Happiness vs. welfare functions: an analysis for the elderly in Argentina

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This study aims to measure the evolution of the aggregate well-being of elderly people in Argentina during 2003-2023 using the more traditional abbreviated social welfare functions and the more recent hedonometer tool. Results show that both indicators have similar patterns: welfare increases during 2003-2011 and has been falling ever since. However, the reasons of this behavior differs in each presidency term. Moreover, we show that the happiness of pensioners measured from public opinion positively correlates with the well-being measured through income and distribution indexes. This result is relevant for policy makers.

Key words: welfare functions, hedonometer, elderly people, Argentina

JEL Codes: D3, D6, I31

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I. Introduction

Since 2003, different policy measures have been implemented for the pensioners' sector in Argentina. These can be divided into two main groups. On the one hand, measures to increase the value of pensions (such as the establishment of indexation rules by Law, together with discretionary increases with redistribution proposes).[1] On the other hand, measures to allow the access to the pension´s system for those who do not meet the regular access conditions.[2] Although all these measures refer to positive announcements (pension increases and greater coverage), it is worth asking whether this optimism is reflected in the welfare of Argentina's pensioners.

For several decades now, the concept of human welfare has been discussed in the academia. In an utilitarian perspective, where welfare comes from the satisfaction that certain actions provide to individuals, Bentham (1789) states that if the interests of a society are the sum of the interests of the individuals, then it is possible to say that an action increases social utility (and therefore social welfare) if it increases the satisfaction of the society more than it decreases it.

A generalized way of evaluating the performance of an economy (and its welfare) is through its per capita consumption (income). Besides, authors such as Pigou (1920) and Deaton (1920) brought into the discussion the issue of income redistribution in the measurement of welfare, arguing that distribution has effects on social progress. The idea of measuring welfare through GDP per capita was extended during the 1950s and 1960s. Towards the end of the 1960s, the relevance of GDP per capita as a proxy for social welfare began to be questioned, and welfare was reinterpreted as the capacity to satisfy certain basic needs such as food, education, etc. Then, the Physical Quality of Life Index (PQLI) was developed as the first index of satisfaction of basic needs.

In the 1980s, the World Bank recommended to take into account indicators related to Human Development (such as education, birth rate, health, nutrition, etc.) because of their contribution to reducing poverty. Following this approach that considers social progress as something broader than economic growth, in the 1990s, the United Nations Development Program developed the Human Development Index, which combines GDP per capita with life expectancy at birth and other schooling indicators. In the 2000's, discussions on social progress give more prominence to the non-monetary aspects of development and the United Nations General Assembly establishes the rights-based Millennium Development Goals.

In this line of analysis, Jakob and Edenhofer (2014) proposed to measure social progress according to a combination of the Sustainable Development Goals (dashboard of welfare indicators) agreed by the United Nations in the 2030 Agenda to address global challenges, such as poverty, hunger, inequality, climate change and environmental degradation. These goals are interrelated and mutually reinforcing, so it is critical to understand how they relate to each other to achieve sustainable progress. On these latter options, the main criticism that arises is the multiplicity of alternative concepts available to complement GDP as a measure of well-being (Fleurbaey and Blanchet, 2013).

[1] The indexation Laws are: Law 26,417 of 2008, Law 27,426 of 2017 and the current Law 27,609 of 2020.
[2] The most important moratorium schemes are those established in Law 25,994 of 2004, Law 26,970 of 2014 and Law 27,705 of 2023.

The latest approaches are based on the measurement of well-being from subjective happiness indicators. Among the novel literature, the World Happiness Report (WHR) stands out. This publication links individual surveys (life evaluations) with aggregate indicators (GDP per capita, life expectancy, etc.) and people's happiness (by estimating a comparable index at country and regional level). Moreover, other quantitate indicators based on emotions that have been developed are the Hedonometer (Dodds et al.,2011) and The Gross National Happiness Index (Greyling et al., 2019).

This paper aims to measure the evolution of the aggregate well-being of elderly people in Argentina during 2003-2023. In doing so, we use two methodologies that are very different conceptually: (i) measurement of well-being based on abbreviated social welfare functions and (ii) measurement of happiness calculated from the hedonometer. In this sense, our work contributes s to the literature in three main aspects. First, it is the first work that measures well-being in the elderly sector in Argentina. Second, it is the first work that calculates and uses happiness score to measure happiness in the elderly group based on the public opinion of social media users. Finally, this is the first study that analyzes whether the happiness of pensioners measured from public opinion correlates with well-being measured by income and distribution.

The article is structured as follows. Section II depicts the methodology and data. Section III presents the results and the concluding remarks are shown in Section IV.

II. Methodology and Data

II.1 Welfare functions

Evaluating the performance of a country or an individual is most commonly done through mean income. In the context of the entire economy, the standard measure is per capita income. By comparing its value over different years, the direction of differences indicates whether society (or individuals) is doing better or worse. However, these indicators fail to consider other aspects of income distribution. Social welfare functions combine mean income with a measure of inequality, assigning different weights to each variable based on the analyst's value judgments. Ultimately, social welfare is equivalent to mean income if the analyst is indifferent about distribution.

The Bergson-Samuelson social welfare function (W) is the prevailing measure of welfare. This function aggregates individual welfare levels, approximated by household income (yt). In analytical terms:

$$W = W(y_1, y_2, y_3, \dots y_N) \tag{1}$$

Where N is the total number of individuals in the economy and y_i refers to a measure of income. In this article, N refers to the total number of elderly and y_i to their reported income in concept of retirement or pensions.

Social welfare functions are subjective, but there's a consensus in the literature that they can be anonymous, Paretian, symmetric, and quasiconcave functions[3]. Among the W functions, the most prevalent are the abbreviated welfare functions, as they solely include the mean (μ) and an inequality parameter (I) as arguments (Gasparini and Sosa Escudero, 2001).

[3] For details see Lambert (1993) and Amiel and Cowell (1996).

$$W = W(y_1, y_2, y_3, \dots y_N) = V(\mu, I) \tag{2}$$

with μ referring to mean income and I to an inequality parameter. These functions might either be non-decreasing in I and non-decreasing in μ.

In this study, we employ four abbreviated social welfare functions as outlined by Gasparini and Sosa Escudero (2001): Bentham (1789), Sen (1976), Kakwani (1986), and Atkinson et al. (1970).

Utilitarian Walfare function (Bentham, 1789):

$$W_b = \mu \tag{3}$$

This function reflects indifference to income inequality, as welfare only relies on the evolution of mean income. Next, the functions below penalize inequality including different indexes as additional arguments.

Sen Walfare function:

$$W_s = \mu(1 - G) \tag{4}$$

with μ referring to mean income and G to the Gini Index.

Kakwani Walfare function

$$W_k = \frac{\mu}{(1+G)} \tag{5}$$

with μ referring to mean income and G to the Gini Index.

Atkinson Walfare function:

$$W_a(\varepsilon) = \left(\frac{1}{N}\sum_{i=1}^{N}\frac{Y_i^{1-\varepsilon}}{1-\varepsilon}\right)^{\frac{1}{1-\varepsilon}} for\ \varepsilon \geq 0, \varepsilon \neq 1 \tag{6}$$

$$ln\ W_a = \frac{1}{N}\sum_{i=1}^{N}\ln y_i\ \ for\ \varepsilon = 1 \tag{7}$$

where the parameter ε can be regulates the convexity of the social indifference curves and it can be interpreted as the degree of inequality aversion. Here, we take two values for the aversion parameter: 1 and 2, with 2 representing more aversion than 1.

$$W_a(\varepsilon) = \mu(1 - A(\varepsilon)), \varepsilon = 1, 2 \tag{8}$$

with μ referring to mean income and A to the Atkinson inequality Index.

II.1.2. Household Survey Data

To analyze the evolution of well-being of the Argentinian elderly population, microdata sourced from the Permanent Household Survey (EPH) was employed. This is the main income survey from Argentina and is conducted by the National Institute of Statistics and Census (INDEC). The survey collects data relative to labor and no-labor income as well as demographic variables and some household conditions. The income measure used thorough this section is income perceived from retirement and pensions for the total population above the legal retirement age -60 years old for women and 65 for men-.[4] For comparability issues, the income has been

[4] The variable used is "v2_m", which asks individuals the amount percieved from retirement or pensions in the last month.

adjusted for inflation using the quarterly Consumer Price Index (CPI) due to the elevated inflation experienced during the analysis period – with an average annual rate of 30%.[5]

II.2. Hedonometer

The hedonometer is designed to calculate a happiness score for a large collection of text. This instrument uses sentiment scores collected by and Dodds et al. (2011) and Kloumann et al. (2012). More specifically, the hedonometer algorithm consists of the analysis of a text through its fragmentation into phrases, and subsequently the phrases into words. Words are associated with scores of positive and negative feelings, whereby a total score for the sentence is obtained by different aggregation procedures for the overall topic. In this paper, each word of each text is tagged with a sentiment score which ranges from 1 to 9 (1=sad, 5=neutral, 9=happy) and the sentiment of a text is an aggregation of the scores of its individual words. Using the LabMT lexicon for Spanish words, the average happiness score of a set a tweets T binned by month *t* has been calculated as:[6]

$$h_{avg}(T) = \frac{\sum_{i=1}^{N} h_{avg}(w_i) f_i}{\sum_{i=1}^{N} f_i} = \sum_{i=1}^{N} h_{avg}(w_i) p_i \tag{9}$$

where $f_i$is the frequency of the *i*th word w_i in the text *T*, *T* corresponds to the aggregation of tweets per month *t*, and $p_i = \frac{f_i}{\sum_{i=j}^{N} f_j}$ is the corresponding normalized frequency.

Additionally, using a time series frequency graph, we identified the months with the highest intensity of retirement-related tweets. Then, for each of those peaks, we analyze the words that have the largest contributions to shifts in the scores with Word-shift graphs. These graphs illustrate the words causing an emotional shift between two word frequency distributions. To estimate the contribution of the *i*th word to the difference of two happiness scores of two texts, T_{ref} (for reference) and T_{comp} (for comparison), we calculate:

$$h_{avg}^{(comp)} - h_{avg}^{(ref)} = \sum_{i=1}^{N} h_{avg}(w_i)(p_i^{(comp)} - p_i^{(ref)}) \tag{10}$$

Or:

$$\delta h_{avg} = \sum_{i=1}^{N} \underbrace{(h_{avg}(w_i) - h_{avg}^{(ref)})}_{I}\underbrace{(p_i^{(comp)} - p_i^{(ref)})}_{II} \tag{11}$$

where $h_{avg}^{(ref)}$ and $h_{avg}^{(comp)}$are the happiness scores of the reference and the comparison text, respectively and $p_i^{(ref)}$and $p_i^{(comp)}$ are the relative word frequency distributions.

Then, each word contribution is the product of two components: the difference between the word score and the reference score (*I*) and the difference between relative frequencies (*II*). Both components can be either positive (+) or negative (-), which yields four different ways that a word can contribute: (a) increased usage of relative positive words (*I*(+) and *II*(+) in eq. (11)),

[5] Since the survey is collected on a quarterly basis and the month each individual was surveyed is not relieved, all values are deflated to the first quarter of 2023.Income has been deflated by official CPI index for the period 2016-2023. During the previous period, reliability of the official index has been questioned, particularly from 2007 onwards. For that matter, for the period 2007-2015 different indexes were used – jan-07 to jan-13 CPI San Luis; feb-13 to apr-16 CPI CABA-.

[6] This list includes the most usual 9,930 words in Spanish, collected from Twitter, google books, songs, etc. The complete list of words is available at https://hedonometer.org/words/labMT-es-v2/.

(b) decreased usage of relative negative words (*I(-)* and *II(-)* in eq. (11)), (c) decreased usage of relative positive words (*I(+)* and *II(-)* in eq. (11)) and, (d) increased usage of relative negative words (*I(-)* and *II(+)* eq. (11)).

II.1.2. Twitter Data

To calculate the happiness index, we use Twitter data collected by Python via the Twitter gardenhose Application Program Interface (API). All tweets retrieved contain the Spanish words “jubilaciones” and “Argentina”. We did not limit the search date of tweets and we obtained tweets during a span from October 10, 2007 to April 18, 2023. As there were very little number of tweets during the first years of the series, we excluded the posts with date before June 2010.[7] The next step was excluding duplicated messages and retweets and finally we reduce the words to their root level by removing suffixes and plurality (Stemming). The final dataset contains 122,642 unique tweets.

We complete the processing of the data by dividing documents (tweets) into smaller units (words). Then, we removed all punctuation marks including period (.), comma (,), question marks (¿?), exclamation points (¡!) and special characters such as ampersand (&), slash (/), backslash (\), emojis, @users, links (http://...), hashtags (#), and the tilde (~), which are uninformative in text-mining based on bag-of-words. All capital letters were transformed into lowercase for the convenience of term unification. We also remove stop words (e.g., articles, prepositions, etc.) since they have little contribution to the document content.

III. Results

III.1. Welfare functions results

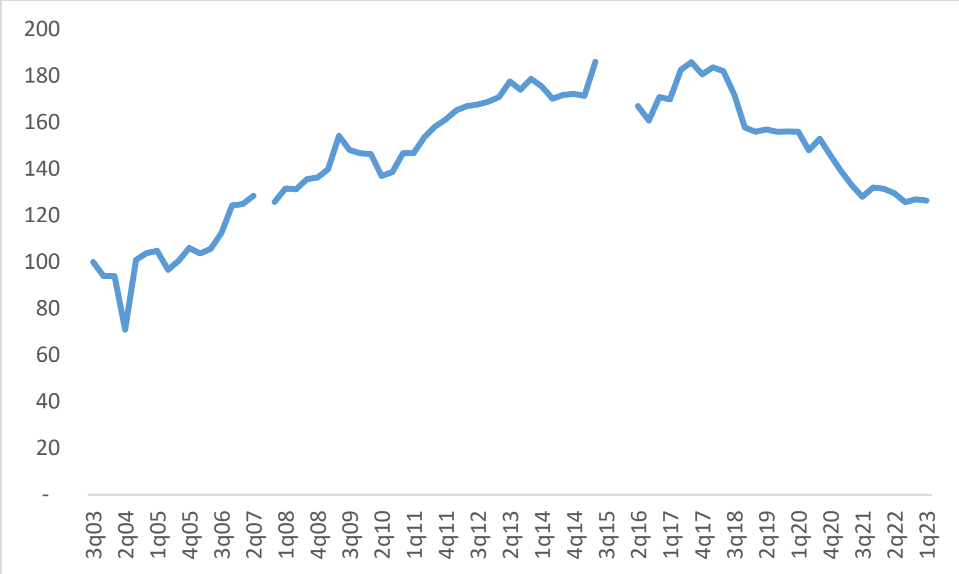
Figures 1 to 3 illustrate the trends in mean income, inequality, and aggregate welfare for the elderly population in Argentina during the period 2003-2023. To facilitate both inter-indicator and intra-indicator comparisons, the results have been normalized to an index with a base of 2003 set at 100.

Over the timeline, two distinct periods may be clearly distinguished: the period spanning 2003 to 2015 and the subsequent period from 2016 to 2023. The initial period demonstrates a substantial improvement in elderly welfare, likely attributed to the recuperation of living conditions following the 2001-2002 crisis and the implementation of policies aimed at improve retirement income and coverage. From then on, welfare seems to start a downward road, within a slightly short sign of recovery during the 2016-2018 period.

Figure 1 depicts the mean income of the elderly population. The trend in average income exhibits growth from 2003 to 2009. Following a short fall, the growth path was restarted and continued until 2015, reaching the highest level of the series by the second quarter. After the resumption of data reporting, mean income continued to rise over the ensuing two years but experienced a marked decline in 2018, subsequently adopting a declining trend. As of the second quarter of 2023, the standard of living for the elderly resembles that of the year 2010.

[7] The database of tweets contains 1 tweet dated 2007, 9 tweets dated 2008, 63 tweets dated 2009 and 18 posted from 2010/01 to 2010/05 which represent 0.01%, 0.09%, 0.66% and 0.19% of the mean annual number of tweets over 2011-2022, respectively.

Figure 1. Evolution of mean income of elderly. 2003-2023

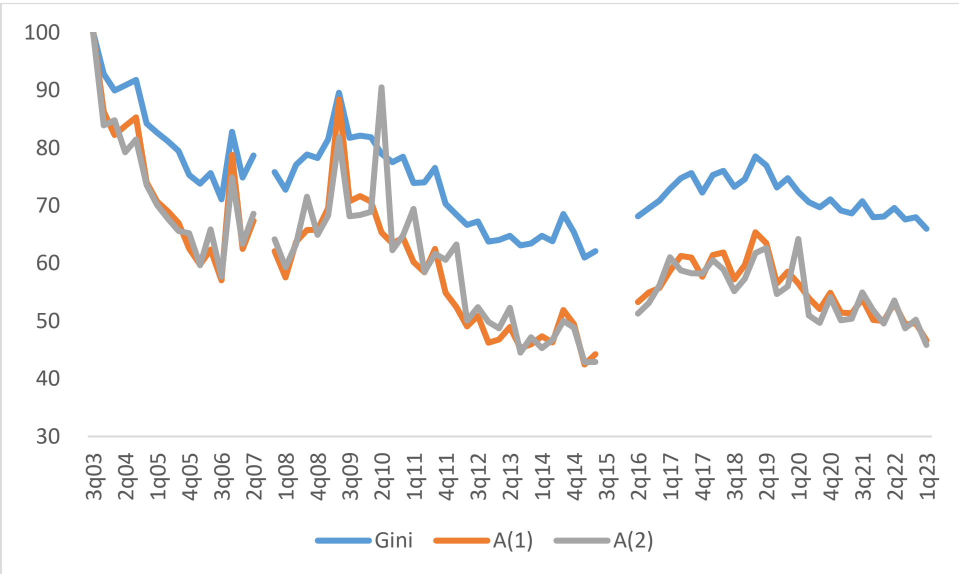


Source: Own calculations based on EPH

Note: Publication of information for the 3q07 was suspended because 4 out of 31 agglomerates couldn't be collected for administrative causes. During 3q15-1q16 there is no information because the publication of key series data was suspended for several months due to the declaration of a "state of administrative emergency" –Order no. 55/2016-.

Figure 2 illustrates the evolution of income inequality from retirement and pensions. The distribution of the elderly's income became more equal between 2003 and 2007, a trend likely attributable to the economic recovery subsequent to the 2001-2002 crisis. From 2008 to mid-2009 there was a slight increase, followed by a downward trajectory until the second quarter of 2015. In the 2016-2019 time-lapse, inequality increased again, reaching similar levels to those observed in 2009. From 2019 to the present days, distribution has become slightly more equal.

Figure 2. Inequality in the distribution of mean income of the elderly. 2003-2023



Source: Own calculations based on EPH

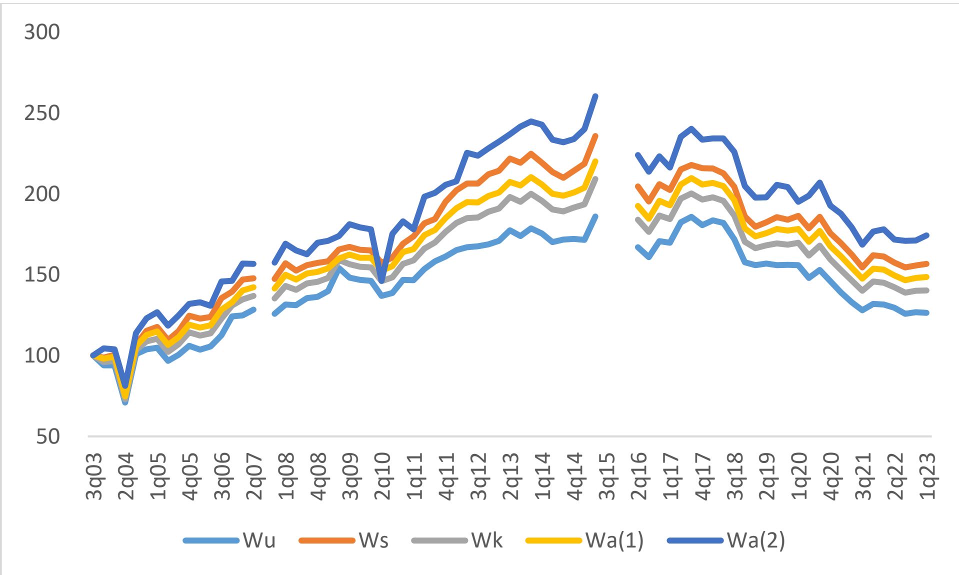
Note 1: Publication of information for the 3q07 was suspended because 4 out of 31 agglomerates couldn't be collected for administrative causes. During 3q15-1q16 there is no information because the publication of key series data was suspended for several months due to the declaration of a "state of administrative emergency" –Order no. 55/2016-.
Note 2: A(1) refers to Atkinson inequality index with e=1 and A(2) with e=2.

Levels tend to differ among the different functions, but they follow similar patterns (Figure 3). Between 2003 and 2015, pensioners' income had the highest growth rate of the last two decades. These changes are in line with a decrease in income inequality. For this reason, all the indices show an increase in aggregate welfare. Between 2016 and 2018 there is a slight increase in well-being, with a small drop in 2017. Since 2018 the growth path has been interrupted, driving all functions to reflect a decline in welfare.

The increase in aggregate welfare during the 2003-2015 period was both the result of an income and distributive improvement. Conversely, in the subsequent four years, the erosion of well-being is attributed to a deterioration in both measures. From 2020 to the present day, welfare continued to fall due to a drop in mean income, despite a concurrent decrease in inequality.

The magnitude of the variations in well-being differs across functions. While they all show usually the same sign in the variation of welfare, their magnitudes differ based on the emphasis placed on inequality. Within the scope of the period under examination, Bentham's function displays the lowest growth (and descent) rates, whereas Wa(2) manifests the highest. This disparity can be attributed to the varying weights assigned to inequality within each function.

Figure 3. Aggregate welfare of the elderly. 2003-2023



Source: Own calculations based on EPH
Note: Publication of information for the 3q07 was suspended because 4 out of 31 agglomerates couldn't be collected for administrative causes. During 3q15-1q16 there is no information because the publication of key series data was suspended for several months due to the declaration of a "state of administrative emergency" –Order no. 55/2016-.

Table 1 summarizes these results according to political periods.

Table 1. ***Evolution of income, inequality and welfare by political periods.***

Period	President	Income	Gini	A(1)	A(2)	Wb	Ws	Wk	Wa(1)	Wa(2)
3q03-4q07	Néstor Kirchner (NK)	↑	↓	↓	↓	↑	↑	↑	↑	↑
1q08-4q11	Cristina Fernández de Kirchner (CFK)	↑	↓	↓	↑	↑	↑	↑	↑	↑
1q12-2q15	Cristina Fernández de Kirchner (CFK)	↑	↓	↓	↓	↑	↑	↑	↑	↑
2q16-4q19	Mauricio Macri (MM)	↓	↑	↑	↑	↓	↓	↓	↓	↓
1q20-1q23	Alberto Fernández (AF)	↓	↓	↓	↓	↓	↓	↓	↓	↓

Source: Own elaboration

When analyzing the evolution of well-being during the last five presidencies, results show that during the tenures of Néstor Kirchner and both terms of Cristina Fernández de Kirchner, welfare increased across all four proposed measures. These trends are the result of a combination of increased pensioners' income along with a decrease in inequality – with the exception of A(2) during the second term of Cristina Fernández de Kirchner, which increased. During the presidency of Mauricio Macri, the well-being of the elderly decreased due to a reduction in pensioners' income and an increase in inequality. Finally, during Alberto Fernández's administration, a decline in income is observed, but there is also a decrease in inequality. However, the reduction in inequality was not sufficient to compensate for the fall in income, resulting in a decrease in well-being as measured by the four functions.

The findings indicate that policies aimed at enhancing pension values and broadening access towards near-universal levels have yielded positive outcomes for welfare. During the period from 2009 to 2015, minimum pension income experienced a 19% real increase, attributed to indexation regulations enforced by law [8] concurrently with an increase in coverage from 70% in 2006 to 90% in 2015. During the Mauricio Macri’s administration, indexation rules were changed and as a result, value of pensions decreased to levels of 2011. Additionally, the Historical Reparation[9] established by Law in 2016 augmented the income of the beneficiaries with higher benefits. Finally, in the last government, adjustments were made to the mobility formula, but the increases failed to offset the inflationary acceleration observed in recent years. To offset the rise in inflation, bonuses were granted -generally intended only for low-income retirees-, which explains the drop in inequality. However, this drop was not strong enough to offset the loss of revenue.

Taking into account these results, we next analyze whether the evolution of the happiness indicator calculated from the emotions expressed by twitter users is related to the evolution of more traditional measures of well-being calculated using well-being functions.

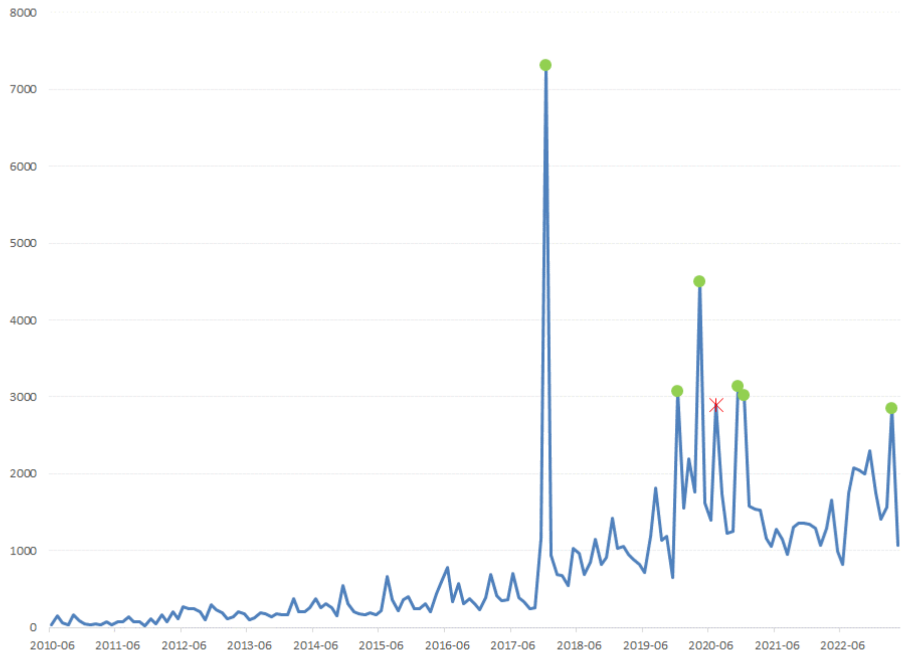
[8] Previous to the sanction of the 26,417 Law, during the 2003-2007 period, increments to pensioner’s where discretionary and higher to beneficiaries with lower incomes.

[9] Historical Reparation was destined to beneficiaries of high incomes who had pending judgements with the state for the lower increments relative to those who percieved the minimun benefit before the sanction of 26.417 Law.

III.2. Happiness results

Figure 4 illustrates the tweet frequency of "jubilados" and "Argentina"–related tweets, showing six peaks in the timeline.[10] This can be considered as a proxy of the intensity of social media activity on Twitter relating to retirement and pensions in Argentina.

Figure 4. Frequency of tweets regarding "jubilados" and "Argentina" from June 1, 2010, to April 18, 2023



Source: Own elaboration.

The highest intensity peak appeared in December 2017, with a second peak in December 2019. The third peak appeared in April 2020, while the next two peaks are located at the end of that year. Finally, the last peak appeared in March 2023.

To go deeper into the events depicted in each peak, we use word clouds to provide a visual representation of text appearing in the tweets of the selected periods. Word clouds highlight words according to frequency. The more frequently a word appears, the bigger it is displayed in the word cloud making it more prominent in the visual presentation. Figure 5 shows the most frequently appearing words in each peak.

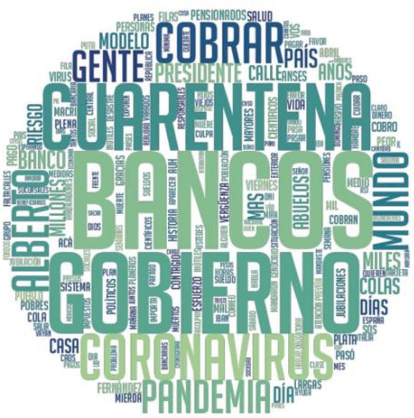
[10] The peak pointed out with a red asterisk was discarded from the analysis because it referred to a crime situation involving an elderly who killed a thief who tried to rob his home. An example tweet of this event is:*"Jubilados en Argentina, haciendo justicia por mano propia, como debe ser, ya que estamos abandonados y es tierra de nadie el país".*

Figure 5. Word clouds showing the keywords appearing most frequently in tweets related to "jubilaciones" and "Argentina", per peak

A. December 2017

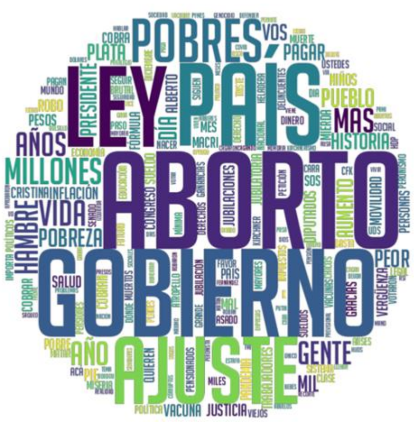
B. December 2019

C. April 2020



D. November 2020

E. December 2020



F. March 2023

Source: Own elaboration.

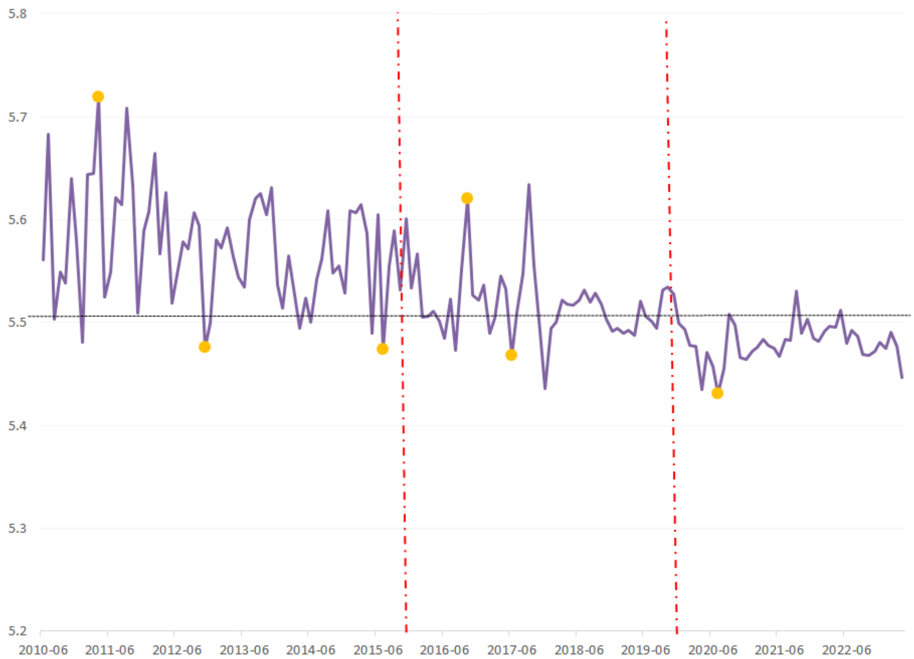
As can be seen, words such as "Gobierno, "país" and "millones" appeared to be more prominen in all the peaks, but it is also possible to distinguish specific words that describe concrete events. For example, in Figure 5.A, the words "reform" "pension", "Macri" and "Congreso" actually tell about the discussion of Law 27,426 that introduced a new rule for the indexation of pensions.

In Figure 5.B, words like "Alberto", "ley", "bono" and "aumento" illustrate the president's announcement of policy measures focused on the retirees. In turn, "coronavirus", "cuarentena", "bancos" and "pandemia" are the prominent words in the tweets of April 2020, showing that the posts were about the difficulty that pensioners had in collecting their pensions at banks at the beginning of the COVID-19 quarantine.

The peaks of November 2020 and December 2020 are similar. In December 2020, the words "ley", "ajuste" and "pobres" show that Twitter posts were related to the approval of the new Law of pensions indexation (Law 27,609) while the words of November 2020 refers to the discussion of that legislation. The word "aborto" also appears in the word cloud of December 2020. This is because the abortion Law in Argentina was also approved in the same parliamentary session in which the indexation Law was pass.[11] In March 2023 (Figure 5.F), the tweets are related to the decision of the Minister of Economy, Sergio Massa, to sale dollar bonds held by the Sustainability Guarantee Fund (FGS) of ANSES, that is why the words "plata", "ANSES", "dólares" and "Massa" were some of the most frequent words in those texts.

Having identified the most relevant retirees' related events from users' twitter posts, we next calculate the expressed happiness over the timeline using the hedonometer algorithm.[12] The idea is to determine how public opinion "jubilados" on Twitter varies in response to retirees news and events.

Figure 6. Happiness score of tweets containing "jubilados" and "Argentina" by month



Source: Own elaboration.

As can be seen in Figure 6, the mean happiness score decreases over the period. Moreover, during the first part of series, the score shows more variability but it shows smoother

[11] Law 27,610 of 2020.

[12] Table A.1 of the Annex shows an example tweet of each of the peaks analyzed in Figure 5.

movements from December 2017. The mean happiness score during the period is 5.5, but when we consider the mean score in different government periods, there are some differences:

Table 2. Average Happiness score by political period

Period	President	Mean happiness Score	% relative to total mean	Std. Dev.
June 2010-October 2015	Cristina Fernández de Kirchner	5.574	0.8%	0.055
November 2015-October 2019	Mauricio Macri	5.519	-0.2%	0.036
November 2019-April 2023	Alberto Fernández	5.481	-0.9%	0.020
June 2010-April 2023		***5.532***		

Source: Own elaboration.

Twitter shows more happiness when referring to elderly people during the presidency of Cristina Fernández de Kirchner (the score is 0.8% higher than the mean score over the entire timeline), during the presidency of Mauricio Mari, happiness decreased 0.2% relative to the mean score while in the last period, the score decreased 0.9%. Moreover, the variability of the index decreased over the period.[13] These results are in line with those obtained using welfare functions.

To make our happiness score more restrictive, we removed from the analysis neutral words whose average happiness score lies between 5±σ. Apart from the general case (σ=0), we re-calculate de happiness scores using σ=0.5;1;1.5 and 2 to bolster the emotional signal of each set of tweets.

Table 3. Average Happiness score by political period with alternative σ values

Period	President	Mean happiness Score σ=0.5	Mean happiness Score σ=1	Mean happiness Score σ=1.5	Mean happiness Score σ=2	% relative to total mean	% relative to total mean	% relative to total mean	% relative to total
June 2010-October 2015	Cristina Fernández de Kirchner	5.905	6.101	6.116	6.432	1.3%	2.0%	2.9%	3.7%
November 2015-October 2019	Mauricio Macri	5.811	5.949	5.911	6.175	-0.4%	-0.5%	-0.6%	-0.5%
November 2019-April 2023	Alberto Fernández	5.742	5.828	5.720	5.885	-1.5%	-2.5%	-3.8%	-5.1%
June 2010-April 2023		***5.832***	***5.980***	***5.945***	***6.205***				

Source: Own elaboration.

The behavior of the happiness score remains over the time series, i.e., happiness shows a decreasing trend during the period under analysis. However, as expected, the relative magnitudes of happiness are (positive/negative) larger when neutral or ambiguous words are not taken into account in the metrics.

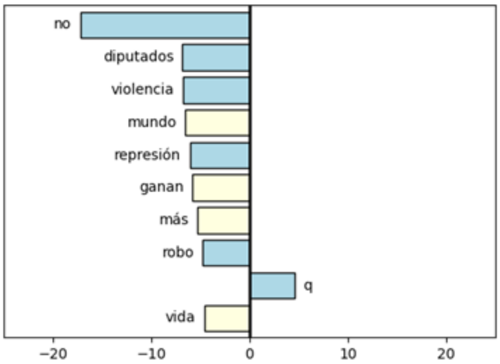
To complete the analysis, for each of the six peaks in Figure 7, we analyze which words contributed most to the shift in happiness between tweets in time t and time t-1. [14] Changes in positive/negative word frequencies produce peaks and dips in the happiness score line.

[13] We have taken October of each year as the cut-off month, which is the month in which elections are held, and not December, which is the month in which presidential terms have effectively ended, since many of the behaviors have more to do with the incoming government (which is in a transition period) than with the outgoing one.

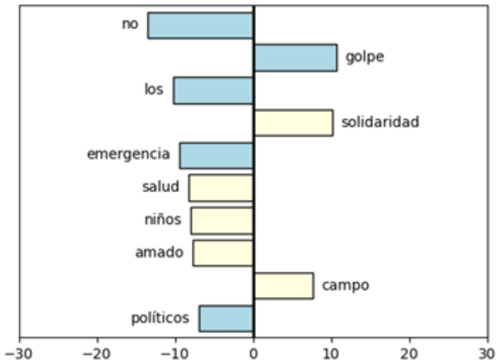
[14] We also calculate the Word-shift taking the text in period *t-1* plus *t+1* as the reference text. Results are robust to these alternative specifications.

Figure 7. Word-shift graph for tweet frequency timeline peaks

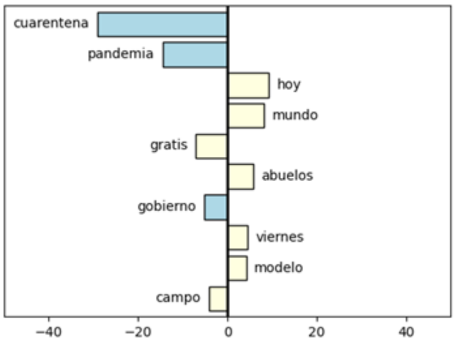
A. December 2017 (↓H from 5.49 to 5.44)



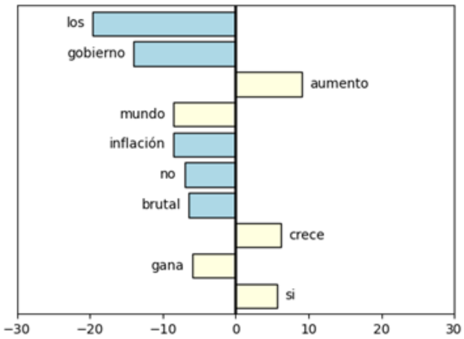
B. December 2019 (↓H from 5.53 to 5.50)



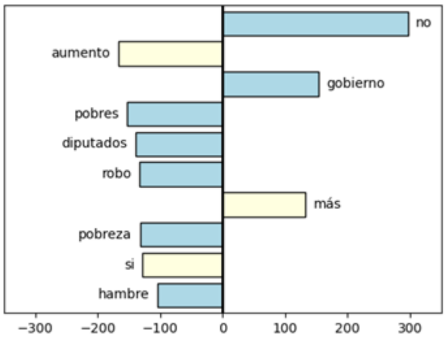
C. April 2020 (↓H from 5.48 to 5.43)



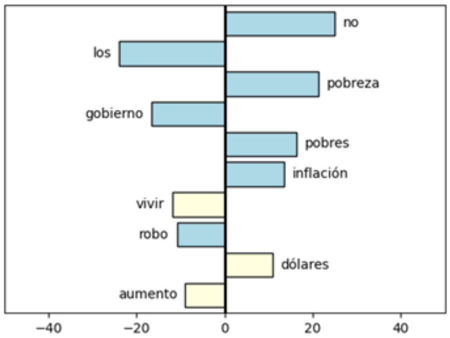
D. November 2020 (↓H from 5.5 to 5.47)



E. December 2020 ***(↓H from 5.47 to 5.46)***



F. March 2023 ***(↓H from 5.49 to 5.48)***



Source: Own elaboration.

Figure 7.A shows that the average happiness decrease (with November 2017 as the reference text) is due to both an increase in the negative words “no”, “diputados”, “violencia”, “repression” and “robo”, and a decrease in the positive words “mundo”, “ganan”, “más” and “vida”.

In December 2019, the average happiness decreases because a combination of increases in negative words such as “no”, “emergencia” and “politicos”, for an increase in the positive words “solidaridad” and “campo” and for a decrease in the positive words “salud”, “niños” and “amado”. The negative word “golpe” appeared relative less often in Decembre 2019 than in November 2019.

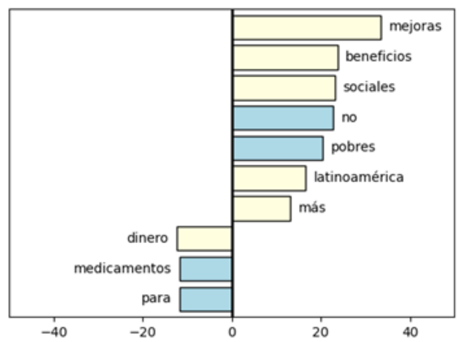
Regarding April 2020, the happiness dip has to do with the COVID-19 pandemia due the higher prevalence of negative words such as “cuarentena” and “pandemia” compared with the relative small contribution of positive words such as “mundo” and “abuelos”. Both graphs 7.D and 7.E refer to the pension’s indexation Law. While the increase in the negative words “gobierno” and “inflación” is not sufficient to compensate de positive effect that words like “ganan” have on the happiness score in November 2020, the relative reduction of “aumento”, together with the increase of words such as “pobres” and “hambre” result in a decrease in happiness.

Finally, the word shift graph of March 2023 shows that negative words such as “pobreza”, “pobres” and “inflación” can help to understand the decrease in happiness.

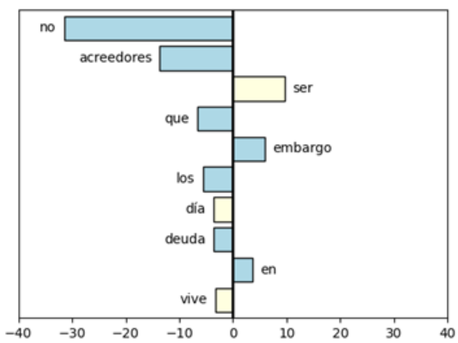
Besides, it is possible to identify other peaks in the hedonometer (yellow dots in Figure 6) which are not peaks in the time series frequency graph.[15] Table A.2 of the Annex describes those events with an example tweet, while Figure 8 includes the Word-shift graphs to show the words that contribute the most to the increase or decrease in happiness.

Figure 8. Word-shift graph for selected happiness timeline peaks

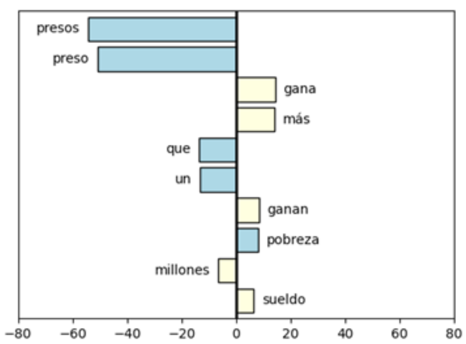
A. April 2011 ***(↑H from 5.65 to 5.72)***



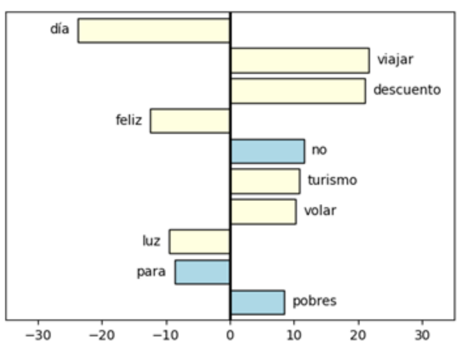
B. November 2012 (↓H from 5.59 to 5.48)



C. July 2015 (↓H from 5.47 to 5.61)

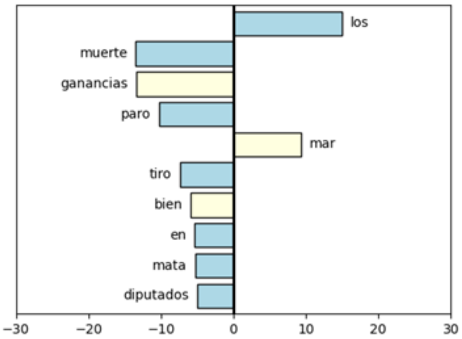


D. October 2016 (↑H from 5.55 to 5.62)

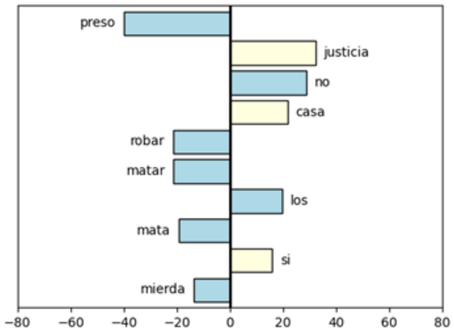


[15] It is worth mentioning that the happiness score increases each September because September 20 is the retiree's day in Argentina.

E. June 2017 (↓H from 5.53 to 5.47)



F. July 2020 (↓H from 5.46 to 5.43)



Source: Own elaboration.

Figure 8.A shows that the happiness spike is due to higher prevalence of positive words such as “mejoras”, “beneficios” and “sociales”, and a relative dearth of negative words such as “pobres”. The negative word “medicamentos” increases relatively less than the increase and decrease of positive words. Something similar occurs in October 2016 (Figure 8.D), where the positive words “viajar”, “turismo”, “Volar” and “descuento” prevail over the effect of the reduction of positive words such as "feliz" or the reduction of the frequency of negative words such as "pobres".

The relative increase of negative words such as "acreedores" and "duda" explain the decrease in the happiness score in November 2012. In turn, the combination of an increase in negative words such as "presos" together with the appearance of the words "ganan" and "sueldo" contribute to the fall in the happiness metric in July 2015.

In the last two graphs of Figure 8, words related to crime and violence such as “mata”, “muerto”, “tiro”, “preso” and “robar” strongly contribute to the reduction of happiness.

III.3. Correlation between welfare and happiness

Tables 1 and 2 show that, for the period 2010-2023, the evolution of well-being has the same pattern whether it is measured through the more traditional welfare function approach or through the novel approach based on the hedonometer. Table 4 shows the correlation between these two kinds of measures.[16]

Table 4. Matrix correlation between welfare measures and happiness measures

	Wu	Ws	Wk	Wa(1)	Wa(2)	σ=0	σ=0.5	σ=1	σ=1.5	σ=2
Wu	1									
Ws	0.972	1								
Wk	0.991	0.995	1							
Wa(1)	0.988	0.996	0.9996	1						
Wa(2)	0.959	0.989	0.983	0.986	1					
σ=0	0.429	0.449	0.444	0.442	0.383	1				
σ=0.5	0.460	0.481	0.476	0.474	0.413	0.993	1			
σ=1	0.471	0.493	0.487	0.485	0.421	0.988	0.996	1		
σ=1.5	0.495	0.513	0.509	0.506	0.440	0.979	0.988	0.995	1	
σ=2	0.435	0.428	0.434	0.429	*0.351*	0.919	0.939	0.942	0.954	1

Source: Own elaboration.

[16]This information is graphically presented in Figure A.1 of the Annex.

Note: All the correlation coefficients are statistically significant at 1% except the correlation between Wa(2) and happiness score with σ=2 (indicated in italics in the Table) , which present a p-value=1.44%.

It can be seen that the correlation between welfare measures and happiness scores are positive and statistically significant with a mean coefficient of 0.45 (minimum value= 0.35 and a maximum value of 0.51). This indicates a moderate (medium strong) linear relationship between these two measures. This is a relevant result because since the emotions of public opinion in Twitter give some idea of how well-being of the elderly varies, it becomes a relievable and powerful tool for policy makers complementary to the traditional measures of welfare.

Finally, and as expected, Pearson's correlation coefficients are higher than 0.90 when correlating welfare functions among them and happiness scores among them.

IV. Concluding remarks

This paper examines the evolution of the elderly's well-being of elderly in Argentina during 2003-2023 using abbreviated social welfare functions and the more recent hedonometer tool.

Regarding the course of the Argentinian elderly population, results show that while the 2003-2015 period was characterized by an increase in all the indicators -probably due to the recuperation of the economy after the collapse during the 2001 crisis- reaching by 2015 unprecedented levels of welfare in the last 20 years, from then on welfare has declined and nowadays is similar to the levels exhibit in 2011.

The mean happiness score measured by the hedonometer decreased over the 2010-2023 period. When we consider the mean score in different government periods, there are some differences. Twitter shows more happiness when referring to elderly people during the presidency of Cristina Fernández de Kirchner than during the presidency of Mauricio Macri, while in the last period, the score decreased again.

These results are similar to those found when analyzing the evolution of welfare functions by periods of government. Well-being increased during the presidencies of Cristina Fernández de Kirchner and decreased during the administrations of Mauricio Macri and Alberto Fernández.

To corroborate the similarity of the results obtained using both methodologies, correlation tests were performed between the indices. The correlation between welfare measures and happiness scores is positive and statistically significant with a mean coefficient of 0.45, indicating a moderate (medium strong) linear relationship between the two measures.

The evidence indicates that Twitter messages provide valuable information regarding the elderly's well-being. This result is relevant since it becomes a relievable and powerful tool for policymakers complementary to the traditional measures of welfare.

It is worth considering that twitter data has some drawbacks because of its unstructured nature. As a social media platform, information can be biased and opinions are subject to user's preferences or demographics, social influence and online behavior, among others. It is worth mentioning that Twitter universe doesn't reflect the real demographics of a country as the population using the platform is probably younger than the country's mean.

There are several directions in which these exercises can be extended. This exercise highlights a way for future research to combine various techniques and data sources, providing policymakers with enhanced tools. This shift away from considering these methods as isolated alternatives has the potential to bring about a more comprehensive and effective policymaking approach.

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Annex

Table A.1. Example tweets in frequency timeline peaks

Period	Example tweets
Decembre 2017	*Argentina aprueba reforma previsional que modificaría la fórmula para calcular las pensiones de jubilados https://t.co/jXROugJQO4 https://t.co/edA9V2TQi1*
Decembre 2019	*Se viene un #Cambio de la fórmula del #Ajuste para los #Jubilados. #Formula #Argentina https://t.co/EcNagsUjJ9 https://t.co/YAcPwB5wVA*
April 2020	*Hoy es día de cobro de jubilados y de la gran parte social de clase media baja de Argentina, tantos días de cuarentena y haciendo un gran sacrificio para que los pobres viejos hagan colas de más de dos km desde ayer... https://t.co/INKfNMIKHc*
November 2020	*El Gobierno presentó ante el Congreso el proyecto para cambiar la fórmula de movilidad jubilatoria. La oposición denunció que perjudica el bolsillo de nuestros abuelos.*
December 2020	*Ayer mientras los argentinos seguían en la legislatura el debate sobre la despenalización del aborto, los jubilados eran perjudicados con la pésima nueva fórmula movilidad jubilatoria tratada en la cámara baja y lo más alarmante un juez falló a favor de @CFKArgentina.*
March 2023	*AHORA Cuando vacía el fondo de garantía en dólares de los jubilados Massa y todos sus CÓMPLICES tampoco saldremos a la calle a defender los intereses de todos los argentinos ???*

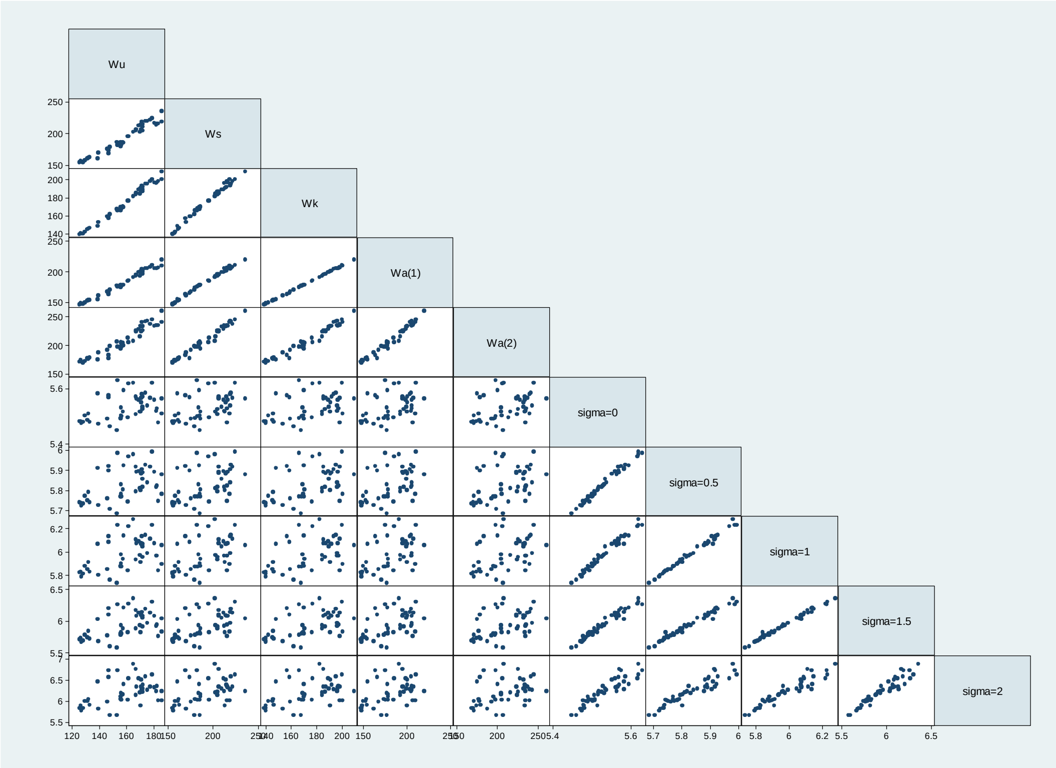
Source: Own elaboration.
Note: We include here stop words and special characters to make the meaning of the texts easier to understand.

Table A.2. Example tweets in hedonometer peaks that are not peaks in the frequency timeline

Period	Example tweets
April 2011	*#Argentina La Presidenta #CFK anunció varios beneficios sociales para jubilados, incluidos rebajas en medicamentos.*
November 2012	*Parte de los acreedores de Argentina dicen que son jubilados y no fondos buitres.*
July 2015	*Los presos cobran mas que los jubilados?! Un incentivo mas para alentar a la delincuencia!!! Bien Argentina*
October 2016	*Descuentos hasta el 50% p q jubilados viajen x #Argentina. Incluye hoteles, paquetes, vuelos y buses hasta el 15/12.*
June 2017	*El peor y más hdp gobierno de la historia #Argentina se cobró una nueva vida, hoy un jubilado en #ANSES.*
July 2020	*Jubilados en Argentina, haciendo justicia por mano propia, como debe ser, ya que estamos abandonados y es tierra de nadie el país.*

Source: Own elaboration.
Note: We include here stop words and special characters to make the meaning of the texts easier to understand.

Figure A.1. Correlation matrix between measures of welfare and happiness score



Source: Own elaboration.

Table A.3. Evolution of income, inequality and welfare. 3q03=100.

Quarter	Income	Gini	A(1)	A(2)	Wu	Ws	Wk	Wa(1)	Wa(2)
3q03	100	100	100	100	100	100	100	100	100
4q03	94	93	86	84	94	99	96	98	105
1q04	94	90	82	85	94	101	97	99	104
2q04	71	91	84	79	71	76	73	75	81
3q04	101	92	85	81	101	107	103	106	114
4q04	104	84	74	74	104	115	109	113	123
1q05	105	83	71	70	105	118	110	115	127
2q05	97	81	69	68	97	110	102	107	119
3q05	101	79	67	66	101	115	107	111	125
4q05	106	75	63	65	106	125	114	119	132
1q06	104	74	60	60	104	123	112	117	133
2q06	106	76	62	66	106	124	114	119	131
3q06	112	71	57	58	112	135	123	128	146
4q06	124	83	79	75	124	139	131	133	146
1q07	125	75	62	63	125	147	135	140	157
2q07	128	79	67	69	128	148	137	142	157
3q07	-	-	-	-	-	-	-	-	-
4q07	126	76	62	64	126	147	135	142	157
1q08	132	73	58	59	132	157	143	150	169
2q08	131	77	64	63	131	153	141	147	165
3q08	136	79	66	72	136	156	145	151	163
4q08	136	78	66	65	136	157	146	152	170
1q09	140	81	70	68	140	158	148	154	171
2q09	154	90	88	82	154	166	159	160	174
3q09	148	82	71	68	148	167	157	162	181
4q09	147	82	72	68	147	165	155	161	179
1q10	146	82	71	69	146	165	155	160	178
2q10	137	79	65	90	137	157	146	153	146
3q10	139	78	63	62	139	161	148	155	175
4q10	147	78	64	65	147	169	157	164	183
1q11	147	74	60	69	147	174	159	166	178
2q11	154	74	58	59	154	182	166	175	198
3q11	158	76	62	62	158	185	170	178	201
4q11	161	70	55	61	161	195	177	185	206
1q12	165	68	52	63	165	202	182	191	208
2q12	167	67	49	50	167	206	185	195	226
3q12	168	67	51	52	168	207	185	195	224
4q12	169	64	46	50	169	212	189	199	228
1q13	171	64	47	49	171	214	191	201	232
2q13	178	65	49	52	178	222	198	207	237
3q13	174	63	45	45	174	219	195	205	242
4q13	179	63	46	47	179	225	200	210	245
1q14	175	65	47	45	175	219	196	206	243
2q14	170	64	46	47	170	214	190	200	234
3q14	172	69	52	50	172	210	189	199	232
4q14	172	65	49	49	172	214	192	201	234
1q15	171	61	42	43	171	219	194	204	240
2q15	186	62	44	43	186	236	209	220	260
3q15	-	-	-	-	-	-	-	-	-
4q15	-	-	-	-	-	-	-	-	-
1q16	-	-	-	-	-	-	-	-	-
2q16	167	68	53	51	167	205	184	193	224
3q16	161	70	55	53	161	195	177	185	214
4q16	171	71	56	56	171	206	187	196	223
1q17	170	73	59	61	170	202	185	193	216
2q17	183	75	61	59	183	215	197	206	235
3q17	186	76	61	58	186	218	200	210	240
4q17	181	72	58	58	181	216	197	206	233
1q18	184	75	61	61	184	216	198	207	234
2q18	182	76	62	59	182	213	196	205	234
3q18	172	73	57	55	172	204	187	196	226
4q18	158	75	60	57	158	186	170	179	205
1q19	156	79	65	62	156	180	166	174	198
2q19	157	77	63	63	157	182	168	176	198
3q19	156	73	57	55	156	186	169	178	206
4q19	156	75	59	56	156	184	169	177	204
1q20	156	72	56	64	156	186	170	178	195
2q20	148	71	54	51	148	179	162	170	199
3q20	153	70	52	50	153	186	168	177	207
4q20	146	71	55	54	146	176	159	168	193
1q21	139	69	51	50	139	170	153	161	188
2q21	133	69	51	50	133	163	147	154	179
3q21	128	71	54	55	128	155	140	148	169
4q21	132	68	50	52	132	162	146	154	177
1q22	132	68	50	50	132	161	145	153	178
2q22	130	70	53	54	130	157	142	150	172
3q22	126	68	49	49	126	155	139	147	171
4q22	127	68	50	50	127	156	140	148	171
1q23	126	66	47	46	126	157	140	149	174

Source: Own elaboration based on EPH.
Note: Publication of information for the 3q07 was suspended because 4 out of 31 agglomerates couldn't be collected for administrative causes. During 3q15-1q16 there is no information because the publication of key series data was suspended for several months due to the declaration of a "state of administrative emergency" –Order no. 55/2016-.