheses; in panels they are clustered

* p<0.05, ** p<0.01, *** p<0.001

Table 8B: Biases in cross sections: Marginal effects in each wage decile, Women
(dependent variable: contribution gap frequency in year t for individual i)

Explanatory variable	Cross-section (CASEN 2015)	Interm. Std. 1, adds (1) to (4)	Interm. Std. 2, adds (5)	Gold Std., adds (6) [a]
Gap Freq.(t-1)		0.1292***	0.1523***	0.0648*
		-0.022	-0.03	-0.027
PGE				0.2145***
				(0.036)
D=2	-0.1299***	-0.1217**	-0.1524***	-0.2099***
	(0.009)	(0.045)	(0.041)	(0.039)
D=3	-0.3138***	-0.3580***	-0.3015***	-0.3152***
	(0.012)	(0.045)	(0.049)	(0.044)
D=4	-0.3712***	-0.3715***	-0.3033***	-0.3214***
	(0.014)	(0.044)	(0.048)	(0.048)
D=5	-0.3885***	-0.3446***	-0.2809***	-0.3125***
	(0.015)	(0.043)	(0.044)	(0.042)
D=6	-0.3492***	-0.3417***	-0.2638***	-0.2657***
	(0.015)	(0.042)	(0.047)	(0.045)
D=7	-0.3911***	-0.3893***	-0.3202***	-0.3504***
	(0.016)	(0.049)	(0.052)	(0.052)
D=8	-0.3839***	-0.3498***	-0.3108***	-0.3293***
	(0.017)	(0.045)	(0.044)	(0.040)
D=9	-0.326***	-0.4057***	-0.3381***	-0.3709***
	(0.031)	(0.052)	(0.050)	(0.048)
D=10	-0.404***	-0.4089***	-0.2988***	-0.3412***
	(0.020)	(0.051)	(0.054)	(0.049)
Obs	22,038	19,191	16,175	22,009
R2	0.28	0.21	0.18	0.10
F	–	9	6	5

Stand. errors in parentheses; in panels they are clustered

* p<0.05, ** p<0.01, *** p<0.001

Note *a:* In the last column the explanatory variables are the interaction terms between the dummy variable for the respective wage decile and participation in gainful employment (PGE_{it}), as defined in Section 3

Table 8. Each entry in these tables presents the estimated coefficient and the standard error, which in the 3 panels is clustered at the individual level. The coefficients measure how much lower is each gap frequency as compared to decile 1 observations, hence the negative values. The first column to the left is the estimation from our cross-section: the CASEN 2015. The second and third columns are the estimates for our two intermediate panels. The column to the right is the gold standard: the estimate from Section 3. These explanatory variables were selected after a multicollinearity test. All panels are based on the EPS..

In Table 8, the difference between the coefficients of the first intermediate standard and those of the cross-section reveals the combined impact of causes (1) to (4), in the case of marginal effects. For men, the share of this combined impact is above 80%. Also, the difference between the two intermediate standards (cause (5)) and the cross-section is modest for men in the case of marginal effects. The same happens with the differences with the gold standard (cause (6)): the marginal effects are relatively small.

For women, marginal effects are quite different: first, the coefficient of PGE (participation in gainful employment) is more than twice the one for men in the gold standard reference. Next, the coefficient for the lagged dependent variable is about half of what it is for men, indicating less inertia in contribution gaps. Controlling for these variables, the cross-section coefficients for women are quite similar to those in the gold standard reference, except for decile 2. In these datasets, the bias from using a cross-section is modest in the case of women, when the aim is to measure the marginal effect of the wage decile.

Summing up, the level of type-2 contribution gaps estimated from a cross-section may be substantially biased downward, both on average and in their relation to wage deciles, for both men and women. At the same time, the ratio of gap levels in wage deciles 1 to 4, is exaggerated in cross-section results, relative to the true results. Regarding marginal effects, the bias in cross-section results is small for women but is large for men. The fact that a major cause of bias is underreporting of gaps imposes a further hurdle on the safe use of cross-sections, since it cannot be repaired without matching with administrative data.

5. Future gap risk and faulty communication policy

Two other uses of the unique 34-year administrative database (HPA) are of interest. One of them computes empirical second moments of overall gaps, specifically the dispersion in future contribution gap histories among individuals that share an initial average relative earnings quintile. The other application estimates the degree to which Chilean outcomes comply with the ILO communication standard to designate a benefit as “pension” and presents some implications for fiscal sustainability.

5.1 Inequality in Future Contribution Gap Risk

This section adopts a forward-looking perspective and quantifies the dispersion of future contribution gaps realized according to historical evidence. At one extreme, this dispersion can be a purely exogenous risk absorbed by individuals, who simply accept covered or uncovered job offers as they arrive.[57] In this perspective, the individual sees long future gaps as a threat to the sufficiency of her contributory pensions and to her future access to short-run social insurance. At another extreme, future coverage outcomes are managed by the individual by choosing between covered and uncovered jobs. In this view, this quantification may help the individual

[57] Whether they compare the new offers with take-home wages and current amenities (high discounters) or with the sum of take-home wages, amenities and the present value of future benefits (low discounters), this risk would still be exogenous at this extreme.

assess opportunities to adapt her future gaps to new developments in her labor options. Both interpretations may coexist.

To provide an empirical measure of the dispersion of future contribution gaps, we use again the administrative data (HPA) described in section 2.1. Starting in 1995, the participants observed in that sample aged 25 to 35 at that date, are ordered according to their "initial" deciles of relative earnings (i.e., average relative earnings observed from 1986 to 1995). Next, we compute the distribution of cumulative gaps for the next 20 years, until 2015, for individuals in each decile of initial average relative earnings. The distribution for the first 3 years looking forward from 1995 (1996-98) is also computed.

These distributions provide empirical measures of the dispersion of future contribution gaps. Since these distributions exhibit skewness, the dispersion of each distribution is measured and reported here with the interquartile range, defined as the difference between the 75th and the 25th percentile in outcomes.

Figure 7: Dispersion in future contribution gaps, by initial relative earnings

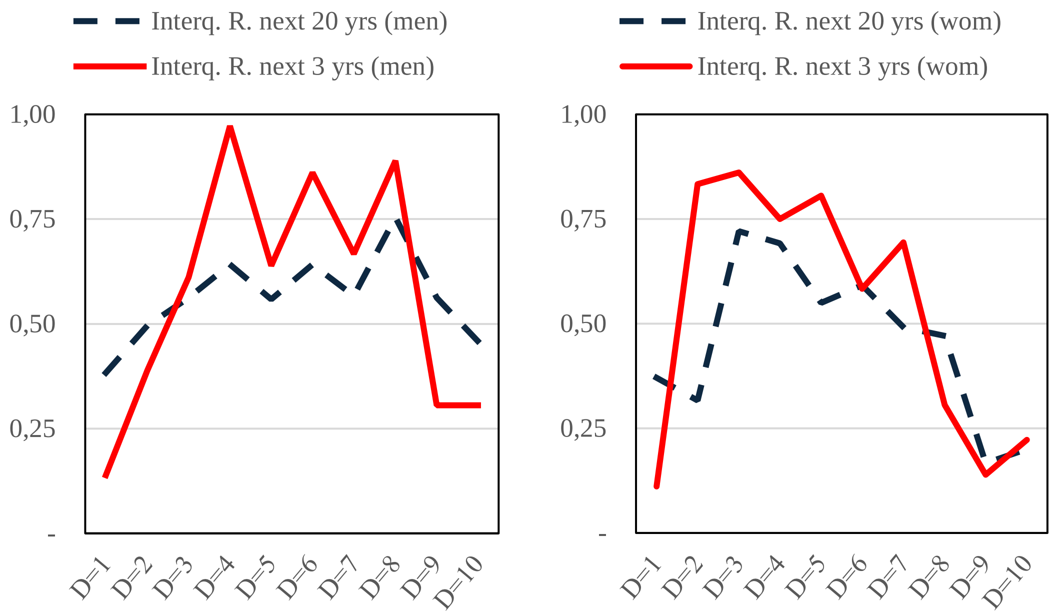

Figure 7. The left figure is for man and the right figure for women, both computed for the set of individuals aged 25 to 35 in December 1995 with at least one previous monthly contribution. Figure 7 presents the interquartile ranges for cumulative gaps over 1996-2015 (next 20 years) and over 1996-1998 (next 3 years) in the vertical axis, for each decile of initial relative taxable earnings (marked in the horizontal axis).

The hump-shaped patterns in Figure 7 show that the dispersion of contribution gaps is larger for men in the earnings deciles ranging from 4 to 8 when considering the 20 years after 1995. This pattern differs slightly for women, who exhibit greater dispersion of cumulative gaps starting from decile 4. Over the 20-year horizon, the future dispersion for men is approximately 1.3 times larger in the middle deciles (3 to 8) compared to the average of the extreme deciles (1, 2, 9, and 10). For women, the interquartile range in the same middle deciles is 2.2 times greater than the average of the extreme deciles.

When dispersion is interpreted as risk, the peak reveals that initial middle-earners exhibit the largest risk of collecting insufficient contributory pensions in old age. In this perspective, the results of Figure 7 imply that the middle earners have the most to gain from a generalized reduction in contribution gaps. If dispersion is interpreted as flexibility, the peak reveals that middle-earners are the group that adapts their gaps most strongly to new labor options and constraints.

Should dispersion in future contribution gaps be the object of insurance, in some form? Not necessarily, because a portion of future gaps is due to individual choice, not to exogenous risk. For this portion, flexibility would make insurance vulnerable to "moral hazard" of a type difficult to control, creating inefficient incentives.

The dispersion measured here is not limited to idiosyncratic uncertainty alone, as it also captures aggregate uncertainty. This later type of uncertainty is not amenable to insurance, but may be muted by partial guarantees, direct and indirect. Funded contributory pensions might use the flexibility of their investment portfolios to mute part of the undesirable risk of experiencing future contribution gaps. Current models on the issue of adapting investment portfolios to labor income risk, such as Benzoni et al (2007) and Gomes (2020), assume no contribution gaps throughout the working life, ignoring contribution gap risk and its covariance with other risk factors.

5.2 Impacts of a faulty communication policy

A standard for an old-age benefit to be described officially as a "pension", rather than "reduced pension" (or other names), is agreed upon by the 66 countries who have ratified ILO Convention No. 102 as of 2024 (including Spain, but not the U.S.A. or Chile).[58] This communication policy standard is that the beneficiary must have at least 30 years of contributions (article 29 of that Convention). The intended message is that to justify the expectation that a contributory pension will be "sufficient", at least 3 decades of contributions must be accumulated by the contributor. This message is an important component of pension communications policy.

This subsection uses the administrative database HPA to estimate how Chilean outcomes measure up to this standard and obtains some lessons. We use the sample of the HPA restricted to a 20-year cohort of older men and women, that ends in December 2015, described in section 2.1. The substantial duration of this ILO standard (30 years) imposes some constraints on measurement because the longest histories of contribution in our sample are only 34.67 years

[58] https://normlex.ilo.org/dyn/normlex/en/f?p=NORMLEXPUB:11300:0::NO::P11300_INSTRUMENT_ID:312247

long and most histories are observed for shorter periods.

Our estimate assumes that the average contribution frequency observed for each individual by the HPA in 1981-2015 applies as well to the portions of his working life that this sample does not observe. It also assumes that the working lives of men end at age 65 and those of women end at age 60, in line with the statutory first age of easy access to contributory pensions. Specifically, let C_i be the number of contribution years projected for individual i. Define:

$$C_i = 45 \cdot (1 - GF_i^{34.67}) \text{ for men ;} \qquad C_i = 40 \cdot (1 - GF_i^{34.67}) \text{ for women} \qquad (15)$$

where the overall gap frequency is obtained from equation (1) in section 2.1 for an averaging period of 34.67 years. Quintiles are built for the average relative earnings defined in equation (5) and from the pool of men and women.

Table 9: Proportion in compliance with the ILO communication standard

Quintile of Average Relative Earnings for an averaging period of 34.67 years.	Proportion of men who comply (%)	Proportion of women who comply (%)
Q1	5.4%	3.2%
Q2	17.2%	4.0%
Q3	32.9%	8.9%
Q4	54.1%	37.0%
Q5	62.3%	60.1%
Average of all quintiles together, within the given gender	41.2%	16.8%
Proportion of each gender among all participants in compliance	70.5%	29.5%

Table 9. Proportion of participants in the HPA panel described in section 2.1 who comply with the 30-year standard agreed by the ILO Convention No. 102, which recommends their old-age benefit to be officially described as a “pension”, rather than a “reduced pension” or other names. The table reports the proportion of compliance in each quintile of average relative earnings.

Table 9 reveals that the 30-year standard is met by less than 20% of the members of the two lower-earning quintiles in our HPA samples. The lower compliance rate of women is not due only to their lower first age of easy access to contributory pensions. If that age had been 45 years, women's average compliance rate for all quintiles together would have risen from 16.8% to merely 18.9% (approximately), which is still half the average for men. These outcomes are another manifestation of the intense inequality in overall gaps reported by section 2.1.[59]

What are the impacts of officially adopting and communicating this standard? One effect

[59] A result that seems idiosyncratic to Chile is the low proportion of compliance in the highest-earning quintile (only 60-62%). This may be due to relatively extensive statutory exemptions from contributions.

may be to pare down expectations on contributory pension amounts entertained by individuals with frequent contribution gaps. This may convince more workers to limit their contribution gaps. It may also drive the political system to design and apply policies to reduce gaps.

Separately, such diminished expectations may also help safeguard fiscal sustainability. What follows offers suggestive support for this effect: the impact of a faulty communication policy on this topic may help explain the massive recent expansion of non-contributory pension expenditure in Chile.

Some historical background is useful. The country's first and by far the largest mandatory pension institution, the *Servicio del Seguro Social* (SSS), which was open to new blue-collar participants from 1924 to 1984, had substantial vesting requirements of the cliff variety. For men, vesting required either 15.4 years of contributions if the average rate of contribution gaps was less than 50%, or 20 years if not. For women, vesting required 10 years of contributions. About half of the participants in the SSS never vested, so their contributory pension was zero. Conversely, the relatively few pensions issued by the SSS paid non-trivial initial amounts.[60]

The 1981 reform created a new funded system and cut the vesting requirement to zero.[61] The official label "pension" was applied to all contributory benefits, in part because Chile did not sign ILO Convention No. 102. Many participants and observers came to expect the benefit amounts from this system to be somehow sufficient, based on previous experience with the meaning of the label "pension". Separately, the high rates of return obtained by the new pension funds in its initial 15 years led observers to predict sufficient pensions for the future. However, no communication standard was available to help educate both observers and participants that the amount of their contributory pension would be as weak as their contribution frequency, regardless of rates of return. As the previous large contribution gap rates continued unabated and no policies to cut them were applied, the stage was set for widespread disappointment with pension amounts.

Starting in the early 2010s, when the first cohorts who joined the pension scheme created in 1981 reached the statutory first age with easy access to contributory pensions, low pension sufficiency became apparent. Correspondingly widespread discontent helped fuel massive (and peaceful) protests in 2016-17 against existing pension policy. They ultimately contributed to new laws in 2019 and 2022 that tripled fiscal expenditure on non-contributory pensions, from 0.7 to 2.0% of GDP in the short term, and to about double that in the long term due to ageing. Of course, other causes were involved in this process. The lesson is that in indirect ways such as this one, faulty pension communication policies may weaken fiscal sustainability.

[60] Inadequate cost of living adjustments and high inflation rendered pension amounts insufficient after a few years. This operated in addition to the zero pension amounts awarded to participants who did not vest.
[61] Other aspects of this reform were a reduction of the pension contribution rate from about 18.8% to 14.5% (initially), access to large real rates of return on pension fund investments for the first 15 years, and a shift in the risk allocation design from defined-benefit to defined-contribution.

6. Why do Earner Gaps Persist? A review

Earners with gaps have the resources to pay contributions. The size and persistence of earner gaps (type-2 gaps) over decades, confirmed in the previous sections for Chile and in the literature more generally, suggest that most policymakers around the world have invested little in reducing these contribution gaps. This fact raises a puzzle that must be solved to understand contribution gaps thoroughly. Proposing a political economy model to organize thinking about this puzzle and providing a quantitative welfare evaluation of earner gaps are outside the scope of this section. Instead, as a first step, this section summarizes mechanisms and evidence in the literature that may help explain this puzzle.

6.1 Traditional explanations of policy inaction

One traditional explanation for inaction to close contribution gaps due to informality is that states lack the capacity (the budgets, the bureaucracy, the technology) required to enforce adequately mandatory contributions for social insurance. In this explanation, governments do not end informality because they are not strong enough.

There is some evidence against this explanation. Detection technology has allowed for some time – even before smartphones became widespread - acceptable government enforcement at a bearable cost in a growing range of activities (Boeri and Garibaldi, 2005). Many informal firms have become visible to enforcers thanks to new technologies.

In emerging economies, enforcement is relatively costlier, but the evidence by Andrade et al (2016) for Brazil shows that enforcement is still cost-effective there.[62] The resource cost of detection has been further reduced by digitalization.[63] Jessen and Kluve (2021) compiled a database of 170 interventions to reduce informality and identified those that are most promising, reducing search costs for policymakers. The high degree of inaction to take these opportunities, as chosen by most governments, cannot be explained by enforcement costs alone, although they remain an obstacle.

Now consider earner gaps due to statutory exemptions. Those self-employed who need to register or obtain a permit to exercise their job can have the permit or registered conditioned on

[62] Evidence by Andrade et al. (2016) for Brazil shows that enforcement was highly effective in making firms register in the states that attempted that policy. The next question is: ¿why did Brazilian politicians choose not to use this effective enforcement technology in all regions and states to cut its large contribution gaps?

[63] In some settings current expenditure could be affected. For example, an increase in the collection of health insurance contributions may allow the Treasury to immediately cut expenditure in the state-managed health system.

contributing based on a presumptive income.[64] Employers can be required to contribute for themselves. The direct resource cost of changing laws to close some of these exemptions is modest although closing all exemptions may be impossible. Despite the low cost of some of these opportunities, few governments invest in them. The thesis that emerging economies lack the means needed to limit in any way this class of earner gaps is excessive.

A second traditional explanation for politician inaction regarding earner gaps, applicable mostly to emerging economies, is that economic development would solve informality. Many hoped that general economic growth would allow social investments in education and infrastructure to mature, so that a higher share of employment would be provided by large employers. Informality would be cut and contribution gaps fall. For example, Brazilian urban areas exhibited a drop of 10.8 percentage points in informality among salaried workers in the private sector over 2003-2012. This outcome has been attributed to increases in average schooling and increasing total factor productivity in Brazil (Haanwinckel and Soares, 2021, section 5.2).[65]

Unfortunately, the Brazilian experience of 2003-2012 appears to be exceptional. In most emerging economies the fraction of jobs that contribute to social insurance stagnated over 1990-2010, despite large productivity increases. This fraction fell in Egypt, Argentina, Mexico and Ghana, and stagnated in India and Indonesia (Rutkowski 2018). This fraction also stagnated in Brazil in other high-growth periods, as was the case in Chile. Moreover, this second traditional explanation does not apply to the earner gaps created by statutory exemptions.

A third traditional explanation is that politicians endorse tough enforcement on large employers but espouse a light approach to small firms and the self-employed because of cost reasons. Indeed, some of the cost for the government of an inspection is a fixed amount per workplace, so a small number of workers per workplace raises average enforcement costs per worker. This interacts with the established correlation between employer size and average employee earnings (La Porta and Schleifer 2014; Bosch, Melguizo and Pagés 2013 in figure 3.10). Thus, a bureaucratic decision-making process that focuses only on the current budget (short-term) would direct fewer inspections to workers with low relative earnings. Evidence for Brazil confirms that some “inspection inequality” exists and small-scale diseconomies are the major explanation (De Paula and Scheinkman 2011; Almeida and Carneiro 2012; Andrade et al. 2016; Abras et al. 2018).[66] This third explanation applies to the earner gaps created by statutory exemptions for the self-employed.

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[64] For a general description and menu of tools see https://www.imf.org/external/pubs/nft/1998/tlaw/eng/ch12.pdf

[65] The specific suggested mechanism is that lower relative wages for skilled workers imply that covered firms, which are intensive in skilled labor, face stronger opportunities to grow than informal firms. According to their model, a large rise in the minimum wage applied in 2003-2012 prevented an even larger drop in informality in Brazil.

[66] Larger employers are also more likely to self-enforce, for reasons of reputation and internal control.

However, policymakers can complement the short-horizon small-scale diseconomy with estimates of externalities from demonstration and reputation effects. Enforcement agencies can be required to measure and project how demonstration effects allow current inspections to impinge on aggregate current and future revenue from non-inspected employers. If the share of total employment in small firms and self-employment is large enough, the aggregate present value of the contribution revenue improvements given by these externalities can overcome the short-term small-scale diseconomies in some cases. However, most governments fail to explore these opportunities, weakening the scale diseconomy argument to avoid enforcement in small firms and the self-employed.

6.2 The view that "gaps are good" for low earners

A common perception is that gaps raise take-home earnings substantially because payment of large contributions is avoided. Because most mandated contributions are perceived as an implicit net tax, a gap is perceived as a tax cut. Combined with the idea that individuals on incomes close to subsistence are advised not to spend on insurance premiums or save for the future, this tax cut is assessed as desirable.

A more nuanced version of the tax cut view takes into account three other items in addition to take-home earnings:

a) Contribution gaps cause the loss of contributory benefits of all branches of social insurance. The valuation of these losses is likely to be dominated by benefits received with a high probability in the near term, such as those provided by insurance for salary losses due to short-term sickness and unemployment insurance.[67] However, as low earners face very high discount rates, as attested by the high interest rates many of them pay in consumer credit, their valuation of these short-term benefits can be modest. In addition, as Brinch et al (2017) find empirically, many are not able or willing to compute and take into account the expected value of future benefit losses. Pension benefits, received dispersedly after many decades, tend to be valued even less, together with labor taxes.[68] As this item is likely to count little for low earners, the "gaps are good" view remains supported.

b) Several countries operate large targeted social welfare programs. Targeting is implemented with estimates of each beneficiary's income or wealth. Since type-2 contribution gaps hide earnings from the targeting algorithms, larger gaps increase access

[67] Most countries require joint payment to all branches of social insurance, to prevent cherry-picking.

[68] Low earners would have additional reasons not to value pension benefits if the design of the pension scheme redistributes against them. One example is a mortality table that does not acknowledge the shorter life expectancy of low earners.

to targeted subsidies, and even more so for low earners (see evidence in Ulyssea, 2020). This item reinforces the perception that "gaps are good" for low earners.

c) Valuation of amenities related to gaps, such as flexible hours. Surveys of informal street vendors confirm that uncovered workers value highly the amenities of their jobs. This item also reinforces the perception that "gaps are good" for low earners.

Gap inequality would be a consequence of low earners valuing the increase in their take-home earnings afforded by gaps, net of these three items, to a greater extent than middle earners.

Another class of argument favoring the "gaps are good" view focuses on the fiscal and political consequences of spending more on enforcement. More enforcement would increase unemployment among informal workers with low earnings because their activities would become uncompetitive and their informal employers would shed labor or even close. The ensuing drop in aggregate demand from unemployed workers would also reduce revenue from value-added and fuel taxes (corporate and personal income tax revenues were zero initially). This argument also applies to potential legal reforms that strip substantial segments of workers from their statutorily exempt status. However, the government can draw on policy tools different from spending less on enforcement, such as investing more on training for low earners and allowing a lower statutory contribution rate during an extended transition. In any case, this argument must take into account the responses of other sectors, where the informal workers may be hired.

6.3 The opposite view: "gaps are bad" for low earners

The opinion that gaps substantially raise take-home earnings forgets the elasticity of labor supply. It assumes that the number of workers of each skill level in each type of job is unresponsive to the level of net take-home wages in those jobs. However, in emerging economies the number of workers of each skill level in each type of job may respond strongly to the level of take-home wages, net of the three items discussed in 6.2.

An increase in gaps that raises net take-home wages in newly uncovered jobs could draw substantial numbers of new workers toward those jobs. The ensuing competition among workers would prevent large increases in net take-home wages. Thus, take-home earnings in newly uncovered jobs could rise by just a little (see the small impact of enforcement on wages in the estimates by Haanwinckel and Soares 2021, Table A.5, column 4). In these settings, gaps would be only modestly good for statutorily exempt and evading workers.[69] Empirical work could

[69] Ulyssea (2020) argues that in the presence of productivity differentials between covered and uncovered jobs, the reallocation of resources towards the covered sector can more than compensate for the losses of output due to informal firms shutting down and may even raise take-home salaries of many of the low earners who join covered jobs.

determine the extent to which labor supply to segments where earners have large gaps responds strongly or weakly to higher increases in net take-home wage.

A consequence of a strong supply response is that most rents associated with avoiding contributions must be transferred to other stages in the value-added chain: employers, customers, and suppliers to the uncovered workers (for example, street vendors tend to be supplied by medium-sized firms). When informal workers provide services to producers of intermediate goods, the customers may be large firms. Customers benefit from reduced prices, as compared to purchasing from formal providers that pay taxes and social security contributions. Since many such employers and customers have middle or high incomes, an increase in earner gaps coupled with rent transfer may be regressive.

Probably the largest hidden cost of gaps for low earners is a detriment to their productivity growth in the medium-term. Jobs without social insurance exhibit slower growth in labor productivity or even stagnation (zero growth). A higher growth rate of productivity in covered jobs may occur for several reasons. One mechanism operates through employers' decisions to invest in the firm-specific human capital of its workers. However, an employer's incentive to invest is lower for higher rates of labor churning of the trained employees. High labor churning rates are correlated with larger contribution gaps (Bosch and Maloney, 2010). Thus, larger gaps are associated with less training, which in turn brings slower growth in labor productivity and wages for low earners. Evidence for this mechanism in Brazil is provided by De Paula and Scheinkman (2011) and Ulyssea (2018).[70] Another mechanism may be operating more recently: digitalization and its improved productivity may be only for formal jobs because the traceability associated with digitalization could lead informal firms to eschew adoption.

Initial evidence for low productivity growth in uncovered jobs was provided by Hurst and Pugsley (2011) for small firms in the U.S.A. This outcome was confirmed later by La Porta and Shleifer (2014) for emerging economies, and by Bobba et al (2021, henceforth BFLT) for Mexico. Hsu and Leyton (2024) find that life-cycle wage growth in Chile is significantly higher for workers in jobs that contribute to social security, even after controlling for schooling and other fixed unobserved characteristics using individual fixed effects. Their simulations show that workers who predominantly hold jobs covered by social security achieve a rate of human capital accumulation more than twice that of workers in uncovered jobs. Moreover, they estimate that the return on human capital is higher in covered jobs.

The literature identifies other direct drawbacks of gaps for the involved workers, ignored by the "gaps are good" view and suffered more intensely by low earners and small firms:

1. Gaps reduce workers' access to credit from regulated lenders because verification of the

[70] The empirical work by BFLT (2021) for Mexico finds that labor productivity rises 1.2% per annum faster in covered than in informal jobs (column "Data" in their Table 6). In 10 years, covered jobs would surge ahead by 12.7%.

earnings of workers undergoing a contribution gap is prohibitively costly. Workers in gaps lose consumer credit from regulated lenders, which is a valuable tool to manage legitimate unexpected spending needs not covered by social insurance. Housing finance also depends on presenting a credible earnings record. Access to modern subscription services (mobile phone plans, internet plans, bank cards, bank transaction accounts, etc.) is closed to individuals who cannot prove regular earnings, unless they prepay. However, prepayment has a high opportunity cost for many uncovered workers.

2. The small firms built around labor with statutory exemptions and informality also have unreliable information and can lose access to credit for working capital, which reduces their productivity. Finance limited to retained earnings hinders their investment, adding a further channel for the stagnation of productivity growth in those jobs.
3. The loss of benefits from short-term social insurance can have scarring effects over time that are not fully perceived by the worker. For example, an unemployed person without benefits (due to gaps) may be pressed to accept the first job offer received even if its match quality is substandard.
4. Gaps among informal workers go together with a loss of labor protections: inadequate workplace safety and other conditions, higher risk of not receiving the agreed salary, non-compliance with minimum wages and required severance pay.

Some categories of earner gaps impose externalities on other public policies. Gaps due to informality are associated with higher tax evasion.[71] Hiding information about salaries from the tax authorities facilitates evasion of value-added tax and corporate taxes, and vice-versa. As informality reduces the tax base, it negatively impacts the provision of public and private goods and reduces the state's capacity for redistributive policies.

The idea that individuals on incomes close to subsistence should be advised to switch to jobs without social security (exempt or informal) has also been questioned. Many exempt and informal jobs are occupied by individuals with consumption way above the poverty level. A less inefficient response to subsistence issues is to legislate a reduced contribution rate for lower earnings, that merges smoothly with the standard rate. Homburg (2006) argues that the efficient response is to subsidize voluntary savings (say subsidize investment in education and housing).

6.4 The political equilibrium around earner gaps

The perception that "gaps are good" for low earners is likely to be shared by large segments of

[71] In principle this does not apply to gaps due to statutory exemptions, which are fully formal.

voters, not just low earners. An abstract reason for voters to favor gaps for low earners is a preference for progressive redistribution, and more specifically, the view that low earners should be helped in their old age by transfers financed by more affluent segments of society, not by their own contributions. Discontent with own mandatory contributions can be projected as discontent with contributions levied on fellow citizens, especially on low earners.[72]

The opposite view is less intuitive because it operates indirectly and in longer lapses. The empirical evidence for this opposite view is in its infancy.

Elected authorities tend to follow the general opinion that holds the belief that “gaps are good” for low earners. This view is prevalent among many public opinion leaders. For example, when the Argentinean authorities launched a National Plan for Labor Regularization in 2003, they clarified that the new enforcement effort would “avoid punishing the weakest segments of the economy” (Bosch et al. 2013, Box 3.2). The prevalence of views similar to “gaps are good” has also been documented for Colombia, Chile and Peru (Holland, 2016).

Evidence from Mexican policy decisions also supports the “gaps are good” view. The penalty established by politicians on employers caught in an informal match, and the probability of being caught, result in an expected penalty of only 26% of the payroll tax amount for a single month. The expected penalty is 0.85 pesos per hour and the payroll tax is 3.26 pesos per hour, both at mean productivity (BFLT 2021, p. 445).

Other participants in the value-added production chains that include statutorily exempt and informal workers also have political influence. If labor supply to the uncovered jobs is highly elastic to take-home wages, the lower costs attained by avoiding contributions when producing services and goods can be passed on as lower prices for customers, relative to prices in formal suppliers, so that they get a pecuniary benefit from low earners’ gaps. These consumer-voters may prefer candidates that share the view that “gaps are good”. Some suppliers and employers of workers with gaps may be medium-sized organizations, which may be willing to provide campaign contributions to politicians who promise forbearance for low-earner gaps if elected. Note that this channel is significant only if “gaps are bad” for workers but it can coexist with widespread beliefs that “gaps are good”.

In countries where the middle classes also have large contribution gaps, the constituency for the tolerance of gaps is larger. These pressures are also stronger in constituencies where the voting turnout of low earners themselves is large.

In response, politicians as a group can then choose to (i) create and preserve statutory exemptions that increase contribution gaps for low and middle-earners[73]; and (ii) defund

[72] For example, “optimism bias”, documented in neuroscience for about 80% of individuals (Sharot, 2011), implies that mandatory contributions for old age cause discontent among most contributors. In addition, the illiquidity of the pension rights earned by a contribution makes this saving inferior to voluntary saving.
[73] A related tool is to establish a lower contribution rate for monthly earnings below some threshold. For example, the statute of the main social insurance institution in Brazil (the *Regime Geral de Previdência*

enforcement of the contribution mandate at the national level, and deny government officials the legal powers needed to enforce.[74] Actual progressiveness of gaps is not required for these actions to be rational for politicians, because the prevalence of those beliefs among voters is sufficient.

In summary, the recent literature in political science appears to explain satisfactorily the fact that most policymakers around the world invest little in reducing contribution gaps by earners. The explanation is a public perception that gaps are good for low earners, which is shared by voters and followed by politicians.

7 Final remarks

This paper documents the links between contribution gaps and earnings or wages. It finds that because of higher gaps, low earners and women bear relatively more cuts to the sufficiency of their contributory pensions, over and above the reduction due to their lower earnings.

The paper demonstrates the importance of separating two types of gaps: those where the individual is out of employment and therefore does not have money at hand to pay contributions (type-1 gaps), and the contrary case of earner gaps (type-2 gaps). This second type of gap can be due to statutory exemptions from the mandate to contribute, or to informality, i.e. noncompliance with the law. This distinction drives our use of different data panels.

Our analysis of the second type of gaps finds that for men, the main barrier to a larger reduction in these gaps is unobserved characteristics that increase persistence and are absorbed by fixed effects. We interpret that a man who holds those characteristics persists in his current level of type-2 gaps for long years even if his wages improve to higher deciles. For women, the outcome and the causes are different. If an exogenous increase in wages moves a woman from wage deciles 1 and 2, to wage deciles 3 to 10, her type-2 gap frequency will fall by almost 100% of the amount predicted by the descriptive statistics, which is a lot. An average woman has the flexibility to reduce her current level of type-2 gaps if her wages improve to decile 3 or higher.

The paper also shows that estimating type-2 gaps from a cross-section survey rather than from our long panels matched to individual-level administrative pension contribution data, underestimates the average gap by about one-third, for both men and women. About half of this total comes from underreporting of gaps in the case of our cross-section. We also show that inequality in contribution gaps can remain hidden if inappropriate data or methods are used to measure it.

Social), applies a lower rate to earnings below 1.75 minimum monthly salaries.

[74] The national-level political mechanisms discussed in the text should not be confused with "local forbearance", whereby a local politician protects or attracts low-earner votes by instructing local bureaucrats to provide forbearance of contribution gaps in specific jobs and areas, on a discretionary basis (Holland, 2016). One example of differences between national and local mechanisms is that statutory exemptions limit, rather than expand, the coverage of the local mechanism.

Given that earners with gaps have resources to pay contributions, the size and persistence of their gaps over decades, as seen in the literature, suggest that most policymakers around the world have invested little in reducing contribution gaps by earners. This fact raises a puzzle that must be solved to understand contribution gaps thoroughly. This paper reviews mechanisms and evidence in the literature and finds that political science explains this puzzle satisfactorily based on a public perception, shared by voters, that gaps are good for low earners. We suggest that it is the task of economists to establish the degree to which this perception is correct or not. Those results could contribute decisively to solve this puzzle. Until then, contribution gaps by earners will not be adequately understood.

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Appendix 1. Complementary tables and figures

Table A.1: Coefficients in robustness exercise 1, where the omitted wage decile is D=10. Panel to the left is for men and panel to the right is for women.

	Men		
Explan. Var.	OLS	FE	FE-IV
Gap Freq.(a-1)	0.7012***	0.2350***	0.1511***
	(0.009)	(0.013)	(0.025)
PGE	-0.0131	-0.0960**	-0.0888*
	(0.024)	(0.032)	(0.037)
D=1·PGE	0.2244***	0.1664***	0.1783***
	(0.017)	(0.025)	(0.041)
D=2·PGE	0.1767***	0.1238***	0.1072**
	(0.013)	(0.021)	(0.039)
D=3·PGE	0.0912***	0.0797***	0.0541
	(0.014)	(0.021)	(0.040)
D=4·PGE	0.0302*	0.0534**	0.0537
	(0.012)	(0.021)	(0.040)
D=5·PGE	0.0352**	0.0463*	0.0382
	(0.011)	(0.019)	(0.036)
D=6·PGE	0.0377***	0.03	0.063
	(0.011)	(0.018)	(0.036)
D=7·PGE	0.0107	0.0136	-0.0205
	(0.010)	(0.016)	(0.029)
D=8·PGE	-0.0001	0.0034	-0.0004
	(0.010)	(0.016)	(0.030)
D=9·PGE	-0.0062	-0.0026	-0.0227
	(0.009)	(0.015)	(0.028)
Constant	0.2478***		
	(0.059)		
Obs	31,125	31,080	30,766
R2(adj/wth/ctr)	0.62	0.12	0.10
F	567	12	5

Stand. errors in parentheses; in panels they are clustered
* p<0.05, ** p<0.01, *** p<0.001

	Women		
Explan. Var.	OLS	FE	FE-IV
Gap Freq.(a-1)	0.6377***	0.1824***	0.0648*
	(0.012)	(0.014)	(0.027)
PGE	-0.0950***	-0.1214***	-0.1267***
	(0.025)	(0.028)	(0.038)
D=1·PGE	0.3315***	0.2553***	0.3412***
	(0.017)	(0.021)	(0.049)
D=2·PGE	0.1980***	0.1448***	0.1314**
	(0.015)	(0.021)	(0.043)
D=3·PGE	0.0610***	0.0573**	0.026
	(0.013)	(0.019)	(0.043)
D=4·PGE	0.0381**	0.0413*	0.0198
	(0.013)	(0.019)	(0.044)
D=5·PGE	0.0368**	0.0388*	0.0287
	(0.014)	(0.019)	(0.041)
D=6·PGE	0.0476***	0.0401*	0.0755*
	(0.012)	(0.020)	(0.038)
D=7·PGE	0.0409**	0.024	-0.0092
	(0.015)	(0.021)	(0.041)
D=8·PGE	0.0247*	0.0059	0.0119
	(0.012)	(0.016)	(0.032)
D=9·PGE	0.0056	-0.0037	-0.0297
	(0.011)	(0.014)	(0.028)
Constant	0.3946***		
	(0.076)		
Obs	22,330	22,199	22,009
R2(adj/wth/ctr)	0.62	0.13	0.10
F	543	12	5

Stand. errors in parentheses; in panels they are clustered
* p<0.05, ** p<0.01, *** p<0.001

Table A.1: The coefficients indicate how much lower each gap frequency is compared to observations in wage decile 10, which accounts for the positive values of most coefficients. The explanatory variables include interaction terms between dummy variables for wage deciles and participation in gainful employment, as defined in Section 3. The first column presents results from an OLS regression using panel data. The second column incorporates individual fixed effects, while the third column instruments the lagged dependent variable and the decile-employment interactions using their two previous lags. Explanatory variables were selected based on a multicollinearity test. All estimates are derived from the EPS dataset.

Table A.2. Long-run effects of the explanatory variables in robustness exercise 1, where the omitted wage decile is D=10. Panel to the left is for men and panel to the right is for women.

Men			
	OLS	FE	FE-IV
PGE	-0.0439	-0.1254	-0.1046
	(0.074)	(0.041)	(0.043)
D=1·PGE	0.7512	0.2175	0.2101
	(0.037)	(0.033)	(0.047)
D=2·PGE	0.5914	0.1619	0.1263
	(0.035)	(0.027)	(0.045)
D=3·PGE	0.3051	0.1042	0.0637
	(0.037)	(0.027)	(0.047)
D=4·PGE	0.1011	0.0698	0.0633
	(0.035)	(0.027)	(0.047)
D=5·PGE	0.1177	0.0605	0.0449
	(0.031)	(0.024)	(0.042)
D=6·PGE	0.1261	0.0392	0.0742
	(0.033)	(0.023)	(0.042)
D=7·PGE	0.036	0.0178	-0.0241
	(0.029)	(0.021)	(0.035)
D=8·PGE	-0.0005	0.0044	-0.0005
	(0.028)	(0.021)	(0.035)
D=9·PGE	-0.0207	-0.0034	-0.0267
	(0.028)	(0.020)	(0.033)

Women			
	OLS	FE	FE-IV
PGE	-0.2622	-0.1485	-0.1355
	(0.058)	(0.034)	(0.040)
D=1·PGE	0.9148	0.3123	0.3648
	(0.030)	(0.026)	(0.048)
D=2·PGE	0.5464	0.1772	0.1404
	(0.032)	(0.025)	(0.045)
D=3·PGE	0.1685	0.0701	0.0278
	(0.029)	(0.024)	(0.046)
D=4·PGE	0.1053	0.0505	0.0212
	(0.031)	(0.024)	(0.047)
D=5·PGE	0.1015	0.0475	0.0306
	(0.030)	(0.024)	(0.044)
D=6·PGE	0.1313	0.0491	0.0807
	(0.030)	(0.025)	(0.041)
D=7·PGE	0.1129	0.0293	-0.0098
	(0.032)	(0.026)	(0.044)
D=8·PGE	0.068	0.0072	0.0127
	(0.026)	(0.020)	(0.035)
D=9·PGE	0.0155	-0.0045	-0.0318
	(0.025)	(0.018)	(0.030)

Table A.2. Each entry in the table correspond to the coefficients in Table A.1 divided by (1-*lambda*), where lambda is the coefficient for the lagged dependent variable *Cont.Gap(t-1).* Standard errors are reported in parentheses. Decile dummies are constructed with wages; the omitted wage decile is D=1.

Table A.3. Variance Inflation Factors for robustness exercise 2, where decile dummies are constructed with earnings.

Before dropping earnings decile dummies			After dropping earnings decile dummies		
Expl. variable	VIF (men)	VIF (women)	Expl. variable	VIF (men)	VIF (women)
D=2	72.8	23.9			
D=3	70.5	21.9			
D=4	69.8	23.3			

D=5	68.0	22.3			
D=6	84.0	26.7			
D=7	86.4	29.7			
D=8	99.6	32.6			
D=9	106.6	47.3			
D=10	126.1	69.0			
D=2·PGE	73.9	23.9	D=2·PGE	2.3	1.6
D=3·PGE	70.4	21.5	D=3·PGE	2.5	1.6
D=4·PGE	69.4	23.0	D=4·PGE	2.4	1.6
D=5·PGE	66.6	22.0	D=5·PGE	2.6	1.7
D=6·PGE	83.3	26.7	D=6·PGE	3.1	1.7
D=7·PGE	85.5	30.1	D=7·PGE	3.4	1.8
D=8·PGE	99.9	33.3	D=8·PGE	3.8	1.9
D=9·PGE	107.7	48.4	D=9·PGE	3.9	2.1
D=10·PGE	129.4	70.3	D=10·PGE	4.4	2.3
PGE	16.7	6.7	PGE	1.8	1.8
Gap Freq. 2 (a-1)	1.2	1.4	Gap Freq. 2 (a-1)	1.2	1.4

Table A.3. The variance inflation factor (VIF)s obtained from regressing variable *j* on the remaining explanatory variables in the model in Section 3, using the following controls, whose VIFs are not shown: calendar year, birth cohort, industry, region, years of schooling. Regressions are run separately for men and women. Deciles are constructed with earnings; the omitted earnings decile is D=1.

Table A.4. Coefficients in robustness exercise 2, where decile dummies are constructed with earnings. Panel to the left is for men and panel to the right is for women.

	Men				Women		
Explan. Var.	OLS	FE	FE-IV	Explan. Var.	OLS	FE	FE-IV
Gap Freq.(a-1)	0.6905***	0.2293***	0.1406***	Gap Freq.(a-1)	0.6080***	0.1761***	0.0538*
	(0.010)	(0.014)	(0.025)		(0.012)	(0.014)	(0.026)
PGE	0.2300***	0.1226***	0.1306**	PGE	0.2533***	0.1534***	0.1893***
	(0.026)	(0.036)	(0.046)		(0.023)	(0.024)	(0.033)
D=2·PGE	-0.0261	-0.0491*	-0.0644	D=2·PGE	-0.1168***	-0.1024***	-0.1381***
	(0.017)	(0.024)	(0.053)		(0.015)	(0.018)	(0.038)
D=3·PGE	-0.1094***	-0.1047***	-0.1084*	D=3·PGE	-0.2591***	-0.2049***	-0.2456***
	(0.017)	(0.027)	(0.047)		(0.016)	(0.021)	(0.041)
D=4·PGE	-0.1929***	-0.1648***	-0.2040***	D=4·PGE	-0.3335***	-0.2574***	-0.3296***
	(0.018)	(0.028)	(0.048)		(0.017)	(0.020)	(0.046)
D=5·PGE	-0.2146***	-0.1731***	-0.1684***	D=5·PGE	-0.3234***	-0.2643***	-0.2868***
	(0.019)	(0.028)	(0.050)		(0.017)	(0.021)	(0.046)
D=6·PGE	-0.2052***	-0.1824***	-0.1942***	D=6·PGE	-0.3232***	-0.2857***	-0.3343***
	(0.020)	(0.031)	(0.049)		(0.018)	(0.022)	(0.044)
D=7·PGE	-0.2412***	-0.2045***	-0.2238***	D=7·PGE	-0.3345***	-0.2990***	-0.3469***
	(0.019)	(0.030)	(0.051)		(0.019)	(0.023)	(0.045)
D=8·PGE	-0.2397***	-0.2188***	-0.2314***	D=8·PGE	-0.3413***	-0.3133***	-0.3868***
	(0.020)	(0.030)	(0.049)		(0.019)	(0.024)	(0.044)
D=9·PGE	-0.2635***	-0.2268***	-0.2319***	D=9·PGE	-0.3691***	-0.3339***	-0.3775***
	(0.020)	(0.031)	(0.051)		(0.020)	(0.029)	(0.051)
D=10·PGE	-0.2602***	-0.2482***	-0.2555***	D=10·PGE	-0.3715***	-0.3520***	-0.3929***

	(0.021)	(0.034)	(0.056)
Constant	0.2211***		
	(0.059)		
Obs	31,475	31,432	31,430
R2(adj/wth/ctr)	0.63	0.12	0.11
F	581	14	5

Stand. errors in parentheses; in panels they are clustered

* p<0.05, ** p<0.01, *** p<0.001

	(0.020)	(0.031)	(0.054)
Constant	0.3974***		
	(0.082)		
Obs	22,467	22,338	22,336
R2(adj/wth/ctr)	0.63	0.15	0.13
F	541	12	6

Stand. errors in parentheses; in panels they are clustered

* p<0.05, ** p<0.01, *** p<0.001

Table A.4. The coefficients represent how much lower each gap frequency is compared to observations in earnings decile 1, which accounts for the negative values of most coefficients. The explanatory variables include interaction terms between dummy variables for earnings deciles and participation in gainful employment, as defined in Section 3. The first column presents results from an OLS regression using panel data. The second column incorporates individual fixed effects, while the third column instruments the lagged dependent variable and the decile-employment interactions with their own two previous lags. Explanatory variables were selected based on the multicollinearity test in Table A.3. All estimates are based on the EPS dataset.

Table A.5. Long-run effects of the explanatory variables in robustness exercise 2, where decile dummies are constructed with earnings. Panel to the left is for men and panel to the right is for women.

Men			
	OLS	FE	FE-IV
PGE	0.7432	0.1591	0.152
	(0.069)	(0.046)	(0.052)
D=1·PGE	-0.0843	-0.0637	-0.0749
	(0.039)	(0.031)	(0.062)
D=2·PGE	-0.3535	-0.1359	-0.1261
	(0.041)	(0.035)	(0.054)
D=3·PGE	-0.6234	-0.2138	-0.2373
	(0.040)	(0.036)	(0.055)
D=4·PGE	-0.6934	-0.2246	-0.1959
	(0.039)	(0.037)	(0.058)
D=5·PGE	-0.6628	-0.2367	-0.226
	(0.039)	(0.040)	(0.056)
D=6·PGE	-0.7791	-0.2653	-0.2604
	(0.038)	(0.039)	(0.058)
D=7·PGE	-0.7746	-0.284	-0.2693
	(0.038)	(0.040)	(0.056)
D=8·PGE	-0.8514	-0.2943	-0.2699
	(0.038)	(0.040)	(0.058)
D=9·PGE	-0.8407	-0.322	-0.2973
	(0.039)	(0.043)	(0.063)

Women			
	OLS	FE	FE-IV
PGE	0.6461	0.1862	0.2
	(0.051)	(0.030)	(0.033)
D=1·PGE	-0.2979	-0.1243	-0.146
	(0.028)	(0.022)	(0.039)
D=2·PGE	-0.6611	-0.2488	-0.2595
	(0.029)	(0.025)	(0.042)
D=3·PGE	-0.8508	-0.3125	-0.3483
	(0.028)	(0.025)	(0.045)
D=4·PGE	-0.825	-0.3208	-0.3031
	(0.028)	(0.026)	(0.045)
D=5·PGE	-0.8245	-0.3468	-0.3533
	(0.029)	(0.028)	(0.045)
D=6·PGE	-0.8533	-0.3629	-0.3666
	(0.031)	(0.029)	(0.044)
D=7·PGE	-0.8706	-0.3803	-0.4088
	(0.029)	(0.030)	(0.043)
D=8·PGE	-0.9415	-0.4052	-0.399
	(0.029)	(0.036)	(0.051)
D=9·PGE	-0.9476	-0.4273	-0.4153
	(0.030)	(0.039)	(0.053)

Table A.5. Each entry in the table correspond to the coefficients in Table A.4 divided by (1-*lambda*), where lambda is the coefficient for the lagged dependent variable *Cont.Gap(t-1)*. Standard errors are reported in parentheses. Decile dummies are constructed with earnings; the omitted earnings decile is D=1.

Figure A.1. Marginal Effects of Belonging to different earnings deciles on type-2 contribution gaps.

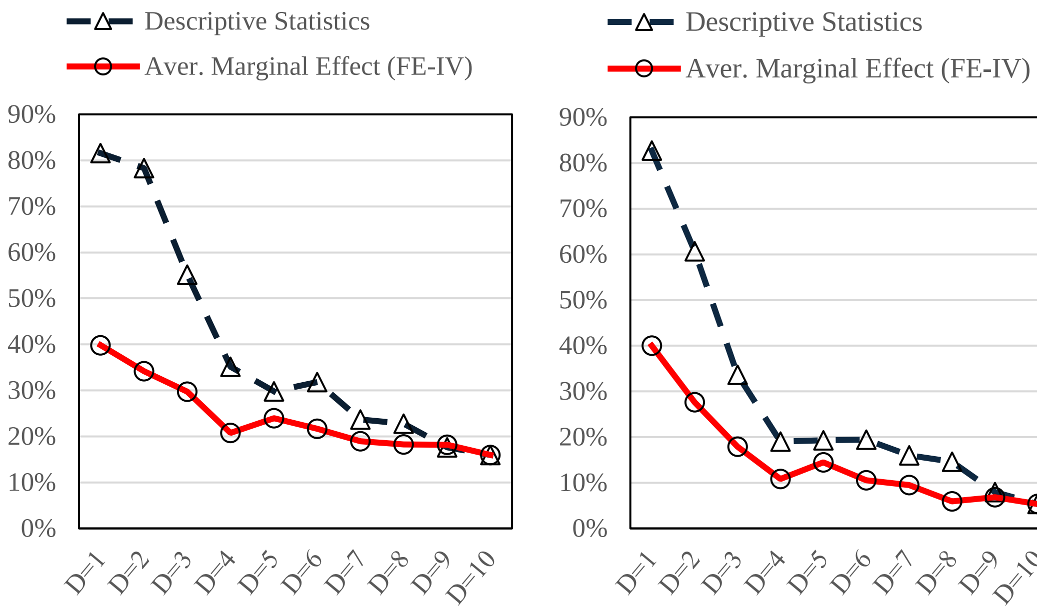

Figure A1. The left panel is for men and the right panel for women. The marginal effect is defined as the difference in the dependent variable (type-2 gap frequency) between the value obtained by setting each decile's dummy to 1, and the value obtained by setting that dummy to 0, plus a constant equal to the average of gaps for individuals in decile 10, obtained from the dependent variable. The FE-IV curves in the figures average marginal effects across individuals in each earnings decile. The "Descriptive Statistics" curve shows the average of the dependent variable in each earnings decile. Decile dummies are constructed with earnings.

Appendix 2: The impact of contribution gaps on Chilean contributory pensions

This Appendix supports the paragraph in the Introduction that compares the impact of overall contribution gaps on pension amounts in Chile, to the impact of 30 years of increases in life expectancy.

1. The fixed assumptions are as follows: Assumed real rates of return credited are 3.5% in active years and 2% afterward, in passive years. The contributory age-earnings profile in CPI-adjusted terms used in this simulation rises linearly by a cumulative 75% from age 20's birthday (January 1) to the end of age 44 (December 31st) and remains constant thereafter until the 65th birthday (January 1).[75] Earnings drop to zero beginning at the 65th birthday. After an old-age pension starts, its amount is adjusted by the rate of change in the Consumer Price Index, so it is constant in real terms. The statutory contribution rate is held constant throughout the active life and its level does not influence the results of this exercise.[76]

[75] Source: Lagakos et al (2018), who find an increase of 50% for poor countries and of 100% for advanced countries, p. 798-9.
[76] Our numbers assume a statutory contribution rate for old-age pensions of 12% of gross salary, close to the average of anglophone countries and to the Chilean historical figure for 1990-2024.

2. The baseline exercise. It asks how much contributory pensions for a single male without dependents fall if life expectancy at age 65 rises from its value of 16.65 years in the 1985 mortality table, to 20.24 years in the 2016 mortality table, both for Chile.[77] In this baseline exercise the frequency of overall contribution gaps is held constant at 40% throughout the active life.[78] Results for the amounts of the contributory pension before taxes, contributions and fees when gross annual earnings at age 20 are $100:

With the 1985 mortality table for males: $78.66 per year.
With the 2016 mortality table for males: $66.90 per year
Reduction in old-age pension amount due to higher life expectancy: 14.9%

3. The comparison exercise. It defines the "excess gap" for any given country as the difference between the average overall contribution gap frequency in that country and the average overall gap frequency for recent male pensioners in Spain reported by Sanchez (2017) for those born in the 1920's. Those with primary education only contributed 37.9 years, while those with some higher education contributed 38.2 years. The simple average is 38.05 years. Their average overall contribution gap for a 45-year career is thus 0.1544.
This exercise raises the overall contribution gap frequency from 15.44% (Spain) to 40% (Chile), keeping life expectancy at the value in the 2016 mortality tables for Chile (20.24 years), and asks for the impact on pension amounts. Results before taxes, contributions and fees are:

With the Chilean overall gap frequency: $66.90 per year
With the Spanish overall gap frequency: $94.29 per year
Reduction in old-age pension amount due to higher gap frequency: 29%

4. Conclusion: The excess overall contribution gap in our HPA sample from Chile reduced the sufficiency of contributory pensions for men by twice the reductions created by 31 years of increases in life expectancy.

[77] Source for the 2016 figure: Official Statement by the Superintendency of Pensions of Chile, November 2015. Available in https://www.spensiones.cl/portal/institucional/594/w3-article-10846.html ; Source for the 1985 figure: Table III-7 in p. 37 of the booklet by Subsecretaría de Previsión Social (2014) *Propuestas para Mejorar las Pensiones de Vejez*, March, Santiago, Chile. Available in https://esdocs.com/doc/1370160/propuestas-para-mejorar-las-pensiones-de-vejez .

[78] Source: administrative data for the 53,467 men who started a contributory pension in 2018. We take the monthly totals for the average "density of contributions" of new male pensioners and weigh them by the number of new pensions for men issued in the month, obtaining 60.0%. The frequency of overall contribution gaps is 1- density = 40%. Given a 12% statutory contribution rate, the men's effective contribution rate for old-age pensions is 7.2% of gross earnings. For recently pensioned women, the density of contribution was close to 45% in 2018, so their frequency of overall contribution gaps was 55% and their effective contribution rate was 5.4%. Source: item #1 in https://www.spensiones.cl/apps/centroEstadisticas/paginaCuadrosCCEE.php?menu=sci&menuN1=pensypape&menuN2=nuepenmes