Drama and Redistribution:

The Impact of Telenovelas on Preferences for Redistribution in Latin America[*]

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Abstract

This paper investigates the impact of telenovelas depicting social class differences on support for redistributive policies in Latin America. Focusing on the 2012 LAPOP survey data from Chile, we examine the influence of the telenovela Pobre Rico and find a significant decrease in support for redistribution policies by 21% among viewers. To generalize these findings, we employed three Natural Language Processing methods to identify telenovelas that portray social class distinctions. Consistently, we observe a reduction in support for redistribution following exposure to such telenovelas, with all methods yielding smaller effect sizes of 6-8%. The decline in support is primarily driven by a shift in lower-income individuals' perception of their own social class, leading them to believe they belong to the middle class and thus require less government support. This study provides evidence of how entertainment media can shape the (mis)perceptions of inequality, thereby influencing policy preferences.

JEL Classification: H11, H23, N16, P16

Keywords: Redistribution, Media, Latin America, Inequality, Perceptions

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1 Introduction

The perceptions about inequality are central to understand the demand for redistributive policies (Stantcheva, 2021; Alesina and Giuliano, 2009). These perceptions usually stem from the individual's exposure to inequality in their country, in their local neighborhood (Domènech-Arumí, 2023), and it can even depend on the perceptions about upwards mobility (Alesina et al., 2023, 2018). The portrayal of inequality in media can skew individuals' perceptions of income inequality within their country, impacting their trust in others (Diermeier et al., 2017), and shape their beliefs in upward mobility (Kim, 2023). This (mis)perception of inequality subsequently impacts individuals' likelihood of approving redistributive policies. Thus, how media depicts socioeconomic disparities through its narrative directly affects societal attitudes toward redistribution.

This study explores the influence of exposure to telenovelas that display social classes on the preference for redistribution in Latin America.[1] First, we analyze the telenovela *Pobre Rico*, which centers around the disparity between the poor and the rich, on preferences for redistribution. Telenovelas, with their wide reach and intense viewer engagement in Latin America, are particularly influential in shaping perceptions due to their pervasive and serialized depiction of social class disparities, making them a critical focus compared to other forms of media. We find that individuals after the premiere of *Pobre Rico* have lower support for redistribution policies. In particular, exposure to the show decreased support for redistribution policies by 0.813 points (p-value = 0.017, sd = 0.34) or by 20% compared to those interviewed before the premiere. I also tested the validity of the results by conducting a placebo test of the airing of *Pobre Rico* in other countries of Latin America and we found no exposure effect.

Second, we explore the effects of other telenovelas across different countries of Latin America, aiming to assess the generalizability of the *Pobre Rico* findings. We begin by gathering data on telenovelas that were aired in Latin America recording a written synopsis, the air time and date, the ending date, the number of episodes, the broadcasting channel, and the genre of the show (e.g. comedy, drama, or melodrama). Subsequently, we use Natu-

[1] "Latin American telenovelas or soap operas are prime time TV shows broadcasted Monday to Friday, with a fixed time, for between 100 and 200 episodes of around one hour each." (Gulesci et al., 2023)

ral Language Processing (NLP) techniques to analyze the synopses and identify which of these telenovelas depict social class disparities. In particular, I implement three methods using telenovela synopses: (i) a dictionary-based approach utilizing related terms extracted from ConceptNet, (ii) a vector embedding approach using the Universal Sentence Encoder (USE), and (iii) categorization via ChatGPT, a generative AI model capable of classifying with minimal or no examples. Following a similar indentification strategy to the *Pobre Rico* case study, this exercise reveals that exposure to social telenovelas consistently decreases support for redistribution across various categorization methods with effect sizes ranging from -6 to -8%. Notably, this effect does not intensify with increased exposure, as viewing one or two telenovelas yields similar outcomes. The most plausible explanation for this trend is that lower-income individuals perceive themselves as belonging to a higher social class, reducing their perceived need for redistribution. Importantly, our findings indicate that this exposure does not alter political attitudes. Furthermore, a placebo test confirmed that the influence of these telenovelas is specific to social class perception and redistribution preferences, without affecting trust in the church or support for minority presidential candidates.

Literature Review This work contributes to the literature that wants to understand the role of media in shaping individuals' social attitudes and behavior. Pioneering studies have focused on media bias (Gentzkow et al., 2015; Martin and Yurukoglu, 2017; Drago et al., 2014; Ash and Hansen, 2023) and the impact of radio and newspapers on political outcomes (Besley and Burgess, 2002; Strömberg, 2004). Recently researchers explored the effects of television on a variety of social and political behaviors for American and African viewers, such as voter turnout (Gentzkow, 2006) teenage education outcomes (Gentzkow and Shapiro, 2008), acceptance of domestic violence (Jensen and Oster, 2009), teenage pregnancy (Kearney and Levine, 2015), HIV attitudes (Banerjee et al., 2019), and approval for domestic violence.

We focus on telenovelas, commonly known as soap operas, which have been recognized as potent tools for shaping individuals' behavior and attitudes across a range of social issues in Latin America. La Ferrara et al. (2012) and Chong and La Ferrara (2009) show how the entrance of a Rede Globo, which essentially introduced telenovelas to viewers in

Brazil, decreased fertility and an uptick in divorce filings, respectively. Moreover, Gulesci et al. (2023) provides evidence suggesting that exposure to characters from the LGBTIQ+ community in telenovelas reduces the support for said community in Latin American countries. The latter study highlights the complex and potentially contradictory effects of media representation on attitudes toward specific communities or topics.

This paper aims to contribute to the existing literature by shedding light on the role of telenovelas in shaping viewers' preferences for redistributive policies. Latin America has a long history of significant income inequality (Fergusson et al., 2023) alongside lower levels of redistribution compared to developed economies (Ocampo and Gómez-Arteaga, 2018). Given the ongoing struggles with income distribution in the region, it's vital to grasp the impact of entertainment media on the survival of various redistributive policies through political approval.

Our paper also extends to the broader literature seeking to understand how perceptions of inequality influence the demand for redistributive policies (Stantcheva, 2021; Alesina and Giuliano, 2009). Alesina et al. (2018) explores the role of upward mobility in shaping perceptions of inequality, shedding light on how individuals' aspirations and opportunities for advancement influence their attitudes toward redistributive policies. Alesina et al. (2023) shows evidence that the (mis)perceptions of inequality about the intensity of immigration decrease support for redistributive policies. Domènech-Arumí (2023) argues that exposure to inequality within one's neighborhood can improve the approval of redistribution policies, adding to our understanding of the complex nature of individual experiences and redistributive preferences. Our study higlight the role of entretainment media to shape individuals perception of their own social class, and our finding that the (mis)perception of their social class as potential driver for lower redistribution is consistent with previous research.

A small part of this literature has studied the portrayal of inequality or upward mobility in the media and its impact on perceptions. Diermeier et al. (2017) shows that intense coverage of inequality in the newspapers worsens individuals' perception of social fairness in Germany. Kim (2023) shows that exposure to programs that promote "rags-to-riches" narratives (e.g. *Americal Idol* or *Shark Tank*) reinforces American's belief in upwards mobility through laboratory and online experiments. In contrast, our study focuses on preferences for redistribution, instead of fairness or upward mobility, allowing a more direct examination of individuals' support for policies addressing inequality. In addition, our results show that telenovelas also shapes individuals (mis)perception of social class. Telenovelas are narrative-driven stories that may offer individuals a more relatable experience compared to contest show contestants or fact-driven media like newspaper articles.

2 Case Study: *Pobre Rico*

Pobre Rico is a comedy television series aired in Chile in 2012 that narrates the story of two babies swapped at birth between a wealthy and a poor family, providing a vivid illustration of social class differences. It juxtaposes the challenges faced by a teen gas station worker with the lifestyle enjoyed by the son of one of the most influential families in the country. The first paragraph of the translated synopsis can be found below:

> *Freddy Pérez and Nicolás Cotapos have led a normal life until now. They are two happy boys and are very comfortable in each of their worlds. Meanwhile, El Rucio, as Freddy is known, lives with his mother Eloísa and his sister Megan in poorer economic conditions. Nicolás lives with his parents Máximo and Virginia, and with his sister Julieta, in a wealthy family. The Cotapos are owners of the Cotapos Holding and Cotapos Airlines, while the Pérez are workers at a gas station.*

This telenovela effectively illustrates the economic gap between the Cotapos (rich) and Pérez (poor) families through their sets and script. Figure D.1 displays screenshots taken from the first episode of the show. Panels (a) and (c) portray the wealth of eich families in Chile, characterized by a spacious residence, adorned with several windows and a fence, alongside modernly decorated living rooms, ownership of at least two cars, and a maid. In stark contrast, panel (b) and (d) presents the reality of low-middle-income families, with modest dwellings featuring only two small windows, the absence of cars, and worn-down living spaces. Another aspect through which the show contrasts the two families is by the way the characters speak. Socioeconomic disparities often manifest in linguistic nuances (Guy, 1988; Anderson et al., 2022), and *Pobre Rico* employs this dynamic. On the one hand, The Cotapos (rich) are articulate, use precise grammar, and employ a formal vocabulary. On the other, The Perez (poor) frequently employ colloquialisms and slang, reflecting the linguistic patterns associated with their socioeconomic status.[2]

Pobre Rico was popular among Chilean viewers. Figure D.2 shows the Google Trends data for Chile and reveals a surge in interest surrounding the show's premiere, with search intensity surpassing even the news on the same TV channel. The debut episode achieved an impressive rating of 33.1, significantly outperforming other channels' average ratings of 8.[3] Moreover, the show's overall rating of 19 exceeded the mean of 16, indicating its widespread appeal. Further attesting to its popularity, the first episode uploaded to YouTube in 2019 amassed a staggering 2 million views.[4] This YouTube viewership surpassed even a famous late-night comedy show *Morandé con Compañía* which averaged 1 million views per episode.

2.1 Empirical Strategy

To assess the impact of *Pobre Rico* on preferences for redistribution, I utilize the 2012 LAPOP survey in Chile. This survey poses a straightforward question to individuals: "Are you willing to pay more taxes if this will go to help those with less money?" used to measure of preferences for redistribution policies.[5] Respondents indicate their agreement on a scale from 1 to 7, where 1 means strongly disagree and 7 denotes strongly agree. Figure 1 shows

[2] This linguistic phenomenon is similar to the ways of speech of different racial groups in the United States.

[3] A TV show's rating typically refers to the Nielsen rating, a measurement system used to determine the audience size and composition of television programming in the United States. A Nielsen rating of 17 means that 17% of households that have a TV were watching the show at a particular time. The Nielsen rating of a TV show is derived from the average rating of its episodes.

To put the rating of 33.1 into perspective, " ... the broadcast of the game [of the Libertadores Cup between River and Boca, the most popular rival Argentinian soccer teams,] reached an average 37 rating points [in Argentina]..." https://sportslatam.com/web/index_php/en/news/television-en/item/1105-historic-ratings-for-the-final-match-of-the-libertadores-cup/

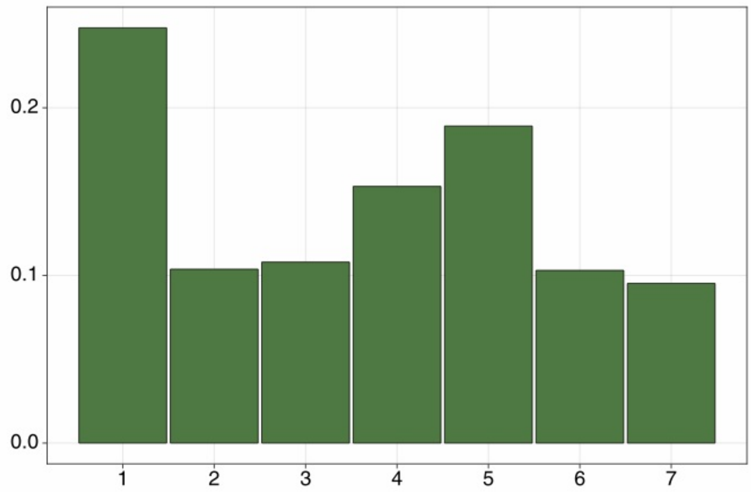
Another example here https://www.latercera.com/el-deportivo/noticia/superclasico-de-record-el-historico-triunfo-de-la-u-sobre-colo-colo-en-el-monumental-rompe-registros-de-audiencia/JMPTM52EGRHLNNPAM5J52JHOE4/ for chile!

[4] The Chilean population in 2017 was around 18 million (INE, 2018). Due to sampling issues, the closest Census in 2012 was canceled and therefore not used for comparison.

[5] Similar questions have been used to measure preferences for redistribution in the literature. Domènech-Arumí (2023) uses a similar question with 0 indicating that people would pay higher taxes for the goverment to provide social security benefits and 10 to those that are not willing to pay higher taxes. He also states that it's *"... a question in the General Social Survey (GSS) commonly used to study distributional preferences [in the U.S.] (Alesina and Giuliano, 2009)."*

the distribution of the answers for this question in LAPOP 2012 with two peaks located at position 1, strongly disagreement of redistributive policies, and another at position 5, relative approval of redistributive policies.

Figure 1: Distribution of the outcome variable



Notes: Distribution of the main outcome variable. The survey asks individuals the question: *Are you willing to pay more taxes if this will go to help those with less money?* Respondents indicate their agreement on a scale from 1 to 7, where 1 means strongly disagree and 7 denotes strongly agree.

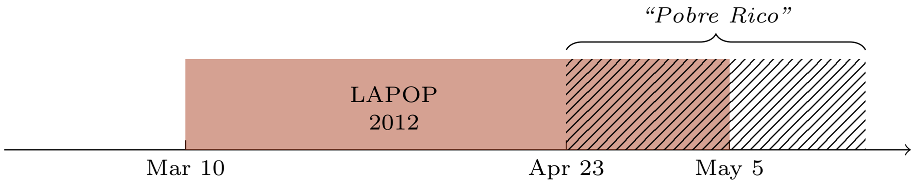
The survey's fieldwork spanned from March 10th to May 5th, coinciding with the initial airing of the series' first episode on April 23rd. Figure 1 illustrates the timeline of these events. This enables a comparison of individuals' responses to the redistribution question before and after the telenovela's debut. Specifically, we will aggregate responses to the redistribution question forming two groups. The control, or not-exposed *Pobre Rico*, group are those who were interviewed between March 10th and April 22nd. The treatment, or exposed to *Pobre Rico*, group are those who were interviewed interviewed between April 23rd and May 5th.

Pobre Rico provides the cleanest identification for two reasons. First, there were no other telenovelas prominently depicting social class disparities during LAPOP's fieldwork in 2012.[6] Other telenovelas, like *Aqui Mando Yo*, occupied the same time slot and competed for viewership but did not displayed social class differences.[7] Before the fieldwork started,

[6] At least given my own categorization of telenovelas that displays social classes.

[7] Focused on the conflict where the husband assumes the role of the homemaker while the wife pursues a

Figure 2: *Pobre Rico* timeline



the last telenovela that displayed social class differences was *Peleles* and ended in January 15th, almost three months before the debut of *Pobre Rico*.[8] Second, LAPOP fieldwork consistently occurs between presidential election years, which helps me to filter out any political noise generated by election years.[9] Priot to the fieldwork, the last election was in January 2010 and the following presidential election was in November 2013.

To measure the causal effect of *Pobre Rico* on prefernces for redistribution we estimate the following regression:

$$y_{id} = \alpha + \beta Pobre\_Rico_d + \gamma X_i + \epsilon_{id} \tag{1}$$

where y_{id} is the outcome variable that measures preferences for redistribution of individual i at date d. Our treatment varaible is $Pobre\_Rico_d$ that takes a value of 1 if the individual was interviewed after April 23$^{\text{rd}}$ and a 0 if they were interviewd before April 23$^{\text{rd}}$. X_i is a vector of individuals characteristics such as gender, age, urban residence, employment, income decile, education, religion, and marrital status. The coefficient of interest (β) will then capture the direct or indirect short-term impact of the exposure to the telenovela *Pobre Rico* on the preferences for redistribution.[10]

One concern is that individuals interviewed before and after the premiere of *Pobre Rico* are not comparable. show. Table 1 presents the mean differences across various observable characteristics within the sample. Particularly, the exposed group, interviewed post-premiere, disproportionally are female, reside in rural areas, and exhibits lower in-

career

[8] *Peleles* shows the story of five former employees, ranging from the general manager to the humble security guard, who find themselves unexpectedly unemployed. Now faced with their new harsh realities, they unite to orchestrate what could potentially be deemed the greatest heist of the century, navigating through layers of intrigue, betrayal, and personal redemption along the way.

[9] Municipal elections happened on October of 2012, almost 6 months after the end of the fieldwork.

[10] We are capturing the direct effect of the telenovela of individuals that watched the show, but also the indirect effects of being exposed to the show from other people talking about it online, home, work, etc.

come levels compared to their pre-premiere counterparts. [11] Although we directly control for these characteristics in our main regressions, this group imbalance may still bias the estimates. One might intuitively expect that individuals with lower incomes would be more likely to support redistribution, suggesting a potential upward bias in my estimates. Similarly, a more rural population tends to be lower income, and thus one should also expect an upwards bias. There is no intuitive relation between support for redistribution and gender, however when you look at the data there is not a clear difference between mean and women.[12] Taking all these potential bias into account, it is most likely that our estimates are upwards biased. Even with this upwards bias, our results still suggest that the exposure to *Pobre Rico*, or any social telenovela, decreases support for redistribution.

Table 1: Balance Table

	Treated N=31	Control N=619	Diff.		T-stat
Female	0.645	0.494	0.151	*	1.706
Age	43.419	42.383	1.036		0.534
Education	11.839	11.551	0.288		0.388
Catholic	0.581	0.664	-0.083		-0.918
Married	0.548	0.565	-0.017		-0.186
Employment status	0.935	0.927	0.008		0.180
Urban	0.548	0.906	-0.358	***	-3.964
Income decile	6.419	7.407	-0.988	**	-2.242

Note: catholics is a dummy for wheter the individuals is catholic or not. employment status refers to wheter the individual is in the working or unemployed.

2.2 Results

Table 2 summarize the estimates of the equation 1 controlling for individual observabel characteristics of characteristics like gender, age, urban, employment, income decile, education, religion, and marrital status. Exposure to *Pobre Rico* is associated with a decrease in approval

[11] Mainly because at the end of the fieldwork they interviewed people outside of Santiago (capital city), which harbors haft of the population of Chile.

[12] There is a difference of -0.05 points (se: 0.112, p_value = 0.65) in a scale from 1 to 7 between men and women for the question "*Are you willing to pay more taxes if this will go to help those with less money?*".

for redistribution by 0.813 points or by 21% (compared to the control group's average 3.87). To explore distributional shifts, columns 2 and 3 examine the impact on the proportion of respondents who rated their approval at 7 or higher and 5 or higher, respectively. Both columns yield negative coefficients, indicating a reduction in approval, particularly among those who initially favored redistribution. Notably, column three highlights a substantial decrease: while 40% of the unexposed group rated their approval at 5 or higher, this proportion plummeted to only 10% among the exposed. Furthermore, column 4 suggests that some individuals with initially low levels of approval for redistribution may have increased their support, although not statistically significant. Column 5 shows follows similar patterns for those that strongly disagree with redistribution. Our results still suggest that the exposure to *Pobre Rico* decreases support for redistribution, even when considering the upwards bias arising from the group imbalance. Moreover, it suggest that our estimates as a lower bound.

Table 2: The effects of the exposure *Pobre Rico* on preferences for redistribution

	Pay more taxes to help the poor?					
	1-7	Strongly approve	Approve	Neutral	Disapprove	Strongly disapprove
Exposure to Pobre Rico	-0.813**	-0.087**	-0.284***	0.180**	0.104	0.064
	(0.340)	(0.035)	(0.073)	(0.086)	(0.102)	(0.084)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
N	650	650	650	650	650	650
R^2	0.036	0.030	0.031	0.030	0.039	0.027
Control mean	3.859	0.116	0.433	0.155	0.412	0.225

Controls: gender, age, urban, employment, income decile, education, religion, and marrital status. The outcome variable is measured from 1 to 7. A rating of Strongly approve is denoted by those who answered 7. Approve (≥ 5) corresponds to a score of 5 or more. Disapprove (≤ 3) indicates a score of 3 or less. Robust standard errors are in parentheses.

Appendix A shows how the effect of *Pobre Rico* it may be due to high income individuals lowering their support for redistribution. We also explored other mechanisms such as political leaning and found no exposure effect, suggesting that the income channel is important. However, the sample size in this case is relativelly small and would need more data to understand the potential mechanisms of this redusction in support for redistribution after being exposed to telenovelas similar to Pobre Rico. In addition we introduced time trends and time windows around the premiere to estimate equatioin 1, which show similar size effects, although more intese effects when we restrcit the sample to smaller window sizes.

Placebo test We also test whether *Pobre Rico* changed preferences for redistribution in other Latin American countries where the telenovela was not broadcasted. The problem is that our question measuring redistribution is not available in other countries for 2012. Thus, we look at a similar question *Would you be willing to pay more taxes than you do currently so that the government can spend more on [income transfer program specific to the country]?* where respondents indicate their answer as yes or no. This question is available for Argentina, Brazil, Chile, Colombia, Costa Rica, Guatemala, Mexico, Peru, Venezuela, and Uruguay in the 2012 LAPOP survey.[13] Table 3 shows the results of this exercise. We find a sizable reduction of a 12pp for the probability of aggreeing with the previous statement (which is a 60% reduction of the support for redistribution), meanwhile there is no effect in the other countries of Latin America.

Table 3: Placebo test with other countries in Latin America

	Chile	others
	(1)	(2)
Exposure to Pobre Rico	-0.1263**	0.0002
	(0.049)	(0.029)
Country Fixed Effects		Yes
Controls	Yes	Yes
N	579	1,524
R^2	0.020	0.056
Control mean	0.198	0.231

Controls: gender, age, urban, employment, education, religion, income and marital status. The controls include gender, age, urban, employment, education, religion, income, and marital status. Robust standard errors are in parentheses for column (1). The regression in column (2) includes Argentina, Brazil, Colombia, Costa Rica, Guatemala, Mexico, Peru, Venezuela, and Uruguay and standard errors are clustered at the country level.

In Appendix A we also tested wether the *Pobre Rico* effect also changes individuals attitudes towards religion and minorities running for president and we found no exposure effects, higlighting that *Pobre Rico*'s main conflict revolves around social classes in particular (at least at the start).

[13]The correlation of our main question and this one is weak but positive (0.3) for the Chilean sample.

3 Generalization of *Pobre Rico*

The case study of *Pobre Rico* offers a compelling glimpse into the economic dynamics portrayed within a Chilean telenovela. However, the social class disparities depicted in *Pobre Rico* may not be representative of all telenovelas, particularly those where the differences between economic classes are not as stark. In this section, I will test whether the reduction in support for redistribution observed in *Pobre Rico* holds true across other years and countries.

To achieve this, I have collected data on telenovelas from various Latin American countries. Using the synopses of these telenovelas, I employ three methods to identify those with social class conflict as a central theme, similar to *Pobre Rico*. The first method is a naive approach that involves using related terms commonly found in social class-focused telenovelas, such as "poor" and "rich," by leveraging the ConceptNet dataset. The second method involves transforming the synopses into vector embeddings and then identifying those telenovelas that are closely related to *Pobre Rico*. The third method uses ChatGPT to categorize each synopsis as either depicting social class conflict or not.

After categorizing the telenovelas, I will apply a similar identification strategy to that used in the *Pobre Rico* case study, with a few caveats, to determine the causal effect of telenovelas that display social class differences on the demand for redistributive policies.

3.1 Data

3.1.1 Preference for Redistribution Surveys

Data on preferences for redistribution were sourced from the Latin American Public Opinion Project (LAPOP). The LAPOP has conducted numerous surveys across Latin America, collecting data on a wide range of socio-political issues, including attitudes toward redistribution policies. However, the specific question I analyzed in the *Pobre Rico* case study is not available in all waves of this survey. To address this limitation, I will use a different question that is commonly employed to measure support for redistribution.[14] Individuals are asked

[14]Since these two question have missing data, the samples are different. For instance, the sample used in regressions for the Pobre Rico case study is about 650 observation, while the sample of this new question has 688 observations.

to rank their agreement to the following statement from 1 to 7. *"The (Country) government should implement strong policies to reduce income inequality between the rich and the poor"*.[15] An answer of 1 indicates strong disagreement with the statement and 7 a strong agreement with the statement. This alternative question is available across all survey waves in the sample, spanning from 2006 to 2023.

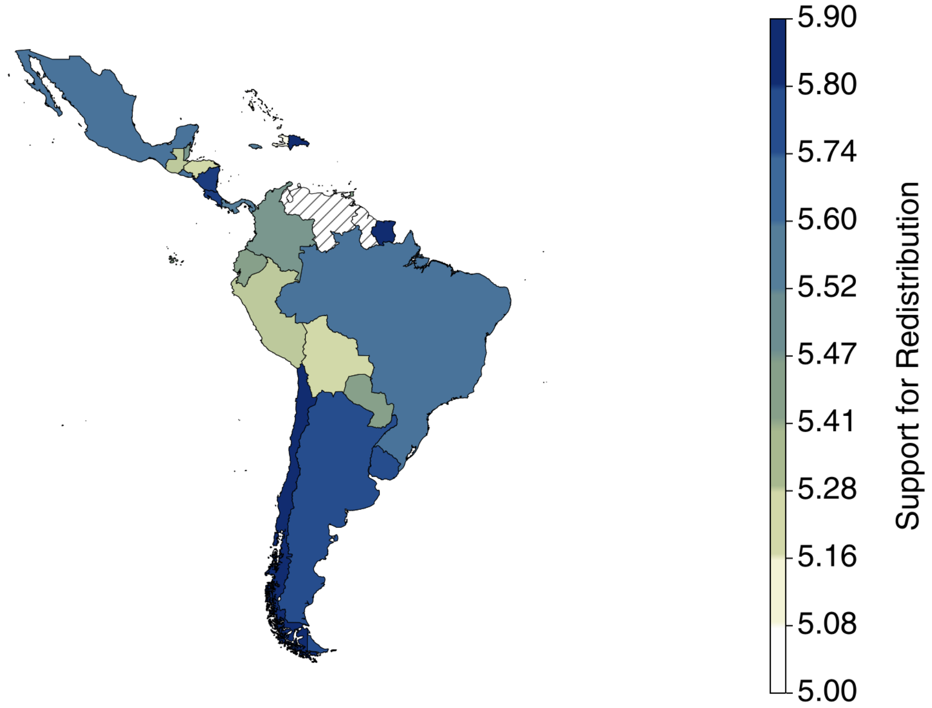
The two survey questions measure support for redistributive policies but do so in different ways. The original question refered to as the "individual" question, "*Are you willing to pay more taxes if this will go to help those with less money?*" focuses on the respondent's personal willingness to contribute financially to redistribution through higher taxes. It directly asks about a specific action that impacts the individual. In contrast, the new question refered to as the "government" question, "*The (Country) government should implement strong policies to reduce income inequality between the rich and the poor*," is broader and centers on the respondent's support for government intervention in reducing income inequality. It doesn't ask for a personal financial commitment but rather gauges general approval for government-led efforts to address inequality. This shift in focus allows the new question to capture a wider range of attitudes toward redistributive policies without tying them directly to personal financial sacrifice. In contrast, this also allows the individual to have lower attachment to the question, making it hard to report lower aggrement. For instance, in the LAPOP 2012, the chilean mean aggrement level for the "individual" question was about 4, while the chilean mean agreement level for the "government" question was about 5.8. The correlation between these questions in *Pobre Rico* is $\rho = 0.3$, which is positive but not high.

Figure 3 shows the mean value of the "govenrment" question across the survey waves in each country. First thing to note is that there is a high level of support for redistribution in latin america in this question with a overall mean of 5.5 of out 7, with most of the individuals in each country concentrating in high values of support. The countries with the highest

[15] Other studies measuring support for redistribution have been using similar questions centering on the role of government to reduce inequality. Alesina and Giuliano (2011) uses as their main measure for support for redistribution this question from the World Value Survey *"Some people think that the government in Washington should do everything to improve the standard of living of all poor Americans (they are at point 1 on this card). Other people think it is not the government's responsibility, and that each person should take care of himself (they are at point 5). Where are you placing yourself in this scale?"*. Alesina et al. (2023) also used question with the role of the government for instance used how big is the governments budget for social causes like education, but also asked question what should be the tax rate for both the top 1% and bottom 90%, which are more related to the original question.

approval for redistributions are Chile, Nicaragua, and Costa Rica, while Haiti and Bolivia exhibit the lowest support.

Figure 3:



Note: blah blah

3.1.2 Telenovelas

Data on telenovelas were collected using various online sources tailored to each country of interest. From each source we gathered a written synopsis, the air time, the duration (air and end date), the number of episodes, the broadcasting channel, and the genre of the show (e.g. comedy, drama, or melodrama). Additionally, we extracted ratings for each telenovela from the IMDb website, which provides an indication of how well-received each telenovela was by its audience. Telenovelas aired in Chile were gathered from the chilenovelas, a Wiki-like page, which provides comprehensive lists of telenovelas along the genre of telenovelas, ratings, duration, airing times, cast members, and synopses. Similar information for Brazilian telenovelas was sourced from teledramaturgia. For other Latin American countries, partial lists of television telenovelas are available on Wikipedias. While the coverage may vary, these sources provided sufficient data to analyze television programming trends across the region.

(ADD a sentence to why should the summaries contain the essence of the telenovelas, here you can cite *Portraying Poverty: The Economics and Ethics of Factual Welfare Television*)

I utilize the synopsis of each telenovela in both its native language, whether Portuguese or Spanish, as well as its English-translated version. For the translation, I use ChatGPT, which provides a comparable quality in translating text from Spanish to English and performs reasonably well from Portuguese to English (Sanz-Valdivieso and López-Arroyo, 2023; Törnberg, 2023).[16]

Table 4: Description of telenovela data

	mean	sd	min	max
Panel A: All telenovelas (N = 333)				
Drama (%)	76.28			
Air time	19:32	3:53	17:55	23:15
N of episodes	156	70	16	564
Synopsis word count	2161	868	212	6710
Rating	17.01	8.66	3.00	46.70
Panel B: ConceptNet Social Class (N = 73)				
Drama (%)	75.34			
Air time	19:32	3:53	17:55	23:15
N of episodes	166	70	23	564
Synopsis word count	2732	868	1114	6710
Rating	18.86	8.66	5.30	38.50

	mean	sd	min	max
Panel C: USE-PCA Social Class (N = 47)				
Drama (%)	72.34			
Air time	19:32	3:53	18:00	23:10
N of episodes	124	70	16	320
Synopsis word count	1808	868	212	5187
Rating	16.63	8.66	4.60	37.50
Panel D: ChatGPT Social Class (N = 112)				
Drama (%)	76.79			
Air time	19:32	3:53	18:00	23:00
N of episodes	169	70	36	545
Synopsis word count	2437	868	818	6119
Rating	19.28	8.66	5.30	46.70

Notes: ...

We have gathered a total of 333 telenovelas from Chile, Brazil, Mexico and Argentina. Table 4 shows some descriptive statistics. Panel A presents the descriptive statistics for all the telenovelas in my sample. The majority of the telenovelas are categorized as dramas or melodramas.[17] On average, a telenovela airs around 19:30, consists of 156 episodes, and has a rating of 17 points. The word count for each synopsis varies significantly, with a mean around 2,000 words, but with some telenovelas having as few as 212 words and others exceeding 4,000 words. This variation in word count could pose challenges depending on

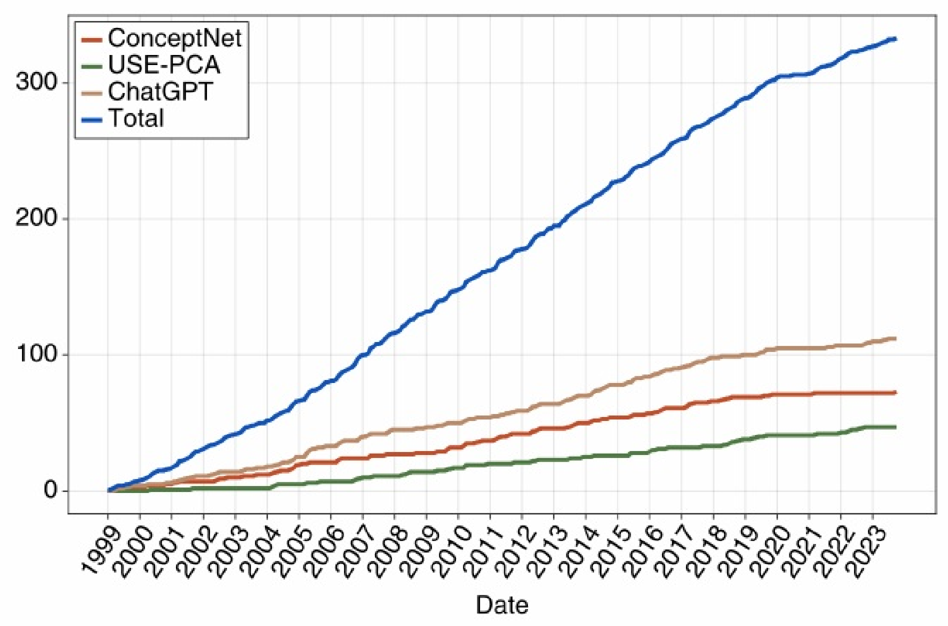
[16] There are other other alternatives like DeepL and Google Translate that come at a higher cost. See Hidalgo-Ternero (2020) for a discussion on the Spanish to English translation of these two alternatives.

[17] for those without a pre-assigned genre, I used ChatGPT to determine the genre

the categorization method used, which will be discussed later. However, given that I employed three different methods, this issue may be mitigated. Panels B, C, and D provide the descriptive statistics for each of the categorization methods.

Telenovelas displaying social class conflict are not that frequent in Latin America. Figure 4 shows the cumulative time series of all the telenovelas collected in our sample and the cumulative sum of the social telenovelas identified with each categorization method, which we will describe in detail in the section bellow. The cumulative sum of social telenovelas by all categorization methods are well below the cumulative line of all telenovelas. This suggest that social class conflict is a common theme when producing telenovelas in LATAM but is far from being the most common theme.[18]

Figure 4:



Note: blah blah

3.2 Categorization of Telenovelas

To accurately identify telenovelas that portray social class disparities, I utilize three natural language processing (NLP) techniques, each designed to efficiently handle the vast amount of data available. Using NLP is essential for several reasons. Human categorization, while

[18]Qualitativly, most telenovelas in my sample are centered around the themes of love, family, and historic events.

valuable, is often unreliable, as it can be influenced by subjective biases and inconsistencies (Evans and Aceves, 2016; Dhar et al., 2021; Rathje et al., 2024; Grimmer and Stewart, 2013). Additionally, manually categorizing a large number of telenovelas is both time-consuming and costly. In contrast, machine-based categorization, though not without its imperfections, offers a more efficient and scalable solution. Importantly, these techniques have been employed in previous research, and there is strong evidence to suggest that they correlate well with human categorization (Rathje et al., 2024; Törnberg, 2023; Michalopoulos and Rauh, 2024).[19] To implement this, I employ three specific methods using the telenovela synopses as input: (i) a dictionary approach using related words extracted from ConceptNet, (ii) a vector embedding approach utilizing the Universal Sentence Encoder (USE), and (iii) categorization through ChatGPT, a generative AI capable of classifying with few or even zero examples.

These three NLP methods each have distinct advantages and limitations. The dictionary-based approach using ConceptNet offers simplicity and transparency, allowing for direct control over keyword selection and efficient processing. However, it may lack flexibility, potentially missing nuanced meanings or synonyms, and can introduce bias through the researcher's choice of terms. The Universal Sentence Encoder (USE) provides a more sophisticated alternative, capturing contextual meanings and handling synonyms effectively, which allows for better generalization to unseen data. This approach, though, is more complex and relies on the quality of the pre-trained model not necesarrily trained to understand Latin American telenovela synopses. Lastly, categorization via ChatGPT offers high flexibility and the ability to understand context and subtle language features with minimal input examples. However, this method is somewhat opaque, making it difficult to interpret its reasoning and prone to generate errors in specialized settings, although I employ methods to reduce this shortcomings. Combining these methods helps to ensure robustness and reliability in the findings, as it mitigates the limitations inherent in any single technique and provides a more nuanced understanding of the data.

[19] For a simple validation exercise of how the categorization performs compared to my own categorization of the Chilean telenovelas please refer to Appendix B.4.

Table 5: ConceptNet Example using "poor"

root		related terms		
		EN	ES	PT
poor	$\longrightarrow$	poor	pobre	pobre
		poorer	pobrete	pobres
		slummy	pobretones	pobretão
		resourceless	pobretón	
			pobres	

3.2.1 ConceptNet

The first approach involves constructing a dictionary comprising terms associated with social class, and assigning a social class score based on the frequency of these terms in each synopsis. After scoring each telenovela I chose a threshold value, δ, and consider all telenovelas as depicting social class differences if their score exceeds this threshold.

To build this dictionary, I begin by compiling a list of root words that typically refer to social class conflict, such as "economic," "wealthy," "inequality," and "social class."[20] Using these root words, I then search for related terms in ConceptNet, a knowledge graph of natural languages that show the relations between words in any language. For example, in Table 5 contains the root word "poor" and some of the related terms found in English (EN), Spanish (ES) , and Portuguese (PT). The word "poor" is related to terms are "poor", "poorer," "resourceless," and "slummy," in English, as well as "pobre" and "pobretón" in Spanish which translate to "poor".

As a concrete example, take the extract from the first paragraph of *Pobre Rico* and *Mama Mechona*, a telenovela about a mother and son going to college at the same time which does not display social class differences, synopses in Example 1. Suppose that the dictionary only contains the word "poor" and it's related terms in English (poor, poorer, slummy, resourceless).

[20]For the full list of words and their related terms please see Table B.1 and B.2 in the appendix.

Example 1: ConceptNet Score

Pobre Rico

Freddy Pérez and Nicolás Cotapos have led a normal life until now. They are two happy boys and are very comfortable in each of their worlds. Meanwhile, El Rucio, as Freddy is known, lives with his mother Eloísa and his sister Megan in **POORER** economic conditions. Nicolás lives with his parents Máximo and Virginia, and with his sister Julieta, in a wealthy family...

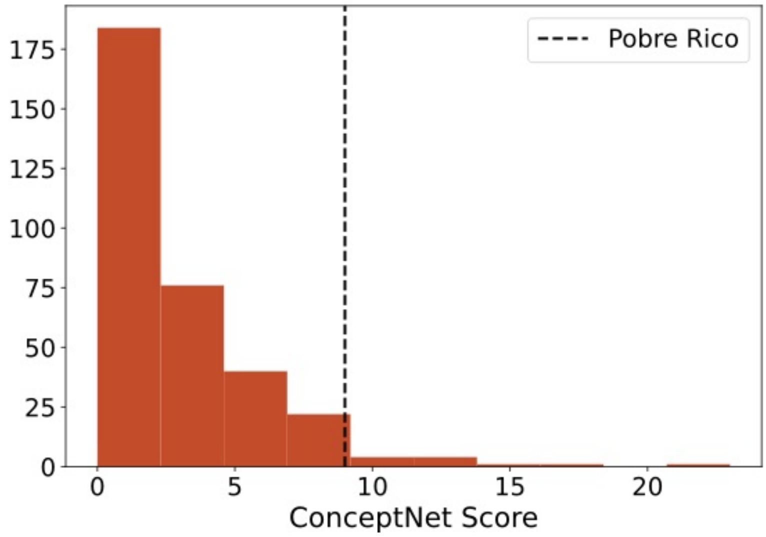
Mama Mechona

Macarena is a 40-year-old woman, homeowner and mother of three children... Macarena decides to rethink her life and decides to turn it around. Secretly, he prepares to take the University Selection Test and registers to study psychology... When her family discovers that Macarena is now a university student, everyone reacts differently.

The telenovela *Pobre Rico* then gets a score of 1, since only one word from the dictionary (the word poor) matches. The telenovela *Mama Mechona* will get a score of zero since neither "poor", "poorer," "resourceless," nor "slummy" appear in it's synopsis.

Using the related word list, I assigned a ConceptNet score to each telenovela based on the presence of these words in its synopsis. If a word from the related word list appeared more than once in a synopsis, it was counted only once, contributing a single point to the score. Figure 5 shows the histogram of the ConceptNet scores across the telenovelas in the sample.

Figure 5: ConceptNet Score Histogram



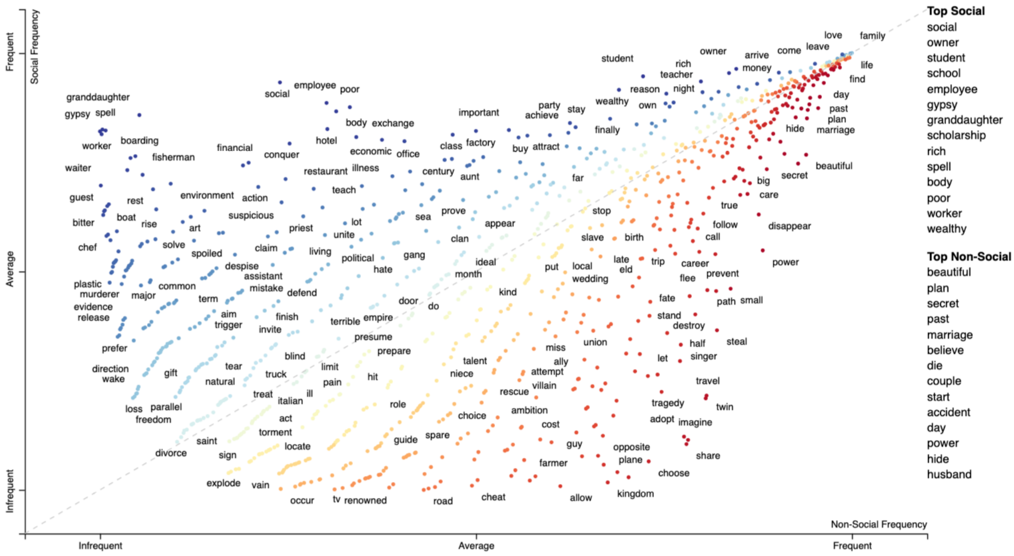
Note: blah blah

Applying this procedure to my telenovela dataset, I obtained a mean score of 2.9 with a standard deviation of 3. *Pobre Rico* has a score of 9, indicating that the average telenovela in the dataset is about two standard deviations away from *Pobre Rico* in terms of social class-related content. To provide context for what these scores represent, consider the telenovela *Chipe Libre*, which has a score of 0. This story revolves around a couple taking a break and exploring new romantic entanglements, leading to a series of complicated and passionate relationships that challenge their views on love and fidelity, with no significant social class conflict depicted. In contrast, a telenovela with a high score of 14 is the Brazilian *Chocolate com Pimenta*, where a poor young woman returns to her hometown as a wealthy lady, seeking revenge on those who humiliated her, while also confronting her unresolved love for a man she believes betrayed her.

I set the threshold $\delta = 5$, meaning that any telenovela with a score equal to or higher than 5 will be considered as depicting some level of social class conflict. This threshold is 4 points (or roughly one standard deviation) below *Pobre Rico*. The lower threshold is intended to include telenovelas that might present more subtle forms of social class conflict compared to *Pobre Rico*. For example, the telenovela *Corazón Rebelde* has a score of 6 and tells the story of of a secret sect torments scholarship students, a group of teenagers at an elite boarding school forms unlikely bonds through music, challenging the school's rigid hierarchy and battling for their dreams against all odds..

In total, 73 telenovelas have a score ≥ 5. Descriptive statistics for these telenovelas are presented in Panel B of Table 4 To assess whether we are indeed capturing social class conflict, we can examine the words frequently used in each category, as shown in Figure 6. The words in the top left quadrant of Figure 6 are frequently used in telenovelas identified by ConceptNet as depicting social class conflict but are infrequent in the remaining telenovelas. These words include "gypsy," "worker," "scholarship," "employee," and "social," all of which may have social class conflict connotations. Other words, such as "rich," "owner," "money," and "wealthy," are common in both categories but are relatively more frequent in the 73 chosen telenovelas. While this categorization is not perfect and may not capture all telenovelas with social class conflict connotations—such as those containing the words "rich" or "kingdom"—this limitation might be mitigated by employing other methods that focus on different features of the same synopses.

Figure 6: ConceptNet Word Scatter



Note: This figure shows the term (or word) importance for each category following Kessler (2017). The social category contains the 73 telenovelas with a ConceptNet score higher or equal than 5. The non-social category contains the remaining telenovelas.

3.2.2 Universal Sentence Encoder (USE)

The Universal Sentence Encoder (USE) is a machine learning model developed by Google that effectively transforms sentences and phrases into vector representations (Cer et al., 2018). It is part of a broader family of models designed to convert words, text, and documents into vectors, commonly referred to as vector embeddings [21]. These vector representations play a crucial role in a variety of natural language processing (NLP) tasks, including classification and semantic similarity. Recently, they have even been integrated into the pipelines of generative A.I. systems, such as ChatGPT, to better comprehend user prompts.

The USE processes text to produce a vector comprising 512 dimensions, which captures both the context and semantic information of the input. This capability extends beyond simple word matching, a limitation exhibited by the ConceptNet method. For instance, the USE can differentiate between the various meanings of the word "capital" in sentences such as “The capital of Denmark is Copenhagen” and “Denmark will need to invest in capital to get out of the crisis.” In contrast, other vector embedding models like GloVe fall short of this nuance (Pennington et al., 2014). Another distinguishing feature of the Universal Sentence Encoder is its comprehensive approach; unlike traditional methods that concentrate on individual words, the USE takes the entire sentence into account. This allows the model to grasp subtleties and contextual elements more effectively. Furthermore, its design eliminates the need for extensive pre-processing of text before it is input into the model, making it more user-friendly.

In this study, I apply the Universal Sentence Encoder (USE) to analyze the translated synopses of various telenovelas. To enhance the interpretability of the resulting 512-dimensional vectors, I employed dimensionality reduction techniques, a common practice that aids in improving performance, visualization, and preventing overfitting (Roweis and Saul, 2000; Singh et al., 2022). Specifically, I chose to retain the first two principal components of each vector for further analysis. [22]

Subsequently, I estimated the cosine similarity between the telenovela Pobre Rico and

[21] For a small overview of other vector embeddings models please refer to the Appendix B.2

[22] For a brief overview of the dimensionality reduction techniques and latent space algorithms utilized, please refer to Appendix B.2.

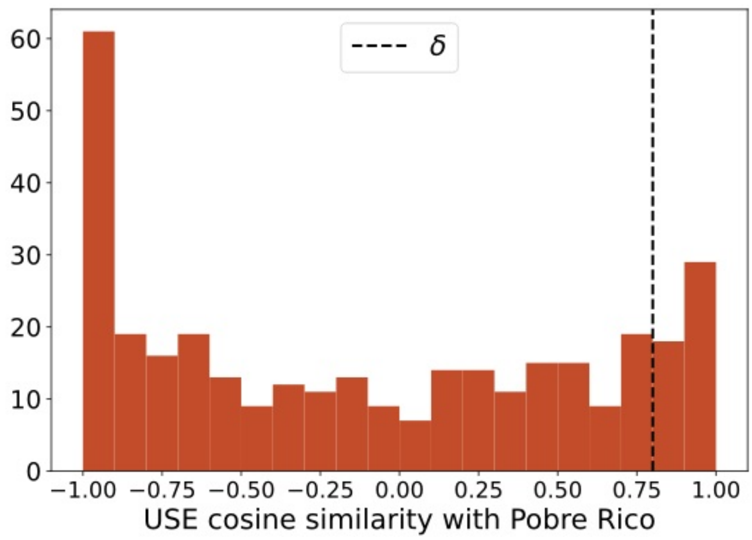
other telenovelas by comparing their synopses.

$$\text{cosine similarity}\left(A, \overrightarrow{\text{Pobre Rico}}\right) = \frac{A \cdot \overrightarrow{\text{Pobre Rico}}}{\|A\| \left\|\overrightarrow{\text{Pobre Rico}}\right\|}$$

where A is the vector embedding of the synopsis of a telenovela, $\overrightarrow{\text{Pobre Rico}}$ is the vector embedding for *Pobre Rico*, and $\|A\|$ is the Euclidean norm of vector embedding A. The cosine similarity ranges from -1 to 1, where the 1 shows that A has the same direction as the $\overrightarrow{\text{Pobre Rico}}$ vector, while a -1 shows that A is at the exact opposite direction.

The underlying premise is that telenovelas exhibiting a high degree of similarity to *Pobre Rico* are likely to portray analogous social class conflicts. Telenovelas with a similarity score exceeding 0.8 are categorized as demonstrating social class conflicts, resulting in a total of 47 telenovelas in this category. Figure 7 illustrates the histogram of similarity scores, revealing a mean similarity of -0.1 with a standard deviation of 0.7. The distribution in the figure indicates that most telenovelas cluster at both extremes, with a notable concentration of telenovelas that are "opposite" to Pobre Rico.

Figure 7: USE Histogram

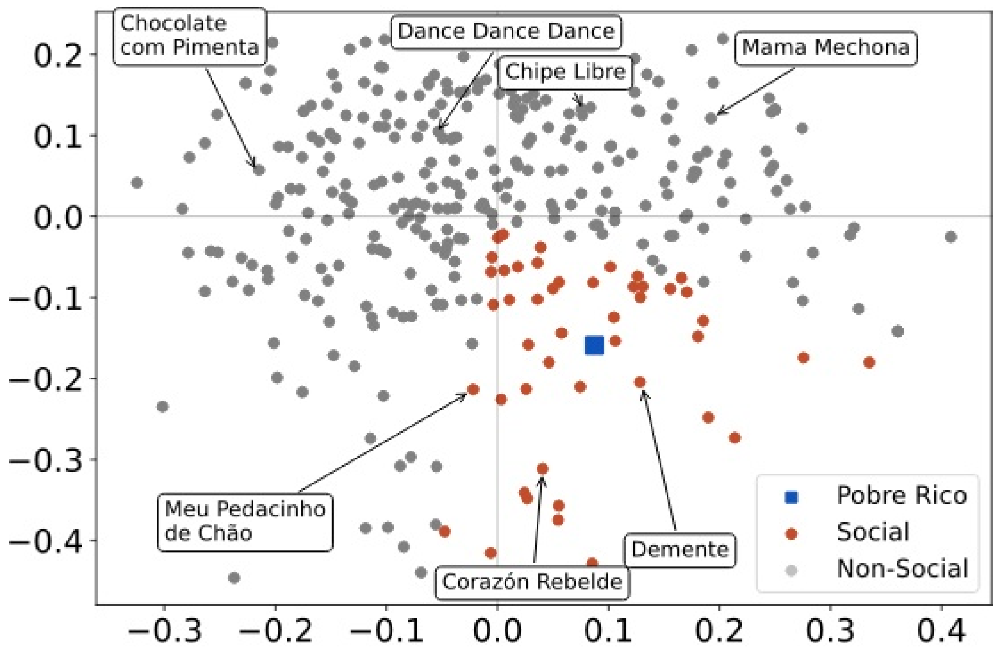


Note: blah blah

For clearer insights, Figure 8 presents a plot of the principal components derived from the USE. The telenovela *Dance Dance Dance* stands in contrast to *Pobre Rico* with a similarity score of -0.99. This telenovelas explores the story of a dancer that pursues her dream of becoming a Broadway dancer while navigating love, rivalry, and family secrets at a prestigious dance school. Although it has the vector interpretation of beign "opposite" to *Pobre Rico*, the interpretation is not as clear. *Dance Dance Dance* has some flavour of social class dynamic since it;s centered around a pretiguious dancing school, but the drama is not centered around these differences and more focused on the conflict between the students competitions and their complicated love lives. Thus, beign a telenovela "opposite" to *Pobre Rico* might reflect not centered around class dinamics or not centered around law and courts displayed in the synopsis of *Pobre Rico*.

On the other hand, *Corazon Rebelde* serves as a fitting example of a telenovela belonging to the Social category, which has also been validated through the ConceptNet method.An example of a telenovela that was classified as social class telenovelas by USE but scored a 0 in the ConceptNet score is *Demente*. This telenovela is is centered around a high-class couple's which world shatters when their son is kidnapped during a carjacking, triggering a tense investigation that uncovers hidden motives and a sinister mastermind pulling the the strings. Unlike ConceptNet, the USE found a closer match to the struggle of a high-class couple against criminals and *Pobre Rico*. ConceptNet can't understand the context of certain words leading to miss more subtler references to class dinamics, while USE is built to undertand the context of the words making it more suitable to pick up sutler hints of social class conflict.

Figure 8: USE latent space

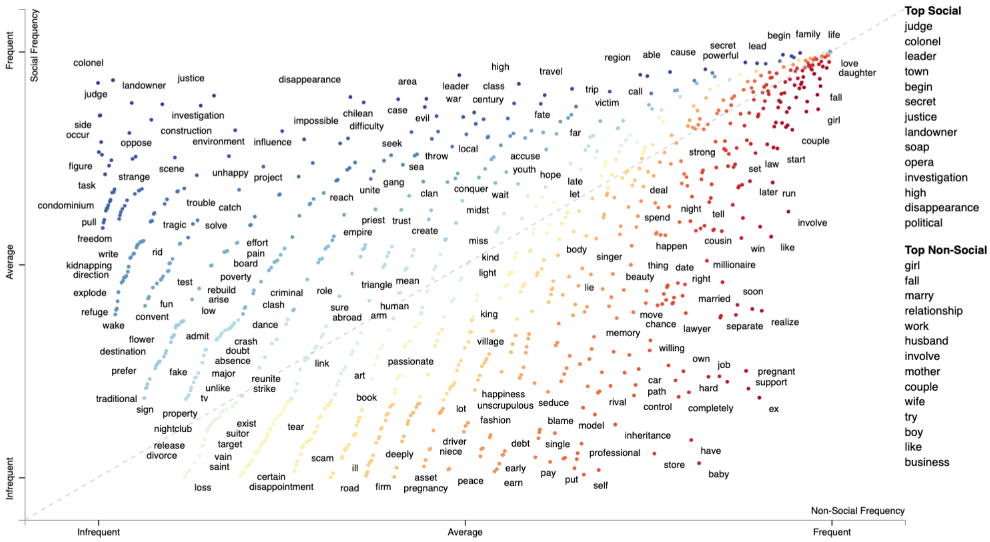


Note: blah blah

It is important to note, however, that the categorization method is not without its limitations. For instance, despite the telenovela *Chocolate com Pimienta* achieving a high score with the ConceptNet approach, the USE analysis yielded a similarity score of -0.7. This discrepancy may arise from the focus of *Chocolate com Pimienta* on romantic themes, in contrast to *Pobre Rico*, which centers more on familial dynamics. Additionally, other telenovelas, such as *Mama Mechona* and *Chipe Libre*, have been accurately classified as not exhibiting social class conflicts, as previously established.

Upon analyzing word importance for the social and non-social categories using the Universal Sentence Encoder (USE), as illustrated in Figure 9, I observed a weak pattern related to social class conflict. Within the social category, several frequent words emerged that suggest themes of social class conflict, including terms such as "leader," "landowner," and "oppose." Words like "political" and "judge" also hold significance, especially because Pobre Rico features a storyline where a judge mandates the switching of families between brothers, highlighting the role of authority and justice in this narrative. Consequently, telenovelas with similar themes surrounding justice are classified within the social category.

Figure 9: USE Word Scatter



Note: This figure shows the term (or word) importance for each category following Kessler (2017). The social category contains the 47 telenovelas with a cosine similarity higher than 0.8 using the USE. The non-social category contains the remaining telenovelas.

Conversely, the non-social category is characterized by words that pertain to family conflicts, such as "marry," "couple," and "mother." Interestingly, these terms are prevalent in both categories, reflecting the dual focus of *Pobre Rico*, where family dynamics also play a crucial role alongside social class issues. Additionally, the word "business" appears frequently in both categories; however, it holds greater importance within the non-social category. While "business" can suggest tensions between workers and owners, it may also provide context for family-oriented stories that do not inherently involve social class conflict.

3.2.3 ChatGPT

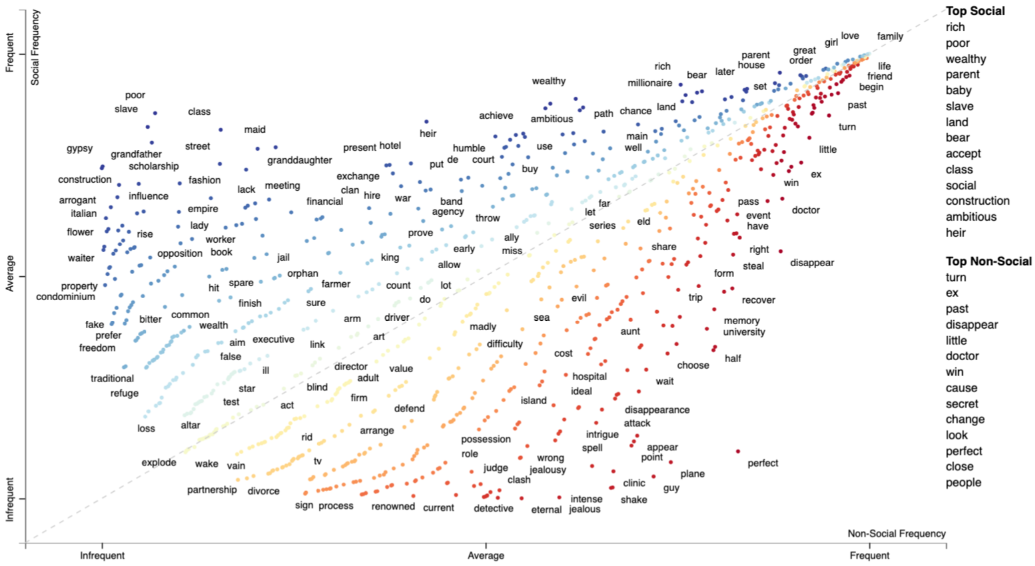
Generative AI tools such as ChatGPT have shown remarkable capabilities in categorizing text data into categories that were not present during their training phase (Wang et al., 2023). This versatility makes ChatGPT an appropriate choice for the specific classification task at hand: determining whether a telenovela—a popular television genre from Latin America—exhibits social class differences. The use of ChatGPT for text classification is not confined to this project; other researchers within the fields of social sciences, psychology, and economics have similarly employed it, and in several contexts, it has demonstrated performance that rivals or even surpasses that of human experts (Rathje et al., 2024; Törnberg, 2023; Michalopoulos and Rauh, 2024). For instance, Michalopoulos and Rauh (2024) utilized ChatGPT to classify and assess films based on the risk-taking attitudes or gender roles depicted within them. Furthermore, Michalopoulos and Rauh (2024) found that ChatGPT frequently aligns with the modal responses of knowledgeable human classifiers, suggesting its reliability in delivering accurate assessments. The narrative complexity of telenovelas bears a resemblance to that of movies, which indicates that a generative AI model, tapping into an extensive array of sources such as online reviews and forum discussions, may achieve better results than human evaluations that can be prone to incomplete recall.

In this project, I employ ChatGPT-4o to classify telenovelas based on whether they portray social class conflict or not. By inputting the translated synopses of each telenovela into the ChatGPT API, I receive not only the classification itself but also a confidence score—ranging from 50 (indicating no confidence) to 100 (indicating complete confidence)—as well as the AI's "chain of thought."[23] To enhance accuracy and mitigate instances of misinformation, Ashwin et al. (2023) suggests that requesting ChatGPT to justify its classifications can help reduce hallucinations. Additionally, I have opted to label as non-social those telenovelas with less than 90% confidence to minimize the risk of false positives.

ChatGPT identified 112 telenovelas as depicting social class conflict, a figure significantly higher than the 73 categorized by ConceptNet and the 47 identified using the USE-PCA method. To evaluate the performance of this classification approach, Figure 10 illustrates the term importance associated with both social and non-social categories as determined by ChatGPT. Notably, some of the most significant words for the social category include "rich," "poor," "wealthy," "slave," and "land," all of which strongly connect to issues of social class. In particular, terms like "poor," "slave," and "gypsy" appear frequently in the social category while being infrequent in the non-social category, indicating that ChatGPT demonstrates an effective ability to identify telenovelas that feature social class conflict, at least based on the importance of key vocabulary.

[23] Details on the prompts used for the classification and the explanations are in Appendix B.3.

Figure 10: ChatGPT Word Scatter



Note: This figure shows the term (or word) importance for each category following Kessler (2017). The social category contains the 112 telenovelas using ChatGPT-4o. The non-social category contains the remaining telenovelas.

Another method of evaluating the model's performance is by analyzing specific examples. I will first present the model's classifications for telenovelas identified in previous methods, followed by an exploration of additional examples. Both *Corazón Rebelde* and *Chocolate com Pimenta* were correctly categorized as depicting social class conflict. In the case of *Chocolate com Pimenta*, which was classified as a social telenovela by ConceptNet but not by the USE model, ChatGPT's reasoning aligns with an excerpt from the synopsis shown in Example 2. On the other hand, *Meu Pedacinho de Chão* was classified as a social telenovela by ChatGPT and the USE model, but not by ConceptNet (score = 1). This telenovela tells the story of a devoted teacher who arrives in a small village and challenges the oppressive rule of a powerful colonel, while navigating romantic entanglements with both the colonel's son and a loyal farmhand amid rising tensions. ChatGPT's reasoning, detailed in Example 3, correctly identifies the conflict between the wealthy, oppressive colonel and the humble townspeople, thus categorizing it as a social telenovela. Conversely, *Dance Dance Dance*, *Chipe Libre*, and *Mama Mechona* were all classified as not containing social class conflict. Example 4 shows the chain of though for *Mama Mechona*. This indicates that while ChatGPT can recognize telenovelas that contain subtle cues of social class differences, these elements may not always be central to the overarching narrative.

Example 2: *Chocolate com Pimenta* with ChatGPT

ChatGPT CoT	*Extract from synopsis*
The narrative frequently highlights socio-economic class differences. Ana Francisca is initially portrayed as poor, which leads to her being mistreated and humiliated by others, particularly by the wealthier characters like Olga and Danilo's family	Danilo falls in love with Aninha [Ana Francisca], to the despair of Olga and his family, who reject her because she is poor. With the help of Bárbara, first lady of Ventura and Danilo's aunt, Olga plots to humiliate her rival.

Example 3: *Meu Pedacinho de Chão* with ChatGPT *CoT*

ChatGPT CoT	*Extract from synopsis*
The summary describes characters from different socio-economic backgrounds: the humble townspeople, the wealthy Colonel and his family, and an orphan boy. The disdain of the Colonel for the orphan boy and the conflicts arising are directly linked to social class differences.	Teacher Juliana arrives in the small town of Santa Fé to teach the children and is faced with a humble people who are cowed by the excesses of Colonel Epaminondas Napoleão, an arrogant man who dictates the rules in the region and solves everything by shouting and using weapons.

Example 4: *Mama Mechona* with ChatGPT *CoT*

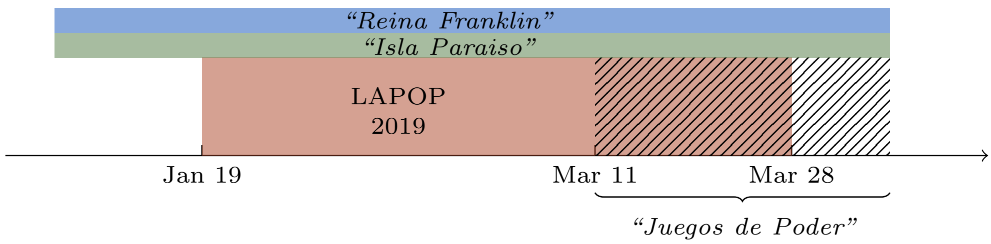
The summary primarily focuses on Macarena's personal transformation, her interpersonal relationships, and her struggle to balance attending university while managing her family. Although it mentions a character who studies to help his family and some life challenges, it does not explicitly center around socio-economic class differences as the primary plot element.

Moreover, ChatGPT successfully identified telenovelas that exhibit social class conflicts overlooked by previous methods. For instance, *Roba da Vida* portrays Sofia's quest for revenge intertwined with the tragedies of a wealthy family, resulting in a tale of love, betrayal, and the struggle for redemption amid their adversities. However, there are instances where ChatGPT may misclassify telenovelas. In the case of *Amor a la Catalán*, which centers on the exposure of a baker's double life, leading to unexpected romances and a fierce familial conflict over his bakery's inheritance, ChatGPT categorized it as depicting social class conflict. Its reasoning was, "The plot involves contrasting relationships with characters from different backgrounds (elegant Isabel vs. popular Yanara), and a significant conflict arises upon the discovery of an inheritance which involves both families." Despite the inheritance struggle, it is worth noting that the families involved belong to similar social classes, highlighting a potential oversight in ChatGPT's classification.

3.3 Empirical Strategy

The previous identification strategy hinged on the requirement that a telenovela illustrating social class differences be aired during the period of fieldwork for surveys. However, a new challenge has emerged for my original empirical approach. There are instances when two or even three telenovelas highlighting social class disparities are airing simultaneously with the premiere of a new telenovela. For example, Figure 11 show sthat during the Chilean LAPOP 2019 survey, both *Reina Franklin* and *Isla Paraiso* were airing when *Juegos de Poder* premiered on March 11th. This situation stands in contrast to the case of *Pobre Rico*, which had no other social class-themed telenovelas airing concurrently during its premiere. To address this complexity, my new treatment variable will account for the varying numbers of telenovelas viewed by individuals before and after the premiere of Juegos de Poder. This approach allows for a clear distinction: before the premiere, individuals were exposed to two telenovelas, while after the premiere, they were exposed to three. By doing so, I can also test the intensity of exposure and investigate whether being exposed to one or two social telenovelas has the same effect as not being exposed to any telenovelas at all.

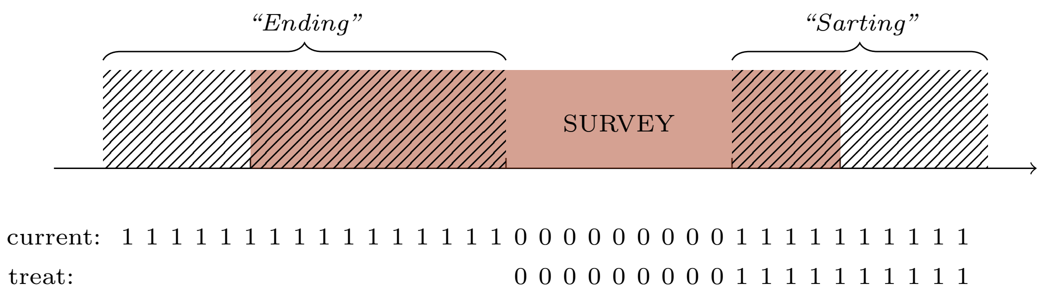
Figure 11:



Note: blah blah

Another scenario necessitates consideration, as illustrated in the Figure 12. Here, the ending telenovela airs at the beginning of the fieldwork and concludes midway through, while the starting telenovela begins in the middle of the fieldwork and continues until the end. In this case, I will categorize the 'exposed' group as those interviewed after the premiere of the starting telenovela. Conversely, the 'not exposed' group will consist of individuals who were interviewed after the ending of the first telenovela but before the premiere of the second. The intention behind this categorization is to exclude individuals exposed to the ending telenovela, thereby isolating the effects of the starting telenovela more clearly.

Figure 12:



Note: blah blah

Fourtelenovelas meet specific identification requirements described above: *Meu Pedacinho de Chão*, *Pobre Rico*, *Juegos de Poder*, and *Demente*. Table 13 presents descriptive statistics for each telenovela alongside the categorization methods employed for their identification in Panel A, and Panel B offers a concise one-line summary for each telenovela. Most of the telenovelas predominantly fall within the drama genre, with *Pobre Rico* being the sole comedic entry. Notably, these productions exhibit an episode count similar to the mean for all telenovelas within my sample, with the exception of *Meu Pedacinho de Chão*, which has a substancial lower episode count. *Pobre Rico* and *Meu Pedacinho de Chão* starkly highlight contrasts between social classes, providing significant commentary on the disparities within society. In contrast, *Juegos de Poder* and *Demnete* illustrate more subtle distinctions in social class, focusing on the complexities and challenges faced by higher-income characters.

Figure 13 shows the categorization methods applied to the treatment variable for each respective country and wave from the LAPOP survey that fulfills the identification criteria. It is noteworthy that the data source encompasses only four out of the thirty-two potential countries and waves included in the LAPOP dataset, each corresponding to the telenovelas previously discussed.

Table 6: Description of Telenovelas with ID

Panel A: Telenovela Statistics

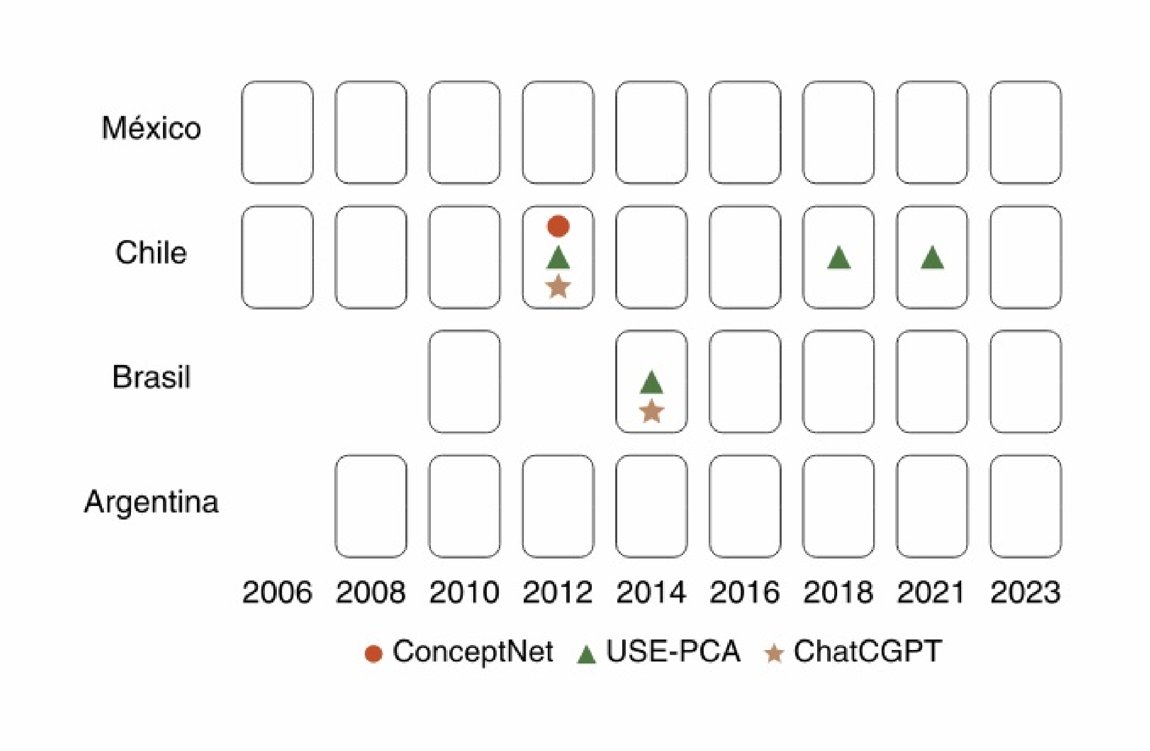
Title	Country	Year	Air Date	Episodes	Genre	Rating	ConceptNet	USE-PCA	ChatGPT
Meu Pedacinho de ChÃ£o	brazil	2014	2014-04-07	96	drama			x	x
Pobre Rico	chile	2012	2012-04-23	227	comedy	19.8	x	x	x
Juegos de Poder	chile	2019	2019-03-11	161	drama	20.0		x	
Demente	chile	2021	2021-03-15	140	melodrama	13.1		x	

Panel B: One-line Summary

Meu Pedacinho de ChÃ£o	*A dedicated teacher arrives in a small village and challenges the oppressive rule of a tyrannical colonel, while navigating the affections of both his son and a loyal farmhand amidst a brewing conflict.*
Pobre Rico	*Two teenagers from vastly different economic backgrounds discover they were swapped at birth, forcing them to switch lives for a year and confront the complexities of family and identity.*
Juegos de Poder	*A presidential candidate's campaign is threatened when his son, involved in a fatal hit-and-run, forces him into a desperate cover-up, leading to a high-stakes confrontation with a relentless prosecutor.*
Demente	*A high-class couple's world shatters when their son is kidnapped during a carjacking, triggering a tense investigation that uncovers hidden motives and a sinister mastermind pulling the strings.*

Notes:

Figure 13:



Note: blah blah

Empirical Model: To estimate the causal effect of telenovelas that display social class differences and the preferences for redistribution, taking into account the previous problems, we run the following regression:[24]

$$Y_{idct} = \alpha + \gamma_1 Exposure0to1_{dc} + \gamma_2 Exposure0to2_{dc} + +\beta X_i + \delta_{ct} + \epsilon_{icdt} \tag{2}$$

where Y_{idct} is the individual answers to the question, that depends on the survey, measuring preferences for redistribution for individual i at interview date d residing in country c in the survey year wave t. X_i is a set of individual controls which include gender, age, urban, employment, education, religion, relative income bracket, and marital status. δ_{ct} are wave×country fixed effects. My treatment variables are $Exposure0toN_{dc}$ that takes a value of 1 if N telenovelas with social class differences currently on the air at interview date d in country c and takes a value of 0 if there are 0 social class telenovelas currently on the air at interview date d in country c. $Exposure0toN_{dc}$ is also restricted to the cases described in

[24]Gulesci et al. (2023) uses a similar specification for their analysis

the Empirical Strategy. Therefore, γ_1 can be interpreted as the effect of 1 additional social telenovela from being exposed to no social class telenovelas. Conversely, γ_2 is the effect of being exposed to 2 social class telenovelas compared not being exposed to any social telenovelas.[25] This specifications allows me to show both the impact of being exposed to any number social telenovela generates, and visualize the intensive effect of an additional social telenovelas.

Similar concerns arise regarding this more generalized model compared to our observations of *Pobre Rico* in isolation. Specifically, the timing of the survey's fieldwork may lead to discrepancies in the comparability of individuals interviewed before and after the premiere of the social class telenovela. This issue is illustrated in Table 7, which presents the balance table for each categorization method. In the corresponding regressions, the set of individual characteristics serves as the dependent variable, while the independent variable consists of the number of current social telenovelas airing on the interview date (d) for each country (c), ensuring that we incorporate country x wave fixed effects.

In Panel A, we observe that individuals interviewed after the premiere of the social telenovela categorized by ConceptNet tend to have a higher proportion of females, a greater representation of the rural population, and lower income levels. However, it is essential to note that the differences concerning female representation and income are not statistically significant. This finding is not surprising, as the ConceptNet categorization only includes the telenovela *Pobre Rico*, which similarly exhibits a notable group imbalance.[26] Although we directly control for these characteristics in our main regressions, this group imbalance may still bias the estimates. One might intuitively expect that individuals with lower incomes would be more likely to support redistribution, suggesting a potential upward bias in my estimates. Similarly, a more rural population tends to be lower income, and thus one should also expect an upwards bias. There is no intuitive relation between support for redistribution and gender, however when you look at the data there is not a clear difference between mean and women.[27] Taking all these potential bias into account, it is most likely

[25] We chose $N = 2$ because that is the maximum number of social telenovela exposure for all categorization methods and the identification cases.

[26] The difference in samples between ConceptNet and the *Pobre Rico* case study is due to the different outcome variables that exhibit varying rates of missing values

[27] There is a difference of -0.02 points (se: 0.007, p_value = 0.02) in a scale from 1 to 7 between men and women for the question "*Are you willing to pay more taxes if this will go to help those with less money?*".

that our estimates are upwards biased. Even with this upwards bias, our results still suggest that the exposure to a social telenovela decreases support for redistribution.

Panel B provides a balance table for the Use categorization method, revealing that the only significant difference is in income levels, pointing to a specific area of imbalance worth noting. Meanwhile, Panel C shows that the sample for the ChatGPT categorization method maintains a commendable balance, with no significant differences among group characteristics. This suggests that the ChatGPT method may provide a more equitable approach for examining social class dynamics in our analysis.

Table 7: Generalization Balance Tables

(a) ConceptNet

	Female	Age	Education	Married	Catholic	Employment status	Urban	Income
Exposure to Social Telenovela	0.110	0.118	0.218	0.017	-0.086	0.017	-0.302**	-0.598
	(0.086)	(1.992)	(0.714)	(0.060)	(0.074)	(0.035)	(0.123)	(0.362)
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Wave Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country × Wave Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	688	688	688	688	688	688	688	688
R^2	0.003	0.000	0.000	0.000	0.002	0.000	0.049	0.005
Within-R^2	0.003	0.000	0.000	0.000	0.002	0.000	0.049	0.005

(b) USE-PCA

	Female	Age	Education	Married	Catholic	Employment status	Urban	Income
Exposure to Social Telenovela	0.024	0.195	-0.012	0.006	-0.004	0.004	-0.086	-0.553***
	(0.035)	(0.774)	(0.300)	(0.020)	(0.049)	(0.014)	(0.056)	(0.207)
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Wave Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country × Wave Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	1,586	1,586	1,586	1,586	1,586	1,586	1,586	1,586
R^2	0.013	0.025	0.113	0.421	0.006	0.001	0.007	0.044
Within-R^2	0.000	0.000	0.000	0.000	0.000	0.000	0.005	0.003

(c) ChatGPT

	Female	Age	Education	Married	Catholic	Employment status	Urban	Income
Exposure to Social Telenovela	0.026	0.164	0.351	0.010	-0.052	-0.013	-0.113	-0.342
	(0.067)	(1.219)	(0.437)	(0.036)	(0.053)	(0.026)	(0.113)	(0.258)
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Wave Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country × Wave Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	803	803	803	803	803	803	803	803
R^2	0.005	0.011	0.075	0.156	0.002	0.000	0.014	0.063
Within-R^2	0.000	0.000	0.001	0.000	0.001	0.000	0.009	0.002

Note: catholics is a dummy for whether the individuals is catholic or not. employment status refers to whether the individual is in the working or unemployed. Standard errors are clustered at interview date level.

3.4 Results

Figure 14 illustrates the effect size of being exposed to N social telenovelas compared to individuals who have not been exposed at all, organized by categorization method. For a comparative backdrop, we also plot the effect derived from the *Pobre Rico* sample for the different support for redistribution.[28] The effect size from each categorization method are negative and hover around 6%, closely aligning with the results obtained from the Pobre Rico sample.[29] This consistency suggests that exposure to any number of social telenovelas slightly diminishes support for redistribution policies. Furthermore, with ConceptNet categorization, which solely utilizes the identification from Pobre Rico, indicates a similar effect size of approximately a 6.2% decrease in support for redistribution. [30]

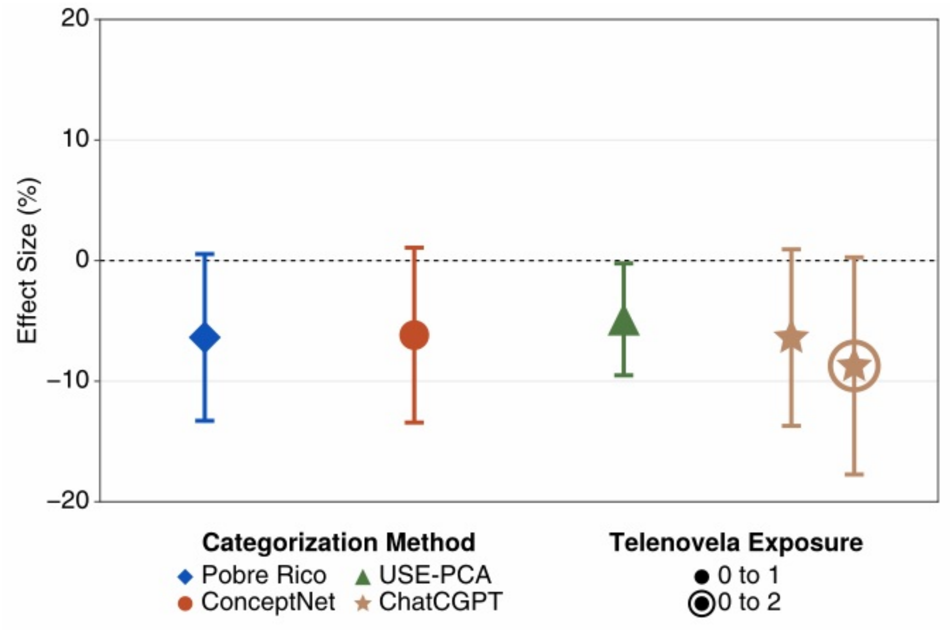
The USE-PCA categorization exhibits the maximum variation in the data, yielding a slightly reduced effect size of -4.8%. In contrast, the ChatGPT categorization permits an examination of the intensity of exposure to social telenovelas. Under this categorization, exposure to one social telenovela correlates with a -6.3% decrease in support for redistribution, while exposure to two telenovelas results in an -8.7% decrease when compared to those with no exposure. Nonetheless, there is no significant difference between the effects of being exposed to one versus two social telenovelas, indicating that there are no intensity effects. Only the effects identified through the USE categorization reach statistical significance at the 95% confidence level, whereas the ChatGPT categorization yields significance at the 90% confidence level for individuals exposed to one or two social telenovelas compared to those who have not been exposed to any.

[28] In Section 2 we used the question *"Are you willing to pay more taxes if this will go to help those with less money?"* but due to the unavailability of this question in other waves of LAPOP, we decided to change the outcome variable to the question *"The (Country) government should implement strong policies to reduce income inequality between the rich and the poor"*.

[29] The exposure of Pobre Rico decreased support for redistribution by 0.38 points or by 6.3% compared to the group with no exposure to the telenovela. This is a reduced effect size compared to the 21% found in the case study section. This difference arrised fromthe nature of the question that does not focus on the individual. First, when individuals are asked about their own taxes people are less willing to give up to give to other and thus the average aggrement level is going to be lower and making the effect size bigger.

[30] the difference in the coefficients comes from using different samples. There is a slight discussion in Section 3.1.1.

Figure 14:

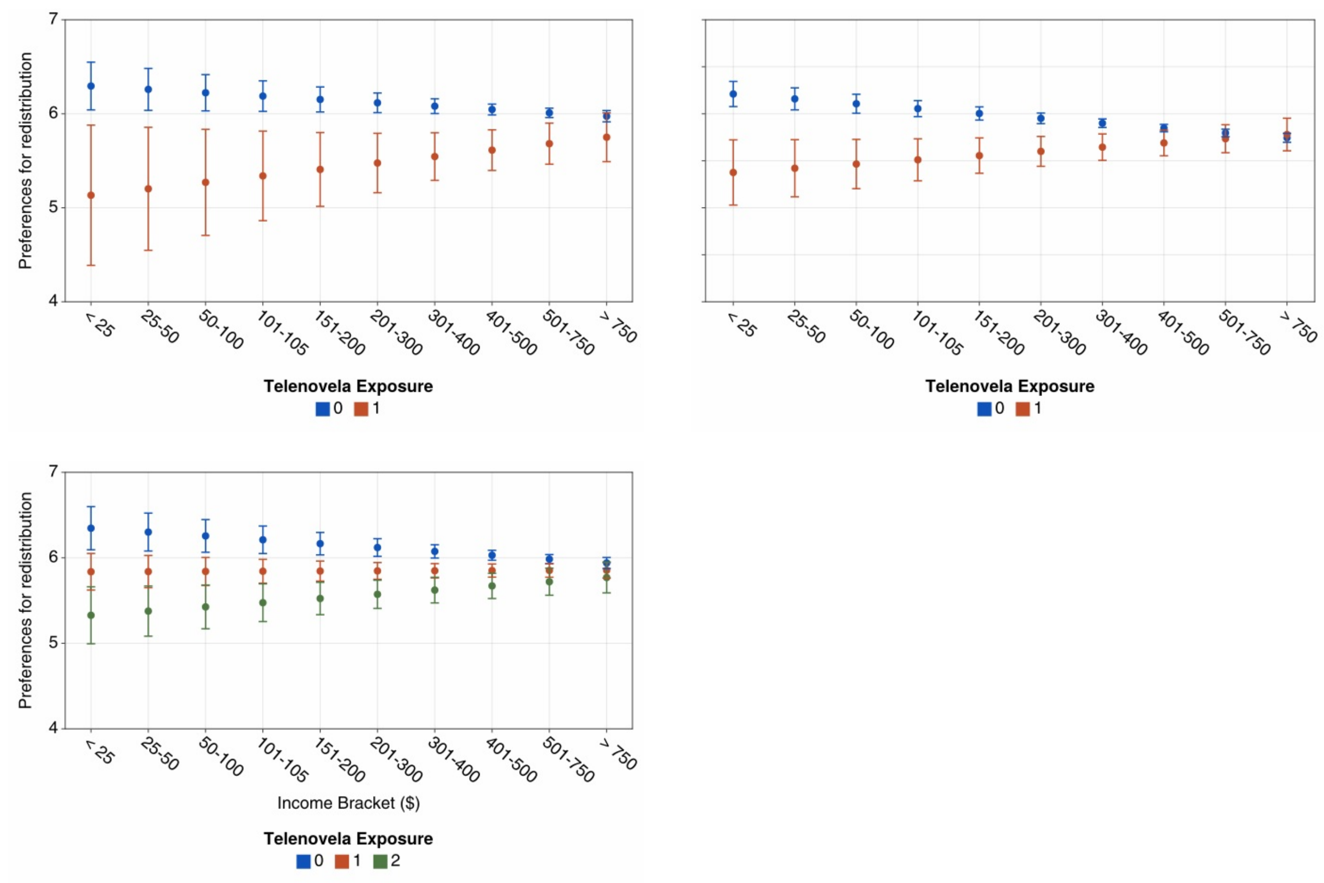


Note: error bars show the 95% confidence intervals. Standard errors are clustered at interview date level. For the full regression results please refer to Table D.1

Mechanism To comprehend the negative effects of social telenovelas on support for redistribution, it is crucial to investigate the channels through which this impact occurs. Initially, we explore whether the effect varies across different income levels. To facilitate this analysis, we run a modified version of equation 2 which interacts the income variable with the treatment $Exposure0toN_{dc}$ for all N. In the LAPOP survey, participants are asked to report their monthly income in the local currency; however, researchers then convert these figures into a common dollar range. The highest monthly income earners in the survey are those who earn $750 per month, a threshold that in some countries places individuals within the top decile of the income distribution. The findings from these regressions are summarized in Figure 15, showcasing results for each categorization method. Across all panels, it becomes evident that individuals with lower incomes who are exposed to any social telenovela exhibit diminished support for redistribution compared to those who have not been exposed. This disparity shrinks as we move up the income spectrum.

Figure 15:

(a) ConceptNet (b) USE-PCA



(c) ChatGPT

Note: error bars show the 95% confidence intervals. Standard errors are clustered at interview date level. For the full regression results please refer to Table D.2

Next, we analyze how exposure to social telenovelas influences individuals' self-perception of their social class. Table 8 displays the regression results derived from estimating equation 2, where the outcome variable reflects individuals' self-reported social class. Both the ConceptNet and ChatGPT methods reveal that individuals report a lower social class when exposed to a social telenovela than those who were not exposed, as evidenced in column (1) of their respective analyses. Conversely, the USE-PCA categorization demonstrates a negligible effect on self-reported social class following exposure to a social telenovela. When examining shifts in self-identification, it is noteworthy that these social telenovelas tend to prompt more individuals to align with the middle class. ConceptNet and ChatGPT reveal a 28% increase in the probability of reporting as middle class after exposure. This finding may elucidate why lower-income individuals exposed to social telenovelas tend to reduce their support for redistribution. If lower-income individuals perceive themselves as belonging to a higher social class, their inclination to support redistributive policies may wane. However, this effect does not appear to influence higher-income individuals similarly, as we do not observe an increase in support for redistribution among high-income individuals identifying as lower class after their exposure to a social telenovela. Consistent with existing literature, our analysis indicates that both income levels and the (mis)perception of social class significantly shape support for redistribution.

Table 8: Generalization Social Class Perception

(a) ConceptNet

	Perception of Social Class					
	1-5	Upper	Upper Middle	Middle	Lower Middle	Lower
Exposure Social Telenovela 0 to 1	-0.306***	-0.015	-0.015*	0.277***	-0.143**	-0.104**
	(0.089)	(0.016)	(0.008)	(0.058)	(0.066)	(0.047)
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Wave Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Country × Wave Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
N	320	320	320	320	320	320
R^2	0.241	0.094	0.018	0.177	0.082	0.110
Within-R^2	0.241	0.094	0.018	0.177	0.082	0.110
Control mean	3.670	0.023	0.023	0.383	0.400	0.170

(b) USE-PCA

	Perception of Social Class					
	1-5	Upper	Upper Middle	Middle	Lower Middle	Lower
Exposure Social Telenovela 0 to 1	0.018	-0.005	-0.007	0.030	-0.037	0.019
	(0.101)	(0.011)	(0.037)	(0.052)	(0.049)	(0.042)
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Wave Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Country × Wave Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
N	1,228	1,228	1,228	1,228	1,228	1,228
R^2	0.117	0.009	0.037	0.059	0.022	0.101
Within-R^2	0.116	0.009	0.025	0.059	0.020	0.100
Control mean	3.617	0.018	0.061	0.379	0.370	0.172

(c) ChatGPT

	Perception of Social Class					
	1-5	Upper	Upper Middle	Middle	Lower Middle	Lower
Exposure Social Telenovela 0 to 1	-0.385***	-0.011	-0.005	0.283***	-0.119*	-0.147***
	(0.078)	(0.012)	(0.013)	(0.056)	(0.070)	(0.046)
Exposure Social Telenovela 0 to 2	0.097	-0.036**	-0.122***	0.290***	-0.169*	0.036
	(0.159)	(0.016)	(0.045)	(0.062)	(0.101)	(0.083)
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Wave Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Country × Wave Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
N	432	432	432	432	432	432
R^2	0.143	0.027	0.069	0.149	0.061	0.102
Within-R^2	0.142	0.026	0.039	0.146	0.059	0.100
Control mean	3.670	0.023	0.023	0.383	0.400	0.170

Note: Controls include blah blah blah... Standard errors are clustered at wave and interview date level.

Another potential channel through which support for redistribution may be altered is through shifts in political views. Exposure to social telenovelas might provide individuals with a revised perspective on their country's realities, thereby affecting their political positions. To examine this possibility, we estimate equation 2 with the outcome variable reflecting respondents' self-reported place in the political spectrum. A position of 1 indicates strong alignment with socialism, while a position of 10 signifies strong conservatism. The results of this analysis are reported in Table 9, revealing no evidence that exposure to social telenovelas alters political thinking. This suggests that the decline in support for redistribution is likely attributable solely to income factors and misperceptions of social class.

We test whether exposure to social telenovelas affects support for other social issues. In Table 10, we estimate equation 2 with outcome variables related to trust in the Catholic Church and support for minority candidates running for president. As anticipated, exposure to one or two social telenovelas shows no impact on these social issues, with all coefficients remaining relatively small, centered around zero, and statistically insignificant. These placebo tests further confirm that the categorization methods effectively target telenovelas with social class as a core theme. For instance, Gulesci et al. (2023) demonstrated that exposure to telenovelas featuring LGBTQ+ characters decreases support for candidates from that community in Latin America. One of the telenovelas analyzed in their work, *Juegos de Poder*, was classified as social using the USE-PCA method; however, we found no effects on support for LGBTQ+ candidates within the context of three other telenovelas that show social class conflict.

Table 9: Generalization Political Leaning

	Conceptnet				USE-PCA				ChatGPT			
	1-10	left	middle	right	1-10	left	middle	right	1-10	left	middle	right
Exposure Social Telenovela 0 to 1	0.602	-0.076	0.047	0.030	0.075	-0.056	0.046	0.010	0.674	-0.076	0.031	0.044
	(0.534)	(0.060)	(0.098)	(0.101)	(0.317)	(0.042)	(0.045)	(0.062)	(0.539)	(0.058)	(0.099)	(0.100)
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Wave Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country × Wave Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	562	562	562	562	1,338	1,338	1,338	1,338	660	660	660	660
R^2	0.056	0.027	0.026	0.072	0.040	0.011	0.035	0.053	0.054	0.025	0.036	0.075
Within-R^2	0.056	0.027	0.026	0.072	0.028	0.011	0.020	0.032	0.047	0.024	0.028	0.058
Control mean	4.858	0.260	0.537	0.203	5.211	0.251	0.467	0.282	4.858	0.260	0.537	0.203

Note: catholics is a dummy for wheter the individuals is catholic or not. employment status refers to wheter the individual is in the working or unemployed. Standard errors are clustered at wave and interview date level.

Table 10: Generalization Placebo

(a) ConceptNet

	Trust in	Running for president ...		
	Catholic Church	Women	LGBTQ+	Gov. Critics
Exposure Social Telenovela 0 to 1	0.093	0.030	0.031	-0.033
	(0.105)	(0.076)	(0.079)	(0.082)
Country Fixed Effects	Yes	Yes	Yes	Yes
Wave Fixed Effects	Yes	Yes	Yes	Yes
Country × Wave Fixed Effects	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
N	680	660	659	660
R^2	0.094	0.058	0.102	0.048
Within-R^2	0.094	0.058	0.102	0.048

(b) USE-PCA

	Trust in	Running for president ...		
	Catholic Church	Women	LGBTQ+	Gov. Critics
Exposure Social Telenovela 0 to 1	0.046	-0.027	-0.021	0.006
	(0.044)	(0.038)	(0.046)	(0.047)
Country Fixed Effects	Yes	Yes	Yes	Yes
Wave Fixed Effects	Yes	Yes	Yes	Yes
Country × Wave Fixed Effects	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
N	1,586	1,555	1,570	1,563
R^2	0.172	0.040	0.072	0.042
Within-R^2	0.154	0.040	0.070	0.035

(c) ChatGPT

	Trust in	Running for president ...		
	Catholic Church	Women	LGBTQ+	Gov. Critics
Exposure Social Telenovela 0 to 1	0.090	0.044	0.037	-0.025
	(0.108)	(0.075)	(0.078)	(0.082)
Exposure Social Telenovela 0 to 2	0.006	-0.006	0.124	0.017
	(0.111)	(0.077)	(0.131)	(0.129)
Country Fixed Effects	Yes	Yes	Yes	Yes
Wave Fixed Effects	Yes	Yes	Yes	Yes
Country × Wave Fixed Effects	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
N	796	774	775	774
R^2	0.123	0.055	0.115	0.053
Within-R^2	0.103	0.055	0.107	0.049

Note: catholics is a dummy for wheter the individuals is catholic or not. employment status refers to wheter the individual is in the working or unemployed. Standard errors are clustered at wave and interview date level.

The analysis reveals that exposure to social telenovelas consistently decreases support for redistribution across various categorization methods. Notably, this effect does not intensify with increased exposure, as viewing one or two telenovelas yields similar outcomes. The most plausible explanation for this trend is that lower-income individuals perceive themselves as belonging to a higher social class, reducing their perceived need for redistribution. Importantly, our findings indicate that this exposure does not alter political attitudes. Furthermore, a placebo test confirmed that the influence of these telenovelas is specific to social class perception and redistribution preferences, without affecting trust in the church or support for minority presidential candidates.

4 Conclusion

This study provides compelling evidence that telenovelas, a dominant form of entertainment in Latin America, significantly influence public perceptions of social class and support for redistributive policies. By analyzing the case of Pobre Rico and expanding the analysis to other telenovelas that depict social class disparities, we find that exposure to these shows consistently decreases support for redistribution across various countries. The findings suggest that lower-income viewers, after watching social telenovelas, may begin to perceive themselves as belonging to a higher social class, which reduces their demand for redistributive policies. Importantly, this shift in support for redistribution is not accompanied by changes in broader political attitudes, indicating that the effect is specific to perceptions of class and inequality.

Our use of Natural Language Processing techniques to categorize telenovelas enhances the generalizability of the results, offering a scalable and efficient way to analyze media content. The consistency of the effect across multiple NLP methods further strengthens the robustness of the findings. Additionally, the placebo tests reinforce the specificity of the results, showing that the observed changes in attitudes are directly linked to the portrayal of social class in telenovelas, without spillover effects into other domains such as political trust or support for minority candidates.

Overall, this research highlights the powerful role of entertainment media in shaping public perceptions and policy preferences, emphasizing the need to better understand how narratives in popular culture can influence societal attitudes toward inequality and redistribution.

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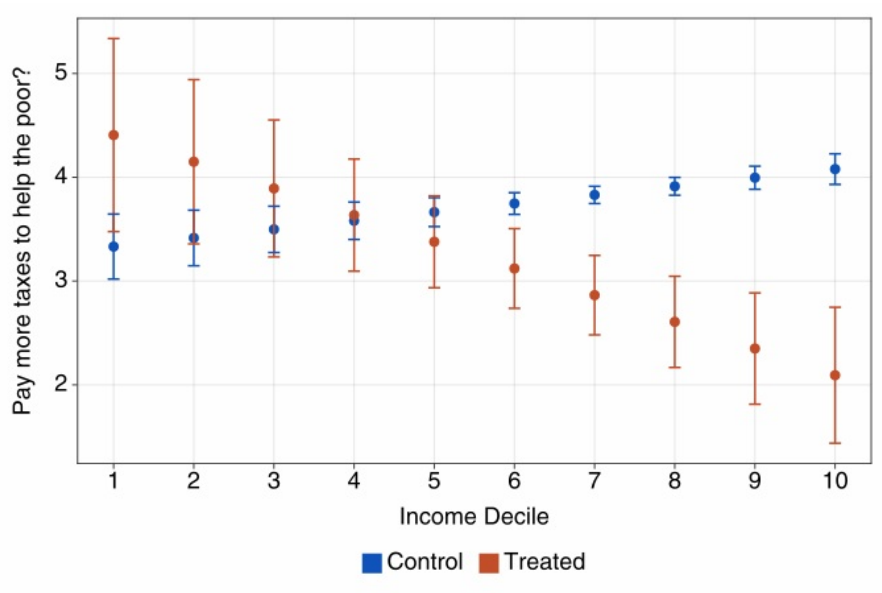
Appendices

A *Pobre Rico* Validity Checks

A.1 Potential Mechanisms

Income Then we estimate regression (1) adding the interaction between our treatment and the income decile variable. (CHANGE THE RESULTS HERE SINCE I CHANGE THE INCOME VAR) Table A.3 show the results show the impact of telenovela exposure on individuals in the top income bracket reduces approval for redistribution in 2 points, or 52% (twice the average effect). Nonetheless, the magnitude of disapproval diminishes as one moves further from the wealthiest decile. Specifically, individuals in the second income decile exhibit no change in their redistribution preferences due to the telenovela, and those in lower deciles may even increase their support. Figure A.1 shows (*margins plot*)...

Figure A.1: Income Effects Plot



Note: blah blah

Pobre Rico is a comedy which downplays the struggles of the poor. For example, the *Pérez* (poor) family are label as poor but in reality they represent a low-middle-income class that fails to represent the problems of extreme poverty (e.g. homelessness, unemployment, etc) where most the the social security programs are designed for. In turn, if high income individuals think that the Pérez (poor) family can get by without their help they would rather use their tax money for other social problems. To test for this mechanism if the exposure to *Pobre Rico* shifted wealthy individuals to other social concerns ... *work in progress*

Political leaning A valid concern arises regarding the possibility that the telenovela may influence individuals' political inclinations rather than solely impacting their preferences for redistribution. To address this concern, we undertook two approaches. Initially, we explored the impact of *Pobre Rico* on other political outcomes and found weak evidence of changes in political thinking. As depicted in Table A.2, individuals exposed to the telenovela exhibit a slight inclination towards the right on the political spectrum; however, this effect remains marginal and statistically insignificant. Subsequently, we looked at questions related to political leaning, such as concerns of violence, trust in religious institutions, and approval for the LGBTQI+ or government critics running for office. Table A.1 shows that across all domains, the coefficients are negligible and insignificant, suggesting minimal influence beyond the specific context of redistribution preferences.

Government Trust (ADD THIS PART)

A.2 Robustness

Other Outcomes (add the other placebo outcomes here)

Time trends and far-away observations Another pertinent concern involves the possibility that individuals may increasingly disapprove of redistribution over time. To tackle this concern, we pursued two approaches. Initially, we incorporated a time trend into the regression 1. Table A.5 shows that the time trend coefficient is positive, suggesting that in 2012 the Chilean population approved of redistribution over time.[31] Despite this trend, the

[31] The negative time trend coefficient found in columns 4 and 5 suggest that the Chilean population is moving away from disapproving of redistributive policies.

coefficient of the effect of exposure to *Pobre Rico* remains negative, albeit with reduced magnitude.

The control group contains observations that are far away from *Pobre Rico's* premiere date which might bias our results (Hausman and Rapson, 2017). To address this potential problem, we ran our regressions restricting our sample to those interviewed within 12, 7, and 5 days of the premiere. The outcomes of this analysis are displayed in Table A.6. The coefficients remain consistently negative and mostly significant, with even more pronounced effects observed with narrower windows.

Table A.1: Placebo test in outcomes

	Trust in the	Running for office...	
	Catholic Church	LGBTQ+	Gov. Critic
Exposure to Pobre Rico	0.050	-0.033	0.017
	(0.089)	(0.088)	(0.095)
Controls	Yes	Yes	Yes
N	667	647	647
R^2	0.101	0.082	0.028
Control mean	0.334	0.701	0.573

Controls: gender, age, urban, employment, education, religion, and marrital status. Robust standard errors are in parentheses.

Table A.2: The effects of the exposure *Pobre Rico* on political leaning

	Political Leaning			
	1-10	left	right	middle
Exposure to Pobre Rico	0.409	-0.039	0.040	-0.001
	(0.484)	(0.068)	(0.078)	(0.095)
Controls	Yes	Yes	Yes	Yes
N	551	551	551	551
R^2	0.058	0.027	0.044	0.015
Control mean	4.856	0.156	0.121	0.723

Notes: Political leaning is measured from 1 (extreme left) to 10 (extreme right). The group left (≤ 3) are those who reported a score of 3 or less. The group right (7 ≤) indicates a score of 7 or more. Each regression controls for gender, age, urban, employment, education, religion, and marrital status. The group middle (4-6) reports a score of between 4 and 6 included. Robust standard errors are in parentheses.

Table A.3: The effects of the exposure *Pobre Rico* on preferences for redistribution and income

Income decile reference point:		Bottom 10%
	Pay more taxes to help the poor?	
Exposure to Pobre Rico	-0.813**	1.414*
	(0.340)	(0.775)
Income Decile	0.062	0.083*
	(0.045)	(0.047)
Exposure to Pobre Rico x Income Decile		-0.340***
		(0.098)
Controls	Yes	Yes
N	650	650
R^2	0.036	0.043
Control mean	3.859	3.859

Controls: gender, age, urban, employment, education, religion, and marrital status. Distance to the rich as the distance in income deciles from the top decile. Robust standard errors are in parentheses.

Table A.4: The effects of the exposure *Pobre Rico* on government trust

	Trust in gov to fight...	
	inequality	poverty
Exposure to Pobre Rico	-0.388*	-0.540*
	(0.214)	(0.302)
Controls	Yes	Yes
N	675	676
R^2	0.029	0.037
Control mean	6.023	3.574

Notes: Trust in the government to fight poverty or inequality is measured from 1 (strongly disagree) to 7 (strongly agree). Each regression controls for gender, age, urban, employment, education, religion, and marrital status. Robust standard errors are in parentheses.

Table A.5: Robustness with time trends

	Pay more taxes to help the poor?			
	1-7	Strongly approve	Approve	Disapprove
Exposure to Pobre Rico	-0.351	-0.076**	-0.174**	-0.009
	(0.343)	(0.039)	(0.074)	(0.102)
Time Trend	0.032***	0.001	0.008***	-0.008***
	(0.007)	(0.001)	(0.002)	(0.002)
Controls	Yes	Yes	Yes	Yes
N	650	650	650	650
R^2	0.069	0.030	0.063	0.073
Control mean	3.859	0.116	0.433	0.412

Controls: gender, age, urban, employment, education, religion, and marrital status. Robust standard errors are in parentheses.

Table A.6: Robustness with time windows around air date

Days away from 1st episode	5	7	12	full sample
	Pay more taxes to help the poor?			
Exposure to Pobre Rico	-1.121***	-0.766*	-0.453	-0.813**
	(0.413)	(0.411)	(0.410)	(0.340)
Controls	Yes	Yes	Yes	Yes
N	87	101	170	650
R^2	0.128	0.102	0.063	0.036
Control mean	3.186	3.148	3.354	3.859

Controls: gender, age, urban, employment, education, religion, and marrital status. Robust standard errors are in parentheses.

B Categorization of Telenovelas

B.1 ConceptNet

B.2 Word Embeddings

There are other dimensionality reduction using a mix between methods. For isntance (Singh et al., 2022) show how a mixture between PCA and LDA have improved text clasification tasks compared to each method on their own.

B.3 Using ChatGPT

B.4 Validation

C Other Surveys

The WVS offers a global perspective on values and beliefs, including attitudes towards redistribution, through its periodic surveys conducted across the world. These surveys cover a

Table B.1: ConceptNet list

root		related terms		
		EN	ES	PT
poor	⟶	poor	pobre	pobre
		poorer	pobrete	pobres
		slummy	pobretones	pobretão
		resourceless	pobretón	
			pobres	
inequality	⟶	inequality	desigualdad	desigualdade
		inequity	inequidad	inequação
		disparity	inecuaciones	eqüidade
		unequal	disparidad	igualdade
		gini coefficient	igualdad	disparidade
economic	⟶	economic	económicas	econômica
		noneconomic	economía	economia
		economy	fisiócratas	ecónomo
		macroeconomic	macroeconomico	macroeconómica
		socio economic	socioeconómico	financeiros
rich	⟶	rich	ricas	rica
		superrich	rico	rico
		richen	opulento	opulento
		richer	pudiente	
wealthy	⟶	wealthy	adinerado	ricas
		inferior	acaudalada	rico
			acaudalado	ricos
			pudiente	
			adinerada	

Table B.2: ConceptNet list continuation

root		related terms		
		EN	ES	PT
owner	⟶	owner	propietarias	proprietária
		proprietor	dueño	dono
		possessor	empresaria	proprietario
		landlord	poseedor	possuidor
		owns	amo	amo
worker	⟶	worker	cuadrillero	operário
		laborer	laburante	obrador
		employee	trabajadora	trabalhador
		farmworker	obrero	assalariado
		manual_laborer	empleado	empregado
elite	⟶	elite	elite	elite
		élite	élite	escol
		elitist	elitista	nata
social class	⟶	social	social	social
		sociability	macrosocial	sociabilidade
		societal	ecosocial	socialização
		social_network	socialista	socialismo
		socialist	socialismo	sociabilizar
distinguished	⟶	distinguished	distinguido	distinta
		illustrious	egregio	assinalada
		esteemed	prestigioso	eminente
		renowned	destacado	notável
		prestigious	ilustre	marcante

representative sample of Latin America in their 7 waves[32], offering a comprehensive dataset for analyzing trends and variations in preferences for redistribution across the region. Questions about redistribution in WVS are also focussed on the role of the government and the most similar question is: *"What do you think about the government responsibility to provide for individuals?"* Where interviewees answer an integer from 1 to 10, 1 shows that the interviewee agrees that the government show ensure that everyone is provided for and 10 show that the interviewees agree that people should take more responsibility and not the government.

[32]The timeline of each wave is the following: wave 1 (1981-1984), wave 2 (1990-1994), wave 3 (1995-1998), wave 4 (1999-2004), wave 5 (2005-2009), wave 6 (2010-2014), and wave 7 (2017-2022).

D Additional Figures and Tables

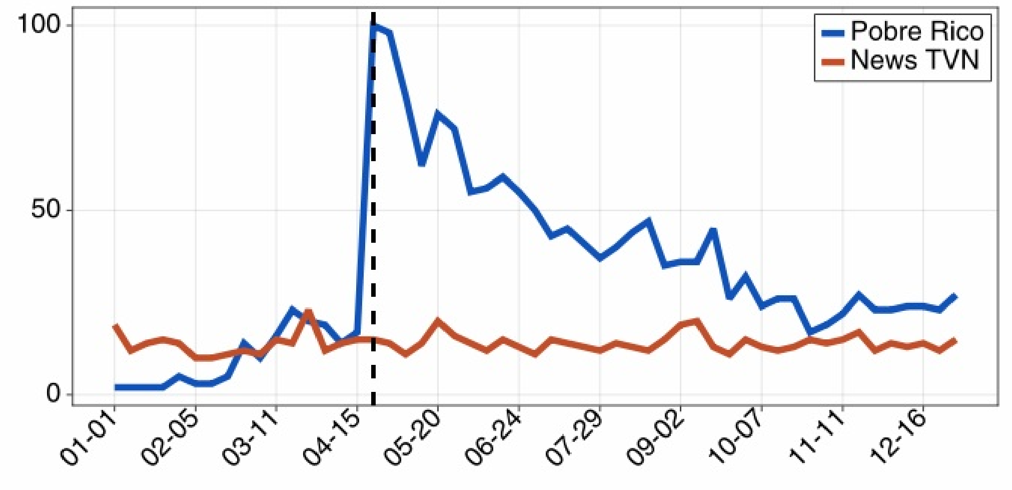
Figure D.1: Visual social class differences in *Pobre Rico*

(a) rich house (b) "poor" house

(c) rich living room (d) "poor" living room

Note: these screenshots were taken from the first episode "Cambiados al Nacer"of *Pore Rico* on YouTube.

Figure D.2: Google Trends in 2012



Note: the y axis is a relative search intensity index. It normalizes the search intensity for each term to the maximum searches in the sample. In this case, the maximum search intensity was achieved by *Pore Rico* around the premiere of the show.

Table D.1: Generalization Full Results

(a) ConceptNet

	1-7	Support for Redistribution Strongly approve	Approve	Neutral	Disapprove	Strongly disapprove
Exposure Social Telenovela 0 to 1	-0.371	-0.174	-0.082	0.079	0.002	-0.006
	(0.222)	(0.109)	(0.059)	(0.064)	(0.024)	(0.004)
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Wave Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Country × Wave Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
N	688	688	688	688	688	688
R^2	0.027	0.025	0.017	0.017	0.023	0.014
Within-R^2	0.027	0.025	0.017	0.017	0.023	0.014
Control mean	6.009	0.491	0.868	0.089	0.043	0.009

(b) USE-PCA

	1-7	Support for Redistribution Strongly approve	Approve	Neutral	Disapprove	Strongly disapprove
Exposure Social Telenovela 0 to 1	-0.284**	-0.080*	-0.067**	0.015	0.051	-0.007
	(0.138)	(0.048)	(0.032)	(0.036)	(0.038)	(0.016)
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Wave Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Country × Wave Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
N	1,586	1,586	1,586	1,586	1,586	1,586
R^2	0.032	0.021	0.024	0.006	0.036	0.015
Within-R^2	0.014	0.020	0.008	0.006	0.011	0.008
Control mean	5.829	0.472	0.825	0.093	0.081	0.018

(c) ChatGPT

	1-7	Support for Redistribution Strongly approve	Approve	Neutral	Disapprove	Strongly disapprove
Exposure Social Telenovela 0 to 1	-0.384*	-0.170	-0.084	0.077	0.007	-0.003
	(0.224)	(0.107)	(0.060)	(0.063)	(0.024)	(0.005)
Exposure Social Telenovela 0 to 2	-0.525*	-0.073	-0.173**	0.039	0.134**	-0.013
	(0.276)	(0.114)	(0.070)	(0.080)	(0.062)	(0.024)
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Wave Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Country × Wave Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
N	803	803	803	803	803	803
R^2	0.039	0.024	0.028	0.020	0.060	0.023
Within-R^2	0.021	0.021	0.017	0.020	0.032	0.019
Control mean	6.009	0.491	0.868	0.089	0.043	0.009

Note: catholics is a dummy for wheter the individuals is catholic or not. employment status refers to wheter the individual is in the working or unemployed. Standard errors are clustered at wave and interview date level.

Table D.2: Generalization Income

	Conceptnet	USE-PCA	ChatGPT
	Support for Redistribution		
Exposure Social Telenovela 0 to 1	-1.054	-0.950***	-0.891*
	(1.046)	(0.299)	(0.521)
Exposure Social Telenovela 0 to 2			-1.453***
			(0.421)
Income	-0.059**	-0.056***	-0.071**
	(0.029)	(0.015)	(0.029)
Exposure Social Telenovela 0 to 1 x Income	0.080	0.087**	0.057
	(0.104)	(0.035)	(0.044)
Exposure Social Telenovela 0 to 2 x Income			0.117**
			(0.044)
Country Fixed Effects	Yes	Yes	Yes
Wave Fixed Effects	Yes	Yes	Yes
Country × Wave Fixed Effects	Yes	Yes	Yes
Controls	Yes	Yes	Yes
N	688	1,586	803
R^2	0.028	0.034	0.044
Within-R^2	0.028	0.016	0.027
Control mean	6.009	5.829	6.009

Note: catholics is a dummy for wheter the individuals is catholic or not. employment status refers to wheter the individual is in the working or unemployed. Standard errors are clustered at wave and interview date level.

Table D.3: Generalization Time Trend

	Conceptnet		USE-PCA		ChatGPT	
	Support for Redistribution					
Exposure Social Telenovela 0 to 1	-0.371	-0.655**	-0.284**	-0.354**	-0.384*	-0.659**
	(0.222)	(0.257)	(0.138)	(0.150)	(0.224)	(0.257)
Exposure Social Telenovela 0 to 2					-0.525*	-0.843***
					(0.276)	(0.300)
Time Trend		0.012**		0.004		0.011**
		(0.005)		(0.005)		(0.005)
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Wave Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Country × Wave Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
N	688	688	1,586	1,586	803	803
R^2	0.027	0.039	0.032	0.033	0.039	0.048
Within-R^2	0.027	0.039	0.014	0.015	0.021	0.030
Control mean	6.009	6.009	5.829	5.829	6.009	6.009

Note: catholics is a dummy for wheter the individuals is catholic or not. employment status refers to wheter the individual is in the working or unemployed. Standard errors are clustered at wave and interview date level.

Table D.4: Generalization Time windows

	Conceptnet				USE-PCA				ChatGPT			
	5	10	20	full sample	5	10	20	full sample	5	10	20	full sample
Exposure Social Telenovela 0 to 1	-0.335	-0.731**	-0.506**	-0.371	-0.172	-0.306*	-0.315**	-0.284**	-0.385	-0.739**	-0.525**	-0.384*
	(0.300)	(0.296)	(0.243)	(0.222)	(0.144)	(0.159)	(0.144)	(0.138)	(0.287)	(0.295)	(0.245)	(0.224)
Exposure Social Telenovela 0 to 2									-0.473	-0.793**	-0.639**	-0.525*
									(0.336)	(0.333)	(0.293)	(0.276)
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Wave Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country × Wave Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	96	162	318	688	372	710	1,216	1,586	206	272	433	803
R^2	0.128	0.075	0.041	0.027	0.047	0.046	0.037	0.032	0.102	0.092	0.069	0.039
Within-R^2	0.128	0.075	0.041	0.027	0.020	0.016	0.016	0.014	0.057	0.044	0.032	0.021
Control mean	6.225	6.225	6.139	6.009	5.775	5.750	5.801	5.829	6.225	6.225	6.139	6.009

Note: catholics is a dummy for wheter the individuals is catholic or not. employment status refers to wheter the individual is in the working or unemployed. Standard errors are clustered at wave and interview date level.