UNIVERSIDAD DE MURCIA

ESCUELA INTERNACIONAL DE DOCTORADO

An Economic Cycles Analysis from a Dual Perspective

Un Análisis de Ciclos Económicos desde una Perspectiva Dual

D. Gonzalo Darío Palmieri

2019

An economic cycles analysis from a dual perspective

Un análisis de ciclos económicos desde una perspectiva dual

Memoria presentada por Gonzalo Darío Palmieri para optar al grado de**:**

Doctor en Economía

Dirigida por el Dr. Máximo Cosme Camacho Alonso

Universidad de Murcia

Facultad de Economía y Empresa

Programa de Doctorado en Economía Interuniversitario

2019

A mis padres y hermanos.......

Agradecimientos

Máximo, agradecerte enormemente tu dedicación, tiempo y sobre todo paciencia. Por saber guiarme no sólo a nivel académico sino también darme ánimos para seguir cuando las fuerzas escaseaban. Estoy férreamente convencido de que sin tu gran trabajo esto no hubiese sido posible. Estaré eternamente agradecido.

A mi familia por su apoyo incondicional. Mica, Valen, por soportarme tal y como soy. Mamá y Papá, por enseñarme con el ejemplo que pase lo que pase, el esfuerzo no se negocia.

A mis compañeros de doctorado durante estos años por los momentos compartidos y haberme resuelto todas mis cuestiones.

Anto donde quiera que estés, esto también es parte tuya.

RESUMEN

El estudio de los ciclos económicos alberga una larga tradición en la literatura económica. Tanto las civilizaciones antiguas como las modernas han sido testigos de cómo su estatus económico general ha variado a lo largo de los años. Comparando las economías primitivas (altamente dependientes de las fluctuaciones climáticas) con las modernas (surgidas a partir de la Revolución Industrial), es posible observar que tanto las relaciones entre ellas como sus estructuras subyacentes han experimentado profundos cambios de complejidad creciente. Sin embargo, las repercusiones de la exposición a los ciclos económicos siguen siendo de vital interés.

Fuertemente asociado a estos profundos cambios, las economías industrializadas han sufrido variaciones que les han llevado a evidenciar una tendencia positiva en el nivel de actividad económica en la historia reciente. Hamilton (2011), con el foco en la economía norteamericana, enumera las explicaciones que tradicionalmente se le atribuyen a este fenómeno: crecimiento de la población, acumulación de stock de capital, así como avance en el capital humano y progreso tecnológico. Sin embargo y como es bien sabido (Hamilton, 2011), las economías no presentan una tasa de variación positiva año a año. Estos períodos en los que la actividad económica rompe con su tendencia creciente son los que generalmente asociamos con recesiones económicas. En este sentido, a la sucesión entre auges (o expansiones) y caídas (o recesiones) es lo que se considera como ciclo económico.

Sin embargo, a pesar de la aparente simplicidad de este concepto, tras él se esconde una realidad más compleja. En primer lugar, no existe consenso con respecto a la definición de actividad económica. En otras palabras, no es posible encontrar un solo indicador que englobe las diferentes opiniones existentes. Muchos economistas abogan por el uso del Producto Interior Bruto (PIB), mientras que otros prefieren el PNB (Producto Nacional Bruto) o incluso el Índice de Producción Industrial (IPI) o algún indicador compuesto de actividad económica.

Respecto al momento en el que los indicadores señalan los cambios de fase, encontramos los indicadores retardados que proveen información relativa a movimientos cíclicos o estados pasados. Aquellos conocidos como coincidentes albergan la característica de reflejar el estado económico actual; mientras que los adelantados son los que debido a sus características inherentes permiten anticipar ciclos futuros. Desde el

trabajo de Burns y Mitchell (1946), estos últimos han sido probablemente los más estudiados en la literatura relacionada y el objeto de deseo por parte de los económetras.

Cada episodio de crisis es por definición distinto de los anteriores, si bien es cierto que, pueden presentar rasgos similares. Es precisamente en esta afirmación dónde se fundamenta el vasto interés en el análisis y estudio de este tipo de indicadores con el fin de seleccionar aquellos que sean capaces de identificar esos rasgos comunes y que por lo tanto faciliten la detección temprana de futuros episodios recesivos. De hecho, existe una corriente de la literatura que ha centrado sus esfuerzos en combinar estos indicadores simples con el fin de obtener indicadores compuestos que alberguen el mayor número de propiedades posibles para una predicción eficiente.

Esta búsqueda de indicadores adelantados eficientes ha traído consigo la necesidad de desarrollar nuevos métodos estadísticos. Como bien menciona Marcellino (2006), esta corriente que combina indicadores simples para obtener otros compuestos se divide en dos ramas: métodos basados en modelos predefinidos y métodos con esquemas de agregación sin modelo base. En estos últimos los indicadores simples se seleccionan en base a diferentes criterios relacionados con el estado actual de la economía, el cual es representado por una variable objetivo ya sea el PIB, IPI, un indicador compuesto coincidente, u otra opción. Estos criterios varían en función del esquema empleado, citando entre los más recurridos la significatividad estadística, *timing* o consistencia, conformidad con el ciclo económico general, pronta disponibilidad de datos, entre otros. Una vez seleccionada la batería de indicadores simples se procede a la agregación de los mismos en base a diferentes esquemas de ponderación (medias simples o agregadas, además de otras variantes). Sin embargo y a pesar de la notable simplicidad de estos métodos, el hecho de que el esquema de ponderación sea fijo y no varíe en el tiempo se considera un hándicap importante.

En segundo lugar, para entender la dificultad en el análisis de los ciclos económicos, existen múltiples interpretaciones del propio concepto de recesión económica. Sin ánimo de ser exhaustivos, algunos economistas definen una recesión económica como el momento en el que se producen dos caídas trimestrales consecutivas del PIB. Aunque esta acepción es la más recurrida en la prensa, el concepto alberga evidentes defectos. Por ejemplo, algunas recesiones ocurren sin llegar a contabilizar dos caídas consecutivas del PIB. Además, el citado concepto se centra en el comienzo de las recesiones pero no define el final de las mismas.

Otros economistas como los que forman parte del NBER (*National Bureau of Economic Research*, por sus siglas en inglés) consideran que la forma más apropiada de definir una recesión es a través de una caída generalizada de la actividad económica que puede durar desde meses a años, y que trae consigo efectos visibles sobre diversos sectores de manera sincronizada. En concreto, el NBER define el ciclo económico como secuencias de expansiones y recesiones. A estas últimas las considera como el período comprendido entre un "pico" y un "valle"; siendo las expansiones el período opuesto (comprendido entre un valle y un pico). Los picos son los momentos en los que de manera sincronizada se observa un deterioro de la actividad económica y los valles los momentos en que comienza la recuperación. Esta corriente sigue el análisis pionero de ciclos económicos o *business cycles* de Burns y Mitchell (1946).

Por último, hay otra gran tendencia entre los analistas de los ciclos que definen las recesiones y expansiones como comparación entre el nivel de actividad económica y el potencial o tendencia a largo plazo. A este tipo de ciclos se les conoce como los ciclos de crecimiento o *growth cycles*. En este contexto, la OCDE define las recesiones como aquellos períodos en los que la economía se encuentra entre un "pico" y un "valle". Los picos son los momentos en los que la actividad se encuentra en su máxima lejanía en comparación con la tendencia de largo plazo. Y por su parte, los valles son los momentos en los que la actividad económica se encuentra por debajo del potencial en su máxima distancia.

En tercer lugar y para entender la complejidad del análisis de los ciclos económicos, destacamos la cuestión relativa al fechado de los cambios de fase cíclica. Si nos centramos en el fechado de los denominados *business cycles* en Estados Unidos, el *Business Cycle Dating Commettee* del NBER se encarga de proveer un registro cronológico para los cambios de fase generalmente aceptado. En el caso europeo, el *Euro Area Business Cycle Dating Committee* (EABCDC) del CEPR (por sus siglas en inglés o *Centre for Economic Policy Research*) también propone un fechado similar para este área económica. Por último, el *Economic Cycle Research Institute (ECRI)* y la OCDE se encargan de estas labores para las principales economías a nivel mundial, aunque existen notables ausencias. Para el caso de los ciclos de crecimiento o *growth cycles,* podemos encontrar fechados de los puntos de cambio de fase del ciclo en el ECRI y en la OECD.

En cuarto lugar, debemos comentar que, si bien existen instituciones encargadas del fechado de los puntos de giro, los retrasos en la publicación de los datos generan una gran incertidumbre en torno al estado de la economía en tiempo real. Esto ha traído consigo la inevitable necesidad de diseñar herramientas y métodos estadísticos para proponer fechados de cambio de ciclo en el momento en el que se producen o incluso para anticiparlos. La literatura relacionada con la identificación de los cambios de fase de los ciclos en tiempo real es bastante extensa. En general, los procedimientos pueden dividirse en dos grandes grupos: los que abogan por métodos paramétricos y los que recurren a herramientas no paramétricas. Entre los métodos paramétricos, los más populares son aquellos que emplean modelos Markov-switching surgidos a raíz del trabajo de Hamilton (1989). Siguiendo a Marcellino (2006), las actualizaciones de estos modelos pasan por los conocidos como *Markov-switching dynamic factor models,* generalización del trabajo de Stock y Watson (1989). Las técnicas basadas en estos modelos permiten construir indicadores bajo el supuesto de que el estado subyacente de la economía se encuentra gobernado por una variable continua inobservable.

En contraposición, entre los métodos no paramétricos más populares cabe destacar las extensiones del algoritmo no paramétrico propuesto por Bry y Boschan (1971). Estos métodos de fechado de cambio de fase del ciclo se basan en la búsqueda de máximos y mínimos locales en indicadores de actividad económica.

Por lo tanto y como se ha podido percibir, la complejidad en el estudio de los ciclos económicos abarca varias dimensiones que, a su vez, se traducen en diversas cuestiones. En esta línea, el objetivo y la motivación de esta tesis consiste en abordar algunas de dichas cuestiones que se mantienen sin resolver en el ámbito de los ciclos. Las preguntas principales que se pretenden responder son las siguientes: ¿Siguen los ciclos económicos ciertos patrones de agregación en determinadas áreas económicas? ¿Producen las recesiones económicas efectos tangibles sobre algunas variables económicas de interés como el grado de desigualdad? ¿Qué tipo de indicadores son más propensos a generar señales significativas de futuras recesiones? ¿Dependen estas cuestiones del tipo de ciclo considerado? ¿Y del grado de desarrollo económico?

Los tres capítulos que siguen a la introducción hacen frente a dichos interrogantes recurriendo a métodos econométricos reconocidos que han sido extendidos con el fin de adaptarlos a la realidad que se pretende estudiar. Si bien cada capítulo pone el foco en una cuestión determinada y distinta de las anteriores, el factor común o hilo conductor que cohesiona la tesis radica en el análisis de los ciclos desde una perspectiva dual. Es decir, en los tres capítulos se establecen comparaciones entre los resultados que se obtienen desde el análisis *growth cycle* y aquellos registrados desde la perspectiva *business cycle.* A lo largo de las líneas siguientes se repasan brevemente los objetivos, metodología y resultados de cada capítulo.

El segundo capítulo de la tesis, se centra en un análisis de los ciclos económicos en América Latina para el período 1980-2013. Mediante la aplicación de métodos de detección de puntos de cambio de fase del ciclo (algoritmo Bry-Boschan) y filtros de extracción de señales cíclicas (filtro Hodrick-Prescott) sobre el Índice de Producción Industrial, se calculan tanto la sincronización como otras características relevantes del ciclo económico: duración, amplitud, curvatura, *deepness* y *steepness.* Además, se emplean técnicas de *Multidimensional Scaling* y test de multimodalidad (test de Silverman) para analizar patrones de agrupación cíclica entre los países de América Latina. Además de establecer patrones comunes y patrones diferenciales en los ciclos de los países de esta región, se indaga si la Gran Recesión ha producido cambios significativos en las estructuras subyacentes. Entre los principales resultados obtenidos cabe destacar la existencia de vínculos significativos entre las economías de la región, además de la presencia de ciertas naciones con ciclos que evidencian un carácter idiosincrático. En adición, el análisis multimodal refleja que la última gran crisis económica financiera e internacional no ha generado impacto significativo alguno sobre las estructuras cíclicas que ya existían antes de la recesión.

El tercer capítulo de la tesis aborda desde un punto de vista crítico a la vez que analítico uno de los fenómenos económicos y sociales que se suponen en el impacto de las recesiones económicas. La prensa está plagada de titulares relacionados con el efecto causal de las recesiones sobre la desigualdad económica. Pero, ¿realmente las recesiones producen incrementos en la desigualdad una vez introducidos los controles oportunos en el análisis? Usando el modelo de proyecciones locales, se mide el efecto de las crisis económicas (tanto *growth* como *business cycle*) sobre la desigualdad de ingreso medida a través del índice de Gini. El estudio comprende una muestra amplia de países a nivel global y abarca el período 1960-2014. En general, se encuentra que ambos tipos de recesiones carecen de impactos significativos sobre los niveles de desigualdad de un país, una vez controlado el rol de otros factores relevantes en la evolución de ésta. Sin embargo, es posible realizar distinciones tanto en función del grado de desarrollo económico como de la región geográfica.

El cuarto y último capítulo de la tesis presenta un análisis de la habilidad predictiva para anticipar recesiones de los indicadores económicos de la OCDE y en concreto de sus *Main Economic Indicators*. La técnica empleada para el análisis se fundamenta en la curva ROC (*Receiver Operating Characteritic* por sus siglas en inglés), y se basa en examinar la calidad de las señales sobre el ciclo generadas por los anteriores indicadores en función de una serie de criterios racionales y presentes en la literatura. Como ha sido común a lo largo de toda la tesis, la comparativa entre *growth* y *business cycles* se mantiene presente. En cuanto a las principales conclusiones obtenidas cabe destacar que, en general, los *Main Economic Indicators* presentan un comportamiento eficiente a la hora de predecir ambos tipos de recesiones. En adición, existen diferencias acordes con el grado de desarrollo económico y algunos indicadores simples evidencian un comportamiento más eficiente que sus pares compuestos.

CONTENTS

CHAPTER 1: Introduction

1. The analysis of economic cycles

The analysis of economic cycles constitutes a long tradition in the economic literature. It has been a major concern from ancient civilizations to the current economies, which have always tried to understand economic fluctuations. Comparing primary (which were highly dependent of climate fluctuations) to modern civilizations (originated since the Industrial Revolution), the underlying structures, interactions and complexity of the economic systems have continuously evolved. However, the interest on the causes and effects of the economic cycles remains intact.

Besides this evolution, modern economies have exhibited a strong and well defined growing trend in the last decades. Although focusing on the US economy, Hamilton (2011) lists the traditional main sources of this sustained uprising movement: the population growth, the accumulation of capital stock, and the technological and human capital progress. However, this author also points out that the economies do not experience a positive change every single year. The periods in which the economic activity breaks its growing trend, are widely known as economic recessions. In fact, the recursive evolution of "ups" (known as expansions), which are followed by "downs" (recessions) in the economic activity are known as the economic cycles.

Although the concept of economic cycle is apparently simple, a much more complex reality is masked for several reasons. The first source of complexity in the analysis of the economic cycles is that there is no general consensus on the definition of economic activity. There is no single indicator generally accepted as the underlying economic activity. Most argue for the use of GDP, others prefer GNP, industrial production, or a composite indicator.

In the related literature, there are many methods that focus on disentangling these economic activity swings, i.e. for being able to clarify the current economic status or even to predict future ones. This brings out the unavoidable necessity of defining different types of economic indicators according to their relation to the current status of the economy. These indicators are classified as leading, coincident and lagged indicators. Lagged indicators provide signals of past economic events, while coincident ones are used to match the current status of the economy. Leading indicators are those whose inherent properties allow them to predict future economic activity movements. Since the seminal work of Burns and Mitchell (1946), these have probably been the most widely studied and have become object of desire by econometricians.

Each economic downturn differs (by definition) from the others, but the literature has tried to seek for some general indicators with broad forecasting abilities. Indeed, many efforts have been undertaken even with the aim of combining simple indicators to provide composed ones. Marcellino (2006) stated that, according to the way in which single indicators are combined to obtain composite indicators, the literature might be divided into “non-model based” studies and “model-based” ones. Under the first approach, variables are selected according to different criteria relative to the current status of the economy (represented by the target variable like GDP, Industrial Production, a coincident composite index, or other options) such as economic significance, consistent timing, conformity to the general business cycle, prompt availability, among others. Once the leading variables group has been addressed, these are filtered and aggregated into the final composite index making use of different weighting schemes (simple or averaged weighting). Despite its simplicity, the fact that the weighting scheme does not variate over time is considered as an important handicap.

The second source of complexity in the analysis of the economic cycles relies on the definition of economic cycle. Some economists consider that an economic recession is a period starting when an economy faces two consecutive-quarter falls in GDP. Although this definition is a very extended one in the media, the concept contains evident drawbacks. For example, the definition states when a recession starts but it says nothing about when a recession ends. In addition, some widely recognized recessions (i.e., the US 2001 recession) does not include two consecutive periods of negative growth rates of GDP.

Some other economists, including the Business Cycle Committee (BCDC) of the National Bureau of Economic Research (NBER), define recessions as general declines in the economy path including coincident impacts on several sectors. The BCDC define the *business cycles* as sequences of expansions and recessions, where a recession is the period comprised between a peak and a trough and an expansion is the period between a trough and a peak. Recessions (expansions) are characterized by significant declines (rises) in economic activity observed at about the same time in many sectors, lasting from months to years. This definition agrees with the seminal contribution of Burns and Mitchel (1946).

Finally, the economic cycle has also been defined by comparing the actual level of economic activity with a long-term trend or potential level of economic activity. Cycles defined in this way are known as *growth cycles*. In this context, the OECD considers economic downturns as the period in which the economy is placed between a peak and a trough; considering the former as the furthest point above the trend level and the latter the furthest below the potential product.

The third source of complexity in the analysis of the economic cycles has to do with the date of the cycle turning points. Focusing on business cycles, the NBER Business Cycle Dating Committee identifies the US business cycle turning points while the Centre for Economic Policy Research (CEPR) dates the turning points in Europe. The Economic Cycle Research Institute (ECRI) provides business cycle turning points for several advanced economies. With regard to growth cycles, both ECRI and OECD date growth cycle turning points for several advanced economies.

Although these institutions provide a detailed chronology of the turning points, they announce the new turning points with a considerable delay of years. With the aim of providing timely recognition of turning points in the economic cycle, some procedures have been proposed in the recent literature. These methods can be classified into parametric methods and nonparametric algorithms. Among the parametric methods, the most popular are the Markov-switching models initially advocated by Hamilton (1989). According to Marcellino (2006) the most promising updates of this framework are the Markov-switching dynamic factor models, which extend the linear proposal of Stock and Watson (1989). These models rely on the assumption that the economic indicators share a common movement, usually known as the underlying economic activity, whose dynamics is governed by a Markov-switching unobservable process.

Among the nonparametric algorithm, the most popular are the extensions of the Bry and Boschan (1971) dating procedure. They focus on searching for local maxima and minima on economic indicators subject to some reasonable constraints.

Therefore and as might be expected, the economic cycle complexities contain several dimensions which might be reflected through different questions. In this line, the purpose of this thesis is to acquire a better and suitable knowledge and understanding of some of these open questions in the analysis of economic cycles. The main questions I try to answer are the following: Do economic cycles evidence a particular pattern of aggregation in certain economic areas? Do economic cycles produce tangible effects on human beings lives? Which kind of indicators are more suitable for forecasting economic recessions? Do these answers rely on the economic cycle concept? And on the degree of economic development?

2. Contribution

This dissertation aims to contribute to the existing literature in different ways. Chapter 2 examines the existence of singular patterns in the economic cycles of Latin America. Chapter 3 attempts to isolate the impact of economic cycles on inequality from a global perspective. Chapter 4 reviews some of the most invoked leading indicators in the literature through simple and rational criteria. In all of them, a dual approach is applied distinguishing between business and growth cycles.

2.1. Chapter 2

This chapter contains a study which focuses on the evolution of the Latin American cycles from 1980 to 2013. By using the industrial production index, the chapter examines the evolution of synchronisation and other relevant features of the economic cycles, such as duration, amplitude, excess, deepness and steepness. Besides the search of common patterns or country-subgroups, this part of my dissertation seeks for concept-specific differences (business or growth cycle). In addition, the study examines whether the Great Recessions produced any significant impact on the underlying cycles distributions.

Regardless of the concept used to define the economic cycle, I find relevant links across the economic cycles of the Latin American nations. However, I also detect certain countries which exhibit idiosyncratic patterns. Regarding the Great Recessions, the study failed to find significant impacts on the underlying cycle patterns.

2.2. Chapter 3

This chapter addresses a widespread economic concern: Is it true that economic recessions cause inequality increases? For this purpose, I employ local projections (Jorda, 2005) to examine the impact of business and growth cycles on income inequality measured through the Gini index. Again, the focus is global and comprises the period between 1960 and 2014.

Overall, the study finds that both definitions of economic recessions failed to generate significant impacts on income inequality, once other relevant controls are included in the model. Besides, the chapter detects distinguishing patterns according to the degree of economic development and geographical region.

2.3 Chapter 4

In the last chapter of my dissertation the predictive content of the OECD Main Economic Indicators is examined to anticipate economic recessions in a broad set of countries. For this purpose, I use Receiver Operating Characteristic (ROC) in order to measure the net forecasting ability to perform inferences on the economic cycle of each indicator at different forecasting horizons.

The main findings of this chapter are the following. The OECD Main Economic Indicators Database evidences an overall accurate performance in predicting growth cycle and business cycle recessions. However, there are significant differences according to the degree of economic development of the countries. In addition, some simple indicators (especially financial ones) perform better than the OECD Composite Leading Indicators.

3. References

Boschan, C. and Bry, G. 1971. Cyclical Analysis of Time Series: Selected Procedures and Computer Programs. *National Bureau of Economic Research*: 13-2.

Burns, A. and Mitchell. 1946. Measuring Business Cycles. *Studies in Business Cycles*, 2.

Hamilton, J. 1989. A new approach to the economic analysis of nonstationary time series and the business cycle. *Econometrica: Journal of the Econometric Society*: 357-384.

Hamilton, J. 2011. Calling recessions in real time. *International Journal of Forecasting* 27: 1006-1026.

Jorda, O. 2005. Estimation and inference of impulse responses by local projections. *American economic review*, 95(1): 161-182.

Marcellino, M. 2006. Leading Indicators. In G. Elliott, C. Granger, and A. Timmermann (eds.), *Handbook of economic forecasting. Amsterdam:* Elsevier.

Stock, J. and Watson, M. 1989. New indexes of coincident and leading economic indicators. *NBER macroeconomics annual*, 4: 351-394.

CHAPTER 2: Synchronisation and other relevant cycle features among the Latin American economies

1. Introduction

The globalization phenomenon and its determinants, the internationalization of trade flows, the interpenetration of financial markets, the international homogenization of policies and the increased mobility of productive resources are factors that have increased interdependences in Latin America during the last decades. As a result, some economic integration areas have emerged such as the Southern Common Market (MERCOSUR, in its Spanish acronym) and the Andean Community of Nations (CAN, in Spanish acronym). In this context, examining the degree of cyclical similarities across their members become of great interest since it could affect the success of the integration processes through the rise of the associated costs, especially for countries with idiosyncratic cycles (Christodoulakis et al. (1995).

Despite the existence of several studies regarding the analysis of international cyclical features on industrialized economies (see de Haan, Inklaar and Jong-A-Pin, 2008), the Latin American cycles still remain relatively unexplored. Some remarkable exceptions are the empirical papers conducted by Iguíñiz and Aguilar (1998), Mejía-Reyes (1999, 2004), Aiolfi, Timmermann, and Catao (2006), Carrasco and Reis (2006), Calderón and Fuentes (2010), and Hurtado-Rendón and Builes-Vásquez (2011). However, our study stands out from the rest by filling the gap left by them. Compared to ours, those contributions do not account for at least one of the following items: (a) they exclusively address a growth cycles or a business cycles analysis; (b) they provide a synchronisation analysis dropping other important characteristics; and (iii) they do not account for the impact of the Great Recession.

In this line and in order to fulfill the objective of this research, we draw an exhaustive analysis of the Latin American cyclical situation by using the industrial productions of Argentina, Bolivia, Brazil, Chile, Colombia, Costa Rica, Ecuador, Mexico, Peru, Uruguay and Venezuela from 1980 to 2013. As it could be previously noticed, we focus on both, growth and business cycles making use of not only synchronisation but also other relevant features such as duration, amplitude, excess, deepness and steepness.

Moreover and with the aim of distinguishing between different subgroups of countries, we use nonparametric density estimation and bootstrap multimodality methods (Silverman, 1981) for testing the number of modes in the distributions of pairwise economic cycle dissimilarities. Multi-dimensional scaling techniques also helped us to understand the formation of these potential subgroups from a graphical perpective.

Among the most relevant findings we might cite the following. We confirm the existence of significant links across the Latin American cycles. Some exceptions are Bolivia, Costa Rica and Ecuador since they exhibit the most idiosyncratic cyclical patterns. Remarkably, we find that the Great Recession did not lead to any significant impact on the pre-existing Latin American cyclical linkages.

2. Methodology

2.1. Growth cycles

The so-called growth cycles are defined on the detrended time series, which are usually referred to as the cycle components. Positive cycles (deviations above trend) are identified with expansionary phases while negative cycles (deviations below the trend) refer to recessions. Although there are an enormous number of ways of detrending the series, we focus on the band-pass filter proposed by Hodrick and Prescott (1997).

Using the cycle components, pairwise growth-cycle synchronisations are measured through their correlation coefficients. Intuitively, the corresponding pairwise distances on growth-cycle synchronisations are obtained as one minus the correlation coefficients.

The pairwise distances on other growth-cycle features are computed as the square root of the sum of the squares of the differences between the corresponding country-specific features. For this purpose, the first feature used in this context is duration, which is defined as the average number of months spent in each phase. Therefore, the duration of expansions (recessions) corresponds to the averaged number of months in which industrial production is above (below) long-term trend. The second feature is the amplitude of the growth-cycle phase, which is computed as the maximum ascent (descent) of the cycle occurred in expansions (recessions).

In line with Sichel (1993), the third growth-cycle feature is deepness, which measures whether the amplitude of troughs exceeds (or is shallower than) that of peaks. This measure can be obtained as the skweness of the cycle components. If C_t is the cycle component of industrial production, $\acute{C}$ is its sample average and S_C its standard deviation, the deepness coefficient is

$$Ds(c)= \frac{1}{TS_C^3}\sum_{t=1}^{T}\left(C_t-\acute{C}\right)^3. \qquad (1)$$

Following Sichel (1993), the last growth-cycle feature is steepness, which relates to whether contractions are steeper (or less steep) than expansions. This feature might be obtained as the skweness of the first difference of the cycle components, ΔCt. By analogy, steepness is defined as follows:

$$St(c)=\frac{1}{TS_{\Delta c}^3}\sum_{t=1}^{T}\left(\Delta Ct-\Delta\acute{C}t\right)^3. \qquad (2)$$

2.2. Business Cycles

The business cycle view of economic cycles focuses on the features that appear in the spirit of the National Bureau of Economic Research Business Cycle Dating Committee. In this context, the analysis of the economic cycles relies on the set of turning points that are located in the series of industrial production, thereby defining specific cycles. Although there are several ways to identify turning points, we employ the Bry-Boschan algorithm (Bry and Boschan, 1971).[1] This method detects local maxima (peaks) and minima (troughs) in the series of industrial production subject to certain censoring rules. Then, expansions are defined as the periods from troughs to peaks and recession are defined as the periods from peaks to troughs.

Based on the information provided by this algorithm, we construct country-specific binary variables, R_{it}, that take the value of one whenever country i is in recession. Using these variables, Harding and Pagan (2002) measure the business cycle synchronisation between countries i and j by using the concordance index

$$IC_{ij}=\frac{1}{T}\sum_{t=1}^{T}\{R_{it}R_{jt}+(1-R_{it})(1-R_{jt})\}. \qquad (3)$$

This index represents the proportion of time in which two nations experience the same state of the economy. Values equal to one indicate that both economies experience the same phase during the whole period; while values equal to zero reflect the opposite

1 In particular, we implement the Bry-Boschan Gauss code created for Stock and Watson (2014).

meaning. Therefore, pairwise distances on business-cycle synchronisation are obtained as one minus concordance indexes.

For the sake of completeness, we also compute pairwise distances on other business cycle features as the Euclidean distances between the corresponding country-specific features. In this context, for each of the two phases of the business cycle, we consider duration, amplitude and excess. Duration reflects the average number of months between turning points. Amplitude measures the average increase in industrial production during expansionary periods or the corresponding drop during recessions.

Excess (Harding and Pagan, 2002) is a relative measure of the shape of expansions and recessions and represents the actual path of time series between turning points against a linear path. In other words, as was noted in Camacho, Pérez Quirós and Saiz (2008), convex actual paths match with positive values of excess, while concave paths refer to negative values of excess. For country i, the excess of recessions ER_i is defined as the average of the excess of each recession h

$$ER_{ih} = A_{ih} - T_{ih} + 0.5M_{ih}, (4)$$

where T_{ih} is the cumulative gain or loss of recession h, which is obtained by the sum of all the amplitudes of each phase; M_{ih}represents the amplitude; and A_{ih} is the triangle approximation $0.5D_{ih}M_{ih}$, where D_{ih} matches with duration. For country i, the excess of expansions, EE_i, can be defined analogously

2.3. Global Structure and Cycle Dynamics

Although trying to draw conclusions from these pairwise distances is appealing, a difficulty with it is that there are many such measures and it is a challenge to organize and present the results in a coherent way. To overcome this drawback, we take nonparametric density estimation approaches to examine the distribution of the pairwise distances. For a given bandwidth h and N countries, the kernel distribution of distances that is obtained from the empirical distances between two countries i and j, d_{ij}, is

$$f_h(d) = \frac{1}{nh}\sum_{i=1}^{N}\sum_{j>i}^{N} K\left(\frac{d-d_{ij}}{h}\Big| \quad \right), \tag{5}$$

where n is the number of different distances and K is the Gaussian kernel.

The nonparametric density estimation approach has the additional advantage of enabling us to explicitly test for the number of modes of the underlying distribution of economic cycle distances. If confirmed, multimodality would point to population heterogeneity, implying the existence of separate population groups. Unimodality would imply that Latin American countries exhibit similar cycles. To test for multimodality, we follow the lines suggested by Silverman (1981), who proposed a simple way to assess the *p*-value that a density is at most *m*-modal against the alternative that it has more than *m* modes.

Since the number of modes in a normal kernel density estimate does not increase as h increases, let h_m be the minimum bandwidth for which the kernel density estimate is at most *m*-modal. Let d be a resample drawn from the estimated economic cycle distances

$$d_{ij} = (1 + h_m^2/s^2)^{\frac{-1}{2}} \left(d_{ij} + h_m \omega_{ij}\right), \tag{6}$$

where s² is the sample variance of the data, and ω_{ij} is an independent sequence of standard normal random variables. Let h_m be the smallest possible h producing at most *m* modes in the bootstrap density estimate

$$f_h\ (d) = \frac{1}{nh} \sum_{i=1}^{N} \sum_{j>i}^{N} K \left(\frac{d-d_{ij}}{h} \middle| \quad \right). \tag{7}$$

Repeated many times, the probability that the resulting critical bandwidths h_m are larger than h_m can be used as the p-value of the test.

Although useful, the kernel density estimation approach does not allow us to understand the economic cycle affiliations detected across the set of countries. To address this deficiency, we also employ classical Multi-Dimensional Scaling (MDS) to project the pairwise economic cycle distances in a map in such a way that the distances among the countries plotted in the plane approximate the economic cycle dissimilarities.[2] In the resulting map, countries which present high economic cycle dissimilarities have representations in the plane that are far away from each other. Therefore, the goals of this analysis are to examine the extent to which our set of countries appear in distinct groups with similar cycles or to explore if some Latin American countries exhibit idiosyncratic cycles.

2 A good reference on MDS techniques is Timm (2002).

3. Empirical Results

Our primary interest is on the industrial production of Argentina, Bolivia, Brazil, Chile, Colombia, Costa Rica, Ecuador, Mexico, Peru, Uruguay and Venezuela. Although we understand that using industrial production indexes as a measure of aggregate activity could be controversial, more comprehensive measures of activity using aggregates such as Gross Domestic Product are not exempt of problems. The frequency of these series is quarterly, the available samples are shorter and they are not usually calculated from national accounts on a quarterly basis but constructed from annual series that are converted to quarterly using indicators.

Table 1 shows the variables used in the analysis and the effective sample periods per country.[3] Data were extracted from the OECD database and from National Ministries of Economy and Industry databases. The time series were filtered with TRAMO-SEATS and the seasonally adjusted series were analysed by using the two alternative approaches: growth cycles and business cycles.

3.1. Results from the growth-cycle analysis

In line with the related literature, the analysis of HP correlations (Table 2) evidences the existence of significant cyclical links among Latin American countries (77.8% of the coefficients have statistical significance). In Brazil and Mexico, the largest economies of the region in terms of GDP, all of the correlation coefficients are statistically significant. Other distinguished cases are Argentina (80% of significant correlations), Peru (90%) and Colombia (80%). By contrast, the most desynchronised nations are Uruguay and Costa Rica, which show relatively lower proportions of significant coefficients (40% and 50% respectively), and Ecuador and Bolivia, which show low average ratios (0.13 and -0.16 respectively).

By pairs of countries, there is remarkably variety of important associations. In line with the results obtained by Mejía-Reyes (1999) and Hurtado-Rendón and Builes-Vásquez (2011), the most important coefficients are those existing between Argentina and Mexico (0.5), Brazil and Argentina (0.45), Peru and Brazil (0.45), Mexico and Peru (0.40) and Argentina and Colombia (0.41).

3 Due to data availability problems, we use the index of economic activity for Bolivia and Ecuador and the non-primary added value index for Peru.

Figure 1 shows the MDS map of growth-cycle synchronisation distances over the sample.[4] This map clearly reflects the information contained in Table 2. Countries with the highest degree of growth-cycle synchronisation as Brazil, Mexico and Argentina are represented by points that are closer together in the map. By contrast, countries with less synchronised cycles as Ecuador, Bolivia and Costa Rica are further apart.

Does it mean that this result agrees with a core-periphery interpretation of the growth-cycle synchronisation across the Latin American countries? To evaluate this fact, we examine the number of modes on the distribution of the pairwise distances on growth-cycle synchronisation that appear in Figure 5. The kernel density plots of this figure seem to have only one mode around 0.15, indicating that these countries are highly synchronised. However, there is a much smaller bump around 0.30 formed by the countries with more idiosyncratic cycles.

By testing for the number of modes in the density probability distribution of the data (Table 6), we fail to reject the null hypothesis of unimodality. This indicates that, in spite of the presence of the small bump in the right-hand tail of the distribution, we do not find different groups of countries in the data in terms of their growth-cycle synchronisation, which does not agree with the core-periphery story.

To complete our growth-cycle analysis, we also compute the distance on other growth-cycle characteristics (amplitude, duration, deepness and steepness). The results, which are displayed in Table 3, show that the average duration is about 16 months in both phases of the growth cycle. However, Venezuela and Costa Rica show cycles that become much longer than the average while Ecuador and Uruguay face the shortest cycles.

Amplitude in expansions and recessions is also relatively symmetric. On average, the maximum ascent of the cycle occurred in expansions is 9, while the maximum descent in recessions is 8.49. With the exception of three countries (Uruguay, Venezuela and Mexico), average amplitudes are greater in expansionary phases. Ecuador, Costa Rica and Venezuela are the countries with the most volatile cycles.

On average, deepness and steepness reach a value of -0.49. This implies that recessions are deeper than expansions and that industrial production falls rapidly in recessions and only recovers slowly over time. Chile and Venezuela have the deepest

4 In these maps, the axes are meaningless and the orientation of the picture is arbitrary.

recessions and Bolivia has the deepest expansion. Bolivia has the steepest expansions and Venezuela the steepest recessions.

The MDS map of growth-cycle features is reported in Figure 2, which provides a visual inspection of the relative dissimilarities on the growth-cycle features of Latin American countries. Notably, the largest countries stick together in the map, reflecting that these countries form a cluster that shows growth-cycle features that are similar among them. In addition, some countries are plotted further away from the cluster formed by the largest countries, which reflects the differences between their cycles and those of the cluster. These countries also appear separate from each other, which indicates that their growth-cycle characteristics are idiosyncratic. This group of countries with idiosyncratic growth cycles is mainly formed by Ecuador, Venezuela, Costa Rica, Uruguay and, to lesser extent, Bolivia.

Figure 6 shows that bimodality is a visual feature of the kernel estimate of the distribution of distances on growth-cycle features, measured as the Euclidean distance across all of the features examined below. It shows that the countries of the cluster exhibit an average distance on their growth-cycle features of about 0.005 while the average distance for the countries with idiosyncratic growth-cycles grows up to about 0.05. This bimodal characterization statistically confirmed by the Silverman test displayed in Table 6.

3.2. Results from the business-cycle analysis

The business cycle synchronisation is examined in Table 4. Typically, the pairwise concordance indexes range between 0.6 and 0.7, which implies that most of the pairs of Latin American countries crossed through identical business cycle phases between 60% and 70% of the time elapsed between 1980 and 2013.[5] This evidences their significant business cycle synchronicity. At the country level, Peru, Chile and Uruguay show the highest average rates (0.76, 0.75 and 0.73 respectively); while Bolivia (0.61) and Ecuador (0.62) represent the least synchronised countries.

Figure 3 shows a graphical representation of the MDS technique, which has been derived only from the distances on business cycle synchronisation. All countries appear

5 All the indexes in the table are statistically significant.

tightly clustered forming only one group. This reveals that the sample of countries is rather homogeneous in terms of business cycle synchronisation.

In line with these uniformly distributed high values of the pairwise concordance indexes, the kernel representation of the distances on business cycle synchronisation plotted in Figure 7 suggests that the underlying distribution of distances is unimodal. This suggests that Latin American business cycle cohere. The fact that we fail to find different sub-populations of Latin American countries is corroborated by the result of the Silverman test displayed in the third row of Table 6. The *p*-value of the null of unimodality is 0.45, which implies that this null cannot be rejected at standard confidence intervals.

As in the case of growth cycles, we complete our business-cycle analysis by examining the distance on other business-cycle characteristics in Table 5. In line with Mejía-Reyes (1999, 2004), we find a large asymmetric behaviour over the business cycle for most economies in the sample. On average, the duration of the business cycles implies that expansions last much longer than recessions (duration of 32.7 and 12.6 months, respectively). This asymmetry is remarkable in Peru (53.25 versus 10 months), Chile (47.8 versus 13.5 months), Costa Rica (43.8 versus 11.5 months) and Uruguay (29.25 versus 8 months).

On average, the gains in expansions are about 18.7% while the losses in recessions are of 10.2%. Moreover, the dispersion in the amplitude of the Latin American business cycles is noticeable. Costa Rica is the nation with the highest increase of its industrial production in times of economic growth (31.8%), followed by Peru (29.6 %), Venezuela (27.6 %) and Uruguay (22.1 %). By contrast, Venezuela (-32.8 %) and Uruguay (-18.5 %) are the countries with the largest falls of industrial product during economic downturns. This singularity places these countries as those with the most volatile cycles. In contrast to these countries, Bolivia show the least volatile business cycle.

Overall, Latin American countries exhibit negative excess in expansions and positive excess during recessions. Therefore, industrial production increases in expansions intensively after the troughs (Bolivia, Ecuador and Colombia are the only exceptions). By contrast, industrial production falls quickly after the peaks during recessions (Chile, México, Uruguay and Venezuela are the exceptions).

The MDS map displayed in Figure 4 greatly helps in the comparison of all the distances in business-cycle features. According to this representation, the countries are grouped in two concentric circles, whose radius lengths reflect the business cycle dissimilarities from the centre to the periphery. The core of countries with more similar business cycles is composed by Argentina, Mexico, Brazil, Uruguay and Colombia. Ecuador, Bolivia Venezuela, Peru, Chile and Costa Rica are located at the periphery.

The kernel approximation to the density distribution of distances in business-cycle features is plotted in Figure 8. The density estimation suggests that the countries with more homogeneous business cycles belong to the mass of the distribution. The long right-hand-side tail of the distribution refer to those countries with more heterogeneous business cycles. In spite of this comment, the Silverman test displayed in Table 6 fails to find two different modes in the distribution of distances in business-cycle features since the p-value of the null of one mode is 0.79.

3.3. Economic cycle structures and dynamic evolution

In the previous sections we show that regardless of the approach used to compute the cycle features, we find evidence of significant linkages in this region. With the exception of the growth cycle features, the Latin American countries exhibited pretty similar cycles during this sample period. This result is of significant importance for the economic integrations that are currently being implemented in the region.

In this context, some results in the recent literature point out that part of the cyclical linkages may rely on presence of the Great Recession. Imbs (2010) argues that world synchronisation has greatly increased due to the Great Recession, mainly due to the linkages observed among developed countries. In addition, Fidrmuc and Korhonen (2010) finds that the rises in synchronisation have been particularly important between the largest Asian emerging economies (China and India) and the industrialized countries. However, Gächter et al. (2012) show a pronounced desynchronisation of business cycles in Economic and Monetary Union during the crisis period, both with respect to dispersion and to the correlation of business cycles. The purpose of this section is to examine the extent to which the economic cycle linkages in Latin American countries documented above were affected by the Great Recession.

For this purpose, we examine the dynamic of the density distributions of pairwise economic cycle distances by repeating the analysis using a shorter sample that ends before the onset of the Great Recession. According to Figure 5 to Figure 8, the modes slightly shifts to the left when the data of the Great Recession are included in the sample, especially in the case of growth cycle and business cycle synchronisation. This agrees with the view that the business cycles of individual countries may have become more closely synchronised because the Latin American countries experienced the effects of this recession roughly at the same time.

The last two columns of Table 6 show the *p*-values of the null of testing for the number of modes in the density probability distribution of the data when the sample ends in 2007. The table shows that we have virtually identical results regardless of whether the data of the Great Recession are included in the sample. As in the case of the entire sample, the unimodality hypothesis is not rejected in the case of growth-cycle synchronisation, business-cycle synchronisation and business-cycle features. In addition, the distribution of growth-cycle features seems to have two modes. Therefore, it seems that the Great Recession did not have significant effects on the pre-existing Latin American cyclical linkages

4. Conclusions

The main conclusions about the situation of Latin America cycles during the last thirty years can be summarized as follows. First, regardless of the approach used to compute the cycle features, we find evidence of significant linkages in this region. Second, the growth-cycle features tend to be more symmetric across the cycle than the business cycle features. Third, with the exception of the growth cycle features, the Latin American countries exhibited pretty similar cycles during this period, with some exceptions such as Bolivia, Ecuador and Costa Rica (idiosyncratic countries). Fourth, the Great Recession did not have any significant impact on the distribution of the cycle distances.

These results are of significant importance for the economic integrations that are currently being implemented in the region. With few exceptions, we find that Latin American countries exhibit similar cycles. Therefore, in contrast with Carrasco and Reis (2006), we find that the cyclical synchronisation and the similarities on other cycle characteristics would not be an obstacle for continuing with the economic integrations already initiated among some of these countries.

5. References

Aiolfi, M., Timmermann, A., and Catao, L. 2006. Common factors in Latin America's business cycles. International Monetary Fund Working Paper Series.

Bry, G., and Boschan, C. 1971. Cyclical analysis of time series: Selected procedures and computer programs. National Bureau of Economic Research.

Camacho, M., Perez Quiros, G., and Saiz, L. 2008. Do European business cycles look like one? *Journal of Economic Dynamics and Control* 32: 2165-2190.

Carrasco, C., and Reis, F. 2006. Evidence about Mercosur's business cycle. *Anais do XXXIV Encontro Nacional de Economia* 179.

de Haan, J., Inklaar, R., and Jong-A-Pin, R. 2007. Will business cycle in the Euro area converge? A critical survey of empirical research. *Journal of Economic Surveys* 22: 234-273.

Fidrmuc, J., and Korhonen, L. 2010. The impact of the global financial crisis on business cycles in Asian emerging economies. *Journal of Asian Economics* 21: 293-303.

Gächter, M., Riedl, A., and Ritzberger-Gruenwald, D. 2012. Business cycle synchronisation in the euro area and the impact of the financial crisis. *Monetary Policy the Economy* 2: 33-60.

Harding, D., and Pagan, A. 2002. Dissecting the cycle: a methodological investigation. *Journal of monetary economics* 49.2: 365-381.

Hodrick, R., and Prescott, E. 1997. Postwar U.S. Business Cycles: an Empirical Investigation. *Journal of Money, Credit and Banking* 29: 1-16.

Hurtado-Rendón, A., and Builes-Vásquez, F. 2011. Synchronisation of business cycles in the Mercosur: 1960-2008. *Echoes of Economy* 1431: 7-35.

Imbs, J. 2010.The first global recession in decades. *IMF economic review* 58.2: 327-354.

Mejia-Reyes, P. 1999. Classical business cycles in Latin America: turning points, asymmetries and international synchronisation. *Estudios Económicos*: 265-297.

Mejia-Reyes, P. 2004. Classical business cycles in America: are national business cycles synchronised. *International Journal of Applied Econometrics and Quantitative Studies* 1-3: 75-102.

Sichel, D. 1993. Business cycle we expect to be: a deeper look. *Economic Inquiry* 31: 224-236.

Silverman, B. 1981. Using kernel density estimates to investigate multimodality. *Journal of the Royal Statistical Society*. Series B (Methodological): 97-99.

Stock, J., and Watson, M. 2004. Estimating turning points using large data sets. *Journal of Econometrics* 178: 368-381.

Timm, N. 2002. Applied multivariate analysis. Springer Texts in Statistics. Springer, Berlin.

6. Tables

Table 1. Data description.

Country	Indicator	Period
Argentina	Industrial production index	January 1994-January 2013
Bolivia	Index of economic activity	January 2008-December 2012
Brazil	Industrial production index	January 1980-January 2013
Chile	Industrial production index	January 2001-February 2013
Colombia	Industrial production index	January 1990-January 2013
Costa Rica	Industrial production index	January 1991-February 2013
Ecuador	Index of economic activity	January 2001-February 2013
Mexico	Industrial production index	January 1980-January 2013
Peru	Index of the non-primary gross added value	January 1992-January 2013
Venezuela	Industrial production index	January 1997-December 2012
Uruguay	Industrial production index	January 2002-February 2013

Notes. Data were extracted from the OECD database and from National Ministries of Economy and Industry databases.

Table 2. Growth cycle synchronisation: 1980-2013.

	PERU	RICA	URU	VEN	MEX	CHIL	ARG	BRA	COL	ECU	BOL
PERU	1										
C. RICA	0.06	1									
URUGUAY	0.23**	-0.14	1								
VENEZUELA	0.13 **	-0.22***	0.39**	1							
MEXICO	0.40**	0.24***	0.15*	0.25***	1						
CHILE	0.36**	-0.01	0.11	0.22***	0.27***	1					
ARGENTINA	0.32**	0.05	-0.02	0.16**	0.5 ***	0.30***	1				
BRAZIL	0.45**	0.13**	0.23**	0.26***	0.29***	0.19***	0.45***	1			
COLOMBIA	0.37**	-0.06	0.03	0.39***	0.38***	0.32***	0.41***	0.29***	1		
ECUADOR	0.22**	0.19***	0.05	0.11	0.23***	-0.01	0.19***	0.19 **	0.35***	1	
BOLIVIA	-0,37**	0.37***	0.04	-0.28**	0.26 **	-0.02	-0,48***	-0,23*	-0,23*	-0.20	1

Notes. The entries show the pairwise correlations of the Hodrick-Prescott cycles. (*) significant at 10 %; (**) significant at 5 %; (***) significant at 1 %.

Table 3. Growth cycle features: 1980-2013

	Amplitude		Duration		Asymmetry	
	Expansion	Recession	Expansion	Recession	Deepness	Steepness
ARGENTINA	6.32	-5.45	18.3	14.6	-0.42	-0.80
BOLIVIA	5.06	-2.83	13.0	17.0	0.88	1.68
BRAZIL	5.74	-4.73	15.6	17.5	-0.88	-1.28
CHILE	4.31	-3.70	16.3	17.0	-2.22	-0.79
COLOMBIA	5.92	-5.55	15.3	19.4	0.04	-0.22
C. RICA	18.73	-18.11	19.9	18.1	0.27	-0.49
ECUADOR	34.17	-32.32	13.5	13.0	0.42	-0.06
MEXICO	2.65	-3.09	18.6	16.0	-0.65 **	-0.14
PERU	4.31	-4.10	14.3	19.9	0.10	0.00
URUGUAY	8.94	-11.99	11.5	13.0	-1.00 **	-0.43
VENEZUELA	10.05	-12.80	21.0	17.4	-1.88	-2.87
AVERAGE	9.00	-8.49	16.4	16.8	-0.49	-0.49

Notes. Duration is the number of months in the cycle phase, amplitude is maximum ascent in expansions or descent in recessions and deepness and steepness measure the skewness of the cycle components and their first differences. (**) Significant at 5% level.

Table 4. Business cycle synchronisation: 1980-2013.

	ARG	BOL	BRA	CHIL	COL	ECU	PERU	MEX	RICA	URU	VEN
ARGENTINA	1										
BOLIVIA	0.63***	1									
BRAZIL	0.69***	0.58***	1								
CHILE	0.69***	0.64***	0.74***	1							
COLOMBIA	0.65***	0.31***	0.69***	0.72***	1						
ECUADOR	0.67***	0.61***	0.54***	0.64***	0.61***	1					
PERU	0.74***	0.75***	0.78***	0.91***	0.70***	0.65***	1				
MEXICO	0.73***	0.61***	0.61***	0.72***	0.63***	0.63***	0.67***	1			
C. RICA	0.68***	0.81***	0.65***	0.81***	0.66***	0.65***	0.78***	0.74***	1		
URUGUAY	0.79***	0.58***	0.77***	0.80***	0.76***	0.54***	0.83***	0.71***	0.72***	1	
VENEZUELA	0.70***	0.54***	0.65***	0.78***	0.80***	0.61***	0.74***	0.73***	0.62***	0.76***	1

Notes*:* The entries show the pairwise concordance indexes of Harding and Pagan (2006). (***) Significant at the 10% level.

Table 5. Business cycle features: 1980-2013.

	Amplitude		Duration		Excess	
	Expansion	Recession	Expansion	Recession	Expansion	Recession
ARGENTINA	20%	-11%	31.8	14	-0.0221	0.007
BOLIVIA	5.90%	-0.40%	19.7	8	0.0015	0.0124
BRAZIL	14.10%	-9.80%	25.8	15.4	-0.0011	0.0095
CHILE	17.40%	-6%	47.8	13.5	-0.015	-0.0092
COLOMBIA	12.20%	-9.20%	28.7	15.2	0.0012	0.0031
C. RICA	31.80%	-9.20%	43.8	11.5	-0.004	0.0105
ECUADOR	10.90%	-2.70%	12.2	8	0.0006	0.0114
MEXICO	14.30%	-9%	33.6	15.8	-0.0135	-0.0009
PERU	29.60%	-3%	53.25	10	-0.0043	0.002
URUGUAY	22.10%	-18.50%	29.25	8	-0.0374	-0.0347
VENEZUELA	27.60%	-32.80%	33.8	18.7	-0.064	-0.0614
AVERAGE	18.70%	-10.20%	32.7	12.6	-0.0144	-0.0046

Notes*:* Duration is the number of months in each phase, amplitude is maximum gain in expansions or loss in recessions and excess is the deviation of actual industrial production from a linear path.

Table 6. Silverman Test.

		1980-2013		1980-2008	
		1 mode	2 modes	1 mode	2 modes
Growth cycle	Synchronisation	0.44	0.63	0.46	0.09
	Other features	0.02	0.45	0.03	0.29
Business cycle	Synchronisation	0.45	0.60	0.35	0.20
	Other features	0.79	0.60	0.45	0.40

Notes: The entries show the *p*-values of the Silverman test of 1 and 2 modes on the distributions of economic cycle characteristics.

7. Figures

Figure 1. Growth-cycle synchronisation. 1980-2013.

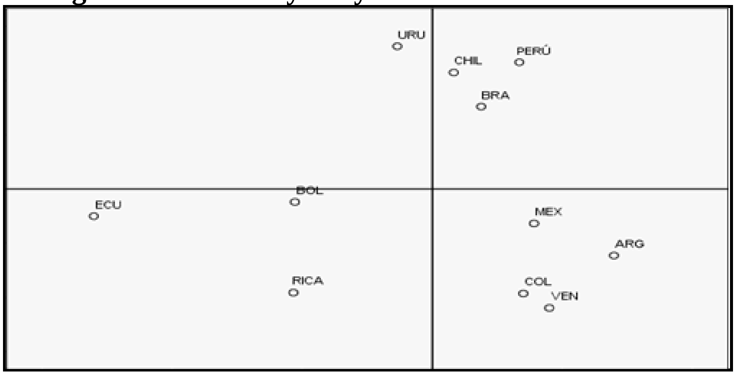


Figure 2. Growth-cycle features. 1980-2013.

Figure 3. Business-cycle synchronisation. 1980-2013.

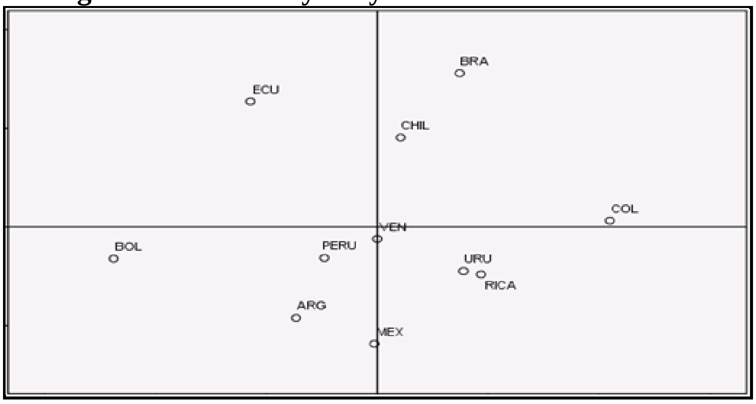


Figure 4. Business-cycle features. 1980-2013.

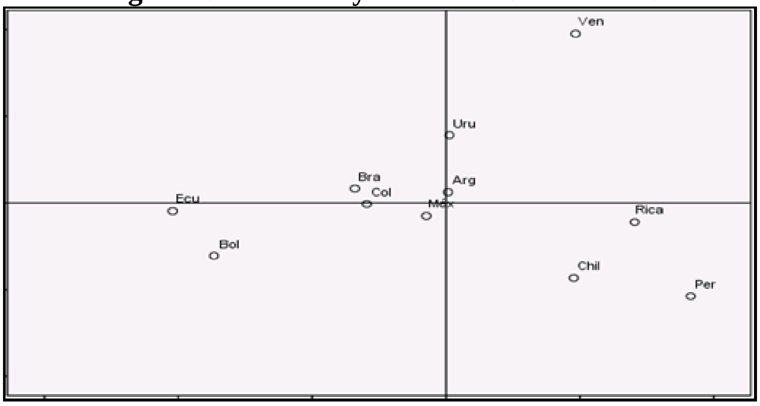


Figure 5. Kernel density function of distances on growth-cycle synchronisation.

A) Period 1980-2013. B) Period 1980-2008.

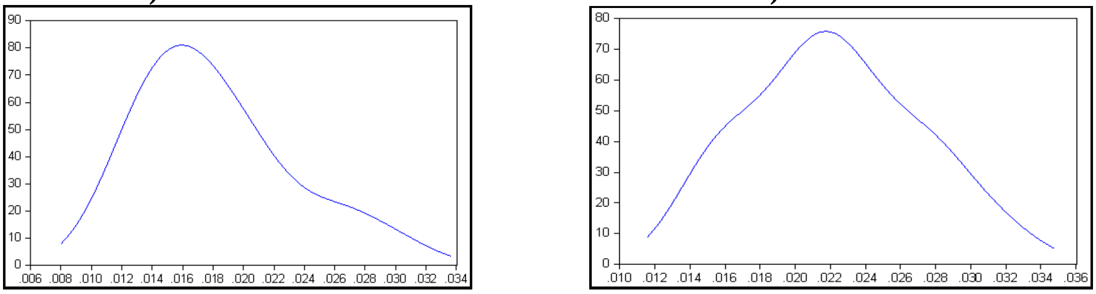


Figure 6. Kernel density function of distances on growth-cycle features.

A) Period 1980-2013. B) Period 1980-2008.

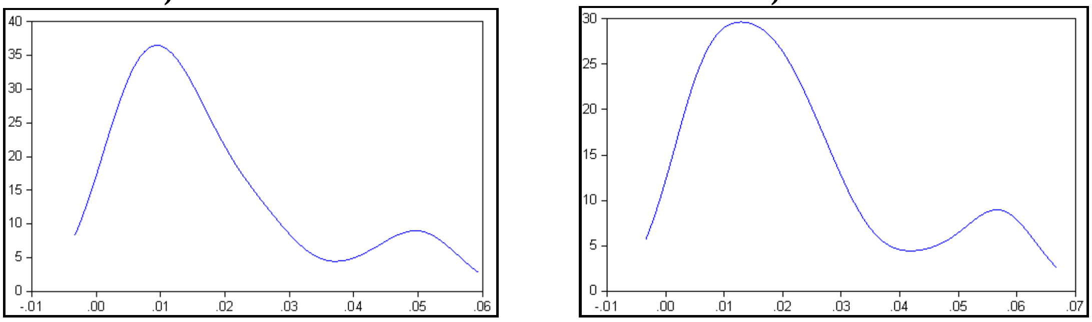


Figure 7. Kernel density function of distances on business-cycle synchronisation.

A) Period 1980-2013. B) Period 1980-2008.

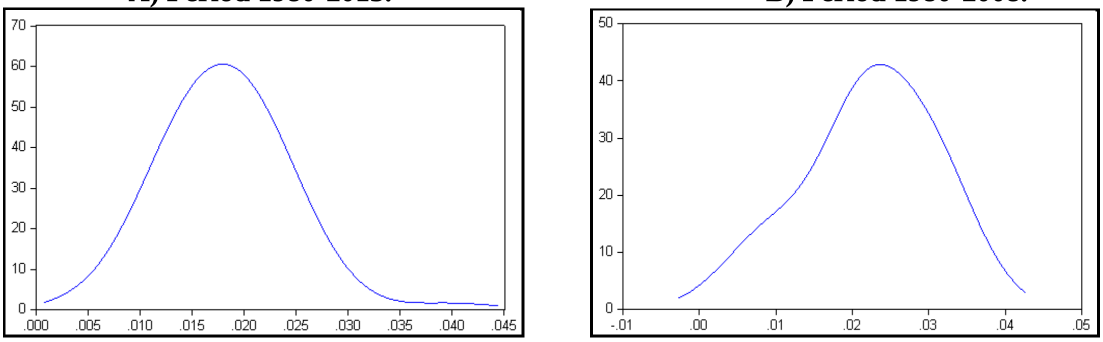
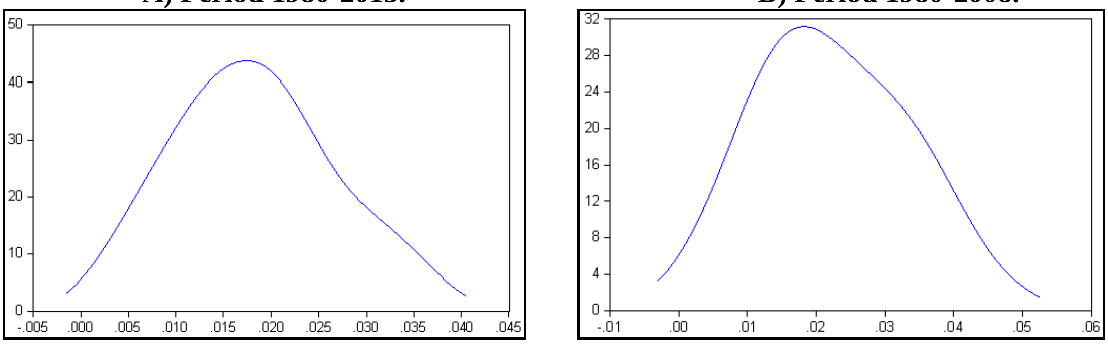


Figure 8. Kernel density function of distances on business-cycle features.

A) Period 1980-2013. B) Period 1980-2008.



CHAPTER 3: Economic recessions and income inequality: Do they go hand in hand?

1. Introduction

The importance of inequality in the academia, mainstream and political circles has considerably increased during the last decades, especially after the Great Recession. One example of this interest on inequality is the survey conducted by the Pew Research Center (Pew Research Center, 2014), which found that the existing difference between the rich and the poor is the biggest concern for nearly the 60 percent of total respondents. In the same vein, some of the most influential people worldwide have assessed their own judgement on this topic such as the ex-President of the United States Barack Obama and the Pope Francis. The former talked about income inequality as probably the most important challenge of our generation; while the latter spoked about fighting against the “economy of exclusion”.

One leading concern in this literature relies on questioning the influence of economic cycles on inequality. As stated in the survey developed by Parker (1998), the interest started with Mendershausen (1946) and Kuznets (1953), who showed that top income shares increased in recessions and decreased in expansions during the US interwar period. Dimelis and Livada (1999) found a countercyclical pattern of inequality in the US and the UK, although inequality did not seem to exhibit a cyclical pattern for Italy while it was procyclical in Greece. Maliar, Maliar and Mora (2005) found a countercyclical behavior of inequality in the US using a neoclassical growth model with heterogeneous agents. In addition, the Great Recession raised a renewal interest on the potential business cycle behavior of inequality. To name a few, Atkinson and Morelli (2011) studied the relation between banking crises and GDP/consumption collapses with inequality in more than a dozen countries (mostly developed). They found that banking crises are more prone to end up with inequality increases than GDP/consumption collapses. Several OECD reports (2011, 2015) evidenced increasing inequality in relation to economic recessions, but also in expansions. This finding holds for both, egalitarian and traditionally non-egalitarian nations. Moreover and after the recent world crisis, the gap between the poor and the rich got even higher reaching it maximum levels in most of OECD nations. Finally, Saez (2013) showed a fall in the US top income shares during the Great

Recession. Nevertheless, he also documented that this fall was temporary and did not undermine the inequality growth experienced from the 1970s.

Therefore and as it can be seen, it is widely considered that economic downturns are associated with inequality rises. However, the question regarding the real net impact that economic downturns cause on income inequality seems still to be unsolved. Let us illustrate this situation using a preliminary and graphical argument contained in Figure 1. The Gini index exhibits a secular trend rather than a cyclical pattern in the US, regardless of whether we focus on business cycles or growth cycles.

At this point and with the aim of adding some light on this literature, we evaluate the net effect of growth-cycle and business-cycle recessions on income inequality in a large set of 43 countries of the five continents between 1960 and 2014. Our benchmark is the local projection approach introduced in Jorda (2005) and used in Jorda, Schularick and Taylor (2013). This approach is based on the premise that impulse responses are properties of the data that can be calculated directly rather than indirectly through a reference model such as a VAR. Within this framework, conditional on experiencing a recession of a particular type (taken here as a given), we can examine what is its effect on income inequality, measured by the Gini index after controlling on a set of relevant controls.

In addition our paper contributes to fill the gap in the related literature in at least one of the following ways: (i) encompasses a comprehensive sample of the world instead of focusing in certain regions or single economies; (ii) makes use of an inequality database within a high degree of comparability between countries; (iii) our research goes beyond a trends analysis since the impact of the economic cycle is obtained after controlling for other relevant factors; (iv) we isolate the effect of the general economic cycle instead of focusing on particular types of economic crises (financial, currency, etc); and (v), with the aim of completeness, we use both growth and business cycle concepts in order to obtain more robust conclusions.

Overall, our empirical results suggest that, regardless of whether we consider a business-cycle or a growth-cycle analysis, recessions do not raise a significantly positive effect on income inequality. However, these results should be carefully considered since we find important differences according to the degree of economic development and geographical region.

2. The local projection approach

We are interested in establishing empirical regularities of the net impact of economic recessions on inequality, once macroeconomic controls are added to the model. For this purpose, we rely on the local projection model advocated by Jorda (2005).

To define the statistical model, some notation is required. For a set of *N* countries, let $\Delta_h y_{i,t+h}$ be the change experienced by the Gini index, $y_{i,t+h}$, of country *i* at time *t*, *h* periods in the future,

$$\Delta_h y_{i,t+h} = y_{i,t+h} - y_{i,t}\ , \tag{1}$$

where $i = 1, \dots, N$, $h = 1, \dots, H$, and $t = 1, \dots, T - H$. Let $C_{i,t}$ be a recessionary indicator that takes the value of 1 when either a business cycle or a growth cycle recession occurs and the value of 0 otherwise. Let $X_{i,t}$ be the set of macroeconomic controls for country *i* at time *t*, which can include lagged values of the changes in the Gini index.

Following Koop, Pesaran and Potter (1996) the cumulated response can be defined as the difference between two forecasts:

$$IR_i(t, h, \mathrm{C}) = E_{i,t}\left[\Delta_h y_{i,t+h} \middle| X_{i,t}\ ;\ C_{i,t} = 1\right] - E_{i,t}\left[\Delta_h y_{i,t+h} \middle| X_{i,t}\ ;\ C_{i,t} = 0\right], \tag{2}$$

which refers to the response across recessions of the Gini index for country *i* at a horizon *h* periods in the future, in response to a change in the treatment variable from expansion to recession conditional on the set of macroeconomic controls. In linear frameworks, the cumulated response is simply the sum of the 1 to *h* standard impulse responses.

Jorda, Schularick, and Taylor (2013) show that impulse responses can be calculated by a sequence of projections of the endogenous variable shifted forward in time onto its lags and the set of macroeconomic controls. In particular, if $x_{i,t}^k$ is the set of exogenous macroeconomic controls, with $k = 1 \dots, K$, we estimate by OLS the cumulated responses using the simple local projection regression

$$\Delta_h y_{i,t+h} = a_i^h + \partial_i^h \Delta y_{i,t-1} + \beta_i^h\, C_{i,t} + \textstyle\sum_{k=1}^{K} \delta_{i,k}^h\, x_{i,t}^k + \varepsilon_{i,t}^h, \tag{3}$$

where $\varepsilon_{i,t}^h$ is an i.i.d. error term with mean 0 and variance σ_i^2.

For the purposes of our contribution, the main parameters of interest are the set of β_i^h coefficients, with $h = 1, \dots, 10$. They represent the conditional path for the cumulated response of the *i*-th country Gini index, after controlling for the past values of the Gini changes and the set of macroeconomic controls. As documented by Jorda (2005), the baseline model used to compute the local projections can be estimated by simple regression techniques with standard regression packages. In addition, it is simple to test for the significance of these effects and to construct confidence bands since standard statistics apply.[6]

3. Empirical application

3.1. Data description

The statistical dispersion of the income distribution of a nation's residents is measured with the Gini coefficient of disposable income (post-tax and post-transfers). A zero value of this coefficient expresses perfect equality whereas a Gini coefficient of 1 reflects maximal inequality among a country´s citizens. The time series of the national annual indices were extracted from the Standarized World Income Inequality Database or SWIID developed by Solt (2016). These indices are designed to provide a great coverage across countries and over time with the aim of maximizing the cross-country comparability of income inequality data.

Controls were downloaded from the World Development Indicators (WDI). The selection of the control variables follows two recent influential researches on inequality determinants: Roine, Vlachos, and Waldenström (2009), and Dabla-Norris et al. (2015). However, due to the fact that our aim relies on the study of the effect of economic recessions instead of addressing income inequality drivers, we restrict the set of controls due to data availability reasons and the existing trade-off between the number of controls and degrees of freedom.

In particular, we control for the development of domestic financial markets with credit to GDP. To control for external trade, we use the sum of imports and exports as a percentage of GDP. We control for the technological progress with the stock of patents. We include the female mortality rate to capture the link between the accesses to health

[6] Since local projections are strictly related to direct forecasting methods, consistency and asymptotic normality under general conditions are released in Weiss (1991).

services and income inequality. Finally, we include other controls such as population size and per capita GDP[7].

The set of 43 countries included in the analysis, which represents an overwhelming share of world GDP, and the effective sample of each control are listed in the Appendix I. We excluded from the analysis countries for which we were not able to obtain local projections from samples of at least 30 degrees of freedom, countries with recession dummies of less than two recessions and countries with less than 4 controls.

Although Appendix II includes further details, dates of business cycle recessions are obtained by applying the annual dating algorithm developed by Berge and Jorda (2013) to seasonally adjusted national GDP time series. In addition, we date the growth cycle recessions as periods of GDP below a Hodrick-Prescott trend. By using these dates, we construct the recessionary dummy indicators, $C_{i,t}$, at time *t* for each country i.

3.2. Business cycle analysis

The conditional responses of income inequality to a business cycle recession are estimated with local projection methods, which are displayed, along with their 90% confidence bands, in Appendix IV.[8] In particular, each figure shows the estimated coefficients β_i^h for changes in the Gini indices computed for up to h=10 years following a recession for each country *i* of the sample.

Table 1 reports the percentage of countries for which a business cycle recession cause inequality to decrease (negative impact) or to increase (positive impact) in the short run (up to three-year impact) and in the medium run (four-to-six year impact). The table shows that a recession causes inequality to decrease in 54% of countries during the first three years after a recession, although the percentage rises to 57% in the medium run. However, the negative effect of a recession on inequality is significant only for 22% of countries in the short run and for 20% of countries in the medium run. This result agrees with those obtained by Roine, Vlachos and Waldesnström (2009), who demonstrated that banking crises have a strong negative impact on the income shares of the rich.

Figure 2 provides a glimpse of how the effect of a business recession on inequality varies across geographic areas. Countries in red (orange) are countries experiencing

7 We performed stationary transformations for those controls evidencing the presence of unit roots.
8 We use a heteroskedasticity and autocorrelation consistent estimator of the model to compute the confidence bands.

significant (non-significant) increases in inequality as a consequence of a business cycle recession, while countries in dark blue (sky blue) are countries facing significant (non-significant) collapses in inequality due to these crises. According to Panel A, a recession cause inequality to decrease in the short run in Brazil, Costa Rica, Finland, Germany, Greece (also found in Dimelis and Livada, 1999), India, Indonesia, Iran, Italy, Kenya, Korea, Norway, Panama, Peru, Philippines, Singapore, South Africa, Spain, Thailand, Tunisia, the United Kingdom and Zambia. In the medium run, a business cycle recession diminishes inequality in Australia, Brazil, China, Costa Rica, Denmark, Finland, France, Greece, Kenya, Korea, Malaysia, the Netherlands, Norway, Panama, Peru, Philippines, Singapore, South Africa, Spain, Thailand, Tunisia, the United Kingdom and Zambia.

Now, we proceed with the geographical analysis by splitting the sample of countries into OECD and non-OECD nations. In line with the findings of OECD (2011 and 2015), Panel B of Table 1 shows that inequality falls during the first three years after a business cycle recession for 38% of OECD countries, while this percentage rises to 70% for non-OECD nations.[9] However, the effect is statistically significant for only 5% of OECD countries, but for 40% of non-OECD countries. Qualitatively, this result hold for a medium run analysis.

To complement the geographical analysis of the effects of a recession on inequality, we classify the countries according to the 2017 Countries Classification by Income conducted by the World Bank, whose list appear in Appendix III. For this purpose, we consider High Income Level countries as developed ones and the rest as emerging markets. In the short run, Panel C of Table 1 reports that a business cycle recession reduces inequality in 43% of high-income countries (5% of which face a significant reduction). Besides and considering middle-income countries, this percentage rises to the 65% (significant reduction in 40%). In the middle run, the percentages are 52% (14% significant) for high-income countries and 60% (25% significant) for middle income countries.

In line with the analysis developed by, among others, Dabla-Norris et al. (2015), we consider that economic development is not the only source of inequality differential patterns. By contrast, geographical or cultural differences could also explain different

9 In the case of US, this result agrees with the findings of Menderhausen (1946), Kuznets,1953, and Maliar, Maliar and Mora (2005).

responses of inequality to business cycle recessions. To analyze this potentially different response, we group in Appendix III the sample of countries into different regional clusters: Asia, Africa, Europe, Latin America and developed Anglo-Saxon regions.[10]

According to the percentages reported in Panel D of Table 1, inequality falls three years after a business cycle recession in the majority of countries for all regions. In particular, this effect holds in all the African and Anglo-Saxon countries, and in a bit more than 50% in Asian, European and Latin American countries. Remarkably, the percentages of countries for which this effect is statistically significant fall considerably. In the medium run, the percentages of countries for which a recession causes inequality to fall are still over 50% in all regions but Anglo-Saxon countries. Again, the percentages that refer to significantly negative effects drop considerably.

3.3. Growth cycle analysis

The estimated coefficients β_i^h for changes in the Gini indices as a consequence of a growth cycle recession and their 90% confidence intervals for each country *i* are plotted for h=1,…,10 in Appendix V. Following the lines of the business cycle analysis, Figure 3 plots a choropleth map in which countries are colored according to the reaction (and significance) of their Gini indices to a growth cycle recession.

To sum up the results, Panel A of Table 2, shows that a growth cycle recession cause inequality to drop in about the same percentage as a business cycle recession did, both in the short run and in the middle run. However, the percentages of countries for which the effect is statistically significant fall remarkably.

In addition, Panel B of Table 2 shows that the short-run negative reaction of inequality to a growth cycle recession is higher in OECD countries than in the case of business cycle recessions (72% versus 38%), but lower than in the case of non-OECD countries (50% versus 70%). This also holds for the medium term.

Regarding the countries classification by income conducted by the World Bank, Panel C of Table 2 show that almost three quarters of high-income countries reduce inequality during the first three years after a growth cycle recession, while this proportion falls to one half for middle-income countries. As in the case of business cycle recessions, the

10 Our results does not change significantly if UK appears in the set of European or in the set of Anglo-Saxon countries.

effect is statistically significant in a lower percentage of countries. Moreover, the negative effect of recessions diminishes as the horizon increases in both groups of countries.

The percentages reported in Panel D of Table 2 shows that a growth recession cause inequality to drop in the short run in about the majority of countries in all areas but Asia. The negative effect is especially important in Latin America (89% of countries) and Europe (77% of countries). To a lesser extent, a growth cycle recession tend to reduce inequality in African and Anglo-Saxon countries (50% in both cases) while the percentage is only of 31% in the case of Asian countries. However, the percentages of countries for which this effect is statistically significant diminish dramatically. Although in lower magnitude, these findings qualitatively hold in the medium term for all regions but Africa.

4. Conclusions

Does an economic downturn cause income inequality to rise? Within the framework of the local projection methods introduced by Jorda (2005), we track the effects of both growth-cycle and business-cycle recessions on the path of the Gini indices for up to ten years after a recession, once a broad set of macro-economic controls are in place.

Using annual data on a set of 43 countries from 1960 to 2014, we document several empirical facts. Overall, we failed to find significant evidence that an economic recession causes income inequality to rise, after controlling for a set of relevant economic aggregates. Perhaps because the Gini indices are typically dominated by secular trends (also suggested in OECD, 2011 and 2015) rather than by cyclical movements, for most countries we estimate a negative effect of recessions on income inequality. Although, the effect loses significance over time.

In spite of this overall conclusion, we find certain distinguishing patterns in the magnitude of the effects of recessions on inequality, which tend to depend on the degree of economic development. In short, business cycle recessions decrease inequality in more than fifty percent of counties, although this negative pattern seems to affect to a greater extent to non-OECD and middle-income economies. In a geographical perspective, the short-run response of the Gini indices to a business cycle recession is always negative in African and Anglo-Saxon countries and affect to more than fifty percent of Asian, European and Latin American countries. The percentages tend to diminish when we focus on significant effects and when the analysis moves to medium terms.

Finally, our results suggest that a growth cycle recession cause inequality to drop in about the same percentage as business cycle recessions, both in the short run and in the middle run. However, the percentages of countries for which the effect is statistically significant fall by more than a half. Now, the negative reaction of inequality to a growth cycle recession is higher in OECD countries and high-income economies. Overall, the geographical pattern of a growth cycle recession effect is similar, although to a lesser extent, to that of a business cycle recession.

5. References

Atkinson, A., and Morelli, S. 2011. Economic crises and inequality.

Berge, T., and Jordà, Ò. 2013. A chronology of turning points in economic activity: Spain, 1850–2011. *SERIEs* 4: 1-34.

Bry, G., and Boschan, C. Cyclical analysis of time series: Selected procedures and computer programs, 1971.

Dabla-Norris, M., Kochhar, M., Suphaphiphat, M., Ricka, M., and Tsounta, E. 2015. Causes and consequences of income inequality: a global perspective. International Monetary Fund, Staff Discussion Note.

Dimelis, S., and Livada, A. 1999. Inequality and business cycles in the US and European Union countries. International Advances in Economic Research, 5(3), 321-338.

Hodrick, R., and Prescott, E. 1997. Postwar US business cycles: an empirical investigation. *Journal of Money, credit, and Banking*: 1-16.

Jordà, Ò. 2005. Estimation and Inference of Impulse Responses Local Projections. *American economic review* 95:161-182.

Jordà, Ò., Schularick, M., and Taylor, A. 2013. When credit bites back. *Journal of Money, Credit and Banking* 45: 3-28.

Koop, G., Pesaran, M., and Potter, S. 1996. Impulse response analysis in nonlinear multivariate models. *Journal of econometrics* 74: 119-147.

Kuznets, S., and Jenks, E. 1953. Shares of Upper Income Groups in Savings. In Shares of Upper Income Groups in Income and Savings (pp. 171-218). NBER.

Maliar, L., Maliar, S., and Mora, J. 2005. Income and wealth distributions along the business cycle: Implications from the neoclassical growth model. *Topics in Macroeconomics* 5.

Mendershausen, H. 1946. Changes in income distribution during the Great Depression. NBER Books.

OECD. Publishing. 2011.Why Inequality Keeps Rising. OECD Publishing.

OECD. Publishing. 2015. In It Together: Why Less Inequality Benefits All. OECD Publishing.

Parker, S. 1998. Income inequality and the business cycle: a survey of the evidence and some new results. *Journal of Post Keynesian Economics* 21: 201-225.

Pew Research Center (PRC). 2014. Emerging and Developing Economies Much More Optimistic than Rich Countries about the Future. Washington.

Roine, J., Vlachos, J., and Waldenström, D. 2009. The long-run determinants of inequality: What can we learn from top income data? *Journal of Public Economics* 93: 974-988.

Saez, E. 2013. Striking it Richer: The Evolution of Top Incomes in the United States (updated with 2012 preliminary estimates), Berkeley: University of California, Department of Economics.

Solt, F. 2016. The Standardized World Income Inequality Database. Social *Science Quarterly* 97. SWIID Version 6.1, October 2017.

Weiss, A. 1991. Multi-step estimation and forecasting in dynamic models. *Journal of Econometrics* 48: 135-149.

6. Tables

Table 1. Business cycle recessions.

Panel A. Total sample

	SR	MR
N-NS	32%	37%
N-S	22%	20%
P-NS	29%	37%
P-S	17%	7%

Panel B. OECD vs non-OECD.

	OECD		Non-OECD	
	SR	MR	SR	MR
N-NS	33%	33%	30%	40%
N-S	5%	14%	40%	25%
P-NS	43%	43%	15%	30%
P-S	19%	10%	15%	5%

Panel C. World Bank high income vs middle income level

	High income		Middle income	
	SR	MR	SR	MR
N-NS	38%	38%	25%	35%
N-S	5%	14%	40%	25%
P-NS	38%	38%	20%	35%
P-S	19%	10%	15%	5%

Panel D. Regional clustering

	Africa		Asia		Europe		Latin America		Anglosaxon (excluding UK)	
	SR	MR	SR	MR	SR	MR	SR	MR	SR	MR
N-NS	25%	25%	42%	33%	46%	38%	13%	50%	75%	25%
N-S	75%	75%	17%	17%	8%	23%	38%	0%	25%	0%
P-NS	0%	0%	25%	42%	23%	31%	38%	50%	0%	50%
P-S	0%	0%	17%	8%	23%	8%	13%	0%	0%	25%

Note. Percentage of countries for which a business cycle recession cause inequality to decrease (negative impact) or to increase (positive impact). For each panel N-NS, N-S, P-NS and P-S refer to Negative-Nonsignificant, Negative-Significant, Positive-Nonsignificant and Positive-Significant effect. Panel A refers to the total sample, Panel B distinguishes between OECD and Non-OECD countries, Panel C distinguishes between high income and middle-income level countries, according to the World Bank, while Panel D provides information according to regional differences. SR and MR refer to up to (short run) three-year and (medium run) four-to-six-year effects.

Table 2. Growth cycle recessions.

Panel A. Total sample

	SR	MR
N-NS	49%	30%
N-S	12%	19%
P-NS	33%	33%
P-S	7%	19%

Panel B. OECD vs non-OECD.

	OECD		Non-OECD	
	SR	MR	SR	MR
N-NS	62%	33%	36%	27%
N-S	10%	24%	14%	14%
P-NS	24%	29%	41%	36%
P-S	5%	14%	9%	23%

Panel C. World Bank high income vs middle income level

	High income		Middle income	
	SR	MR	SR	MR
N-NS	57%	38%	41%	23%
N-S	14%	24%	9%	14%
P-NS	24%	24%	41%	41%
P-S	5%	14%	9%	23%

Panel D. Regional clustering

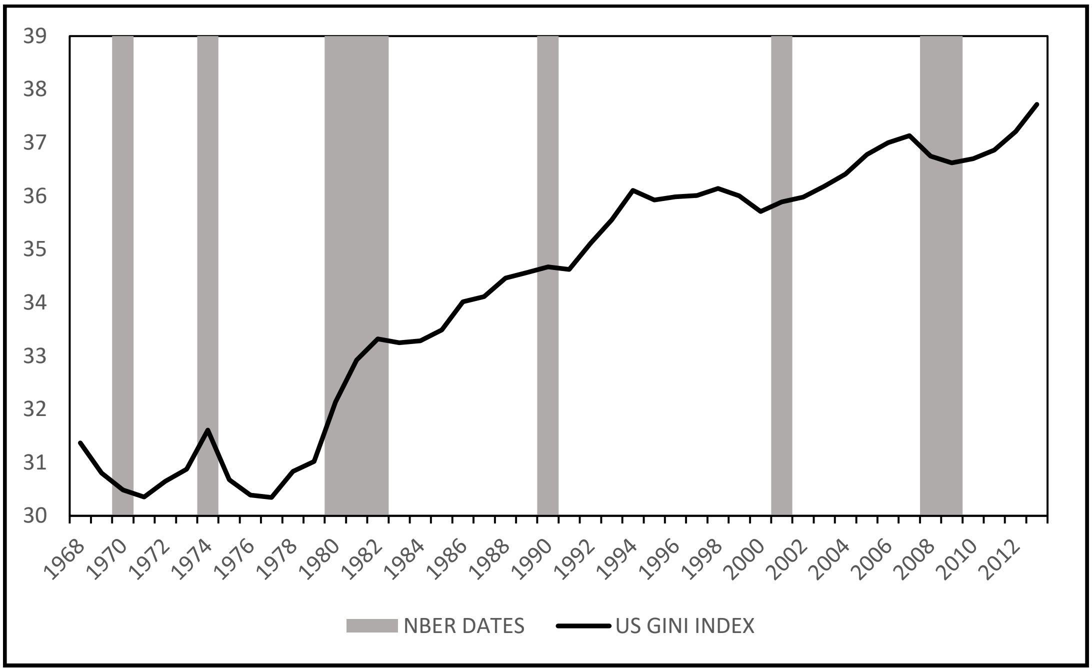
	Africa		Asia		Europe		Latin America		Anglo-Saxon (excluding UK)	
	SR	MR	SR	MR	SR	MR	SR	MR	SR	MR
N-NS	25%	25%	23%	31%	69%	38%	67%	22%	50%	25%
N-S	25%	0%	8%	8%	8%	23%	22%	33%	0%	25%
P-NS	50%	50%	62%	31%	23%	31%	0%	33%	25%	25%
P-S	0%	25%	8%	31%	0%	8%	11%	11%	25%	25%

Note. Percentage of countries for which a growth cycle recession cause inequality to decrease (negative impact) or to increase (positive impact). For each panel N-NS, N-S, P-NS and P-S refer to Negative-Nonsignificant, Negative-Significant, Positive-Nonsignificant and Positive-Significant effect. Panel A refers to the total sample, Panel B distinguishes between OECD and Non-OECD countries, Panel C distinguishes between high income and middle-income level countries, according to the World Bank, while Panel D provides information according to regional differences. SR and MR refer to up to (short run) three-year and (medium run) four-to-six-year effects.

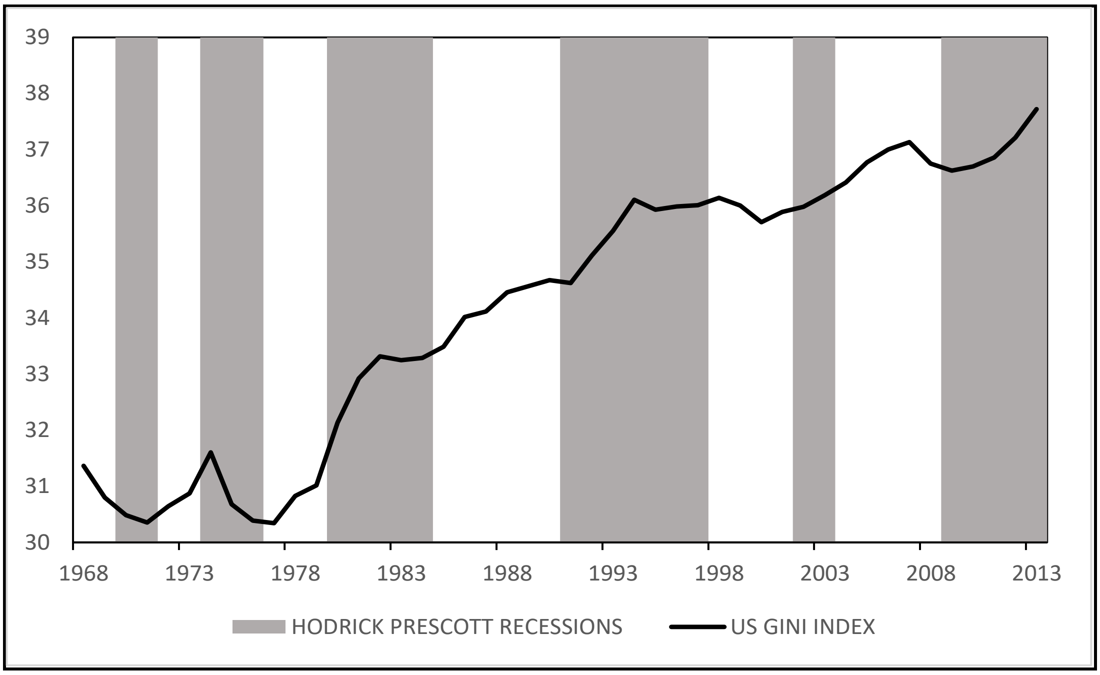
7. Figures

Figure 1. US downturns and Gini index.

Panel A: Business cycle recessions



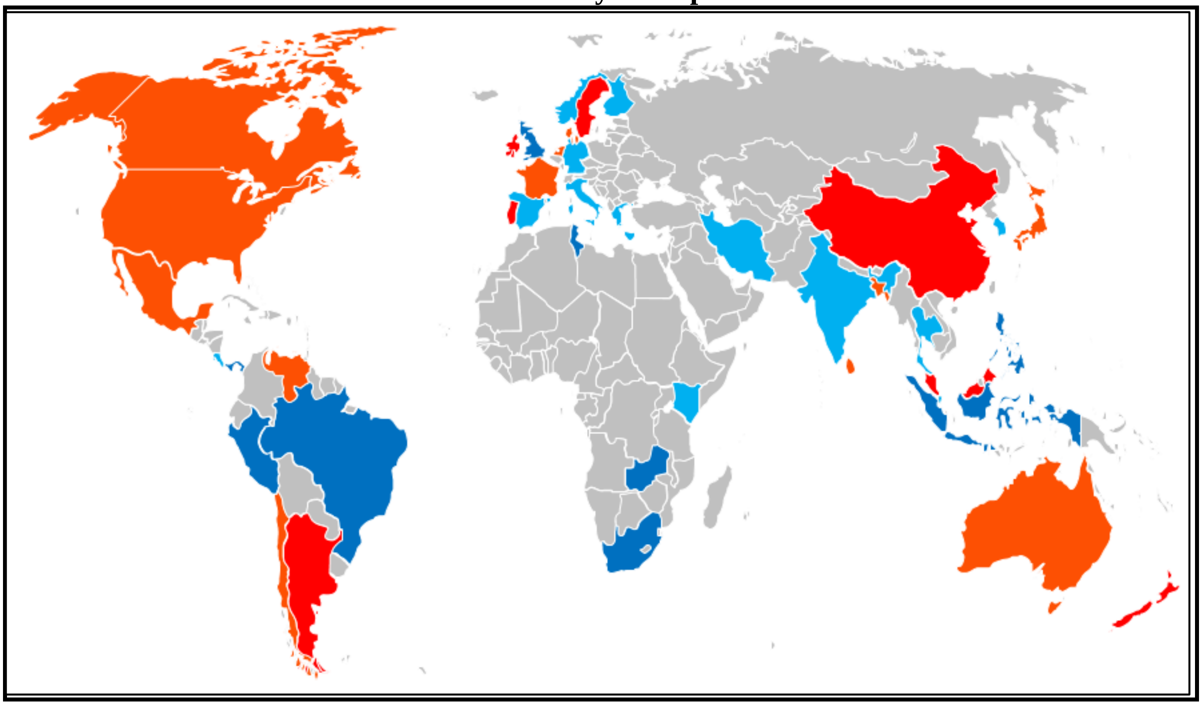
Panel B: Growth cycle recessions



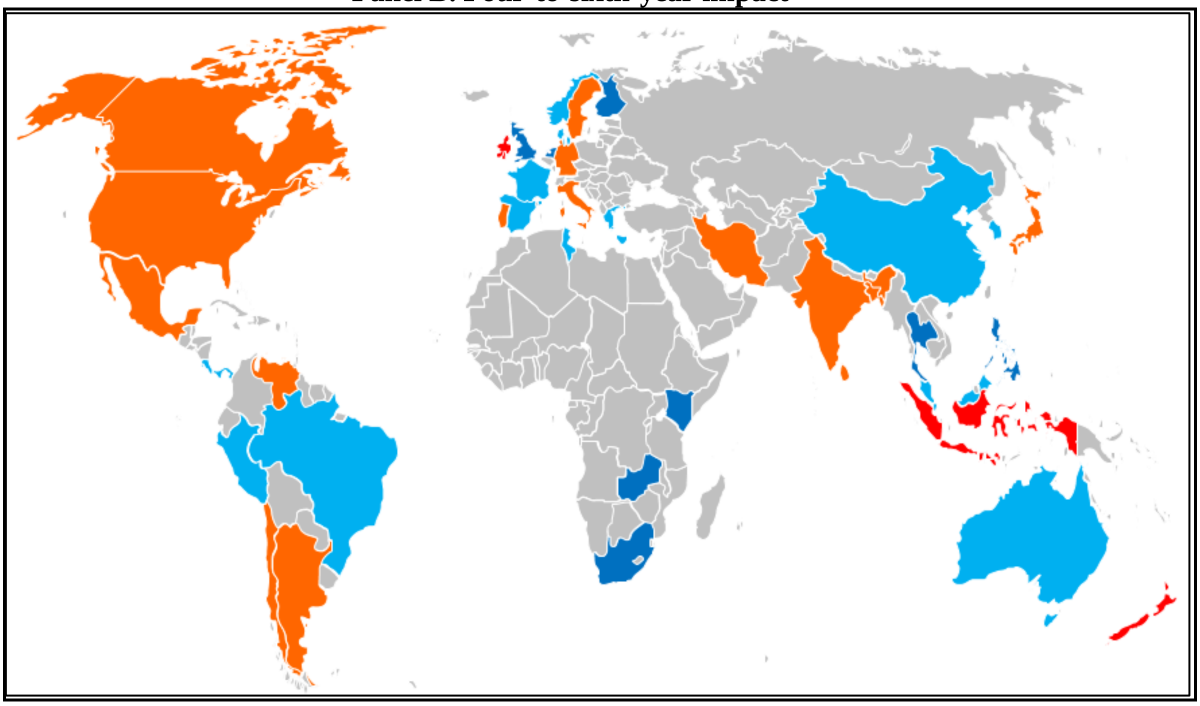
Notes. Business cycle recessions refer to NBER recessions while growth cycle recessions refer to negative deviations from a Hodrick-Prescott trend.

Figure 2. Impact of a business cycle recession.

Panel A. Three-year impact



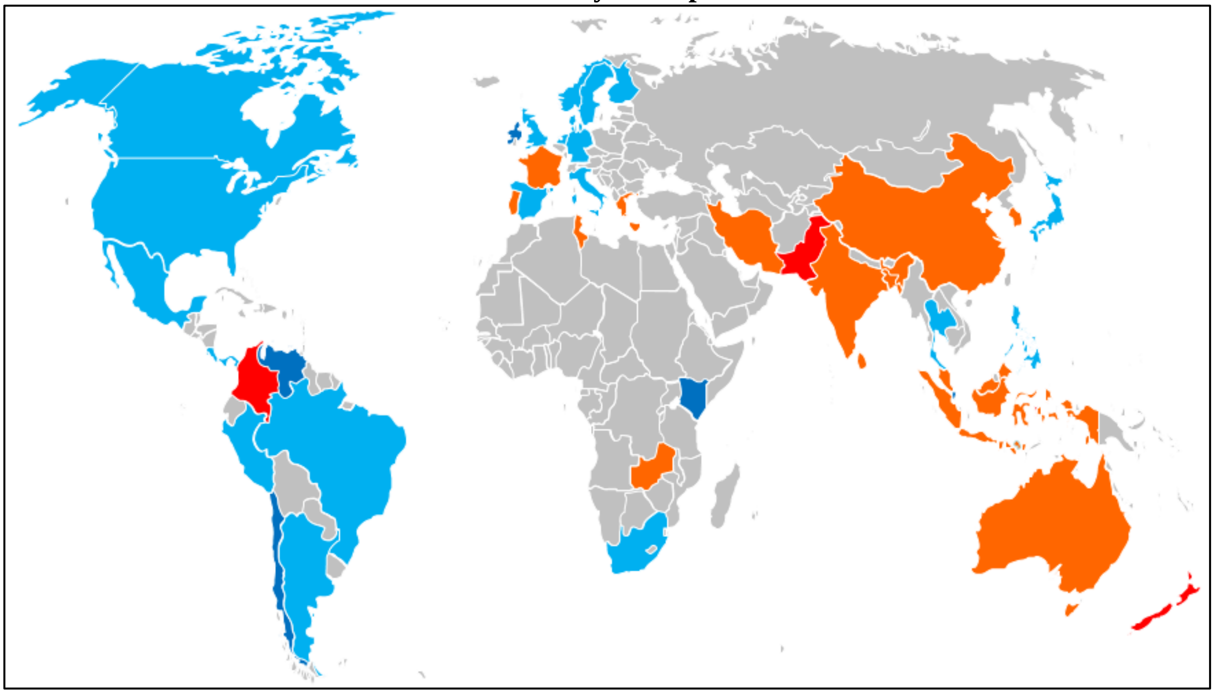
Panel B. Four-to-sixth-year impact



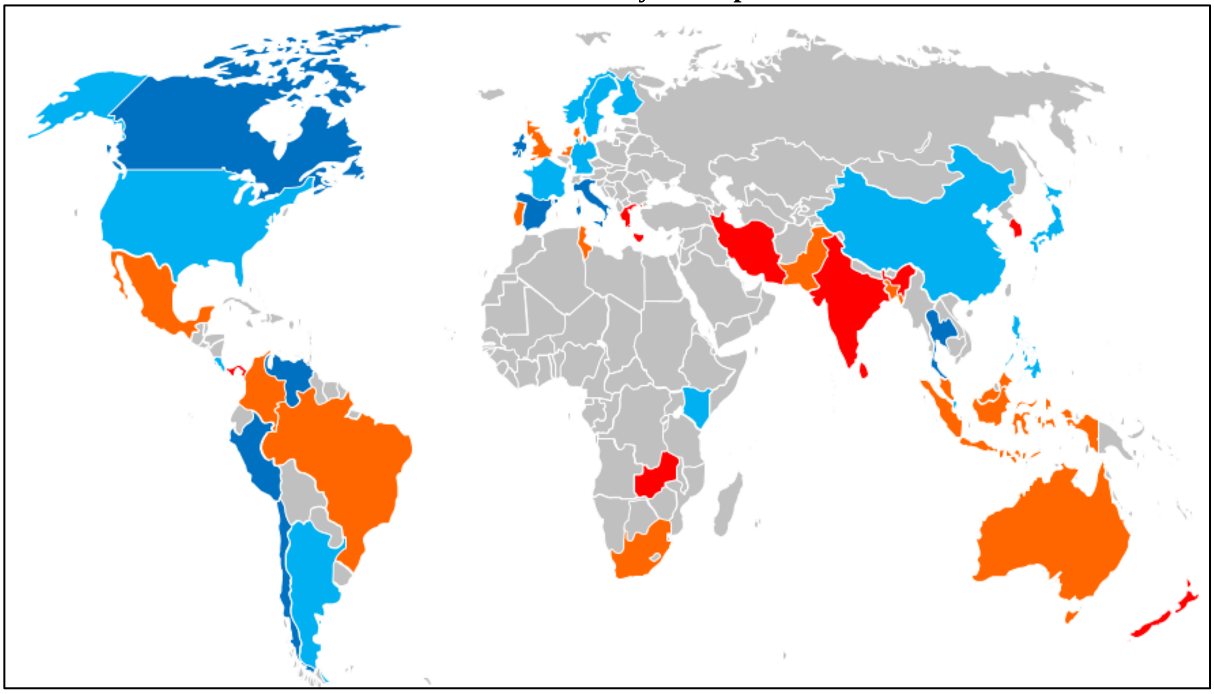
Notes: Countries in red (orange) experience significant (non-significant) increases in inequality due to business cycle recessions. Countries in dark blue (sky blue) experience significant (non-significant) decreases in inequality due to business cycle recessions.

Figure 3. Impact of a growth cycle recession.

Panel A. Three-year impact



Panel B. Four-to-sixth-year impact



Notes: Countries in red (orange) experience significant (non-significant) increases in inequality due to growth cycle recessions. Countries in dark blue (sky blue) experience significant (non-significant) decreases in inequality due to growth cycle recessions.

8. Appendix

8.1 Appendix I. Countries, variables and effective sample used in the analysis.

COUNTRY	GINI INDEX	PRIVATE CREDIT TO GDP	TRADE OPENESS	GDPpc	POPULATION	PATENTS STOCK	FEMALE MORTALITY	GROWTH CYCLE CHRONO	BUSINESS CYCLE CHRONO	SAMPLE
ARGENTINA	1961-2013	1960-2015	1960-2015	1960-2015	1960-2015	1969-2014	1960-2014	1960-2015	1961-2014	1970-2013
AUSTRALIA	1972-2014	1960-2015	1960-2015	1960-2015	1960-2015	1963-2014	1960-2011	1960-2015	1961-2014	1973-2011
BANGLADESH	1963-2010		1960-2015	1960-2015	1960-2015		1960-2014	1960-2014	1961-2014	1964-2010
BRAZIL	1970-2014		1960-2015	1960-2015	1960-2015	1965-2014	1960-2014	1960-2015	1961-2014	1971-2014
CANADA	1965-2013	1960-2008	1960-2015	1960-2015	1960-2015	1960-2014	1960-2011	1960-2015	1961-2014	1966-2008
CHILE	1968-2013	1960-2015	1960-2015	1960-2015	1960-2015	1963-2014	1960-2014	1960-2015	1961-2014	1969-2013
CHINA	1964-2013		1960-2015	1960-2015	1960-2015		1960-2014	1960-2015	1961-2014	1965-2013
COLOMBIA	1970-2014	1960-2015	1960-2015	1960-2015	1960-2015	1963-2014	1960-2014	1960-2015	-	1971-2014
COSTA RICA	1969-2014	1960-2015	1960-2015	1960-2015	1960-2015	1967-2014	1960-2015	1960-2015	1961-2014	1970-2014
DENMARK	1973-2014	1960-2015	1960-2015	1960-2015	1960-2015	1963-2014	1960-2011	1960-2015	1961-2014	1974-2014
FINLAND	1971-2014	1960-2015	1960-2015	1960-2015	1960-2015	1963-2014	1960-2012	1960-2015	1961-2014	1972-2012
FRANCE	1970-2013	1960-2015	1960-2015	1960-2015	1960-2015	1963-2014	1960-2013	1960-2015	1961-2014	1971-2013
GERMANY	1960-2013	1970-2015	1970-2015	1970-2015	1960-2015	1963-2014		1970-2015	1971-2014	1971-2013
GREECE	1974-2014	1960-2015	1960-2015	1960-2015	1960-2015	1960-2014	1960-2014	1960-2015	1961-2014	1975-2014
INDIA	1960-2011	1960-2015	1960-2015	1960-2015	1960-2015	1960-2014	1960-2014	1960-2015	1961-2014	1962-2011
INDONESIA	1964-2013		1960-2015	1960-2015	1960-2015	1963-2014	1960-2014	1960-2015	-	1965-2013
IRAN	1969-2011	1960-2014	1960-2014	1960-2014	1960-2015	1963-2014	1960-2014	1960-2014	1961-2013	1970-2011
IRELAND	1973-2014	1960-2015	1960-2015	1970-2015	1960-2015	1963-2014		1970-2015	1971-2014	1974-2014
ITALY	1967-2013	1963-2015	1960-2015	1960-2015	1960-2015	1960-2014	1960-2010	1960-2015	1961-2014	1968-2010
JAPAN	1961-2011	1960-2015	1960-2015	1960-2015	1960-2015	1963-2014	1960-2012	1960-2015	1961-2014	1964-2011
KENYA	1960-2006	1961-2015	1960-2015	1960-2015	1960-2015	1965-2014	1960-2014	1960-2015	1961-2014	1966-2006
KOREA	1966-2013	1960-2015	1960-2015	1960-2015	1960-2015	1960-2014	1960-2014	1960-2015	1961-2014	1967-2013
MALAYSIA	1968-2012	1960-2015	1960-2015	1960-2015	1960-2015	1963-2014	1960-2014	1960-2015	1961-2014	1969-2012
MEXICO	1963-2014	1960-2015	1960-2015	1960-2015	1960-2015	1963-2014	1960-2014	1960-2015	1961-2014	1964-2014

8.1 Appendix I (continued). Countries, variables and effective sample used in the analysis.

COUNTRY	GINI INDEX	PRIVATE CREDIT TO GDP	TRADE OPENESS	GDPpc	POPULATION	PATENTS STOCK	FEMALE MORTALITY	GROWTH CYCLE CHRONO	BUSINESS CYCLE CHRONO	SAMPLE
NEW ZEALAND	1973-2014		1971-2014	1977-2015	1960-2015	1963-2014		1977-2015	1977-2014	1978-2014
NORWAY	1973-2013	1960-2015	1960-2015	1960-2015	1960-2015	1963-2014	1960-2014	1960-2015	1961-2014	1974-2013
PAKISTAN	1969-2011	1960-2015	1967-2015	1960-2015	1960-2015	1964-2014	1960-2014	1960-2015	-	1970-2011
PANAMA	1969-2014	1960-2015	1960-2014	1960-2015	1960-2015		1960-2014	1960-2015	1961-2014	1970-2014
PERU	1972-2014	1960-2015	1960-2015	1960-2015	1960-2015	1972-2014	1960-2014	1960-2015	1961-2014	1973-2014
PHILIPPINES	1971-2012	1960-2015	1960-2015	1960-2015	1960-2015	1963-2014	1960-2014	1960-2015	1961-2014	1972-2012
PORTUGAL	1973-2014		1960-2015	1960-2015	1960-2015	1963-2014		1960-2015	1961-2014	1974-2014
SINGAPORE	1972-2013	1963-2015	1960-2015	1960-2015	1960-2015	1966-2014	1960-2014	1960-2015	1961-2014	1973-2013
SOUTH AFRICA	1974-2012		1960-2015	1960-2015	1960-2015	1963-2014		1960-2015	1961-2014	1975-2012
SPAIN	1973-2014	1960-2015	1960-2015	1960-2015	1960-2015	1965-2014		1960-2015	1961-2014	1974-2014
SRI LANKA	1970-2013	1960-2015	1960-2015	1961-2015	1960-2015	1963-2013	1960-2014	1961-2015	1962-2014	1971-2013
SWEDEN	1960-2013	1960-2015	1960-2015	1960-2015	1960-2015	1963-2014	1960-2014	1960-2015	1961-2014	1964-2013
THAILAND	1969-2011	1960-2015	1960-2015	1960-2015	1960-2015		1960-2014	1960-2015	1961-2014	1970-2011
TUNISIA	1965-2010	1965-2015	1965-2015	1965-2015	1960-2015	1963-2014	1960-2014	1965-2015	1966-2014	1966-2010
UNITED KINGDOM	1961-2015	1960-2015	1960-2015	1960-2015	1960-2015	1963-2014	1960-2013	1960-2015	1961-2014	1964-2013
US	1960-2014	1960-2015	1960-2015	1960-2015	1960-2015	1960-2014	1960-2013	1960-2015	1961-2014	1961-2013
VENEZUELA	1972-2013	1960-2013	1960-2014	1960-2014	1960-2015		1960-2014	1960-2014	1961-2013	1973-2011
ZAMBIA	1972-2010	1965-2015	-	1960-2015	1960-2015	1966-2014	1960-2014	1960-2015	1961-2014	1973-2010

8.2. Appendix II. Cycle dating

Business cycles

Defining business cycle recessions reduces to event classification problem because most of the countries do not have agencies that determine turning points in economic activity. We overcome this problem by relying on the nonparametric dating algorithm early developed by Bry and Boschan (1971) to replicate the NBER decision procedure. In short, this algorithm isolates local maxima (peaks) and minima (troughs) in the seasonally adjusted national GDP time series subject to certain censoring rules. Then, expansions are defined as periods from troughs to peaks and recession as those from peaks to troughs.

Berge and Jorda (2013) extend this method, originally designated to monthly data to an annual context. In particular, if z_t denote the logarithm of real GDP at year *t*, the algorithm identifies a peak in *t* when $\Delta z_t > 0$ and $\Delta z_{t+1} < 0$, while *t* corresponds to a through when $\Delta z_t < 0$ and $\Delta z_{t+1} > 0$.

Growth cycles

The growth cycle chronology is defined on the basis of the detrended GDP time series. For this purpose, we extract the cyclical component of the real GDP using the band-pass filter proposed by Hodrick and Prescott (1997). This method isolates the cyclical component through the minimization of product deviations from trend, subject to restrictions about trend smoothing[11]. Then, sequences of positive values of the obtained cycle belong to growth cycle expansions while sequences of negative ones correspond to growth cycle recessions.

11 The smoothing parameter is the standard one used for yearly data.

8.3 Appendix III. Countries classification.

COUNTRY	LABEL 1= OECD CLASSIFICATION	LABEL 2= WORLD BANK INCOME LEVEL CLASSIFICATION (2017)	LABEL 3= WORLD´S REGION
ARGENTINA	NON-OECD	WORLD BANK MIDDLE INCOME LEVEL	LATN AMERICA
AUSTRALIA	OECD	WORLD BANK HIGH INCOME LEVEL	ANGLO-SAXON
BANGLADESH	NON-OECD	WORLD BANK MIDDLE INCOME LEVEL	ASIA
BRAZIL	NON-OECD	WORLD BANK MIDDLE (UPPER)	LATIN AMERICA
CANADA	OECD	WORLD BANK HIGH INCOME LEVEL	ANGLO-SAXON
CHILE	OECD	WORLD BANK HIGH INCOME LEVEL	LATIN AMERICA
CHINA	NON-OECD	WORLD BANK MIDDLE INCOME LEVEL	ASIA
COLOMBIA	NON-OECD	WORLD BANK MIDDLE INCOME LEVEL	LATIN AMERICA
COSTA RICA	NON-OECD	WORLD BANK MIDDLE INCOME LEVEL	LATIN AMERICA
DENMARK	OECD	WORLD BANK HIGH INCOME LEVEL	EUROPE
FINLAND	OECD	WORLD BANK HIGH INCOME LEVEL	EUROPE
FRANCE	OECD	WORLD BANK HIGH INCOME LEVEL	EUROPE
GERMANY	OECD	WORLD BANK HIGH INCOME LEVEL	EUROPE
GREECE	OECD	WORLD BANK HIGH INCOME LEVEL	EUROPE
INDIA	NON-OECD	WORLD BANK MIDDLE INCOME LEVEL	ASIA
INDONESIA	NON-OECD	WORLD BANK MIDDLE INCOME LEVEL	ASIA
IRAN	NON-OECD	WORLD BANK MIDDLE INCOME LEVEL	ASIA
IRELAND	OECD	WORLD BANK HIGH INCOME LEVEL	EUROPE
ITALY	OECD	WORLD BANK HIGH INCOME LEVEL	EUROPE
JAPAN	OECD	WORLD BANK HIGH INCOME LEVEL	ASIA
KENYA	NON-OECD	WORLD BANK MIDDLE INCOME LEVEL	AFRICA
KOREA	OECD	WORLD BANK HIGH INCOME LEVEL	ASIA
MALAYSIA	NON-OECD	WORLD BANK MIDDLE INCOME LEVEL	ASIA
MEXICO	OECD	WORLD BANK MIDDLE INCOME LEVEL	LATIN AMERICA
NETHERLANDS	OECD	WORLD BANK HIGH INCOME LEVEL	EUROPE
NEW ZEALAND	OECD	WORLD BANK HIGH INCOME LEVEL	ANGLO-SAXON
NORWAY	OECD	WORLD BANK HIGH INCOME LEVEL	EUROPE
PAKISTAN	NON-OECD	WORLD BANK MIDDLE INCOME LEVEL	ASIA
PANAMA	NON-OECD	WORLD BANK MIDDLE INCOME LEVEL	LATIN AMERICA
PERU	NON-OECD	WORLD BANK MIDDLE INCOME LEVEL	LATIN AMERICA
PHILIPPINES	NON-OECD	WORLD BANK MIDDLE INCOME LEVEL	ASIA

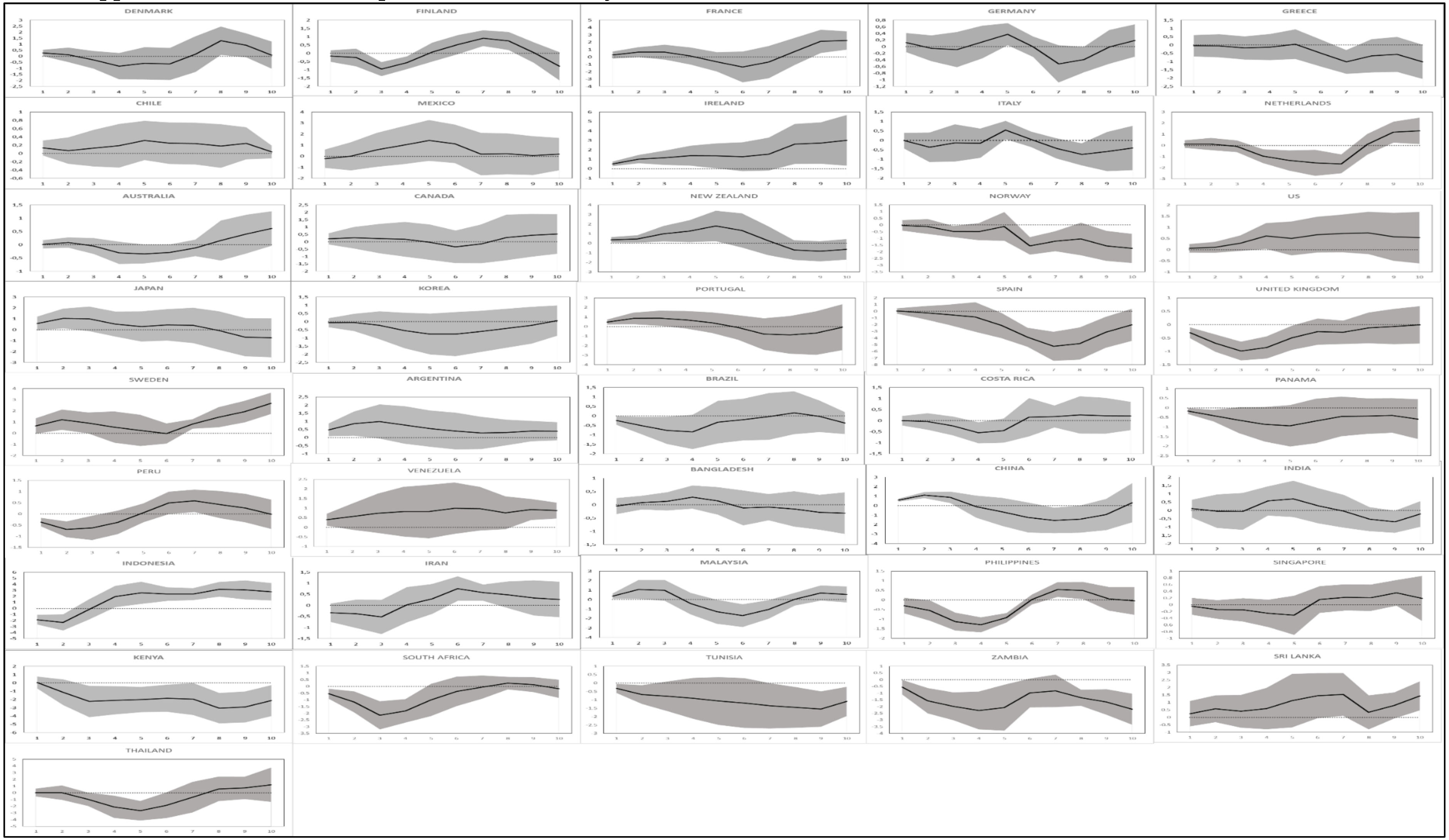
Note. Countries classified according to three different labels: (1) OECD vs non-OECD membership; (2) World Bank Income Level Classification from 2017; and (3) Region or political/cultural association.

8.3 Appendix III (continued). Countries classification.

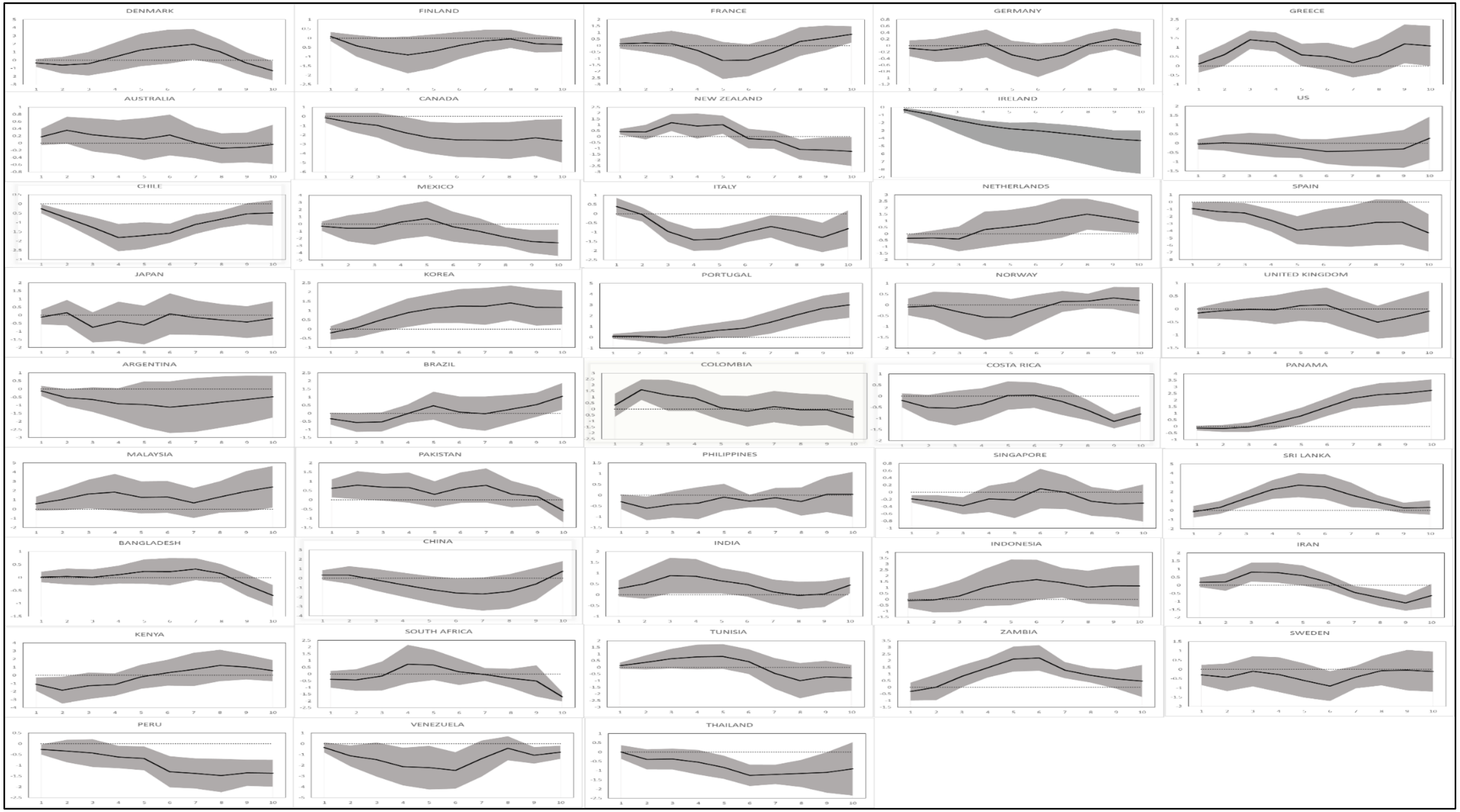
COUNTRY	LABEL 1= OECD CLASSIFICATION	LABEL 2= WORLD BANK INCOME LEVEL CLASSIFICATION (2017)	LABEL 3= WORLD´S REGION
PORTUGAL	OECD	WORLD BANK HIGH INCOME LEVEL	EUROPE
SINGAPORE	NON-OECD	WORLD BANK HIGH INCOME LEVEL	ASIA
SOUTH AFRICA	NON-OECD	WORLD BANK MIDDLE INCOME LEVEL	AFRICA/ANGLO-SAXON
SPAIN	OECD	WORLD BANK HIGH INCOME LEVEL	EUROPE
SRI LANKA	NON-OECD	WORLD BANK MIDDLE INCOME LEVEL	ASIA
SWEDEN	OECD	WORLD BANK HIGH INCOME LEVEL	EUROPE
THAILAND	NON-OECD	WORLD BANK MIDDLE INCOME LEVEL	ASIA
TUNISIA	NON-OECD	WORLD BANK MIDDLE INCOME LEVEL	AFRICA
UNITED KINGDOM	OECD	WORLD BANK HIGH INCOME LEVEL	EUROPE/ANGLO-SAXON
US	OECD	WORLD BANK HIGH INCOME LEVEL	ANGLO-SAXON
VENEZUELA	NON-OECD	WORLD BANK MIDDLE INCOME LEVEL	LATIN AMERICA
ZAMBIA	NON-OECD	WORLD BANK MIDDLE INCOME LEVEL	AFRICA

Note. Countries classified according to three different labels: (1) OECD vs non-OECD membership; (2) World Bank Income Level Classification from 2017; and (3) Region or political/cultural association.

8.4. Appendix IV. Gini index responses to a business cycle recession



8.5. Appendix V. Gini index responses to a growth cycle recession.



CHAPTER 4: OECD's Main Economic Indicators performance at anticipating recessions

1. Introduction

A decade from the beginning of the Great Recession, leading indicators have weakened around the world and start pointing towards increasing concerns about the health of the global economy. Among others, the external factors that contribute to the global fragility are the deceleration in world trade, the slowdown in emerging markets, the increasing concerns about the sovereign-bank loop and debt sustainability in some euro area countries, and the doubts around the total effects of Brexit.

Anticipating whether the economic downturn is likely to turn to a new change in the economic cycle phase is crucial for households, investors and policymakers in order to be prepared for the potential impacts of the adverse circumstances that characterize recessions. However, contrary to what one might think, recognizing economic cycle turning points in real time is not easy. Among others, Stock and Watson (2003) and Hamilton (2011) review the difficulties in foreseeing the economic downturns.

With the aim of giving advance warnings of turning points, the Organization for Economic Co-operation and Development (OECD) compiles a set of monthly statistical publications presenting a wide range of Main Economic Indicators (MEI) for the 35 OECD countries as well as for Brazil, China, India, Indonesia, the Russian Federation and South Africa. In addition, the OECD develops Composite Leading Indicators (CLIs) that are designed to provide early signals of turning points in economic cycles through qualitative rather than quantitative information on short-term economic movements.

The CLIs are computed by combining a set of selected single indicators for each country, which, at least from a theoretical point of view, is done in order to reduce the risk of false signals and to provide the composite indicators with better forecasting and tracking qualities than any of its individual components. However, monitoring the ongoing development of the economic activity from economic indicators is rather complex because each cycle has its unique characteristics as well as features in common with other cycles. This implies that some indicators will perform better in one cycle and others in a different cycle. Thus, the relative performance of the single indicators with respect to CLIs at classifying the state of economy between expansionary and recessionary periods will ultimately be a matter of practice.

The main purpose of this paper is evaluating the usefulness of the OECD's main economic indicators for predicting recessions by focusing on identifying the relevant predictors and on whether they perform better than the composite leading indexes. In particular, we screen lots of potential predictors, evaluate their relevance performance for anticipating phase changes in a large set of counties, and check whether they are able to produce more accurate warnings of ongoing recessions than the composite aggregates. Thus, we aim to identify which are the more reliable OECD's indicators when searching for potential turning points at different forecasting horizons in a country. In line with, among others, Drehmann and Juselius (2014), we evaluate the indicators in terms of its timeliness and its accuracy at forecasting both business cycles and growth cycles.

To this end, the methods that we use in this paper to measure the recession/expansion classification ability of the OECD's leading indicators belongs to the Receiver Operating Characteristic (ROC) framework. By using this nonparametric method, which addresses the tradeoff in signal detection between true and false positive rates, we evaluate the performance of the OECD's leading indicators at predicting the distinct phases of the economic cycles. While not claiming to be exhaustive, examples of recent contributions that apply ROC methods to the study of business and financial cycle analyses are Berge and Jorda (2011), Jorda, Schularick and Taylor (2011), Berge (2015), and Camacho, Perez-Quiros and Poncela (2018).[12]

Using the ROC analysis, we examine the timeliness, or relative classification ability of the cycle phases of each OECD's leading indicator over horizons ranging from 0 to 20 months in advance. In addition, we also examine the accuracy and the stability of these indicators by checking whether they provide significantly better classifications than a coin-toss classifier within more than one year in advance.

The main findings of our study are summarized in the following lines. First, the OECD's MEI show a high overall performance in providing early signals of economic downturns worldwide. Although many indicators achieve its maximum classification

12 Examples of other recent economic applications are Cohen, Garman, and Gorr (2009), Gorr and Schneider (2011).

ability at horizons very close to zero, they perform much better than a random classifier at horizons up to 20 months into the future.

Second, we find a significantly better performance of MEI to anticipating recessions in OECD members than in non-OECD nations in terms of classification accuracy, although the timeliness registers tend to be similar. Third, MEI tend to perform better at anticipating business cycles than growth cycles, especially in terms of accuracy.

Fourth, we detect that the composite leading indicators perform worse than some of their single component indicators. In particular, our results show that measures of short-term interest rates, term spreads and credit indicators are very good classifiers of both growth cycles and business cycles.

Our paper is structured as follows. Section 2 outlines the ROC framework and describes our measures of accuracy and timeliness. Section 3 develops the empirical evaluation of OECD's MEI as classifiers of the distinct phases of the economic cycles. Section 4 concludes.

2. Methodology

2.1 Receiver Operating Curve analysis

The Receiver Operating Characteristic (ROC) curve approach dates back to Peterson and Birdsall (1954), although it has recently been adopted into business cycle analysis by Berge and Jorda (2011).

Let s_{it} be a dichotomous variable denoting the true state of the economic activity of country *i* at time *t*, with $s_{it} = 0$ when *t* is an expansion and $s_{it} = 1$ when *t* is a recession. When the focus is on growth cycles, we assume that the OECD can determine the value of this variable and we compute s_{it} from the reference cycle chronology provided by the OECD's dating committee for each country of the sample. In particular, they determine the turning points as the deviation-from-trend series of national GDP for all countries, except for China for which the OECD relies on the value added of industry at 1995 prices.

When the focus is on business cycles, we determine s_{it} by using the business cycle reference chronologies provided by the Economic Cycle Research Institute (ECRI). In this case, the turning point identification relies on the Burns and Mitchel (1946) view of business cycles as alternating fluctuations of periods of recession and recovery in the aggregate economic activity, observed simultaneously in many economic activities.

We denote Y_{jit} as the *j*-th observable indicator for country *i* that is used for computing inferences on the phase of the economic cycle at time *t* in that country. Given a threshold c_{ji} and assuming that the indicators are procyclical, a recession is called when $Y_{jit} < c_{ji}$ whereas an expansion is determined when $Y_{jit} \geq c_{ji}$. This allows us to generate a binary indicator that takes the value of 1 when a recession is called ($Y_{jit} < c_{ji}$) and 0 when an expansion is given ($Y_{jit} \geq c_{ji}$).

Besides these variables, we can define the following True Positive ($TP(c_{ji})$) rate and False Positive ($FP(c_{ji})$) rate as

$$TP(c_{ji}) = p\left(Y_{jit} < c_{ji} \mid S_{jit} = 1\right), \tag{1}$$

$$FP(c_{ji}) = p\left(Y_{jit} < c_{ji} \mid S_{jit} = 0\right). \tag{2}$$

Now, we can define the ROC curve as a probability curve, usually displayed graphically, that represents the trade-off set of different outcomes of $TP(c_{ji})$ and $FP(c_{ji})$ obtained as a result of varying c_{ji} between -∞ and ∞. As c_{ji} tends to -∞, both $FP(c_{ji})$ and $TP(c_{ji})$ tend to zero, while as c_{ji} tends to ∞, both $FP(c_{ji})$ and $TP(c_{ji})$ tend to one. Thus, the ROC curve is usually represented as the plot of $TP(FP(c_{ji}))$ on the first quadrant of the coordinate plane with $FP(c_{ji})$ in the x-axis and $TP(c_{ji})$ in the y-axis.

When the indicator is an uninformative classifier with respect to the phase cycle, $FP(c_{ji}) = TP(c_{ji})$ for all c_{ji}, which implies that the ROC curve coincides with the 45 degrees line connecting the origin to (1,1). A perfect classifier will provide a ROC curve placed on the left and upper part of the unit quadrant. In practice, the ROC curve of OECD's indicators generates ROC curves between these two extremes located above the diagonal.[13]

---

[13] For countercyclical classifiers, which would generate ROC curves below the diagonal, we just multiply the indicators by minus one.

A standard measure of overall classification ability is the Area Under the ROC (*AUROC*) curve. For a perfect classifier of the phase cycle, *AUROC*=1 whereas any deviation from this perfect classification decreases the *AUROC* until 0.5, which is the expected *AUROC* for a random classification. The improvements of OECD's indicators over a random classification results in a ROC curve at least partially above the straight line, which will take values between 0.5 and 1. Therefore, *AUROC* is closely related to the ranking quality of the classification and becomes a natural non-parametric statistic for evaluating the performance of OECD's economic indicators as predictors of phase changes.

Formally, the area under the ROC curve is given by

$$AUROC = \int_0^1 TP(FP(c_{ji}))dFP(c_{ji}) . \tag{3}$$

Let Z_{jit} be the observations of the *j*-th OECD's indicator for country *i*, Y_{jit}, for which $S_{it} = 1$. Let X_{jit} be the observations of the same indicator for which $S_{it} = 0$. Let n_{i1} and n_{i0} be the total number of recessionary and expansionary periods in country *i*, respectively. Finally, let $I(\cdot)$ be a binary indicator that takes on a value of one when the condition is true and of zero otherwise. Green and Swets (1966) proposed a simple nonparametric estimate of *AUROC* as

$$AU\hat{R}OC = \frac{1}{n_0 n_1}\sum_{\tau'=1}^{n_0}\sum_{\tau=1}^{n_1}\left\{ I\left(Z_{ji\tau} < X_{ji\tau'}\right) + \frac{1}{2} I\left(Z_{ji\tau} = X_{ji\tau'}\right)\right\}. \tag{4}$$

Since the last term rarely occurs, this statistic can be viewed as an estimate of the probability $p\left(Z_{ji} < X_{ji}\right)$ that the *j*-th OECD's indicator for country *i* ranks a randomly chosen within-recession figure lower than a within-expansion value.

There exist a number of methods that have been proposed to approximate the distribution of the AUROC. In this paper, we rely on the approach developed by Hsieh and Turnbull (1996), who show that, under standard regularity conditions the estimator is asymptotically normally distributed

$$\sqrt{n_1}\left(AU\hat{R}OC - p\left(Z_{ji} < X_{ji}\right)\right) \to N\left(0,\sigma^2\right), \tag{5}$$

where

$$\hat{\sigma}^2 = \frac{AU\hat{R}OC\left(1 - AU\hat{R}OC\right) + \left(n_1 - 1\right)\left(Q_1 - AU\hat{R}OC^2\right) + \left(n_0 - 1\right)\left(Q_2 - AU\hat{R}OC^2\right)}{n_1 n_0}, \quad (6)$$

and where $Q_1 = \dfrac{AU\hat{R}OC}{2 - AU\hat{R}OC}$ and $Q_1 = \dfrac{2AU\hat{R}OC^2}{1 + AU\hat{R}OC}$.

2.2. Timeliness and Accuracy

Although the ROC approach can be used to rank the OECD's leading indicators according to their relative performances at classifying the two phases of the cycle, evaluating the usefulness of its leading properties may crucially depend on both, their timeliness and accuracy.

Early symptoms of deteriorations in economic conditions should be given to economic agents with sufficient time in advance to let them react against its adverse situations, although the warnings cannot come too early because there are costs associated to these reactions. To assess the relative classification ability of an OECD's indicator Y_{ji} to predict future recessions, we estimate the ROC curves of the indicators dated at t and the recessionary indicators dated at $t+h_{ji}$, with h_{ji} ranging from 0 to 20, which are denoted as $AUROC(Y_{ji}, h_{ji})$. Then, we approximate the timeliness of the indicator as the value of the leading month h_{ji} for which $AUROC(Y_{ji}, h_{ji})$ achieves its maximum. To approximate the timeliness of a group of indicators G, we compute three statistics: (i) the percentage of indicators whose $AUROC(Y_{ji}, h_{ji})$ maximize at $h_{ji}>0$, with $i,j \in G$; (ii) the average over G of the leading months; and (iii) the average of the *AUROC* maxima.

Besides timeliness, an OECD's is required to provide accurate signals of ongoing recessions. In this paper, we consider that an indicator is a good (accurate) classifier of economic cycles when it anticipates the phase changes for at least one year. This implies that it should reject the null of $AUROC(Y_{ji}, h_{ji}) = 0.5$ against the alternative of $AUROC(Y_{ji}, h_{ji}) > 0.5$ for more than 12 values of h_{ji} out of its 20 possible values. As in the case of timeliness, we approximate the accuracy of a group of indicators by using the percentage of indicators achieving this condition.

3. Empirical results

3.1. Preliminary data analysis

Our dataset, which go back at least 20 years and, in many cases, back to 1960, covers the monthly OECD's main economic indicators for the 35 OECD countries as well as for Brazil, China, India, Indonesia, the Russian Federation and South Africa. We use a sample of 150 single indicators, including national business tendency and consumer opinion surveys, financial indicators, international trade indicators, labour indicators, national accounts, monetary aggregates and production and sales variables.

The database also includes composite leading indicators, which are designed to provide early signals of short-term economic movements. According to Nilsson and Gyomai (2011), the OECD's composite leading indicators are composed by business tendency surveys (39%), real quantitative variables (30%), financial variables (24%) and consumer surveys (7%).

Table 1 describes the two classifications that we use to analyze both timeliness and accuracy of OECD's indicators. According to Classification 1, we classify the single indicators according to the OECD groups Monetary and Financial Indicators, Real Quantitative Indicators, and Business and Consumer Survey Indicators. For a deeper analysis, we also perform a more detailed classification, that we call Classification 2. In the first group, we distinguish indicators of Inflation, Monetary Aggregates, Asset Prices, Interest Rates, Credit, and Interest Rate Spreads. The second group is divided into indicators of Trade, Demand, Production and Employment. Finally, the third group is divided into surveys indicators related to Economic Situation Expectations, Employment Expectations, Demand Expectations, Production Expectations, Consumer Confidence, Inflation Expectations and Trade Expectations.

3.2 Growth cycle chronology: total sample

In this section, we evaluate the performance of OECD's main economic indicators to anticipate the OECD growth cycle chronology. These reference cycle dates are calculated according to the growth cycle spirit, in the sense that the turning points occur when the deviation-from-trend of national GDP data reached a local maximum (peak) or a local minimum (trough). Thus, growth cycle peaks (end of expansion) occur when activity is furthest above its trend level, whereas growth cycle troughs (end of recession) occur when activity is furthest below its trend level.

According to Classification 1, Table 2 provides insight into the timeliness of OECD's main economic indicators by showing the percentage of indicators of each group for which $AUROC(Y_{ji}, h_{ji})$ maximizes at $h_{ji}>0$ (columns labelled as Time), along with the average lead period and the average of the maximum *AUROC* achieved. The figures of the table suggest that only a few indicators (24%) achieve *AUROC* maxima at horizons $h_{ji}>0$.

However, Figure 1, which displays the percentage of leading indicators for which the null of *AUROC*=0.5 is rejected against the alternative of *AUROC*>0.5 across horizons $h_{ji}=0,1,\ldots,20$, suggests that many of the indicators have valuable information to forecast growth-cycle recessions at distant horizons.

To be precise, almost half of the Monetary and Financial Indicators are leading indicators of growth cycle recessions. In fact, this is the group evidencing the highest leading behaviour, followed by Real Quantitative Indicators (35%) and, to a lesser extent by Business and Consumer Surveys (20%).

Moving to Classification 2, Table 3 shows that Interest Rates and Spreads contain the highest timeliness proportions (92% and 75%, respectively). Employment (72%), Inflation (70%) and Credit (50%) also show relevant leading classification abilities. In addition, these indicators present the highest anticipated signals. Interest Rates, leading the growth-cycle recessions by 17 months on average, is the group of indicators with highest leading properties.

The good performance of financial indicators, especially those related to interest rates and spreads, as promptly indicators of phase changes is in line with some results obtained in the related literature. Among others, Davis and Fagan (1997), Estrella and Mishkin (1998), Stock and Watson (2003), and Marcellino (2006) also find this leading behaviour of financial indicators. As a potential explanation of this result, Marcellino (2006) points out the short publication delay of final financial data.

Interestingly, we find that Confidence Indicators (8%), Trade Expectations (10%), Asset Prices (10%), Demand Expectations (11%) and Economic Situation Expectations (12%) tend to behave most as coincident indicators of the growth-cycle recessions.

Focusing on accuracy, Tables 2 and 3 reveal that the composite indicators tend to present the highest proportions of variables with significant signals of recession in more than one year of the periods prior to the beginning of a growth-cycle recession. Among the single leading indicators, those with highest degree of accuracy are the Real Quantitative Indicators, especially the indicators related to trade, demand and employment.

Within the group of Monetary and Financial indicators, variables related to credit provide the most consistent and accurate classifications of the growth cycle. Among others, Gourinchas and Obstfeld (2012) and Gersl and Jasova (2017) also find that credit variables provide accurate signals at anticipating banking and financial crisis.

It is worth pointing out the lack of relevance of Monetary Aggregates as leading indicators of growth-cycle recessions. In line with the results of Estrella and Mishkin (1998) and Berge (2015), we find that only 17% of these indicators lead the recessions with an average lead time of only 2 months. In addition, we fail to find a good performance of asset prices as leading indicators of expansions and recessions, which is in line with the results of Burgstaller (2002).

Let us make one final remark on the relative performance of the composite leading indicators with respect to the single indicators. In terms of accuracy, we find that composite indicators tend to be more accurate than most single indicators. In line with this finding, the Conference Board´s Business Cycle Indicators Handbook (2001) detects that the composite indicators provide a better summary of the information of the economic development than the single indicators because they provide less volatile signals. In addition, Marcellino (2006) also finds that the different features and sources of economic recessions can be better captured by composite indexes.

However, the composite leading indicators achieve their highest *AUROC* values either contemporaneously or within the first few months. In particular, only the trend-restored composite leading indicator's *AUROC* holds a relatively noticeable percentage of maximum AUROCs achieved at $h_{ji}>0$ with an average lead time different from 0 (average of 6 months). Therefore, although OECD Composite Leading Indicators behave accurately, they do not provide their most intensive signals at leading time horizons relative to some of their single components.

In terms of timeliness, this result agrees with the findings of other studies. Estrella and Mishkin (1998) find that spread yields provide better in-sample and out of sample forecasts than the Conference Board Composite Leading Indicator (CBCLI) and the composed index developed by Stock and Watson (1989). Dueker (1997) find similar insights regarding the forecasting performance of the US yield slope over CBCLI. Finally, Qi (2001) finds that although CBCLI outperforms interest spreads at one-quarter-ahead forecast horizon, the latter does it better from two-quarter-ahead to six-quarter-ahead horizons.

3.3. Growth cycle chronology: OECD vs non-OECD countries

In this section, we develop a comparative assessment of the classification performance of OECD's main economic indicators for OECD members with respect to non-OECD countries, with the help of Tables 4 to 7. Regarding timeliness, the leading indicators of OECD countries exhibit the same leading properties than non-OECD countries. By contrast, their accuracy at anticipating growth cycles falls from 77% for OECD members to 62% for non-OECD states.

This result is mainly driven by the poor performance of indicators based on surveys, whose accuracy falls from 76% in OECD countries to 53% in non-OECD nations. As pointed out by Curtin (2004), despite the efforts undertaken by the OECD to improve the sentiment indexes in non-OECD countries, it seems that there are still ways of improvements in computing their surveys-expectations indicators.

Another significant difference between the relative performance of the main economic indicators in OECD versus non-OECD countries, besides the higher accuracy of variables in the formers, is that all groups (Classification 1) present lower degrees of timeliness, with the exception of monetary variables.

3.4. Business cycle chronology: total sample

In the business cycle analysis, we are precluded from using the large sample of countries of the growth cycle analysis because the ECRI´s business cycle chronology is not available for most of these countries. In particular, this section focuses on Australia, Austria, Brazil, Canada, France, Germany, Italy, Japan, Korea, Mexico, New Zealand, Russia, South Africa, Spain, Sweden, Switzerland, the UK and the US.[14]

On average, OECD's leading economic indicators generate more timely and more accurate predictions of the business cycle than of the growth cycle. According to Table

[14] Although ECRI develops the business cycle chronology in China, there is only one recession in the sample. India was also excluded from the business cycle analysis due to data availability restrictions. Data restrictions also precludes us from separating OECD and non-OECD countries.

2, as in the case of growth cycles, the indicators with higher timeliness are Monetary and Financial variables, being interest rates, spreads and credit those placed on the top of the ranking. As in the case of the growth cycle analysis, Figure 2 suggests that many of the indicators contain valuable information to forecast business-cycle recessions at distant horizons.

Monetary and Financial ones register a slightly decreasing pattern as the forecasting horizon increases but the percentage of variables with *AUROCs* significantly higher than 0.5 start to steadily rise at one-year forecasting horizon. This is in line with previous studies that highlight the relevance of financial variables for predicting business cycle recessions at long horizons, such as Berge (2015) and Drechsel and Scheufele (2010).

In terms of accuracy, Real Quantitative Indicators exhibit again the larger percentages of variables providing *AUROCs* significantly greater than 0.5 for more than one year. However, there are two remarkably differences in business cycle analysis. The first difference is the much better performance of the indicators based on surveys (from 73% to 82%). This result is in line with the increasing role of survey indicators in forecasting the future economic developments. Some examples are as in Levanon (2010), García-Ferrer and Bujosa (2010), Christiansen, Eriksen and Möller (2014). This remarkably increase in accuracy percentages also holds for Monetary and Financial variables.

The second difference with respect to the growth cycle analysis is the much higher timeliness (keeping similar accuracy) of composite leading indicators at performing business cycle classifications. However, the composite leading indicators again fail to outperform some of their single components both in terms of accuracy and timeliness.

4. Concluding Remarks

There has been a recent upswing interest of using leading indicators for forecasting potential phase changes of the economic cycles. With the help of Receiver Operating Characteristic (ROC) techniques, this paper explores the effectiveness of the monthly OECD's Main Economic Indicators, which is one of the most important sources of worldwide comparable key economic statistics in providing early warning signals of recessions.

Our empirical results suggest that OECD’s indicators show a high overall performance in providing early signals of economic downturns worldwide. However, our results also suggest some lines of improvements in the way the OECD elaborates the leading indicators. First, despite the effort of the OECD in the development of economic indicators in non-OECD nations, the leading indicators perform worse in these countries, especially in terms of providing accurate signals of phase changes.

Second, we find that the composite leading indicators perform worse than some of their single component indicators, especially in the case of financial indicators such as short-term interest rates, the term spreads and credit indicators.

5. References

Berge, T. 2015. Predicting recessions with leading indicators: Model averaging and selection over the business cycle. *Journal of Forecasting* 34: 455-471.

Berge, T., and Jorda, O. 2011. Evaluating the classification of economic activity into recessions and expansions. *American Economic Journal: Macroeconomics* 3: 246-77.

Burgstaller, J. 2002. Are stock returns a leading indicator for real macroeconomic developments? Johannes Kepler University of Linz Working Paper, 0207.

Burns, A., and Mitchell, W. 1946. Measuring Business Cycles. New York: National Bureau of Economic Research.

Business Cycle Indicators Handbook. 2001. The Conference Board. New York.

Camacho, M., Perez-Quiros, G., and Poncela, P. 2018. Markov-switching dynamic factor models in real time. *International Journal of Forecasting* 34: 598-611.

Christiansen, C., Eriksen, J., and Møller, S. 2014. Forecasting US recessions: The role of sentiment. *Journal of Banking and Finance* 49: 459-468.

Cohen, J., Garman, S., and Gorr, W. 2009. Empirical calibration of time series monitoring methods using receiver operating characteristic curves. *International Journal of Forecasting* 25: 484-497.

Curtin, R. 2004. Consumer Sentiment Surveys: Worldwide Review and Assessment, lavoro presentato alla 27esima Conferenza del CIRET. Varsavia, Settembre.

Davis, E., and Fagan, G. 1997. Are financial spreads useful indicators of future inflation and output growth in EU countries? *Journal of Applied Econometrics* 12: 701-714.

Drechsel, K., and Scheufele, R. 2010. Should we trust in leading indicators? Evidence from the recent recession (No. 10/2010). *IWH Discussion Papers*.

Drehmann, M., and Juselius, M. 2014. Evaluating early warning indicators of banking crises: Satisfying policy requirements. *International Journal of Forecasting* 30: 759-780.

Dueker, M. 1997. Strengthening the case for the yield curve as a predictor of US recessions. *Federal Reserve Bank of St. Louis Review* 79: 41.

Estrella, A., and Mishkin, F. 1998. Predicting US recessions: Financial variables as leading indicators. *Review of Economics and Statistics* 80: 45-61.

García-Ferrer, A., and Bujosa-Brun, M. 2000. Forecasting OECD industrial turning points using unobserved components models with business survey data. *International Journal of Forecastin*g 16: 207-227.

Gersl, A., and Jasova, M. 2017. Credit-based early warning indicators of banking crises in emerging markets. *Economic Systems* 42: 18-31.

Gorr, W., and Schneider, M. 2013. Large-change forecast accuracy: Reanalysis of M3-Competition data using receiver operating characteristic analysis. *International Journal of Forecasting* 29: 274-281.

Gourinchas, P. and Obstfeld, M. 2012. Stories of the twentieth century for the twenty-first. *American Economic Journal: Macroeconomics* 4: 226-65.

Green, D., and Swets, J. 1966. Signal detection theory and psychophysics (Vol. 1). New York: Wiley.

Hamilton, J. 2011. Calling recessions in real time. *International Journal of Forecasting* 27: 1006-1026.

Hsieh, F., and Turnbull, B. 1996. Nonparametric and semiparametric estimation of the receiver operating characteristic curve. *The Annals of Statistics* 24: 25-40.

Jorda, O., Schularick, M., and Taylor, A. 2011. Financial crises, credit booms, and external imbalances: 140 years of lessons. *IMF Economic Review* 59: 340-378.

Levanon, G. 2010. Evaluating and comparing leading and coincident economic indicators. *Business Economics* 45: 16-27.

Marcellino, M. 2006. Leading Indicators. In G. Elliott, C. Granger, and A. Timmermann (eds.). *Handbook of economic forecasting*. Amsterdam: Elsevier.

Nilsson, R., and Gyomai, G. 2011. Cycle extraction: a comparison of the phase-average trend method, the Hodrick-Prescott and Christiano-Fitzgerald filters. OECD Working Paper No. 39.

Peterson, W., Birdsall, T., and Fox, W. 1954. The theory of signal detectability. *Transactions of the IRE professional group on information theory* 4: 171-212.

Qi, M. 2001. Predicting US recessions with leading indicators via neural network models. *International Journal of Forecasting* 17: 383-401.

Stock, J., and Watson, M. 1989. New indexes of coincident and leading economic indicators. *NBER macroeconomics annual* 4: 351-394.

Stock, J., and Watson, M. 2003. How did leading indicator forecasts perform during the 2001 recession? *FRB Richmond Economic Quarterly* 89: 71-90.

6. Tables

Table 1. Variable grouping.

Classification 1	Classification 2
Monetary and Financial Indicators	Inflation Monetary Aggregates Asset Prices Interest Rates Credit Trade Interest Rates Spreads
Real Quantitative Indicators	Trade Demand Production Employment
Surveys Indicators (BTS or CS)	Surveys-Economic Situation Expectations Surveys-Employment Expectations Surveys-Demand Expectations Surveys-Production Expectations Surveys-Confidence Indicator Surveys-Inflation Expectations Surveys-Trade Expectations

Notes. This table contains the two different divisions made in this paper

Table 2. Total sample, classification 1.

	Growth cycles				Business cycles			
	Accuracy	Time	Lead	Max AUROC	Accuracy	Time	Lead	Max AUROC
CLI	84	17	2	0.70	81	31	1	0.76
Monetary and Financial	69	49	7	0.60	87	51	6	0.63
Real Quantitative	84	35	5	0.58	89	39	4	0.68
Surveys	73	20	3	0.65	82	20	2	0.77
Total Sample	75	24	3	0.64	83	27	3	0.75

Notes. For each group, accuracy shows the percentage of indicators with AUROC>0.5 for more than 12 out of the 20 months prior to the start of recessions. Time evaluates the timeliness as the percentage of indicators for which the AUROC maximizes a positive lead time, whose average is reported in column labelled as Lead. The averages of the maximum ROC curves appear in columns labelled as Max AUROC.

Table 3. Total sample, classification 2.

	Growth cycles				Business cycles			
	Accuracy	Time	Lead	Max AUROC	Accuracy	Time	Lead	Max AUROC
y-o-y change CLI	84	21	0	0.78	94	50	1	0.91
Amplitude adjusted CLI	100	5	0	0.75	83	22	0	0.83
Normalized CLI	100	5	0	0.74	83	22	0	0.83
Trend-restored CLI	50	37	6	0.54	61	28	4	0.50
Inflation	81	70	12	0.56	90	40	8	0.64
Monetary aggregates	58	17	2	0.56	50	50	4	0.60
Asset prices	63	10	1	0.63	85	15	1	0.63
Interest rates	65	92	17	0.55	86	86	16	0.50
Credit	100	50	9	0.54	100	100	20	0.66
Spreads	75	75	3	0.72	93	86	6	0.82
Trade	84	43	5	0.58	100	60	7	0.61
Demand	84	16	2	0.59	91	17	0	0.72
Production	79	42	6	0.56	88	47	6	0.61
Employment	83	72	11	0.61	82	55	6	0.72
Economic situation	75	12	1	0.66	89	17	1	0.80
Employment expectation	72	18	2	0.64	82	18	2	0.77
Demand expectation	74	11	1	0.67	78	12	0	0.81
Production expectation	73	43	6	0.65	88	47	6	0.61
Confidence	70	8	1	0.67	87	9	0	0.81
Inflation expectation	74	31	5	0.56	71	23	3	0.60
Trade expectation	74	10	2	0.67	72	17	0	0.65
Total Sample	75	24	3	0.64	83	27	3	0.75

Notes. See notes of Table 2.

Table 4. OECD countries, classification 1.

	Growth cycles			
	Accuracy	Time	Lead	Max AUROC
CLI	84	18	2	0.71
Monetary and Financial	69	49	7	0.60
Real Quantitative	84	36	5	0.59
Surveys	76	20	3	0.65
Total Sample	77	24	3	0.65

Notes. See notes of Table 2.

Table 5. OECD countries, classification 2.

	Growth cycles			
	Accuracy	Time	Lead	Max AUROC
y-o-y change CLI	81	19	0	0.77
Amplitude adjusted CLI	100	6	0	0.76
Normalized CLI	63	6	0	0.75
Trend-restored CLI	83	41	6	0.54
Inflation	65	75	13	0.56
Monetary aggregates	75	20	2	0.56
Asset prices	77	10	1	0.63
Interest rates	60	90	16	0.55
Credit	100	50	9	0.53
Spreads	100	71	4	0.71
Trade	76	35	3	0.58
Demand	85	18	2	0.59
Production	53	46	6	0.57
Employment	83	72	11	0.61
Economic situation	84	13	1	0.66
Employment expectation	78	18	2	0.64
Demand expectation	76	10	1	0.67
Production expectation	53	46	6	0.57
Confidence	75	6	1	0.67
Inflation expectation	75	31	5	0.57
Trade expectation	71	9	1	0.68
Total Sample	77	24	3	0.65

Notes. See notes of Table 2.

Table 6. Non-OECD countries, classification 1.

	Growth cycles			
	Accuracy	Time	Lead	Max AUROC
CLI	83	13	1	0.69
Monetary and Financial	70	52	9	0.62
Real Quantitative	86	29	4	0.55
Surveys	53	19	2	0.65
Total Sample	62	24	3	0.64

Notes. See notes of Table 2.

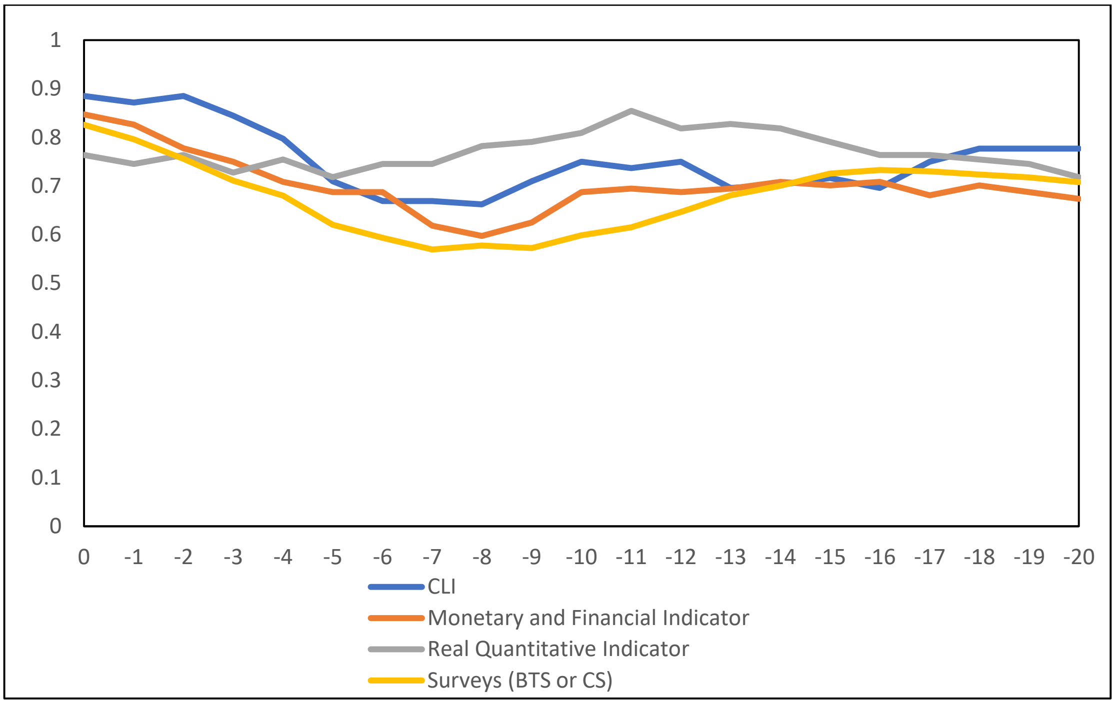
Table 7. Non-OECD countries, classification 2.

	Growth cycles			
	Accuracy	Time	Lead	Max AUROC
y-o-y change CLI	100	33	1	0.80
Amplitude adjusted CLI	100	0	0	0.71
Normalized CLI	100	0	0	0.71
Trend-restored CLI	33	17	3	0.53
Inflation	67	33	6	0.63
Monetary aggregates	50	0	0	0.54
Asset prices	63	13	3	0.68
Interest rates	67	100	19	0.56
Credit	-	-	-	-
Spreads	100	100	3	0.81
Trade	83	83	13	0.54
Demand	80	0	0	0.62
Production	100	20	4	0.50
Employment	-	-	-	-
Economic situation	56	6	0	0.57
Employment expectation	46	23	2	0.63
Demand expectation	47	18	1	0.69
Production expectation	52	30	2	0.64
Confidence	44	15	1	0.68
Inflation expectation	100	29	3	0.50
Trade expectation	60	20	4	0.58
Total Sample	62	24	3	0.64

Notes. See notes of Table 2.

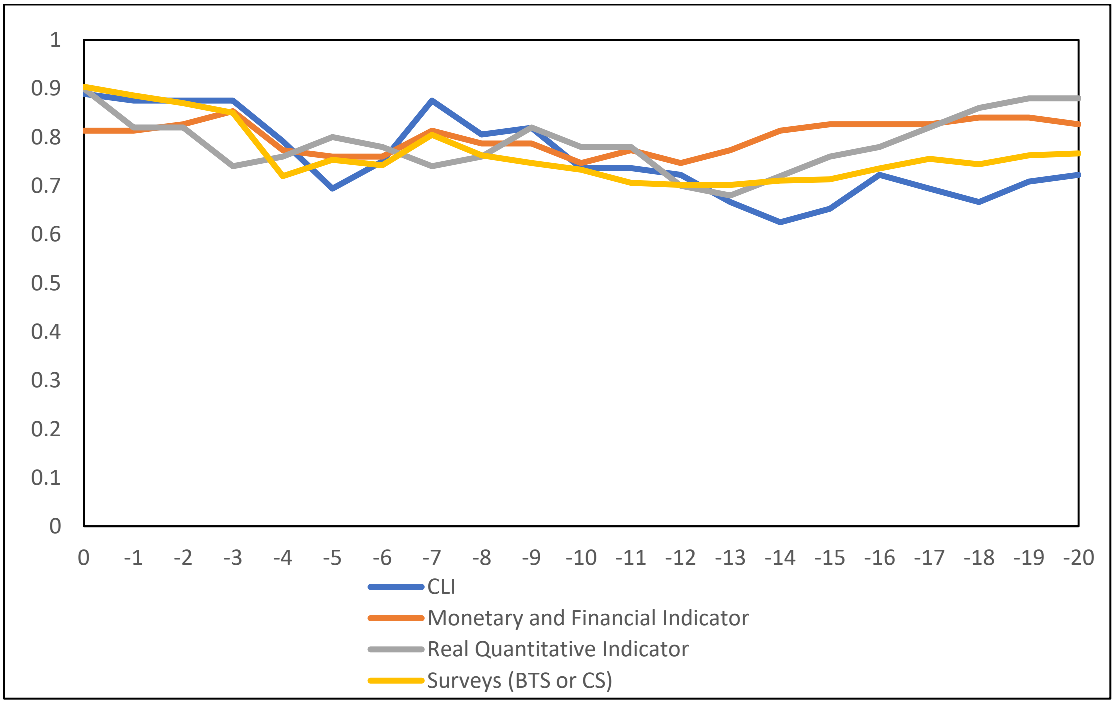
7. Figures

Figure 1. Total Sample, growth cycle, Classification 1.



Notes. The figure plots the percentage leading indicators for which the null of AUROC=0.5 is rejected against the alternative of AUROC>0.5 across horizons 0,1,…,20.

Figure 2. Total Sample, business cycle, classification 1.



Notes. The figure plots the percentage leading indicators for which the null of AUROC=0.5 is rejected against the alternative of AUROC>0.5 across horizons 0,1,…,20.