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Fooled by the cycle: Permanent versus cyclical improvements in social indicators ☆

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ABSTRACT

This paper studies the time series behavior of a set of widely-used social indicators and uncovers two important stylized facts. First, not all social indicators are created equal in terms of the importance of cyclical fluctuations. While some social indicators such as the unemployment rate and monetary poverty show large cyclical fluctuations, other social measures such as the Human Development Index are, by construction, dominated by long-run trends. Second, interestingly, yet not surprisingly, a large part of the cyclical fluctuations in social indicators can be explained by cyclical changes in income (proxied by real GDP per capita). For this reason, countries with large cyclical income volatility exhibit, in turn, large cyclical changes in some of these social indicators (particularly in those indicators that are more prone to cyclical fluctuations). Since cyclical income volatility is much larger in the developing world, these two critical stylized facts raise fundamental issues regarding the duration of improvements in social indicators (like the ones observed in many developing countries during the last commodity super-cycle). After a detailed conceptual and methodological discussion of these issues, and relying on a global sample of industrial and developing countries, we dig deeper into the importance of cyclical versus permanent components by extending the seminal contribution of Datt and Ravallion (1992). In particular, we show that more than 40 percent of the fall in monetary poverty observed in Latin America and the Caribbean during the so-called Golden Decade can be attributed to cyclical changes in income. While in principle universal, our concerns are particularly relevant in the developing world where, compared to developed countries, output volatility is larger and driven, to a large extent, by external factors (such as commodity prices).

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1. Introduction

As academics and policymakers celebrated the substantial improvements in poverty rates and social indicators across developing economies in the pre-pandemic world, especially since the early 2000s, it is crucial to keep in mind that a large part of these social gains took place during a period of booming commodity prices and economic bonanzas for many developing countries.[1,2] After "parties" of this magnitude are over, one would expect periods of recessions to reverse part of the gains in the reduction of poverty that were achieved in good times. While obvious, this fact seems to have been often overlooked by the poverty literature, which has mostly focused on measuring the importance of income growth on poverty without distinguishing between trend and cyclical arguments.[3] This "degree of temporariness" is critical to properly assess whether some of these social gains are here to stay or may most likely (at least partially) fade away. Particularly during good times, when everything seems on track, one would like to account for the importance of cyclical effects on poverty before viewing those gains as permanent.

To illustrate this point, Fig. 1 traces the evolution of three widely-used social indicators (unemployment rate, monetary poverty, and the Human Development Index) as well as the cyclical component of real GDP per capita from 1991 to 2017 for a sample of 15 Latin America and the Caribbean (LAC) countries. Note that, in order to make comparisons with social indicators easier to the naked eye, the cyclical component of real GDP per capita is inverted along the *y*-right-axis of Fig. 1. The Human Development Index (HDI), developed by the United Nations Development Programme, is an index that averages achievement in three key dimensions of human development: a long and healthy life, education, and a decent standard of living.[4] Monetary poverty represents the population with an income below 5.50 dollars per person a day in 2011 purchasing power parity (PPP). Finally, the unemployment rate measures the number of people unemployed divided by the total labor force. In terms of the relationship between each social indicator and the cyclical component of real GDP per capita, the measures of unemployment rate and HDI stand at opposite extremes.[5] The unemployment rate displays large cyclical fluctuations, following closely the business cycle. On the other hand, the HDI, which is built from more structural factors, appears uncorrelated with the business cycle and dominated by the trend component.[6] Monetary poverty falls somewhere in between, exhibiting both trend and cyclical components. Assigning a value of 100 to all four measures for the year 2003, we can easily compare the improvement of social conditions until 2014. This period is typically referred to as the Golden Decade due to the long-lasting boom in commodity prices faced by the region.[7]

Depending on which social indicator is used, a very different picture emerges. Both the unemployment rate and monetary poverty responded strongly to the economic tailwinds and declined markedly in this period (40.3 and 44.5 percent, respectively, for the region as a whole). The inverse of the HDI indicator (a normalization to facilitate comparison) also fell during the Golden Decade, indicating social gains. Interestingly – and in line with the structural nature of this social indicator – the rate of decline of the inverse of the HDI during the Golden Decade (7.3 percent) is not very different from the preceding decade.

For a casual observer standing in the year 2014, taking the large cyclically-driven gains in the unemployment rate and monetary poverty at face value would lead to an over-optimistic (and, in fact, misleading) evaluation of the permanent improvements in social conditions in the region. This myopic view of reality becomes evident once the economic cycle begins to take a turn for the worse in 2013 and a large part of these social gains quickly start to dissipate. In Brazil (with about one third of LAC's population), for example, the poverty rate increased by about 3 percentage points between 2014 and 2017 (when real GDP per capita fell by 8.2 percentage points). Had she been more careful, our casual observer could have prevented such over-optimism (or conveying a misleading picture) by either controlling for the cyclical component of the unemployment rate and monetary poverty or simply basing her analysis on more structural measures (i.e., less correlated with the business cycle) such as the HDI indicator.

[1] Needless to say, the pandemic has brought about an entirely new set of issues regarding poverty during a global health crisis (see, for example, ECLAC, 2021), which falls beyond the scope of this paper.

[2] Extreme poverty (commonly measured as the population with an income below 1.9 dollars per person a day in 2011 purchasing power parity) stood at 10 percent of the world's population in 2015, down from 36 percent in 1990. As the incidence of extreme poverty has reached such low levels in many middle-income countries around the world, a more informative threshold commonly used in these economies is 5.50 dollars per person a day in 2011 purchasing power parity, hereafter referred to simply as monetary poverty. Even under this less restrictive definition, monetary poverty in lower and upper middle-income countries fell from 78.6 percent circa 1995 to 41.2 percent circa 2015.

[3] See, among many others, Bourguignon (2003), Gasparini et al. (2007), Ferreira et al. (2013), and Alvaredo and Gasparini (2015).

[4] The health dimension is assessed by life expectancy at birth, the education dimension by years of schooling for adults aged 25 and over and the expected years of schooling for children of school-entering age, and the standard of living dimension by the national income per capita.

[5] Throughout the paper we will refer to this relationship as "cyclicality." Typically used in macroeconomics to describe the effects of the business cycle on fiscal or monetary policy (see, for example, Frankel et al., 2013; Vegh and Vuletin, 2013; and Vegh and Vuletin, 2015), we borrow this terminology to describe the cyclical movements in social conditions associated with fluctuations in the business cycle.

[6] For sure, there are, among others, two social indicators that are typically associated with structural factors: the Multidimensional Poverty Index (MPI) and the Human Capital Index (HCI), the latter recently developed as part of the 2019 World Bank Human Capital Project. Unfortunately, the MPI series are not comparable over time, which is obviously crucial for our analysis, and a sufficiently large dataset is not yet available for the HCI. Nonetheless, these measures will be a highly relevant resource for future research on social gains.

[7] While, in a slight abuse of language, the Golden Decade is typically defined as the period 2003–2013 (given that commodity prices, and oil in particular, started a sharp decline in 2014), we will be using the period 2003–2014 to take into account that monetary poverty in LAC reached its lowest point in 2014.

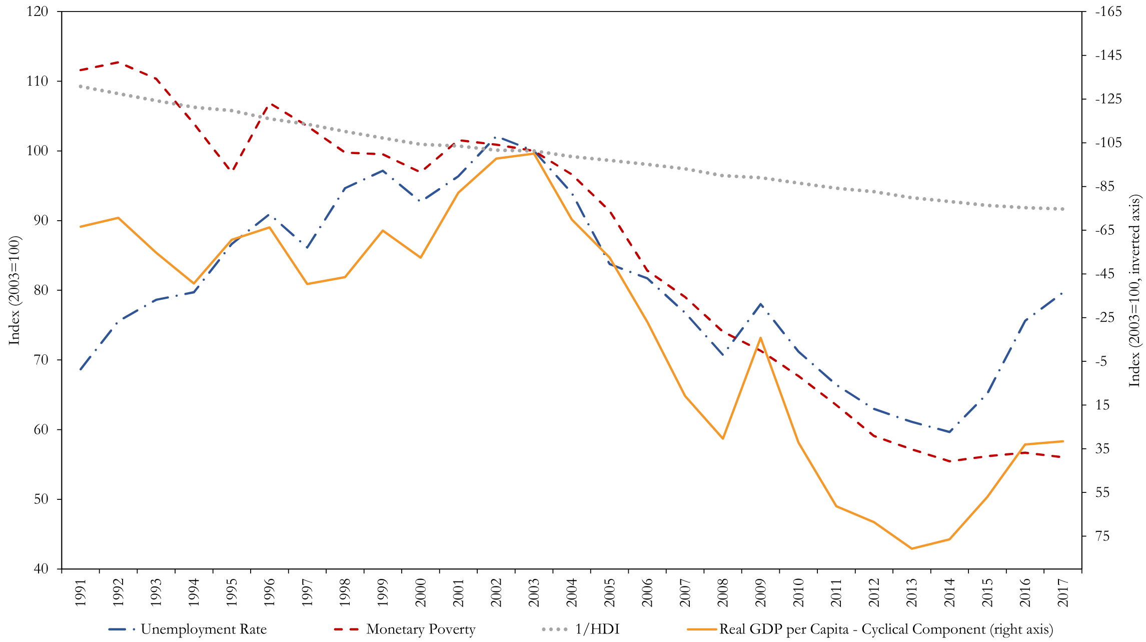

Fig. 1. Evolution of Unemployment Rate, Monetary Poverty, HDI, and the Cyclical Component of Real GDP per Capita in LAC. Notes: Poverty line of 5.50 dollars per person a day (2011 PPP). Averages for LAC are weighted by population. LAC aggregate based on 15 countries for which microdata are available: Argentina, Bolivia, Brazil, Chile, Colombia, Costa Rica, the Dominican Republic, El Salvador, Ecuador, Honduras, Mexico, Panama, Paraguay, Peru, and Uruguay. In each year and for all indicators, the sample is restricted to the countries for which data on monetary poverty is available. The cyclical component of real GDP per capita is defined as the cycle over the trend. Sources: Authors' estimations based on SEDLAC (CEDLAS and World Bank), Human Development Report Office (United Nations), and WEO (October 2018).

This paper shows the importance of the cyclical and trend components in the evolution of relevant (yet quite different) social indicators such as the unemployment rate, monetary poverty, and the HDI. Using a worldwide sample of countries, we find that not all indicators are created equal in terms of the importance of cyclical fluctuations. While the cyclical component explains 72.1 percent and 32.1 percent of the variance of the unemployment rate and monetary poverty, respectively, it only explains 3.3 percent of the variance of the HDI. Moreover, while the unemployment rate and monetary poverty display varying degrees of temporariness in their movements over time across countries, the predominance of long-lasting changes in the HDI is remarkably common across all the economies in our sample. Not surprisingly, we find that this heterogeneity is in large part due to the strong relationship between the cyclical components of the social indicators and the cyclical component of income (i.e., the business cycle). These stylized facts strongly suggest that more structural indicators of social conditions such as the HDI would clearly provide a better picture of permanent gains of social well-being because, by construction, they would not depend on the vagaries of the business cycle and other cyclical changes. In other words, relying on inherently cyclically-driven social indicators, especially over relatively short periods of time, may yield a misleading reading of the social situation because part of the improvement during economic booms could be (at least partially) reversed when the inevitable recession comes along.[8] In fact, for a world sample of developing and industrial countries, we conclude that fluctuations in cyclical income explain 47.4 and 23.3 percent of the variance in unemployment rate and monetary poverty, respectively. The equivalent figure for the HDI is only 1.7 percent.

We then dig deeper into the importance of cyclical versus permanent income components by extending the seminal contribution of Datt and Ravallion (1992). In particular, we show that for LAC as a whole, 41.2 percent of the fall in monetary poverty during the Golden Decade was due to cyclical income factors, 23.8 percent was due to permanent income growth, and 35 percent was due to redistribution. Put differently, almost two thirds of the fall in monetary poverty associated with income gains is explained by cyclical income. One should thus be careful about how to assess permanent social gains, particularly in economies where output is highly volatile which, as we show, increases the cyclical effects on social indicators.

The paper proceeds as follows. Section 2 resorts to a univariate time series approach to compute the relative weight of the cyclical and trend components in the variance of each social indicator. Section 3 links the cyclical component of social indicators to the business cycle and shows that, everything else equal, cyclical income volatility plays a crucial role in driving the cyclicality of social indicators. Using household survey data for a set of LAC countries, Section 4 decomposes the fall in monetary poverty during the Golden Decade into permanent income growth, cyclical income, and redistribution. Section 5 concludes.

[8] An alternative, naturally, would be to construct cyclically-adjusted monetary poverty measures. However, as discussed in Riera-Crichton et al. (2016) in the context of fiscal policy, cyclically-adjusted measures have also serious shortcomings.

2. How cyclical are social indicators?

When examining the evolution of social indicators over recent decades, we should always keep in mind that any change in the underlying indicator can be decomposed into a cyclical component, typically driven by short-term factors, and a trend component that responds to structural considerations. Taking this distinction into account is critical for policymakers since policies and programs implemented to deal with cyclical fluctuations of social indicators are intrinsically different from those designed to improve structural factors. Moreover, measuring the lasting success in the fight against poverty using social indicators with large cyclical fluctuations could be misleading since the analysis would be highly sensitive to the time span under consideration. In other words, given the significant influence that business cycles have on the cyclical component of some social indicators like the poverty rate, a policymaker would draw very different conclusions if the response of poverty were evaluated during a boom or a complete (boom-bust) business cycle. In fact, the importance of the cyclical component in social indicators is magnified for the case of emerging markets subject to large external shocks, such as changes in the terms of trade, global liquidity, and world economic activity.[9] All these shocks are cyclical in nature and thus will tend to amplify emerging markets' business cycles and, in turn, the cyclical components of social indicators.

To formalize the intuition discussed above, we need to compute the relative importance of the cyclical and trend components in each social indicator. We do so with a simple variance decomposition analysis. First, we decompose each time series into a cyclical (C) and trend (T) components:

$$S_t = S_t^C + S_t^T. \tag{1}$$

We proxy the trend component with a simple linear trend.[10] Then, taking the variance of (1), we can compute the portion of the variance corresponding to each component:[11]

$$W^C = \frac{Var\left(S_t^C\right)}{Var(S_t)}, \; W^T = \frac{Var\left(S_t^T\right)}{Var(S_t)} \;, \; W^C + W^T = 1, \tag{2}$$

where W^C and W^T represent the share of the total variance explained by the cyclical and trend components, respectively.

Fig. 2 summarizes this simple variance decomposition exercise. The height of the bars in Fig. 2 denotes W^C; that is, the relative importance of the cyclical component in the total variance of each indicator for a worldwide sample.[12] As we can easily observe, the share of the total variance explained by the cyclical component is much higher for the unemployment rate and monetary poverty than for more structural measures of social welfare such as the HDI. Specifically, we find that the cyclical component explains 72.1 percent of the variance of the unemployment rate. At the other extreme, the cyclical component explains only 3.3 percent of the variance of the HDI indicator (and hence 96.7 percent is explained by the trend component). Monetary poverty falls in between, with 32.1 percent of its variability due to cyclical movements (and hence 67.9 percent to the trend component).[13]

These results are a clear indication that, in terms of the relevance of cyclical fluctuations, not all social indicators are created equal. Going back to our casual observer, the importance of the cyclical movements in the total variance of each social indicator shows that using the unemployment rate or monetary poverty to measure long-lasting improvements in social conditions will probably lead to a biased conclusion. Moreover, the bracketed lines on top of each column in Fig. 2 representing the standard errors across countries show significant differences in how homogeneous these results are in our worldwide sample. While the importance of cyclical fluctuations of the HDI is small and quite homogenous, the shares for the monetary poverty are highly heterogeneous across economies. As a result, when analyzing long-term gains in social welfare, our casual observer may be misled not only by focusing on largely cyclical-driven indicators like the unemployment rate but also by concentrating on countries where monetary poverty is of a cyclical nature. To highlight the potential biases introduced by these important stylized facts, we now resort to a simple two-country example.

2.1. The perils of random sampling: An illustration using Argentina and Chile

Thus far, we have shown that not all social indicators are created equal, especially when it comes to the importance of cyclical fluctuations. This stylized fact leads to a powerful policy warning: given the prevalence of cyclical gains, a policymaker focusing on an indicator over a relatively short time span could be highly misled when it comes to evaluating long-lasting improvements in social conditions in her country.

[9] See, for example, Vegh et al. (2018).

[10] Our definition of trend-driven change calls for truly long-term factors driving the trend component in our set of social indicators. As social indicators data are not available for time spans longer than three decades, the identification of this type of low frequency signals is more difficult. Thus, applying any sort of band-pass filter runs the risk of attaching to the trend component some relatively low frequency cyclical fluctuations. Our decomposition (for the social indicators and real GDP per capita) is thus based on the following regression: $Y_t = \beta t + \varepsilon_t$, where t is the linear trend, β is the regression coefficient, and ε_t is a white noise error. The trend component is obtained from $Y_t^T = \widehat{\beta} t$ and the cyclical component is extracted from the residual: $Y_t^C = Y_t - Y_t^T$.

[11] Since we use a linear trend, the cyclical and trend components are uncorrelated by construction.

[12] See Appendix A for the complete list of countries used in the analysis.

[13] Using a quadratic trend would yield 48.6 percent for the unemployment rate, 23.6 percent for monetary poverty, and 1.3 percent for the HDI indicator.

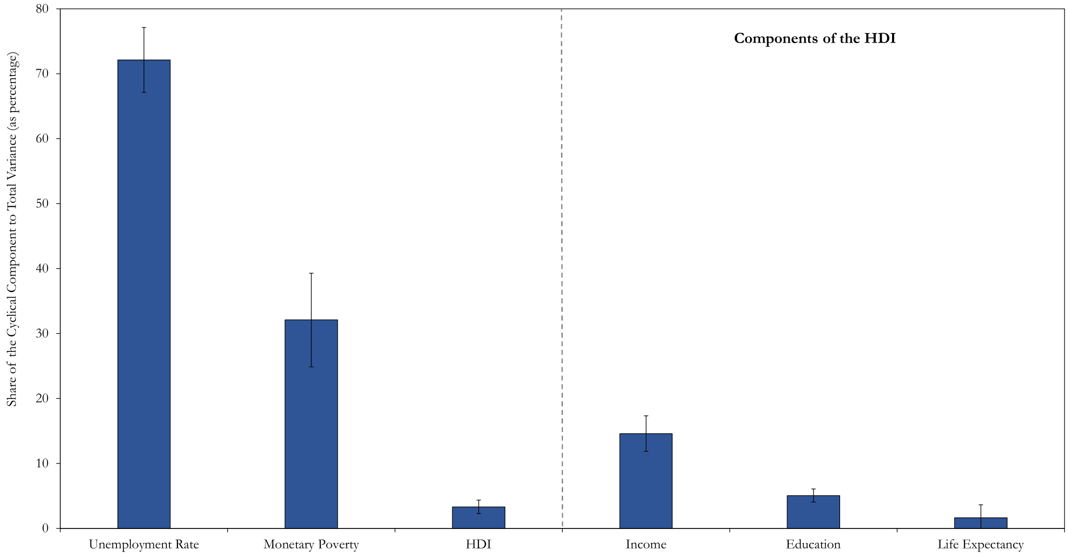

Fig. 2. Contribution of the Cyclical Component of each Social Indicator to its Total Variance, World Sample. Notes: Poverty line of 5.50 dollars per person a day (2011 PPP). The figures reported correspond to the median value across countries. Black lines denote two standard error intervals (weighted by real GDP). Estimations of the contribution of the cyclical component based on a univariate model. Sources: Authors' estimations based on PovcalNet (March 2019), SEDLAC (CEDLAS and World Bank), Human Development Report Office (United Nations), and WEO (October 2018).

To illustrate this warning, consider a simple example with two countries and our three main social indicators: the unemployment rate that will be quite cyclical in nature, monetary poverty that could be driven by either cyclical fluctuations or trend-driven movements, and the HDI, with almost no cyclical component. Furthermore, to factor in the heterogeneity regarding the importance of cyclical fluctuations across countries, we purposefully picked two well-known emerging markets with vastly different shares of cyclical fluctuations in monetary poverty: Argentina and Chile.

Suppose now that our policymaker is trying to evaluate the long-run improvement of social conditions but is restricted for the sake of argument to one decade of data. Fig. 3, Panels A, C, and E show the 10-year difference in the unemployment rate, monetary poverty, and the inverse of the HDI, respectively. These figures provide us a clear sense of the potential biases in perception across different samples. Firstly, if the policymaker is following the series of the unemployment rate, no matter the country, she will be at risk of reaching wildly different conclusions depending on the sample period she chooses to study. While someone studying the case of Chile could boast from a very decent 3.4-percentage-point decrease in the unemployment rate in 2012, the same policymaker would have to explain an increase of 3.0 percentage points in 2003. To a much greater degree, the same story unfolds for Argentina with a whopping 15.3-percentage-point increase in 2002 and 15.3-percentage-point decrease in 2012. It is worth noting that while the importance of cyclical fluctuations in the unemployment rate hinders the ability to diagnose trend-driven gains in both countries, this problem is much more severe in Argentina. In fact, and following the previous univariate-based variance decomposition analysis, the cyclical component explains 62.3 and 95.2 percent of the variance of the unemployment rate in Chile and Argentina, respectively. We will explore the root of these differences in the next section.

In the same vein, for the case of monetary poverty, a policymaker evaluating social welfare gains in Argentina in 2002 would reach the opposite conclusions than one evaluating the situation in 2012. These large differences make it almost impossible to understand the long-term evolution of social conditions in this country. On the other hand, a policymaker using the same indicator in Chile would be much less exposed to sample-dependent variation in her conclusions. In other words, since the monetary poverty indicator in Chile is dominated by its trend component, we can approximate the long-run gains in the underlying indicator with relative short-time samples. In fact, and following the previous univariate-based variance decomposition analysis, the cyclical component explains 84.8 percent of the variance of monetary poverty in Argentina (this figure is larger than the world-sample average associated with the unemployment rate), but only 2.3 percent in Chile (a figure very close to the world-sample average associated with the HDI).

In sharp contrast, a policymaker using the HDI indicator would not fall into misleading sample-dependent conclusions regardless of the country under study. Indeed, the cyclical component explains 0.5 and 2.7 percent of the variance of the HDI rate in Chile and Argentina, respectively.

Finally, Fig. 3, Panels B, D, and F translate the previous results (i.e., Panels A, C, and E) into density plots for the 10-year differences in the unemployment rate, monetary poverty, and the inverse of the HDI, respectively. The relatively high dispersion in the distributions of the 10-year differences in the unemployment rate displayed in Fig. 3, Panel B shows that both Argentina and Chile are highly exposed to myopic views of the long-term improvements in the unemployment rate. While the case of Argentina is more extreme, both countries display relatively high standard deviations for the 10-year difference observations. For monetary poverty, Fig. 3, Panel D, tells us that, again, a policymaker from Argentina is quite exposed to large errors assessing

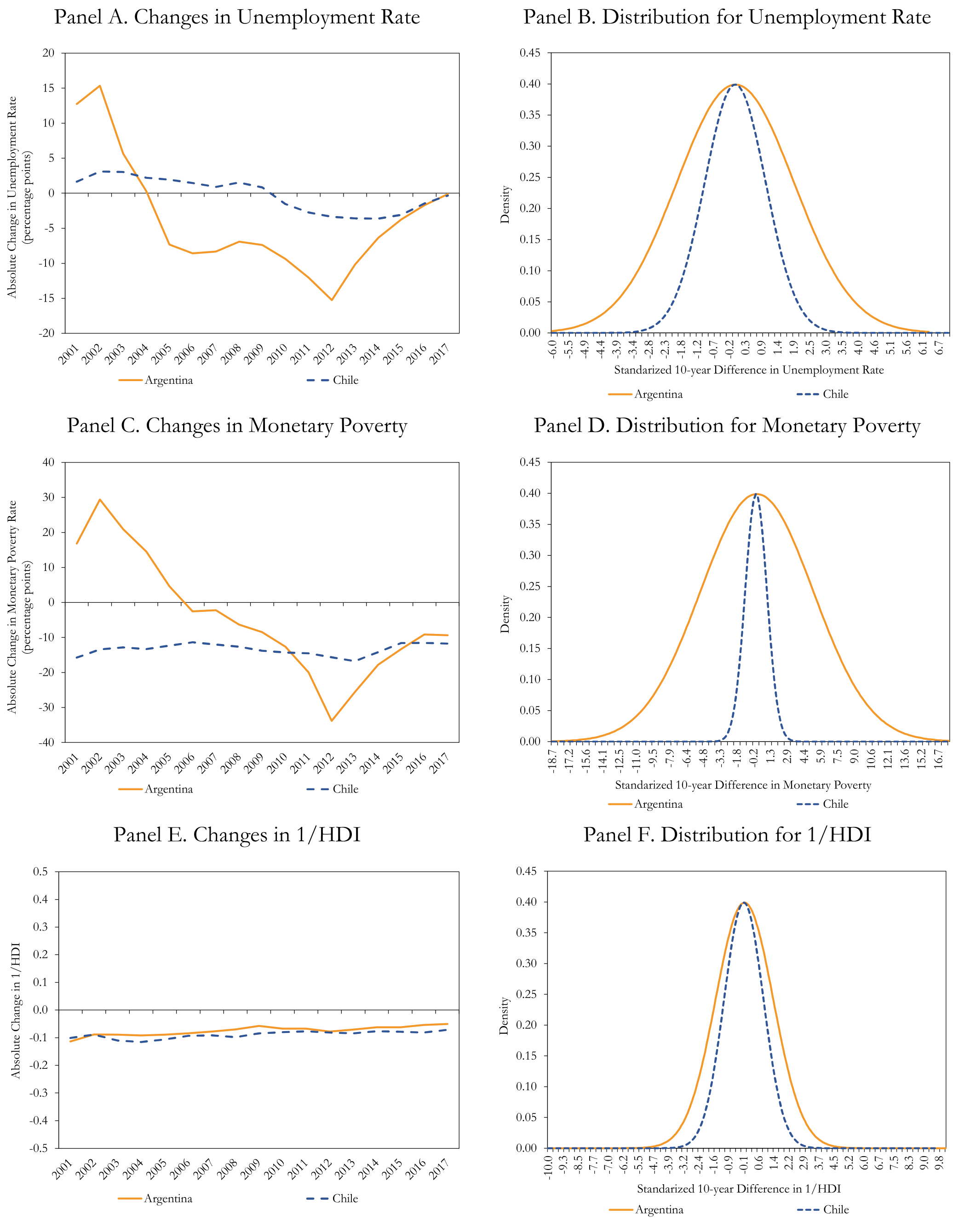

Fig. 3. Argentina versus Chile: 10-year Difference in Social Indicators. Notes: Poverty line of 5.50 dollars per person a day (2011 PPP). For panels B, D, and F, we fitted a standard normal distribution taking the first two moments (mean and standard deviation) of the 10-year differences in each social indicator. Sources: Authors' estimations based on SEDLAC (CEDLAS and World Bank), Human Development Report Office (United Nations), and WEO (October 2018).

long-term improvements. In this case though, given the dominance of the trend component of monetary poverty in Chile, the Chilean policymaker would be correct in her assessment of long-term gains no matter the year she starts the study or the length of available data. Finally, using the HDI, the latter situation would apply to both countries. The HDI not only lowers the chances of sample-dependent errors but also eliminates the differences across countries, as shown in Fig. 3, Panel F.[14]

[14] Appendix C also illustrates that not all social indicators are created equal in Indonesia and Thailand, two other emerging economies where long time series are available.

2.2. Are structural indicators such as the HDI structural enough?

The above sections emphasized the potential bias implicit in social indicators largely driven by cyclical fluctuations when trying to evaluate long-lasting improvements in social conditions. A simple solution would be to extract the trend component of each indicator and use it in the evaluation of long-run gains in poverty reduction. A practical problem with this approach is the risk of sample-dependent bias explained above due to, precisely, the short-sample nature of available data.[15] An alternative solution comes from the type of indicator used. Throughout the paper, we have seen that social indicators based on structural factors such as the HDI are much less influenced by cyclical fluctuations. The large trend component of this type of indicators implies that we can better proxy long-run improvements in social conditions with relatively short periods of available data.

Having said that, indicators such as the HDI are also subject, to some extent, to the same type of conceptual critique. Why? Because the HDI is an index that also includes a criterion based upon income. Fig. 2 shows the relative importance of the cyclical component in the total variance of each underlying indicator of the HDI. While this share is relatively low for all components, this simple exercise clearly shows that while structural components such as education and life expectancy have a cyclical share that explains little of their total variance, the measure of income included in the HDI is, as expected, much more important in terms of cyclical fluctuations. Again, including such cyclically-driven components in the construction of structural measures like the HDI should affect some countries more than others depending on the underlying volatility of the business cycle.

3. What drives the cyclical fluctuations of social indicators?

Whereas the large differences in the time series behavior of various social indicators uncovered in our previous section may be striking at first sight, they should hardly come as a surprise given the importance of business cycle fluctuations in some of these social indicators.

While the drivers of the trend component of social indicators may be diverse – and to some degree independent from long-term income growth (for example, drivers could be related to long-term trends in income redistribution and technological diffusion) – the cyclical components of the social indicators used in this study should be, in principle, tightly related to business cycle fluctuations. This is particularly the case of social indicators such as the unemployment rate and monetary poverty. The reason lies in the fundamental link between these social indicators and income. For example, in the case of the unemployment rate, any Keynesian model with price or wage rigidities would predict a strong correlation between the unemployment rate and the business cycle. Specifically, negative real or monetary shocks should lead to short-term rises in the unemployment rate. Changes in monetary poverty should also depend, at least partially, on the evolution of income per capita. In contrast, by construction, business cycle fluctuations should have much less of an effect on the HDI (especially the non-income components such as education and life expectancy).[16]

To visualize the strong relationship between the business cycle and the fluctuations of our social indicators, Fig. 4 further explores the same two-country example used in our previous section. Note that, as in Fig. 1, and in order to make comparisons with social indicators easier to visualize, the cyclical component of real GDP per capita is inverted along the y-right-axis of Fig. 4. In Fig. 4, Panel A, we compare the evolution of the unemployment rate, the monetary poverty, and the HDI versus real GDP per capita. In terms of monetary poverty, two very different pictures emerge. In Argentina, the monetary poverty is clearly dominated by the business cycle. In contrast, monetary poverty in Chile is mainly determined by long-term income (as opposed to cyclical considerations). This matches perfectly the behavior of real GDP per capita dominated by a very volatile business cycle in Argentina but driven by the trend in Chile. On the other hand, the HDI evolves at a constant rate in both countries, independently of the cyclical behavior of output.

Finally, the unemployment rate displays a highly cyclical behavior in both countries although the amplitude of the cycle is clearly larger in the case of Argentina. This, as shown in Fig. 4, Panel B, is fully consistent with the behavior of the business cycle (measured by the cyclical component of real GDP per capita), which displays a much larger amplitude in Argentina than in Chile.

The above two-country example gives us an illustration of the strong correlation between the business cycle and the cyclical component of our social indicators. Extending this analysis to our worldwide sample, Fig. 5 depicts the relationship between the volatility of the cyclical component of real GDP per capita (along the x-axis) and the volatility of the cyclical component of each of our six social indicators (along the y-axis) using a simple set of scatter plots. As expected, in all cases, the effect of the volatility of the cyclical component of real GDP per capita, measured by the slope of the fitted line, is positive and highly significant (except for life expectancy). Moreover, this simple bivariate relationship explains relatively well differences in the volatility of cyclical components across countries.

To capture the full extent of the role of the business cycle in driving movements in social indicators (i.e. not only on their cyclical component as we just showed), we use a similar variance decomposition approach as in Section 2. For this multivariate version, we first run the following regression:

[15] Section 4 will discuss how to overcome (when necessary) some of this micro-based survey data limitations.

[16] Naturally, in the final analysis, the extent to which business cycle fluctuations end up affecting different social indicators could also depend on the existence of policy buffers such as unemployment insurance benefits and/or other country-specific characteristics affecting the transmission mechanism between cyclical income changes and social indicators' responses. Section 4 discusses the relevance of redistribution arguments in more detail.

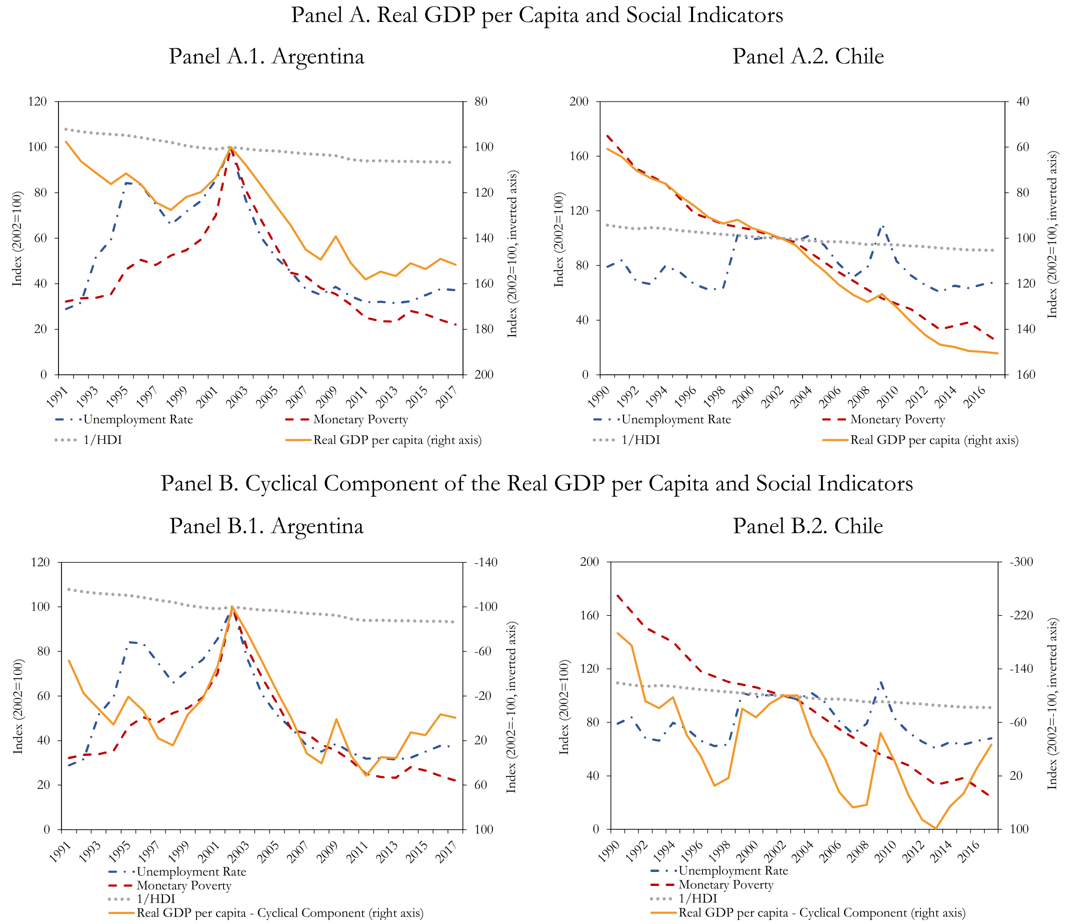

Fig. 4. Argentina versus Chile. Notes: Poverty line of 5.50 dollars per person a day (2011 PPP). The cyclical component of the real GDP per capita is defined as the cycle over the trend. Sources: Authors' estimations based on SEDLAC (CEDLAS and World Bank), Human Development Report Office (United Nations), and WEO (October 2018).

$$S_t = \beta_1 Y_t^C + \beta_2 Y_t^T + \varepsilon_t. \tag{3}$$

As before, we proxy the trend component of output with a simple linear trend. Then, taking the variance of (3), and given that, by construction, Y_t^C and Y_t^T are uncorrelated, we can compute the portion of the variance allotted to each component:

$$W^{Y^C} = \frac{\beta_1^2 \mathrm{Var}\left(Y_t^C\right)}{\beta_1^2 \mathrm{Var}\left(Y_t^C\right) + \beta_2^2 \mathrm{Var}\left(Y_t^T\right)}, \quad W^{Y^T} = \frac{\beta_2^2 \mathrm{Var}\left(Y_t^T\right)}{\beta_1^2 \mathrm{Var}\left(Y_t^C\right) + \beta_2^2 \mathrm{Var}\left(Y_t^T\right)}, \quad W^{Y^C} + W^{Y^T} = 1, \tag{4}$$

where W^{Y^C} represents the share of the variance of the social indicator driven by income, which is explained by the business cycle. On the other hand, W^{Y^T}, captures the share of the variance of the social indicator driven by income that is explained by the trend component of output.

The height of the bars in Fig. 6 denotes W^{Y^C}; that is, the average share of the variance of the social indicator driven by income that is explained by the business cycle for a worldwide sample. This share is much higher for the unemployment rate and monetary poverty than for more structural measures of social welfare such as the HDI. We find that, by itself, the business cycle component explains 47.4, 23.3, and 1.7 percent of the variance of the social indicator driven by income for the unemployment rate, monetary poverty, and HDI, respectively. This clearly shows how some indicators such as the unemployment rate or monetary poverty are heavily exposed to sampling bias due to common and well understood ups and downs in economic activity. Moreover, as in the case of Argentina above, and given that W^{Y^C} is a function of $\mathrm{Var}\left(Y_t^C\right)$, the potential bias of interpreting trend-driven gains in social conditions for such indicators would

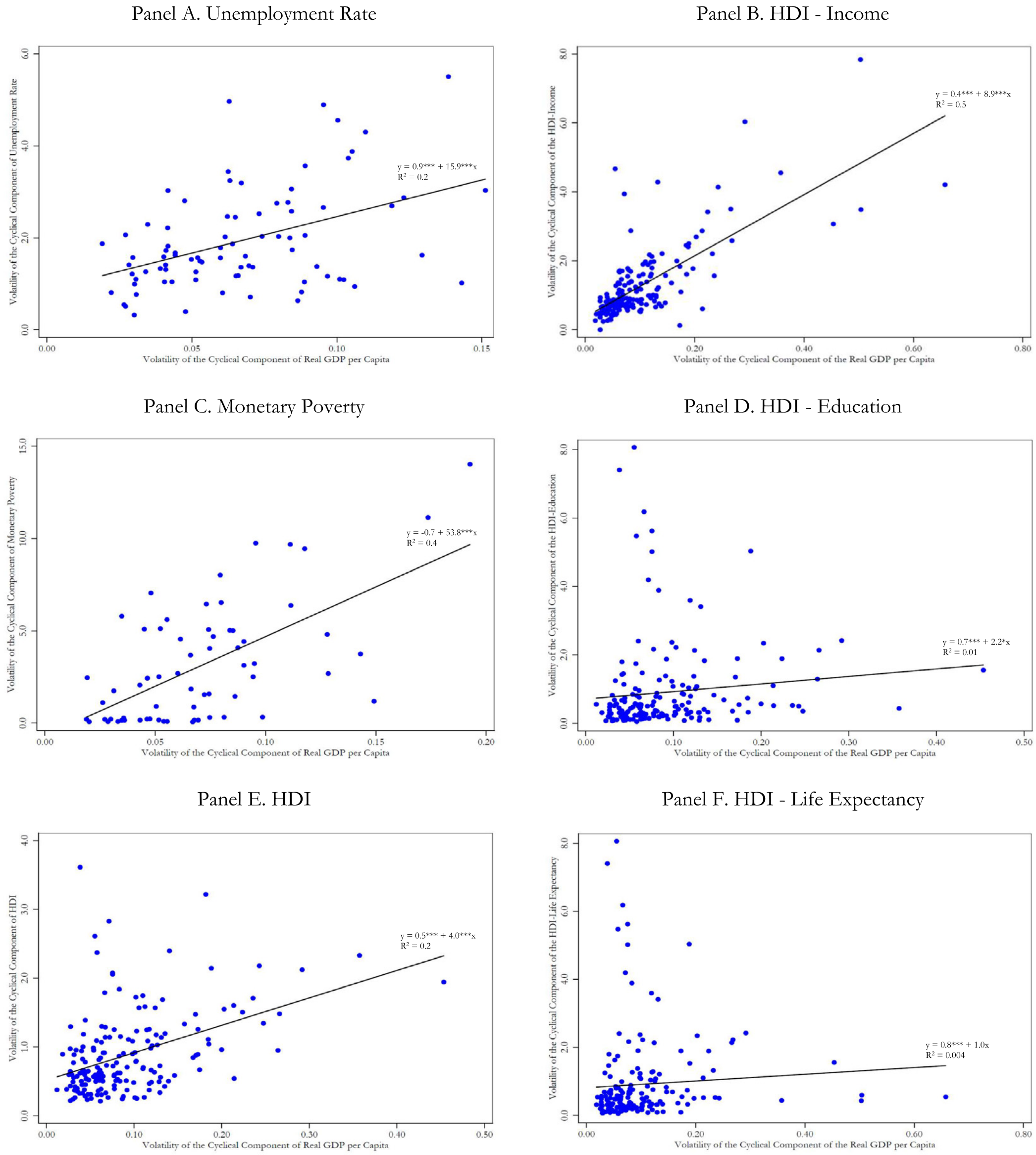

Fig. 5. Volatility of the Cyclical Components of Social Indicators and Real GDP per Capita, World Sample. Notes: Poverty line of 5.50 dollars per person a day (2011 PPP). Volatility is defined as the standard deviation of the cyclical component of each variable. The cyclical component for all social indicators is defined as the cycle and for the real GDP per capita as the cycle over the trend. Sources: Authors' estimations based on PovcalNet (March 2019), SEDLAC (CEDLAS and World Bank), Human Development Report Office (United Nations), and WEO (October 2018).

mechanically grow with the volatility of the business cycle (see equation (4)).[17] The next section zooms on the role of the business cycle driving movements in cyclical social indicators such as monetary poverty using microdata for a set of LAC countries.

[17] We are forced by virtue of the sample length to rely upon a linear deterministic trend. In light of well-established evidence regarding the different stationary nature of real GDP in emerging markets (see for example seminal paper by Aguiar and Gopinath, 2007), a natural concern is the extent to which the findings of Fig. 6 are robust to other detrending more "flexible" techniques. While most data for monetary poverty and HDI (and its components) start in mid-1990s to early 2000s, we have 32 countries in our sample with unemployment rate data starting in the year 1980 (which gives us almost 4 decades of continuous data). Using this data, we cannot reject the null hypothesis that the median contribution of the business cycle to the variance in the unemployment rate is the same across well-known more "flexible" detrending techniques. In particular, and based on a nonparametric K-sample test on the equality of medians, a contribution based on a linear trend (45.2 percent) is statistically the same as that based on a Hodrick-Prescott filter (38.5 percent) or a Christiano-Fitzgerald filter (42.2 percent).

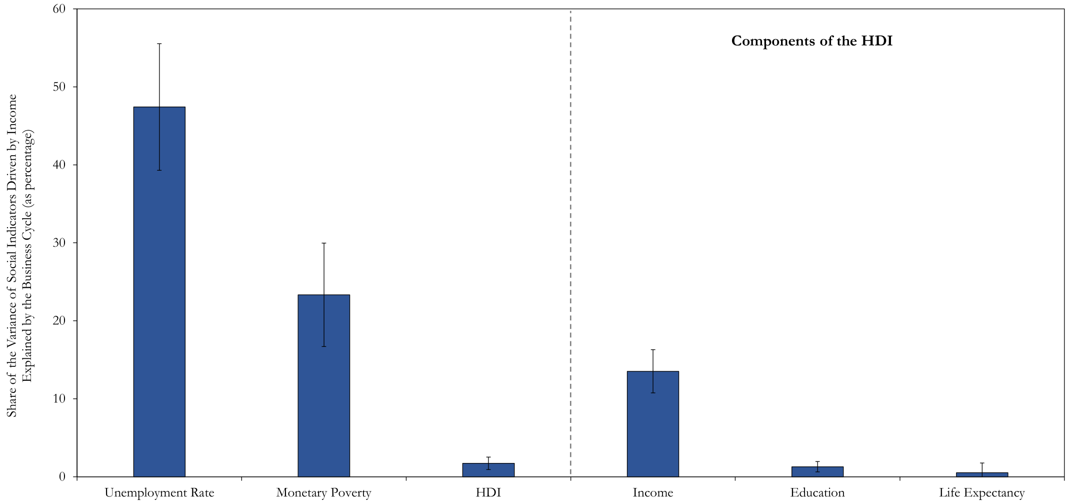

Fig. 6. Contribution of the Business Cycle to the Variance Driven by Income of Each Indicator, World Sample. Notes: Poverty line of 5.50 dollars per person a day (2011 PPP). The figures reported correspond to the median value across countries. Black lines denote two standard error intervals (weighted by real GDP). Estimations of the contribution of the cyclical component based on a bivariate model. Sources: Authors' estimations based on PovcalNet (March 2019), SEDLAC (CEDLAS and World Bank), Human Development Report Office (United Nations), and WEO (October 2018).

4. A microdata approach on the importance of business cycle fluctuations on monetary poverty: An application to LAC

The previous section showed that while some social indicators (such as the unemployment rate) are cyclical in nature, fluctuating considerably in the short run along with the business cycle, others (such as the HDI, especially its non-income components) follow long-term trends and bear very little relation to the business cycle. Interestingly, monetary poverty lies somewhere in between the two extremes with large heterogeneity across countries. In particular, whether monetary poverty behaves more like the unemployment rate (i.e., affected by cyclical considerations) or the HDI (i.e., determined essentially by the long-run trend) crucially depends on the volatility of the business cycle. In high-volatility countries (such as Argentina), changes in monetary poverty are much more closely related to the business cycle than in low-volatility countries (such as Chile).

Given this insight, and based on our motivating example of Fig. 1, a natural question arises: how much of the fall in the monetary poverty during the Golden Decade in LAC was permanent and how much was cyclical? As shown in Fig. 1, emerging regions such as LAC made tremendous progress in terms of reducing monetary poverty during this period, with the headcount ratio for the 5.50-dollar poverty line falling by almost 20 percentage points (from 42.1 percent in 2003 to 23.4 percent in 2014). Needless to say, the relative importance of permanent versus cyclical reductions in poverty has critical implications for (i) assessing the long-lasting magnitude of the fall in poverty, and (ii) the public policies that may be put in place to deal with permanent versus cyclical falls in poverty.

To decompose the fall in monetary poverty between permanent and cyclical components, we follow the very influential methodology proposed in a seminal paper by Datt and Ravallion (1992). Using microdata from household surveys, Datt and Ravallion (1992) decompose the change in poverty between two points in time into (i) a "growth component" and (ii) a "redistribution component." The growth component is identified as the change in monetary poverty between two years that would have occurred if the income of each household member had changed in the same proportion as the national mean income, keeping constant the shape of the income distribution (measured by the Lorenz curve). The redistribution component reflects the change in monetary poverty that would have occurred if the income distribution had changed as it did, but with no changes in mean income.[18,19]

Applying Datt and Ravallion's (1992) methodology to the period 1995–2010, Ferreira et al. (2013) show that monetary poverty – using a poverty line of 4 dollars a day (2005 PPP) – fell about 17 percentage points, of which 66 percent was due to the growth component and the remaining 34 percent to the redistribution component. In other words, the substantial increase in mean income in LAC was the main driving force behind the dramatic progress in poverty reduction, even though

[18] We use a slightly different methodology from the one proposed by Datt and Ravallion (1992). Following Gasparini et al. (2013) and Inchauste et al. (2014), we get rid of the problems of (i) whether to use the initial or end year as the reference period and (ii) how to interpret the residual change in poverty that is not accounted for, by computing the decomposition twice, alternating the reference period, and taking the average growth and redistribution effects.

[19] One important limitation of this decomposition is that since growth, inequality, and poverty are jointly determined in general equilibrium, this approach cannot explain the fundamental factors behind poverty changes. However, it is very useful to illustrate the way incomes have changed and affected poverty. See Ferreira (2012) for further discussion.

redistribution arguments still played an important role.[20] We obtain virtually identical figures after expanding the sample until 2017 and using the 5.50-dollar (2011 PPP) poverty line: a growth component of 67 percent and a redistribution component of 33 percent. This redistribution component is largely explained by the increase in social expenditure in most countries in the region, and the implementation or expansion of existent non-contributory social protection systems, such as the conditional cash transfer programs (López-Calva and Lustig, 2010; Gasparini and Cruces, 2010). The resources allocated to these programs increased as a percentage of GDP in the 2000s, as did the number of countries implementing them and the share of the population covered (Stampini and Tornarolli, 2012; Cecchini and Madariaga, 2011). These programs have a higher redistributive impact than social spending in general because they target specifically the most vulnerable. Further, the fact that transfers are in cash implies that the programs have a direct impact on income inequality, the most common measure of inequality (Gasparini et al., 2016).

4.1. Beyond Datt and Ravallion: Decomposition for the Golden Decade

To further split the "growth component" into what we call a "cyclical income component" and "permanent income component," we need to know the growth rate of the mean income trend during the period under analysis.[21] If one had a long time series of mean income, one would compute its permanent component by using any trend-cycle filter. Unfortunately, for most countries in LAC, data are not available for very long periods (say, for more than 25 years). For this reason, and as is common practice in this literature (Ahluwalia et al., 1979; Bhalla, 2002; Bourguignon and Morrison, 2002; Sala-i-Martin, 2006), we proxy the average trend growth in mean income by the average trend growth in real GDP per capita.[22]

The "permanent income component" is identified as the poverty change between two subsequent years that would have occurred if the income of each household member had changed at a rate equal to the average annual growth rate of the trend of real GDP per capita, keeping constant the shape of the income distribution. The "cyclical income component" is computed as a residual between the "growth component" identified before using Datt and Ravallion's decomposition and the "permanent income component."

Fig. 7 shows our findings. The cyclical income component is the most important factor behind the fall in monetary poverty observed in LAC during the Golden Decade. Out of the 18.8-percentage-point fall in monetary poverty, 7.7 percentage points are explained by the cyclical income component, 6.6 percentage points by the redistribution component, and only 4.5 percentage points by permanent income gains.[23] In other words, more than 40 percent of the fall in monetary poverty was due to cyclical income factors and about 24 percent to permanent income gains. In terms of population, this would imply that around 45 million people got out of poverty in LAC during the Golden Decade due to cyclical income gains. Therefore, one could argue that this group might be at risk of falling into poverty again, as the temporary gains achieved during the expansionary phase of the business cycle dissipate.

Fig. 8 illustrates the same idea over time. The solid line shows the actual evolution of poverty during the period 1996–2017. The dashed line shows the time path of poverty if one excluded the cyclical income component. This line clearly indicates that the fall in poverty during the period 1996–2017 would have been 15.2 percentage points (as opposed to 21.4 percentage points). Why? Because, by and large, most of the income gains in this period were cyclical (especially during the Golden Decade) as opposed to being related to permanent changes. The dotted line shows the evolution of poverty if one also excluded the redistribution component.

Naturally – and in line with previous discussions pointing to the effect of different output fluctuation profiles in Argentina and Chile – Figs. 7 and 8 hide important country-specific differences. Following our comparisons of Argentina and Chile, Fig. 9 is equivalent to Fig. 7 but focusing exclusively on these two countries. During the Golden Decade, the importance of "redistribution" is significant in both countries, but more pronounced in Argentina. Notably, while virtually all monetary poverty gains observed during the Golden Decade in Chile associated with the "growth component" have been driven by its "permanent income component," in Argentina this factor explains very little (i.e., most of the "growth component" has been driven by its "cyclical income component"). In the same vein, Fig. 10 is equivalent to Fig. 8 but solely focusing on these two countries.

Fig. 11 is equivalent to Fig. 10 but, instead of focusing on the Golden Decade, goes all the way back to 1991. This more "historical" picture illustrates in a very vivid manner all the points discussed throughout the paper regarding the crucial effect of cyclical income fluctuations on monetary poverty and the long-lasting nature of those gains. In countries like Argentina, monetary poverty changes prove to be a very poor indicator of long-lasting social gains. Notice, for example, that the

[20] In fact, the relative importance of the redistribution effect is much lower in other regions. Alvaredo and Gasparini (2015) carry out this decomposition for developing countries by region, using the 2-dollar (2005 PPP) poverty line and find that, during the period 1999–2010, characterized by poverty alleviation in all regions in the world, the shares of growth and redistribution effects were, respectively, 99 and 1 percent for East Asia and Pacific, 91 and 9 percent for Europe and Central Asia, 67 and 33 for LAC, 79 and 21 for Middle East and North Africa, 91 and 9 for South Asia, and 100 and 0 for Sub-Saharan Africa.

[21] Naturally, one could also envisage a permanent and a cyclical component for the redistribution effect. This issue, however, has not yet been addressed in the literature and falls outside the scope of our analysis.

[22] Two points are worth noting. First, we cannot reject the null hypothesis that, for the LAC region, the correlation of the mean income and real GDP per capita (0.78) is statistically significant at the one percent level. Second, for LAC countries for which we have more than 25 years of data (like Argentina, Brazil, Costa Rica, and Honduras) we cannot reject the null hypothesis that the average growth in the trend of the mean income is not different, statistically speaking, from the average growth in real GDP per capita trend.

[23] For a long and large enough cyclical shock, the increase in the permanent income may be enough to lead to some permanent gain in terms of poverty reduction. In other words, cyclical gains in poverty could have a permanent effect if shock absorbers are well designed. As discussed in Galeano et al. (2021), this is not the case in LAC because few countries have, for example, unemployment insurance mechanisms and, for those who have it, coverage is very low.

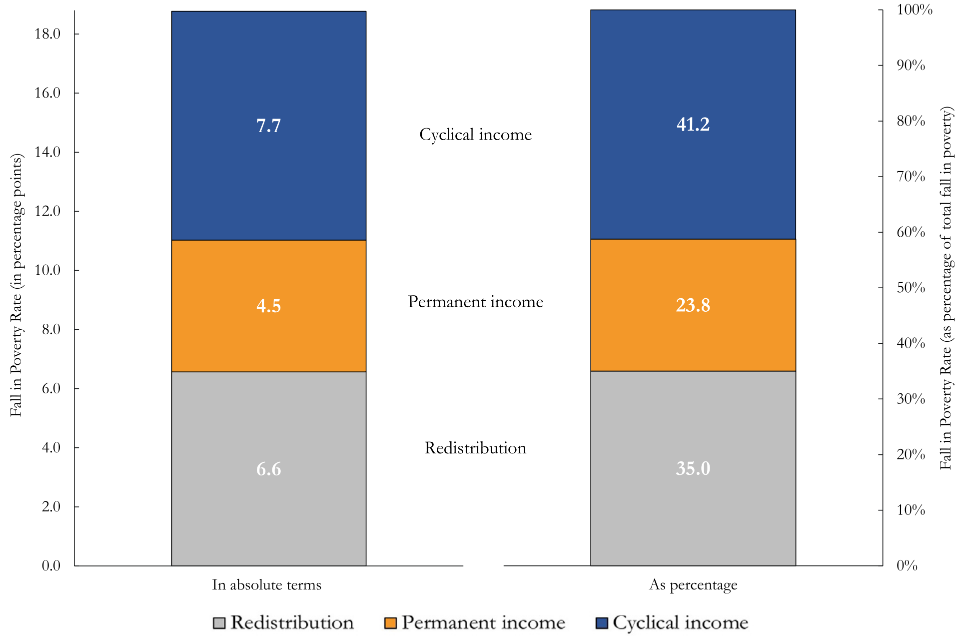

Fig. 7. Decomposition of the Fall in Monetary Poverty Rate in LAC during the Golden Decade. Notes: Poverty line of 5.50 dollars per person a day (2011 PPP). LAC aggregate based on 15 countries in the region, weighted by population, for which microdata are available at the national level: Argentina, Bolivia, Brazil, Chile, Colombia, Costa Rica, Dominican Republic, El Salvador, Ecuador, Honduras, Mexico, Panama, Paraguay, Peru, and Uruguay. See Appendix B for details. Sources: Authors' estimations based on SEDLAC (CEDLAS and World Bank) and WEO (October 2018).

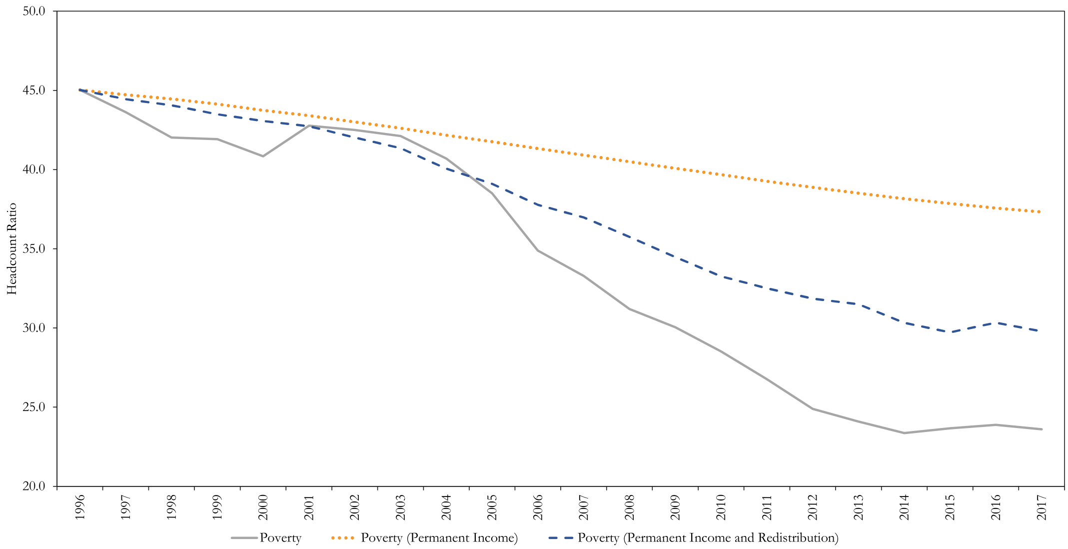

Fig. 8. Monetary Poverty in LAC: Total, Permanent Income, and Redistribution. Notes: Poverty line of 5.50 dollars per person a day (2011 PPP). LAC aggregate based on 15 countries in the region, weighted by population, for which microdata are available at the national level: Argentina, Bolivia, Brazil, Chile, Colombia, Costa Rica, the Dominican Republic, El Salvador, Ecuador, Honduras, Mexico, Panama, Paraguay, Peru, and Uruguay. See Appendix B for details. Sources: Authors' estimations based on SEDLAC (CEDLAS and World Bank) and WEO (October 2018).

monetary poverty rate observed during the last 5 years or so is not that different from the one observed during the early 1990s (with values around 15 percent). Since Argentina has a relatively low permanent increase in income (of about 0.75 percent per year), most of its monetary poverty fluctuations are driven by large up- and down-swings in income. On the other hand, in countries like Chile monetary poverty gains are more permanent in nature.

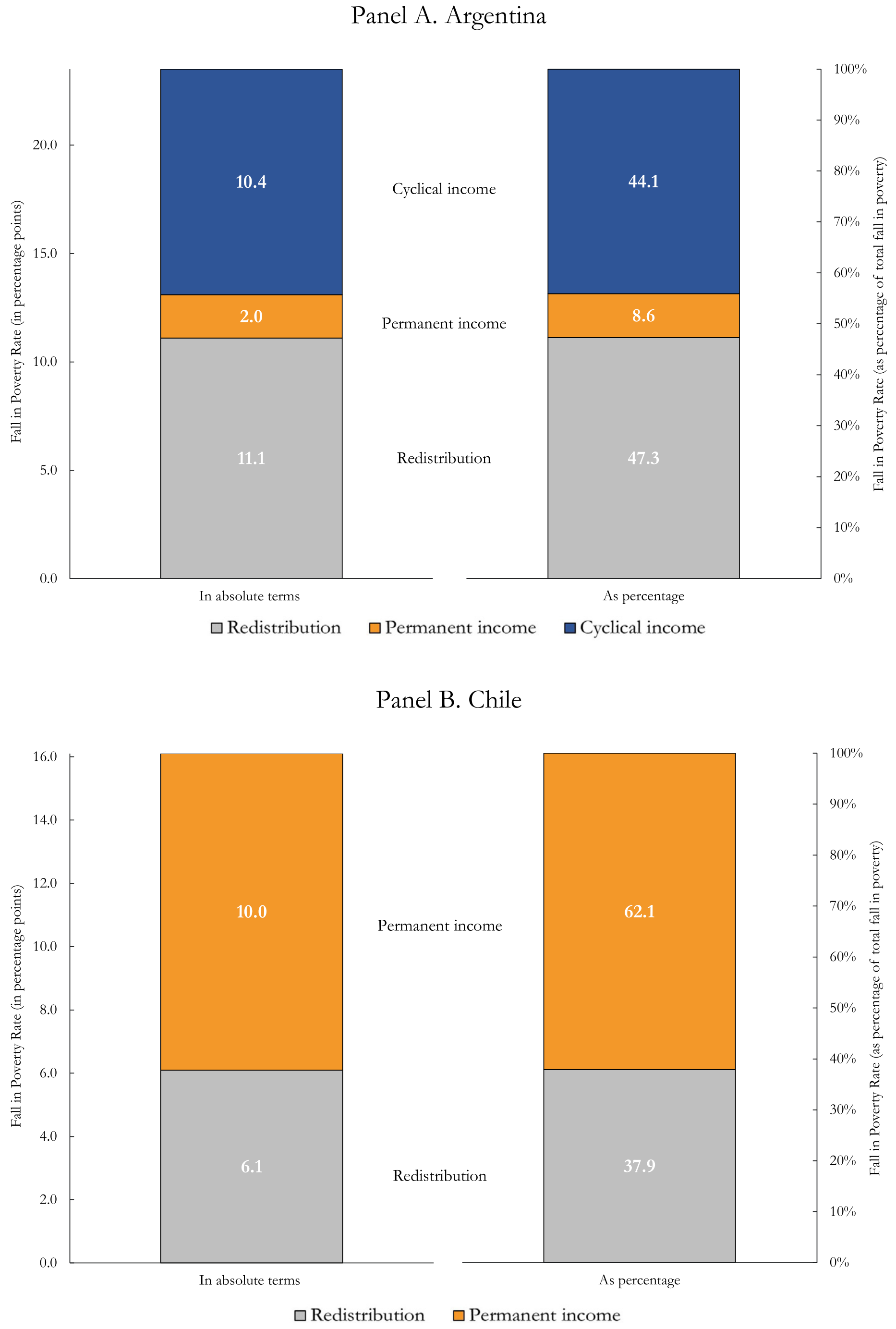

Fig. 9. Decomposition of the Fall in Monetary Poverty Rate in Argentina and Chile during the Golden Decade. Notes: Poverty line of 5.50 dollars per person a day (2011 PPP). See Appendix B for details. Sources: Authors' estimations based on SEDLAC (CEDLAS and World Bank) and WEO (October 2018).

5. Output volatility and exposure to external risks in the developing world

In principle, the concern about how important is output volatility and how it may affect the degree of temporariness of improvements in social indicators is universal. In this section, however, we argue that these concerns are more relevant in the developing world for two main reasons. First, output volatility is larger in the developing world than in industrial countries. Indeed, Fig. 12 shows that, on average, the real gross domestic product volatility is more than 50 percent larger in the developing world. Second, Fig. 13 shows that the influence of external factors such as changes in the short-run real interest

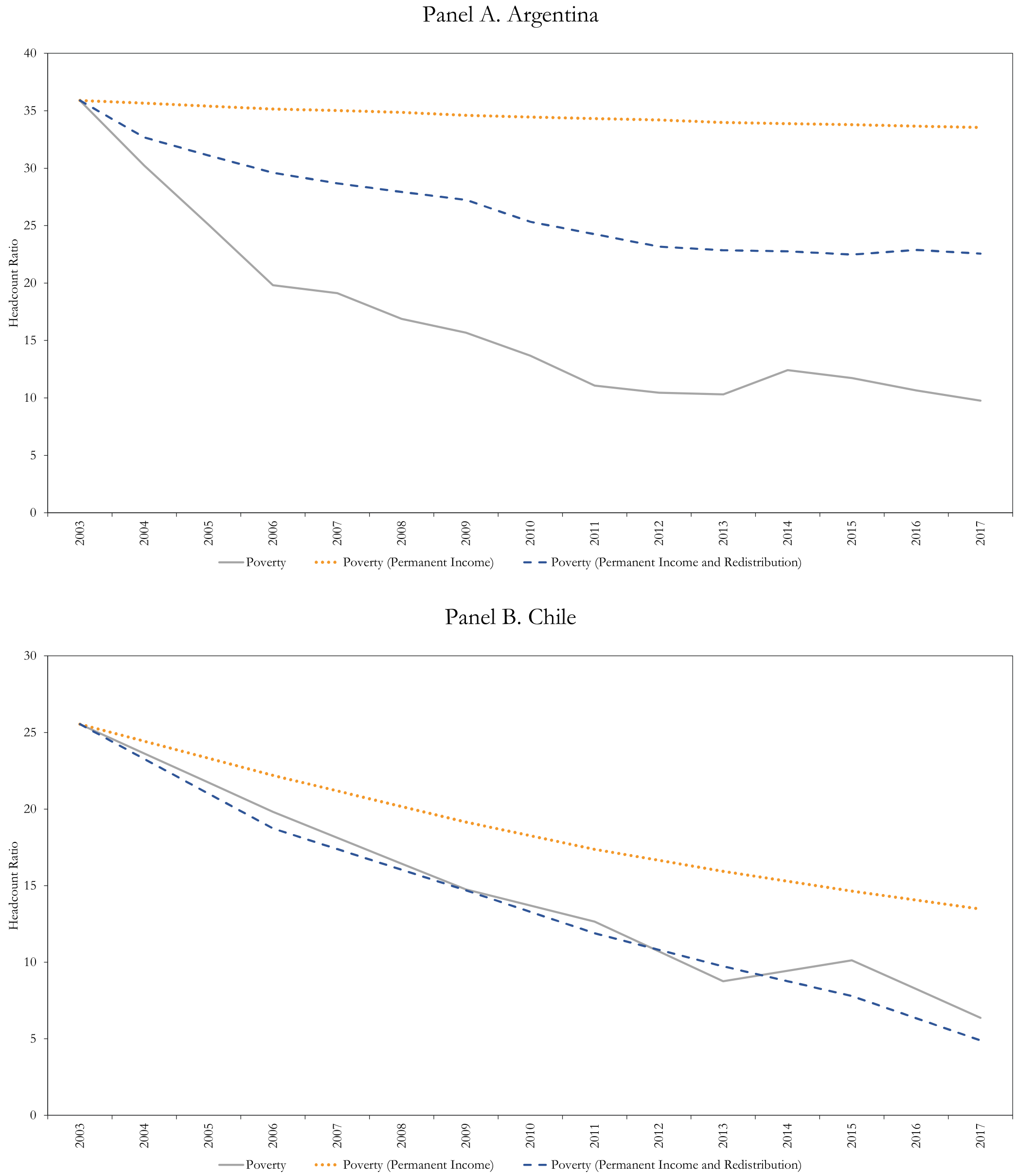

Fig. 10. Monetary Poverty in Argentina and Chile: Total, Permanent Income, and Redistribution. Notes: Poverty line of 5.50 dollars per person a day (2011 PPP). See Appendix B for details. Sources: Authors' estimations based on SEDLAC (CEDLAS and World Bank) and WEO (October 2018).

rate in the United States (a proxy in global liquidity) as well as in commodity terms of trade and output in the United States (as proxies of international exogenous real demand shocks) on output volatility is, on average, about one third larger in the developing world. That is to say, the role of external factors, such as global liquidity and global external demand factors, which are outside policymakers' control, are more important in the developing world.[24]

These two critical macroeconomic empirical regularities increase the practical relevance of our arguments for the developing world due to the larger and mostly externally-driven output volatility. For this part of the world, it proves challenging to distinguish how much of the deterioration of some social indicators is permanent or transitory.

[24] Appendix D discusses the structural vector autoregression model for each country with available data used to identify the impact of external factors on output volatility. The analysis focuses on a total of 52 economies and covers the period 1960–2017.

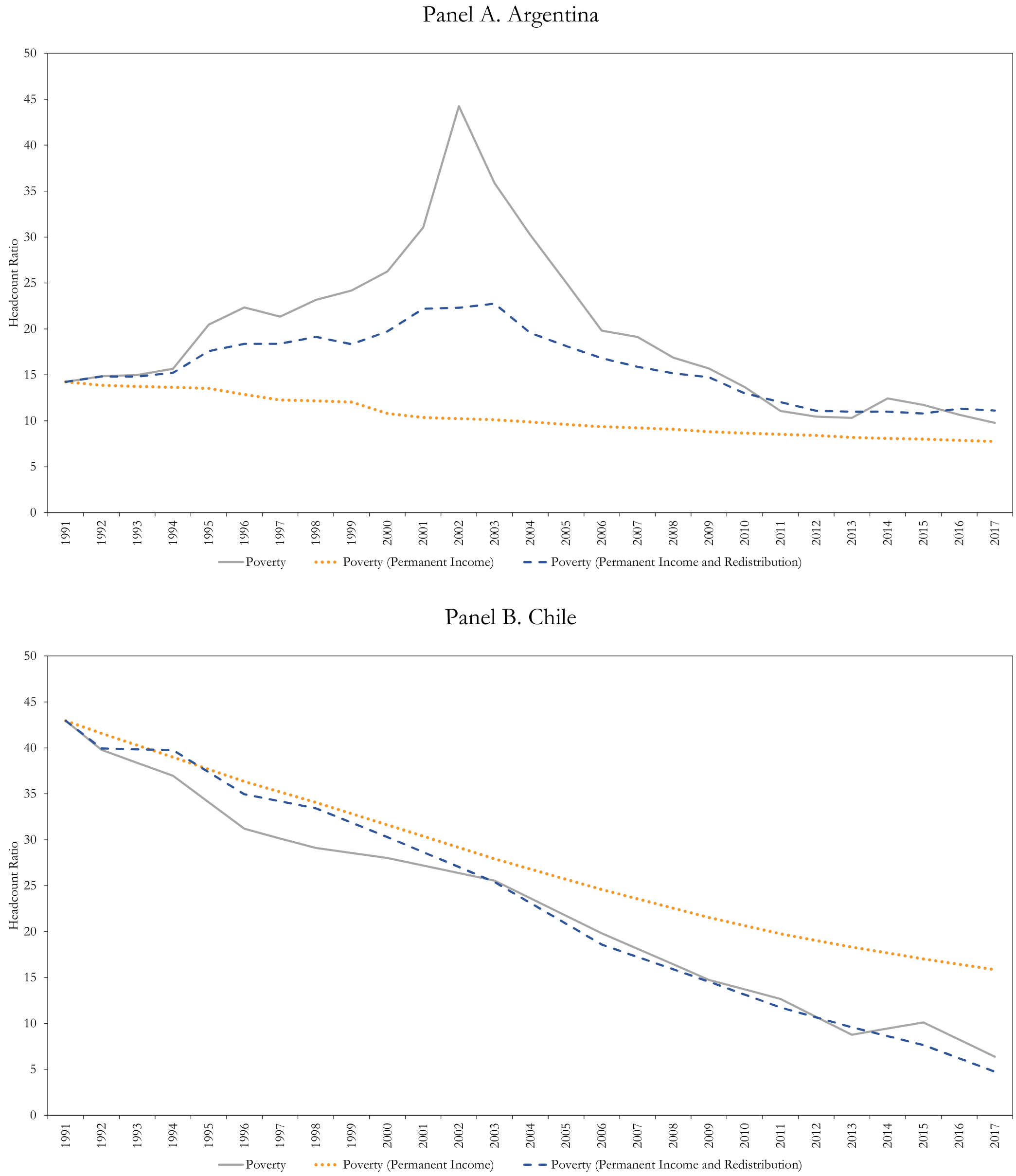

Fig. 11. Monetary Poverty in Argentina and Chile: Total, Permanent Income, and Redistribution. Notes: Poverty line of 5.50 dollars per person a day (2011 PPP). See Appendix B for details. Sources: Authors' estimations based on SEDLAC (CEDLAS and World Bank) and WEO (October 2018).

6. Final thoughts

In this paper, we have uncovered a set of important stylized facts regarding the trend versus cyclical nature of social indicators. First, not all social indicators are created equal. Indicators such as the unemployment rate or monetary poverty are mainly driven by relatively large cyclical fluctuations. In contrast, more structural indicators such as the HDI are mainly driven by the trend changes. Furthermore, while the trend dominance among structural measures such as the HDI is quite common across countries, the dominance of the cyclical component in monetary poverty and the unemployment rate is highly heterogeneous. These stylized facts call for caution when estimating the long-term improvements in social conditions using cyclical indicators such as the unemployment rate or monetary poverty and relatively short time series. The risk of misinterpreting the behavior of social indicators seems to decrease substantially if we resort to structural indicators such as the HDI.

We also find that the degree of temporariness of the gains/losses in social indicators is strongly associated to differences in the amplitude of business cycles across countries. As a corollary, we would expect that macroeconomic policies devoted to moderate business cycles would decrease the volatility of cyclical changes in social conditions.

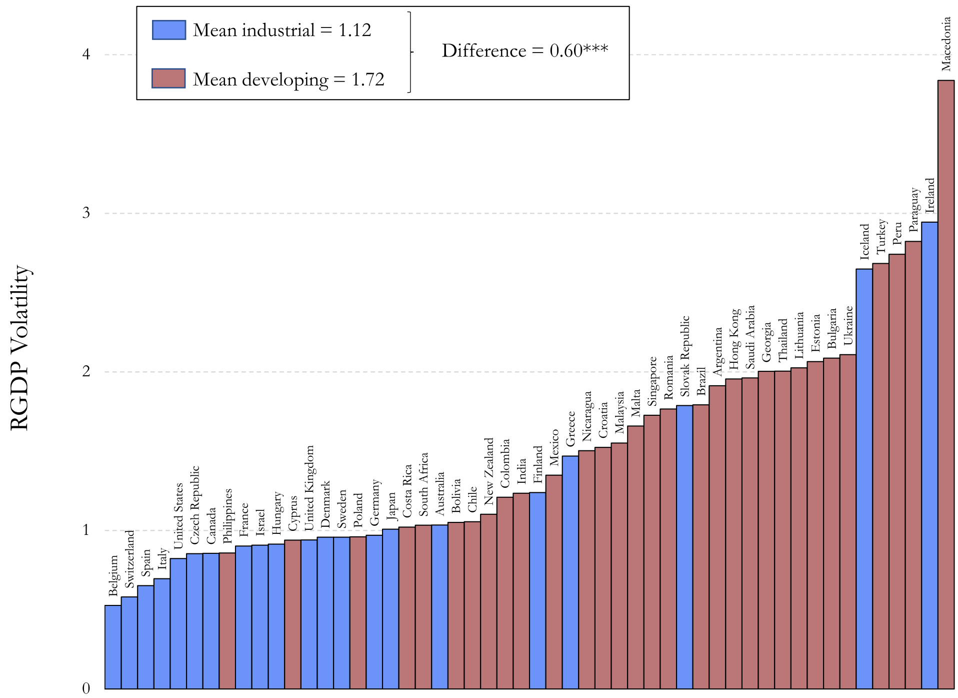

Fig. 12. Real Gross Domestic Product Volatility. Notes: The reported volatilities correspond to the standard deviation for the growth rates for GDP. Sources: Authors' estimations based on WDI and WEO.

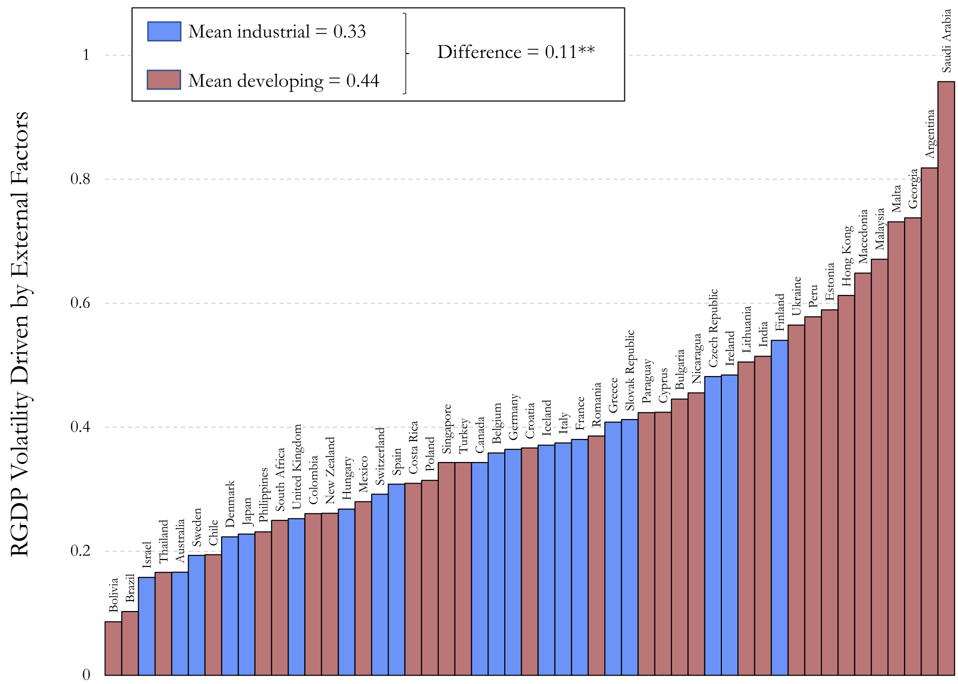

Fig. 13. Real Gross Domestic Product Volatility Driven by External Factors. Notes: See Appendix D for details. Sources: Authors' estimations based on WDI and WEO.

Finally, using microdata for LAC countries to study the behavior of monetary poverty during the Golden Decade confirms the importance of business cycles in explaining the changes in social indicators. Out of the 18.8-percentage-point decrease in monetary poverty between 2003 and 2014, 7.7 percentage points or 41.2 percent can be attributed to the widespread business cycle booms in the region. This means that a large share of the improvements in social conditions could vanish once these cycles turn recessionary.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A: Sample of countries

Due to data availability ability, the sample of countries differs by social indicator. The largest sample is given by the HDI indicator and includes Afghanistan, Albania, Algeria, Angola, Antigua and Barbuda, Argentina, Armenia, Australia, Austria, Azerbaijan, The Bahamas, Bahrain, Bangladesh, Barbados, Belarus, Belgium, Belize, Benin, Bhutan, Bolivia, Bosnia and Herzegovina, Botswana, Brazil, Brunei Darussalam, Bulgaria, Burkina Faso, Burundi, Cabo Verde, Cambodia, Cameroon, Canada, Central African Republic, Chad, Chile, China, Colombia, Comoros, Congo, Dem. Rep., Congo, Rep., Costa Rica, Côte d'Ivoire, Croatia, Cyprus, Czech Republic, Denmark, Djibouti, Dominica, Dominican Republic, Ecuador, Egypt, Arab Rep., El Salvador, Equatorial Guinea, Eritrea, Estonia, Ethiopia, Fiji, Finland, France, Gabon, Gambia, The, Georgia, Germany, Ghana, Greece, Grenada, Guatemala, Guinea, Guinea-Bissau, Guyana, Haiti, Honduras, Hong Kong SAR, China, Hungary, Iceland, India, Indonesia, Iran, Islamic Rep., Iraq, Ireland, Israel, Italy, Jamaica, Japan, Jordan, Kazakhstan, Kenya, Kiribati, Korea, Rep., Kuwait, Kyrgyz Republic, Lao PDR, Latvia, Lebanon, Lesotho, Liberia, Libya, Lithuania, Luxembourg, Macedonia, FYR, Madagascar, Malawi, Malaysia, Maldives, Mali, Malta, Mauritania, Mauritius, Mexico, Micronesia, Fed. Sts., Moldova, Mongolia, Montenegro, Morocco, Mozambique, Myanmar, Namibia, Nepal, Netherlands, New Zealand, Nicaragua, Niger, Nigeria, Norway, Oman, Pakistan, Palau, Panama, Papua New Guinea, Paraguay, Peru, Philippines, Poland, Portugal, Qatar, Romania, Russian Federation, Rwanda, Samoa, São Tomé and Principe, Saudi Arabia, Senegal, Serbia, Seychelles, Sierra Leone, Singapore, Slovak Republic, Slovenia, Solomon Islands, South Africa, Spain, Sri Lanka, St. Kitts and Nevis, St. Lucia, St. Vincent and the Grenadines, Sudan, Suriname, Swaziland, Sweden, Switzerland, Tajikistan, Tanzania, Thailand, Timor-Leste, Togo, Tonga, Trinidad and Tobago, Tunisia, Turkey, Uganda, Ukraine, United Arab Emirates, United Kingdom, United States, Uruguay, Uzbekistan, Vanuatu, Venezuela, Vietnam, Yemen, Rep., Zambia, and Zimbabwe.

Appendix B: Poverty data

Most of the data for monetary poverty comes from PovcalNet, an interactive computational tool that allows users to replicate the calculations made by World Bank researchers when estimating the extent of absolute poverty in the world.

The PovcalNet data for LAC are taken from the Socio-Economic Database for Latin America and the Caribbean (SEDLAC). SEDLAC was developed by the Center for Distributional, Labor, and Social Studies (CEDLAS) of the Universidad Nacional de La Plata (Argentina), in partnership with the Latin America team of the World Bank's Poverty and Equity Group. Methodological and technical revisions to the SEDLAC project began in 2015 to better align its data with the household surveys harmonized by the World Bank for other regions. These revisions of the welfare aggregate constitute the move of the SEDLAC project from version 02 to version 03.[25]

As the revision of this project is still in process, data reported in PovcalNet are based on SEDLAC-03 for most recent years and on SEDLAC-02 for previous years, with the cut-off period being generally the year 2000 (except for Argentina, for which data using SEDLAC-03 begins in 2003, and Chile, which uses SEDLAC-02 throughout the whole period). Given this problem of

Table B1
Data Summary for Poverty Calculations.

Country	Period	SEDLAC version
Argentina	1991–2017	02
Bolivia	1997–2017	02
Brazil	1992–2017	03
Chile	1990–2015	02
Colombia	2001–2017	03
Costa Rica	1990–2017	03
Dominican Republic	2000–2016	03
Ecuador	2003–2017	03
El Salvador	1995–2017	02
Honduras	1991–2017	02
Mexico	1992–2014	03
Panama	1995–2017	03
Paraguay	1995–2017	02
Peru	1997–2017	03
Uruguay	1995–2017	03

[25] For details on the main methodological changes in SEDLAC-03 that directly affect welfare measurement, see Atamanov et al. (2018).

comparability, we recalculate headcount ratios for some countries so that the SEDLAC version used in each country is the same for the whole period under analysis.[26] Because of this, poverty rates for some countries and years may differ from the figures reported in PovcalNet.

Table B.1 summarizes the data used for each country.

Appendix C: The perils of random sampling: An illustration using Indonesia and Thailand

This appendix replicates the analysis of Section 2.1 for two other non-Latin American countries. Considering the long time series requirements (especially difficult to obtain for monetary poverty), we conduct this analysis for two ASEAN countries: Indonesia (a lower-middle income country) and Thailand (an upper-middle income country). Much like Fig. 3 in Section 2.1 for Argentina and Chile, Fig. C.1 illustrates for Indonesia and Thailand how, given the prevalence of cyclical gains, a policy-

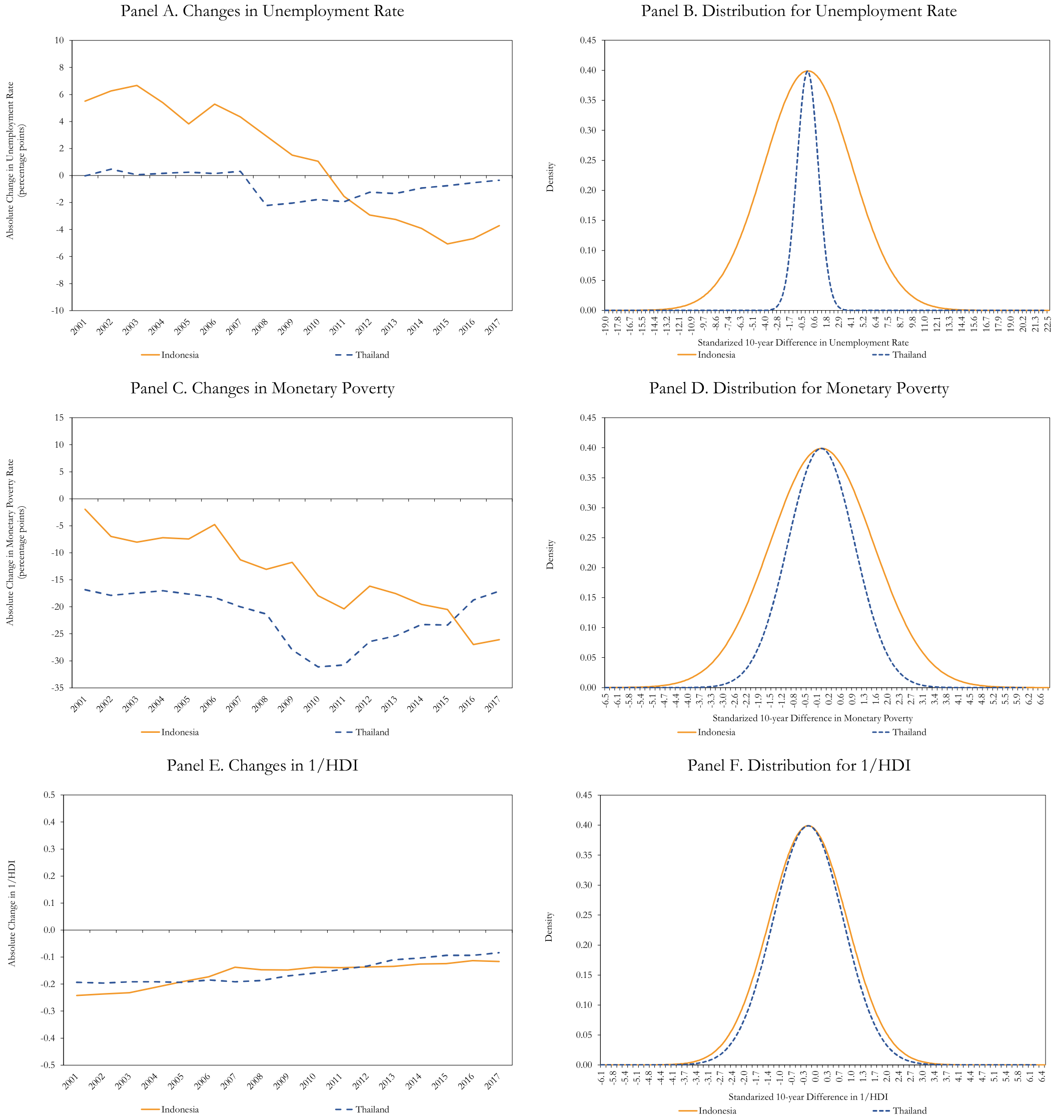

Fig. C1. Indonesia versus Thailand: 10-year Difference in Social Indicators. Notes: Poverty line of 5.50 dollars per person a day (2011 PPP). For panels B, D, and F, we fitted a standard normal distribution taking the first two moments (mean and standard deviation) of the 10-year differences in each social indicator. Source: Authors' estimations based on World Bank, Human Development Report Office (United Nations), and WEO (October 2018).

[26] Notice that even though the SEDLAC project may remain the same, the frequent changes in survey methodologies over time introduce comparability issues with previous surveys that are difficult to deal with. In addition, there are comparability issues across countries since national agencies often use different survey standards. However, we can still draw general conclusions from the available data.

maker focusing on an indicator over a relatively short time span could be highly misled in her efforts to evaluate long-lasting improvements in social conditions in her country. This is particularly true for the unemployment rate (Panels A and B) and, to a lesser extent, for monetary poverty (Panels C and D). On the other hand, the non-fluctuating nature of HDI changes would avoid sample-dependent conclusions regardless of the country under study.

Appendix D: Structural vector autoregression

To understand the relative importance of external factors in driving each country's business cycle or output fluctuations around trend, we estimate a VAR per country with a set of external and internal factors and calculate the impact of each factor in determining short-term movements of real output growth. This effort translates into computing the variance decomposition of each VAR system. We run a VAR for 54 countries with quarterly data typically ranging from the early 1990s to 2017.

The variance decomposition proceeds as follows. Using an orthogonalized VAR system, we can compute an accounting of the forecast error variance; that is, what percent of the k-step ahead forecast error variance is due to which variable. Formally, we start with the moving average representation of our orthogonalized VAR system:[27]

$$x_t = C(L)\eta_t,\ \mathrm{E}(\eta_t\eta_t') = \mathrm{I},$$

where x_t is a vector including our variable of interest, real domestic output growth, a set of external factors represented by the log change in CTOT, US real output growth, and change in real US policy rates and a set of internal factors represented by the change in real public expenditure, change in real exchange rate, change in domestic real interest and change in real trade balance. C(L) = C0 + C1L + C2L2 + … where C is the matrix of orthogonalized coefficients and L the lag operator.

The k-step ahead forecast error variance is given by:

$$x_{t+k} - E(x_{t+k}) = C_0\eta_{t+k} + C_1\eta_{t+k-1} + \cdots + C_{k-1}\eta_{t+1}$$

And since the η are uncorrelated and have unit variance, then:

$$var(x_{t+k}) = C_0C_0' + C_1C_1' + \cdots + C_kC_{k-1}'$$

Finally,

$$v_{k,\tau} = \sum_{j=0}^{k-1} C_j I_\tau C_j'$$

is the variance of k-step ahead forecast errors due to the τth shock.

Since we typically work with the share of each shock in the overall variance, we divide $v_{k,\tau}$ by the overall variance:

$$V_{k,\tau} = v_{k,\tau}/\sum\nolimits_\tau v_{k,\tau}$$

In our specification, we use one lag in all VAR systems and we report the variance of the 8th step ahead forecast errors. The choice of lag length was based on several information criterion tests. The choice of the 8th step ahead was made to ensure that the role of different factors had already begin to stabilize (some factors may take more than one period to affect growth).

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