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Nonlinear dynamics and real time economic conditions in ECOWAS

Gohou Danon

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Thèse

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par **Gohou F. DANON**

**Sous la direction de Francis BIESMANS et de Olivier
DAMETTE**

**Dynamiques non linéaires et conditions économiques en
temps réel dans les pays de la CEDEAO**

20 décembre 2022

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Resumé

Les économètres cherchent à suggérer la manière la plus efficace de réduire l'impact des ralentissements économiques ou de maintenir la croissance économique pendant une période prolongée. Depuis de nombreuses années, ils créent des techniques d'analyse macroéconomique qui permettent de reconnaître et de prédire instantanément les cycles économiques. Cependant, l'absence d'un suivi immédiat des situations macroéconomiques et d'une chronologie standard pour identifier les points de retournement des cycles économiques en Afrique de l'Ouest sont des inconvénients notables, en particulier pour une région qui s'efforce d'avoir une monnaie unifiée depuis longtemps.

Dans cette situation particulière, la thèse vise à offrir divers instruments pour permettre une analyse plus significative de l'environnement macroéconomique des pays de la CEDEAO, à la fois avant et après un événement donné. En abordant ces préoccupations, nous visons à améliorer la discussion concernant la volonté des États membres de la CEDEAO de renoncer à leur autonomie monétaire et d'adopter une monnaie unifiée. Pour atteindre cet objectif, nous proposons plusieurs techniques économétriques couramment utilisées dans les pays développés, ce qui nous permet d'apporter une solution au problème susmentionné.

Nos propositions s'articulent autour de trois méthodes économétriques. Tout d'abord, nous appliquons la technique des ondelettes à différentes paires de cycles économiques de treize États membres de la CEDEAO afin d'analyser leur degré de convergence. Nos

résultats indiquent que sept pays de la zone du franc CFA et cinq autres économies de la CEDEAO, à savoir le Nigeria, le Ghana, la Gambie, la Guinée et le Cap-Vert, sont prêts à abandonner leur souveraineté monétaire en faveur d'une politique monétaire commune.

La deuxième proposition se concentre sur le suivi en temps réel des conditions macroéconomiques en Côte d'Ivoire. À cette fin, nous calibrons le modèle de projection sur une série mensuelle de plusieurs variables économiques. Un algorithme Matlab utilise une version du modèle now-casting utilisé par la Réserve Fédérale de New York. Notre Indice des Conditions Macroéconomiques (ICM) présente des résultats qui, dans une certaine mesure, sont parallèles à ceux de l'Institut National de la Statistique de Côte d'Ivoire.

Enfin, la thèse propose une chronologie de référence mensuelle des points de retournement du cycle économique pour la Côte d'Ivoire en utilisant une analyse en trois étapes. Tout d'abord, nous utilisons la routine Bry-Boschan pour générer des phases de cycle économique de type NBER. Un modèle de Markov fini automatise ensuite un nouvel ensemble de points de retournement en utilisant dix indicateurs coïncidents. Sur la base de critères spécifiques, un récit affine les phases cycliques dérivées des deux premières étapes et identifie les points de retournement finaux du cycle économique pour la Côte d'Ivoire. Selon nos résultats, la Côte d'Ivoire a connu sept (7) périodes de récession entre 1996 et 2019. Les crises politiques répétées semblent avoir été des sources importantes de ralentissement.

Pour conclure, nous notons que les progrès réalisés dans la collecte des données dans plusieurs instituts statistiques en Afrique de l'Ouest, d'une part, et le développement d'outils d'analyse économique pertinents observés dans les pays industrialisés, d'autre part, peuvent être utilisés pour l'analyse macroéconomique dans les pays de la CEDEAO. En outre, les modèles factoriels paramétriques, y compris l'apprentissage automatique appliqué au big data, offrent de nouveaux outils suffisamment flexibles pour s'adapter à des fréquences de données variables et peuvent être utiles pour l'analyse macroéconomique dans les pays de la CEDEAO.

Summary

Econometricians aim to suggest the most effective way to reduce the impact of economic downturns or maintain economic growth for a prolonged period. They have been creating macroeconomic analysis techniques for many years, which can instantly recognize and predict business cycles. However, the absence of immediate tracking of macroeconomic situations and a standard chronology for identifying business cycle turning points in West Africa are notable disadvantages, particularly for a region striving for a unified currency for a long time.

In this particular situation, the thesis aims to offer various instruments to enable a more meaningful analysis of the macroeconomic environment for ECOWAS nations, both before and after a given event. In addressing these concerns, we aim to enhance the discussion regarding the willingness of ECOWAS member states to surrender their monetary autonomy and adopt a unified currency. To achieve this objective, we propose several commonly used econometric techniques in developed countries, enabling us to provide a solution to the abovementioned issue.

Our proposals are structured around three econometric methods. First, we apply the wavelet technique to different business cycle pairs of thirteen ECOWAS member states to analyze their degree of convergence. Our results indicate that seven countries in the CFA franc zone and five other ECOWAS economies, namely Nigeria, Ghana, The Gambia, Guinea, and Cape Verde, are ready to abandon their monetary sovereignty in favor of a common monetary policy.

The second proposal focuses on monitoring macroeconomic conditions in Ivory Coast in real time. To this end, we calibrate the now-casting model on a monthly series of several economic variables. A Matlab algorithm employs a version of the now-casting model the New York Federal Reserve uses. Our Macroeconomic Conditions Index (MCI) reports findings that, to some extent, parallel those of the National Institute of Statistics of Ivory Coast.

Finally, the thesis proposes a monthly reference chronology of business cycle turning points for Ivory Coast using a three-stage analysis. First, we employ the Bry-Boschan routine to generate NBER-type business cycle phases. A finite Markov model then automates a new set of turning points using ten coincident indicators. Based on specific criteria, a narrative refines the cyclical phases derived from the first two steps and identifies the final turning points of the business cycle for Ivory Coast. As per our findings, Ivory Coast experienced seven (7) periods of recession between 1996 and 2019. Repeated political crises appear to have been significant sources of downturns.

To conclude, we note that the progress made in data collection in several statistical institutes in West Africa, on the one hand, and the development of relevant economic analysis tools observed in industrialized countries, on the other hand, can be used for macroeconomic analysis in ECOWAS countries. Furthermore, parametric factor models, including machine learning applied to big data, offer new tools that are flexible enough to adapt to varying data frequencies and can be useful for macroeconomic analysis in ECOWAS countries.

Introduction Générale

Le niveau de vie des citoyens, le niveau des inégalités ou la puissance économique d'un pays peuvent être influencés par les fluctuations de l'activité économique. Ces changements de régime économique sont caractérisés par des périodes de croissance et d'expansion économiques rapides et une période de contraction. À l'instar des chocs pétroliers, budgétaires et monétaires, la stabilité politique est également au coeur de la dynamique du cycle économique ([Rădulescu et Druica, \(2014\) \[6\]](#)). Dès lors, les mécanismes capables d'atténuer les récessions ou de maintenir les expansions économiques, le plus longtemps possible, restent au coeur des enjeux politiques.

Depuis la crise des subprimes en 2007, la datation des points de retournement des cycles économiques est devenue incontournable, avec l'usage de données de plus en plus variées compatibles avec des algorithmes sophistiqués. Ainsi, [Gregory and Smith \(1995\) \[3\]](#) soulignent à cet égard la présence notable de la théorie quantitative, qui a pratiquement remplacé la théorie macroéconomique au cours des quinze dernières années. Selon les auteurs, ce phénomène s'explique, entre autres, par le besoin croissant de méthodes économétriques pour le traitement des données dans les analyses macroéconomiques. En effet, Gregory et Smith rappellent qu'avec les précédentes méthodes macroéconomiques, l'absence de tests statistiques formels dans les exercices de mesure, est embarrassant. Autrement dit, des propriétés statistiques étaient dérivées des modèles sans étudier les données. Or, de nos jours, les propriétés des données sont essentielles pour justifier les prédictions de la théorie.

Cette thèse propose de mettre à disposition des instruments de datation des points de retournement et de mesure des cycles économiques, en pseudo temps réel, pour la Cote D'Ivoire. Nous proposons également un nouvel élément d'analyse empirique afin d'enrichir le débat sur le projet de future zone monétaire commune des pays membres de la CEDEAO. La suite de cette introduction générale se présente comme suit :

1. le contexte et les motivations qui fondent la thèse font l'objet de la [section 1](#),
2. les cycles économiques étant le thème principal de cette thèse, une définition en est donnée à la [section 2](#)
3. Finalement, la problématique, la contribution et un résumé des différents chapitres forment l'ossature de la [section 3](#)

0.1 Contexte et motivation

La profondeur des crises économiques à répétition ravive l'intérêt pour plus de précision dans la surveillance des cycles économiques. La période dite de "grande modération", depuis les chocs pétroliers des années 70-80, a cédé la place à des changements brusques et asymétriques des structures économiques lors de la grande récession de 2007-2009. Ces fluctuations consacrent un environnement dans lequel les politiques conventionnelles perdent naturellement leur efficacité. L'usage de méthodes non conventionnelles tel que le "*forward guidance*" par les banquiers centraux, est symptomatique de la complexité de la prise de décision à partir de prévisions rationnelles sur la base des conditions macroéconomiques actuelles.

Ces changements structurels, propres à un environnement aussi erratique, sont de plus en plus préoccupants pour les décideurs politiques. L'indisponibilité de l'information dans le temps, reste une caractéristique des économies en développement. En effet, lorsqu'elles existent, les statistiques du PIB, par exemple, sont accessibles après un décalage relativement important. Ainsi l'écart entre l'effectivité d'une récession et son annonce, constitue

un biais majeur en termes d'analyses et de prévisions. Dans les économies avancées, le recours à des ensembles de séries macroéconomiques de haute fréquence, permet de répondre avec une relative pertinence, aux nouveaux défis de la recherche sur les cycles économiques. En effet, l'obtention de prévisions robustes du taux de croissance trimestriel du PIB, peut par exemple nécessiter l'examen de la dynamique d'un panel de données déséquilibrés en termes de longueur et de fréquence. A cet égard, l'analyse économique a fait des progrès considérables en matière de datation et de prévision de récessions dans les économies avancées.

Le Bureau National de la Recherche Économique (NBER) aux États-Unis a établi une chronologie officielle des dates d'entrée et de sortie des récessions depuis 1978. Pour les pays européens, le Centre for Economic and Policy Research (CEPR) fournit une chronologie de référence du cycle des affaires. L'Economic Cycle Research Institute (ECRI) présente également une chronologie des points de retournement des cycles économiques pour plus de vingt et deux pays dans le monde. En France, le Comité de datation des cycles de l'économie française (CDCEF), identifie les points de retournement du cycle des affaires économiques pour l'économie française [Ferrara, Mignon et al. \(2021 \[4\]\)](#). Si la nature non observable des cycles rend difficile leur datation, les progrès économétriques ont permis aux chercheurs et aux banques centrales d'Europe, d'Asie et des États-Unis de prévoir les conditions macroéconomiques en temps réel à travers notamment la technique du "now-casting". Au-delà des techniques éprouvées de "clustering", l'approche de la transformée en ondelettes, facilitent l'analyse de la synchronisation des cycles économiques.

Ainsi, les pays avancés ne manquent pas d'outils d'aide à la mise en place des politiques économiques relativement pertinentes. La littérature est, par contre, moins mature dans le contexte des économies en développement et particulièrement dans la Communauté Économique des États de l'Afrique de l'Ouest (CEDEAO). Si le manque de données économiques clés a considérablement entravé la réalisation d'études plus poussées en termes de prévisions immédiate par exemple, il faut noter que la recherche en matière d'analyse

des cycles économiques, n'a relativement pas suivi, ni les méthodologies récentes, ni les progrès observés dans la collecte des données statistiques des dernières années en zone CEDEAO. Dans ce contexte, notre motivation reste l'application des méthodes modernes afin de mettre à disposition des instruments modernes de surveillance et d'estimation des conditions macroéconomiques en temps réel. Cette étude tente de combler un vide, en termes d'outils d'anticipation des chocs et/ou de facilitation des tâches des décideurs politiques en matière d'ajustements des déficits budgétaires.

0.2 Définition et typologie des cycle économiques

Définir les cycles économiques avec précision n'est pas un exercice aisé en raison des diverses caractéristiques inhérentes aux types de cycles. L'objet de notre étude est loin d'être la justification des hypothèses associées aux cycles économiques. Néanmoins, nous présentons un bref aperçu des trois types de cycles économiques couramment rencontrés dans la littérature, à savoir le cycle des affaires, le cycle de croissance et le cycle du taux de croissance.

0.2.1 Le cycle des affaires

L'œuvre originale de [Burns and Mitchell \(1946\)](#) [1] formalise le fait que les cycles économiques représentent les fluctuations de l'activité économique agrégée d'un pays. Cette définition de référence soutient le travail du comité de datation du Bureau national de la recherche économique (NBER). Depuis des décennies, cette institution formule une chronologie officielle des points de retournements de la conjoncture aux États-Unis. Selon [Burns and Mitchell](#), *“Les cycles économiques désignent un type de fluctuations qui affectent l'activité générale des pays dans lesquels la production est essentiellement le fait d'entreprises privées. Un cycle est constitué d'expansions qui se produisent à peu près au même moment dans de nombreuses branches de l'activité, expansions qui sont suivies*

par des phases de récessions, des contractions et des reprises, qui affectent elles aussi l'ensemble des activités économiques, les reprises débouchant sur la phase d'expansion du cycle suivant. Cette suite de phases n'est pas périodique (au sens strict du terme) mais seulement récurrente ; la durée des cycles d'affaires varie entre plus d'un an et dix ou douze ans ; ils ne sont pas divisibles en cycles plus courts de caractère similaire avec des amplitudes proches des leurs.”.

En d'autres termes, le cycle des affaires fait référence au niveau global de l'activité économique qui se caractérise par l'alternance de périodes d'expansion ou de croissance positive et de périodes de contraction ou de croissance négative. Ces phases sont délimitées par des points de retournement qui annoncent la fin d'une récession (pour les creux ou point de retournement bas) ou la fin d'une expansion (pour les pics ou point de retournement haut). [Burns and Mitchell](#) mettent ainsi en évidence deux propriétés statistiques, à savoir la persistance d'un mouvement commun à plusieurs agrégats macroéconomiques au cours du cycle et le phénomène de non-linéarité observé au cours des phases successives. Ce dernier phénomène est caractérisé par une asymétrie en termes de durée et d'amplitude. En effet, la littérature observe que les phases d'expansion sont plus longues et plus étendues que les phases de récession.

0.2.2 Le cycle de croissance

Au cours des trois décennies d'après-guerre, marquées par une croissance économique massive, et surtout jusqu'à la première crise pétrolière de 1973, les pays industrialisés ont connu un taux de croissance relativement stable. Les récessions économiques classiques étaient donc des événements rares. Dans ce contexte, il n'est pas étonnant que [Mintz et al \(1969\)](#) [5], une économiste du National Bureau of Economic Research (NBER) aux Etats-Unis, introduisent la notion de cycle de croissance qui correspond parfaitement aux caractéristiques des fluctuations économiques de l'époque. Ce concept constitue l'une des

bases de travail de l'OCDE¹, qui publie régulièrement des indicateurs composites avancés (CLI) représentant les écarts entre le niveau de l'activité économique mondiale et sa tendance à long terme.

En effet, contrairement à la succession de périodes de récession et d'expansion du cycle des affaires, le cycle de croissance se caractérise par l'alternance d'une croissance supérieure et une croissance inférieure à un niveau de long-terme. Dans ce contexte, le cycle classique fréquemment utilisé aux États-Unis et le cycle de croissance privilégié en Europe, présentent des différences fondamentales. Si le cycle de croissance permet une croissance positive dans une période de contraction ou de ralentissement cyclique (à condition que le niveau de croissance en question reste inférieur à la croissance à long terme), la récession dans le cycle des affaires est une croissance négative sur toute la durée de la phase.

Enfin, l'interprétation des points de retournement peut être relativement intéressante du point de vue de la prévision. En effet, les pics (creux) marquent la fin d'une expansion (contraction) pour le cycle des affaires. Cependant, dans le cadre du cycle de croissance, les pics (creux) annoncent le passage du taux de croissance en dessous (au-dessus) de sa tendance à long terme. En d'autres termes, les creux indiquent un minimum local qui indique une croissance positive (ou négative) par rapport à la croissance à long terme. Au-delà de la question de l'estimation empirique de la tendance, le cycle de croissance reste un atout pour les autorités en charge de la politique monétaire et budgétaire dans le sens où tout ralentissement économique (écart de production inférieur à la croissance de long terme), indique une récession, l'inverse n'est pas vrai car une reprise de l'activité économique peut suivre un ralentissement cyclique sans passer par une phase de croissance négative.

¹L'Organisation de coopération et de développement économiques (OCDE), une institution internationale de recherche économique avec 35 pays membres.

0.2.3 Le cycle d'accélération

Plus récemment, la rareté des récessions, notamment dans la zone euro, a conduit à considérer le cycle d'accélération comme une nouvelle catégorie de cycle économique. Ainsi, le cycle d'accélération est essentiellement l'alternance entre des baisses et des hausses des taux de croissance. En d'autres termes, les phases d'accélération ou d'augmentation du taux de croissance font périodiquement place à des phases de ralentissement ou de diminution du taux de croissance.

En effet, les points de retournement des phases descendantes (ou ascendantes) des taux de croissance sont marqués par l'apparition d'un minimum (maximum) local. Il est aisé de constater une relative similitude entre les cycles de croissance et d'accélération dans un contexte de rareté des récessions considéré du point de vue classique. Cependant, l'interprétation des points de retournement est tout à fait différente. Ainsi, l'apparition d'un faible taux de croissance signale le début d'une phase d'accélération quand un pic du taux de croissance annonce une phase de décélération. Contrairement aux études du NBER et de l'OCDE, qui s'appuient respectivement sur les définitions des cycles d'affaires et de croissance, l'institut de recherche sur les cycles économiques (ECRI²), s'intéresse à la datation des cycles d'accélération.

0.3 La thèse

Cette thèse vise à tester diverses méthodologies d'analyse des cycles économiques en Afrique de l'Ouest. Je démontrerai comment les États membres de la CEDEAO peuvent surveiller en temps réel les conditions économiques grâce à une amélioration de la collecte de données et à des outils économétriques modernes. Cette thèse vise à établir une boîte à outils pour une analyse économique régionale plus appropriée. La section suivante est organisée comme suit: la [sous-section 1](#) expose le problème, la [sous-section 2](#) met en

²The Economic Cycle Research Institute (ECRI) based in New York City, is an independent institute formed in 1996[1] by Geoffrey H. Moore, Anirvan Banerji, and Lakshman Achuthan

évidence la contribution de cette thèse, et la [sous-section 3](#) donne un aperçu des différents chapitres de cette thèse.

0.4 La contribution de la thèse

Cette thèse propose de tester plusieurs méthodologies liées à l'analyse des cycles économiques en Afrique de l'Ouest. Nous montrons qu'avec le développement de la collecte des données statistiques, des outils économétriques modernes éprouvés peuvent contribuer à la surveillance en temps réel des conditions économiques des pays membres de l'UEMOA (Union Économique et Monétaire Ouest Africaine). Nous tentons ainsi d'établir une base d'outils économétriques qui permettront de déchiffrer et d'anticiper les fluctuations économiques dans cette région. Le reste de la section est présenté comme suit: la problématique est exposée à la [sous-section 1](#), puis notre contribution est présentée à la [sous-section 2](#). La [sous-section 3](#) présenter les différents chapitres de la thèse .

0.4.1 La problématique

La structure des cycles économiques subit des changements significatifs au fil du temps en réponse à l'évolution de l'environnement économique, tels que la Grande Récession de 2008-2009, la crise de la dette publique en 2010 et la pandémie de COVID-19. En conséquence, les cycles classiques, de croissance et d'accélération alternent, et les points de retournement de l'économie peuvent différer en nombre et en volatilité. Par conséquent, des méthodes sophistiquées au-delà de la prévision ou de la datation traditionnelle des cycles économiques sont nécessaires pour une analyse pertinente des fluctuations économiques. Des algorithmes avancés facilitent l'application de telles méthodes dans un cadre multi-varié, bien que l'analyse des cycles économiques reste difficile.

Parallèlement, de nouvelles formes de collecte de données, en particulier le Big Data, couplées à la technologie de l'apprentissage automatique, améliorent les performances des

méthodes de prévision en temps réel, y compris la technique de "now-casting" empruntée à la météorologie. Ces avancées ont considérablement réduit le temps nécessaire à la publication du taux de croissance du produit intérieur brut (PIB) des économies avancées. De plus, les progrès de la technologie de l'information permettent de générer des estimations en temps réel des points de retournement des cycles économiques à partir de variables économiques concomitantes. L'analyse mathématique du traitement du signal et de l'image, connue sous le nom d'économétrie, mesure le degré de synchronisation entre les cycles économiques. La transformation en ondelettes permet une analyse approfondie de la synchronisation des cycles économiques et aide à évaluer la faisabilité d'une monnaie unique.

Les techniques modernes d'analyse des cycles économiques ont été utilisées pour répondre aux questions économiques, fiscales et monétaires dans les pays avancés. Cependant, à notre connaissance, elles n'ont pas encore été pleinement utilisées dans les économies de la CEDEAO à des fins de prévision. Par conséquent, cette thèse propose d'introduire des outils modernes qui utilisent des algorithmes éprouvés liés à des méthodes économétriques récentes largement utilisées dans les pays industrialisés pour permettre une analyse macroéconomique plus pertinente dans la CEDEAO.

0.4.2 Notre Contribution

La récente hausse des indices majeurs des marchés financiers ne reflète peut-être pas une santé économique prouvée et pourrait résulter d'une bulle. Lorsqu'une telle bulle passe inaperçue par diverses évaluations des risques, son éclatement éventuel peut entraîner des corrections importantes similaires à l'impact de la crise de la COVID-19. Les effets de telles crises sur l'activité économique réelle peuvent être frustrants pour les banquiers centraux, dont le travail consiste à s'assurer que la croissance ne cause pas de tensions ou d'embarras sous forme de fluctuations de prix.

Malgré les nombreux outils disponibles pour analyser les conditions macroéconomiques

en temps réel dans les économies avancées, les difficultés à mesurer le cycle économique obligent les décideurs politiques à explorer de nouveaux concepts tels que l'intelligence artificielle et d'autres politiques non conventionnelles.

Dans le contexte des États membres de la CEDEAO, nous utilisons certains des derniers algorithmes de la littérature empirique pour atteindre trois objectifs méthodologiques dans l'analyse macroéconomique : premièrement, nous examinons les faits stylisés communs des cycles économiques dans les États membres de la CEDEAO. Deuxièmement, nous prévoyons une croissance future basée sur l'état actuel de l'économie ivoirienne. Enfin, nous datons les points de retournement de l'activité économique en Côte d'Ivoire. En atteignant ces trois objectifs, notre contribution à l'analyse macroéconomique en Afrique de l'Ouest est principalement méthodologique.

Notre première contribution montre qu'une monnaie unique dans la CEDEAO est faisable sur la base de données stylisées analysées à l'aide de la méthode de transformation en ondelettes. De plus, l'analyse de la cohérence en ondelettes indique que douze États membres de la CEDEAO présentent des niveaux significatifs de synchronisation.

Notre deuxième contribution est la création d'un indice des conditions macroéconomiques (ICM) pour la Côte d'Ivoire, en utilisant l'algorithme de prévision en temps réel. Cette technique réduit la période entre la fin d'un trimestre fiscal et la publication officielle du taux de croissance pour ce trimestre. La prévision en temps réel est un outil avancé utilisant des données en temps réel pour estimer la croissance économique précoce. Le but de l'ICM est de prédire la croissance en fonction de l'état actuel de l'économie ivoirienne. Nous avons utilisé la version de prévision en temps réel du modèle de la Réserve fédérale de New York. Nous avons suivi la méthodologie présentée par Bok, Caratelli, Giannone, Sbordone et Tambalotti (2018), accessible sur le site web de NYFED. Nous avons également personnalisé le modèle pour qu'il convienne à l'environnement économique ivoirien, où les données trimestrielles du PIB sont publiées six à neuf mois plus tard.

Notre troisième contribution suggère un cycle de référence mensuel pour les points de

retournement historiques des fluctuations économiques en Côte d’Ivoire entre 1996 et 2019. Nous avons utilisé deux algorithmes pour estimer le cycle de référence : les modèles de Bry-Boschan et de points de changement multiples en mélange. Le modèle de Bry-Boschan examine généralement une seule variable et est une méthode couramment utilisée dans la littérature. En revanche, le modèle de points de changement multiples en mélange est un algorithme récemment développé par [Camacho, Gadea, et Loscos \(2020\)](#) [2], qui considère plusieurs variables concordantes. Selon l’environnement économique, nous combinons les sorties de ces algorithmes avec un récit pour identifier les points de retournement critiques. Nous montrons également comment les crises politiques coïncident fréquemment avec les points de retournement du cycle économique en Côte d’Ivoire.

L’utilisation d’outils économétriques avancés et de techniques améliorées de collecte de données a facilité l’incorporation de plus d’éléments analytiques dans le débat sur la proposition de monnaie unique de la CEDEAO. Grâce à notre travail, nous avons expérimenté efficacement l’estimation de la croissance en temps réel et développé une chronologie de base des points de retournement du cycle économique en Côte d’Ivoire.

0.4.3 Présentation des chapitres

Cette thèse comprend trois chapitres examinant l’utilisation de modèles économétriques récents pour analyser les cycles économiques en Afrique de l’Ouest. L’objectif est de fournir des outils pour la prise de décisions en matière de politique économique, monétaire et fiscale dans la région. La thèse vise à contribuer à trois domaines principaux.

Tout d’abord, elle cherche à contribuer à la discussion en cours sur la création d’une monnaie unique, appelée ”eco”, pour les États membres de la CEDEAO ([chapitre 1](#)). Ensuite, elle propose un moyen en temps réel de surveiller la croissance économique, ce qui peut réduire l’incertitude et prévenir les fluctuations de prix indésirables. Le [chapitre 2](#) propose un indice pour la surveillance en temps réel des conditions économiques en Côte d’Ivoire basé sur des estimations du taux de croissance. Enfin, la thèse fournit

une chronologie de référence des points de retournement dans le cycle économique en Côte d'Ivoire. Cet outil aidera à analyser les fluctuations économiques et à anticiper les problèmes potentiels dans les finances publiques ([chapitre 3](#)).

Chapitre 1

Depuis plus de 35 ans, la possibilité d'établir une monnaie unique dans la CEDEAO a été un sujet de discussion, avec des défis rencontrés dans le processus. La région doit résoudre plusieurs problèmes, tels que la mobilité des facteurs et l'intégration régionale, pour créer une zone monétaire optimale. Les systèmes de production des économies d'Afrique de l'Ouest doivent être alignés et soutenir la complémentarité avec les économies industrialisées d'Europe, d'Amérique et d'Asie. Malgré ces défis, le [premier chapitre](#) de cette étude montre qu'une politique monétaire commune est faisable en utilisant le modèle de transformée en ondelettes. En évaluant les cycles économiques des pays membres de la CEDEAO, l'étude vise à minimiser les conflits d'intérêts et les objectifs de politique économique divergents, permettant ainsi à une politique monétaire standard de fonctionner plus efficacement dans la région.

L'étude utilise la transformée en ondelettes et les méthodes de classification hiérarchique sur le taux de croissance de la série logarithmique naturelle du PIB réel pour enquêter sur la nature de la corrélation dans les cycles économiques de la CEDEAO. La recherche a constaté que les États membres de la CEDEAO manquent d'une structure pour allonger les cycles économiques par rapport à d'autres régions d'Afrique. Cependant, l'étude observe deux groupes régionaux distincts basés sur la devise et le statut économique. Le premier groupe, appelé "Eco-12", comprend les principales économies de la CEDEAO, tandis que le deuxième groupe, nommé "éco-périphérique", comprend la Sierra Leone et la Guinée-Bissau. Le *Eco-12* est composé de cinq pays hors UEMOA (Cabo Verde, Ghana, Gambie et Nigéria) et de sept économies de la zone franc CFA, à savoir le Bénin, le Burkina Faso, le Mali, la Côte d'Ivoire, le Niger, le Sénégal et le Togo.

Nos résultats suggèrent qu’une politique monétaire unique pourrait avoir un impact significatif sur les économies des États membres de la CEDEAO et que la plupart des économies de la CEDEAO pourraient abandonner leur souveraineté monétaire. Cependant, pour mettre en œuvre une politique monétaire commune dans la région, nous devons être en mesure de prévoir avec précision le taux de croissance en temps réel des économies de la région. Par conséquent, le prochain chapitre évalue la capacité des décideurs politiques à prendre des décisions éclairées sur l’activité économique mondiale.

Chapitre 2

En Afrique de l’Ouest, chaque pays utilise généralement un institut national de statistique (INS) pour collecter des données et publier les taux de croissance trimestriels du produit intérieur brut (PIB). Cependant, contrairement aux économies avancées, le taux de croissance officiel n’est pas publié avant neuf à douze mois après le trimestre de référence. Ce retard entrave les décisions de politique économique, car les banques centrales cherchent à s’assurer que la croissance économique génère des fluctuations de prix prévisibles. En même temps, les gouvernements planifient la lutte contre la pauvreté et l’inégalité.

Pour remédier à cela, le **deuxième chapitre** crée un indice pour prévoir relativement tôt le taux de croissance du PIB en examinant 18 variables économiques mensuelles. De plus, le modèle factoriel dynamique (DFM) dans un cadre d’espace d’état prévoit la croissance mensuelle du PIB en Côte d’Ivoire, permettant la lecture de données en temps réel et des estimations de croissance économique précoce.

Notre “*indice des conditions macroéconomiques*” (ICM) estime les taux de croissance du PIB entre janvier 2000 et juin 2020, et l’exercice de validation rétroactive montre qu’il peut approcher les meilleures pratiques en matière de prévisions macroéconomiques. Bien que le suivi en temps réel des taux de croissance du PIB puisse nous aider à comprendre l’état actuel de l’économie, il est également essentiel de connaître les points de retournement historiques d’une économie pour prévoir les tendances futures et anticiper

les changements potentiels. Dans le prochain chapitre, nous estimons chronologiquement les points de retournement des activités économiques de la Côte d'Ivoire.

Chapitre 3

Ce chapitre présente une chronologie des phases de croissance et de récession de l'économie ivoirienne, en utilisant diverses approches statistiques et économiques pour calculer un cycle de référence qui capture les points de retournement. Celles-ci comprennent l'approche de Bry-Boschan pour les mesures de récession, le modèle de points de changement multiples (MMCP) pour l'analyse de dix indicateurs concomitants, et la moyenne des paires individuelles de sommets et de creux pour calculer les points de retournement. De plus, une narration est utilisée pour déterminer les points de retournement finaux, en tenant compte des circonstances économiques de la période.

De janvier 1996 à décembre 2019, l'économie ivoirienne a connu sept épisodes de récession, chacun durant en moyenne onze mois, comparé à environ deux ans pour les phases d'expansion. L'analyse montre que la plupart des points de retournement du cycle économique en Côte d'Ivoire ont été associés à des crises politiques, à l'exception de la récession de 2008, qui était liée à la crise financière mondiale. Bien que les estimations antérieures données par notre modèle de prévision soient cohérentes avec les données officielles du PIB, comprendre les points de retournement historiques d'une économie peut être utile pour prévoir les tendances futures et prendre des décisions stratégiques.

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General Introduction

The global economy's ups and downs can significantly affect people's living standards, income inequality, and a country's economic strength. When economic growth is swift, it can lead to prosperity, while recessions or contractions can lead to hardship. Macroeconomic theory and policies aim to identify the most effective ways to prevent or manage recessions and promote sustainable economic growth. Along with factors like oil prices and fiscal and monetary policies, infrastructure and political stability also affect the business cycle's dynamics, as noted by [Rădulescu and Druica](#) in their 2014 study.

Since the subprime crisis of 2007, which developed into a financial crisis, accurately identifying turning points in economic cycles has become increasingly important. To achieve this, economists now use a wider range of data, which they analyze using sophisticated algorithms. However, this approach relies heavily on quantitative theory, which has largely replaced traditional macroeconomic theory over the past 15 years. In their study, [Gregory and Smith \(1995\)](#) [3] attribute this trend to the growing need for econometric methods to process macroeconomic data. The authors note that older macroeconomic methods relied on models with properties derived from them without studying the data. However, in the present day, understanding the properties of the data is critical to substantiate the theory's predictions.

This thesis aims to develop tools to date turning points and measure economic cycles in near real-time for Ivory Coast. Additionally, the study proposes a new method of empirical analysis using wavelet transform to enrich the discussion on the possibility of a

future single currency for ECOWAS member states. The general introduction is structured as follows:

- [Section 1](#) discusses the context and motivation behind the thesis, with business cycles being the primary focus.
- [Section 2](#) provides some definitions related to the topic.
- Finally, [section 3](#) outlines the problem and the thesis's contribution and summarizes the different chapters that make up the backbone of the thesis.

0.1 Background and motivation

The recent economic crises have increased interest in monitoring cyclical fluctuations in advanced and developing economies. However, the period of stability following World War II, known as the "great moderation," was disrupted by the Great Recession of 2007-2009, which created an environment where traditional policies became less effective. To address this, central bankers have turned to unconventional methods, such as forward guidance, but making rational forecasts in a complex and uncertain environment is challenging.

Developing economies, in particular, face structural changes and unpredictable environments. As a result, these economies often need more readily available information, and GDP statistics may be delayed. In contrast, advanced economies have high-frequency macroeconomic data that enables researchers to respond quickly to new challenges. For example, reliable forecasts of quarterly GDP growth require analyzing an unbalanced data panel in terms of length and frequency. Advanced economies have made significant progress in dating and predicting recessions, with organizations such as the National Bureau of Economic Research (NBER¹), Centre for Economic and Policy Research (CEPR²), Economic Cycle Research Institute (ECRI³), and French economic cycle dating

¹NBER has maintained a record of recession entry and exit dates for the United States since 1978

²CEPR provides European countries with a reference business cycle timeline

³ECRI offers a chronology of business cycle turning points for more than twenty-two countries worldwide

committee (CDCEF⁴) providing business cycle timelines for various countries.

However, the literature needs to mature in the context of developing economies, such as the ECOWAS zone, where the lack of key economic data hinders immediate forecast studies. There is a need for research in economic cycle analysis to keep up with recent methodologies and progress in data collection in these regions. In addressing this gap, this study proposes using modern methods to develop new real-time instruments for monitoring and estimating macroeconomic conditions. These tools can anticipate shocks and facilitate policymaker tasks in adjusting budgetary deficits.

0.2 The types of economic cycles

It is not easy to precisely define economic cycles due to the variety of inherent characteristics associated with different types of cycles. Furthermore, this study does not aim to justify any assumptions related to economic cycles. Nonetheless, we provide a concise summary of the three common types of business cycles found in the literature: business cycles, growth rate cycles, and growth cycles.

0.2.1 The Business cycle

In their seminal work published in 1946, Burns and Mitchell formalized the idea that business cycles reflect the fluctuations of a country's overall economic activity. This definition is a benchmark for the National Bureau of Economic Research (NBER) dating committee, which has officially identified turning points in the U.S. economy for many years. According to Burns and Mitchell, *“Business cycles are a type of fluctuation found in the aggregate economic activity of nations that organize their work mainly in business enterprises. These cycles consist of expansions, followed by general recessions, contractions, and revivals, which merge into the next cycle's expansion phase. This sequence of changes is recurrent but not periodic, with durations ranging from more than one year to ten or*

⁴CDCEF identifies business cycle turning points specifically for the French economy

twelve years. Consequently, business cycles cannot be divided into shorter cycles of similar character, and their amplitudes do not approximate their own”.

The business cycle refers to the ups and downs of overall economic activity, marked by alternating periods of expansion (growth) and contraction (decline). These phases are defined by turning points, which signal the end of a recession (low turning point) or an expansion (high turning point). The authors of the original work on business cycles identified two statistical properties: a common movement of several macroeconomic variables over the cycle and non-linearity observed during successive phases. This means that expansion phases are longer and more extensive than recession phases. To capture these patterns, researchers use a dynamic factorial model to study co-movement and a Markov switching model to analyze non-linear turning points.

0.2.2 The Growth Cycle

In the three decades following World War II, industrialized countries experienced steady economic growth, with classic economic recessions being rare. However, [Mintz, Ilse, and others \(1969\)](#) [4] from the National Bureau of Economic Research (NBER) introduced the concept of a growth cycle, which characterizes economic fluctuations in the United States and Europe. The growth cycle is one of the bases for the OECD⁵'s Composite Leading Indicators (CLIs), which are regularly published to represent differences between global economic activity and its long-term trend.

Indeed, unlike the succession of recession and expansion periods of the traditional or classical business cycle, the growth cycle alternates between higher and lower economic growth compared to long-term economic growth. In this context, the business or classical cycle frequently used in the United States and the growth cycle favored in Europe have fundamental differences. While the growth cycle allows for positive growth in a period of

⁵The Organization for Economic Co-operation and Development (OECD): an international economic research institution with 35 country members.

cyclical contraction or slowdown (provided that the level of growth in question remains below long-term growth), the recession in the business cycle is negative growth throughout the phase.

Finally, the interpretation of the turning points can be relatively attractive from a forecasting point of view. Thus, peaks (troughs) mark the end of the business cycle's expansion (contraction). However, in the context of the growth cycle, peaks (troughs) signal a shift in the growth rate below (above) its long-term trend. In other words, the troughs indicate a local minimum of positive (or negative) growth relative to long-term growth. Beyond the question of empirical estimation of the trend, the growth cycle remains an asset for monetary and fiscal policymakers in the sense that any economic slowdown (output gap below long-term growth) indicates a recession. At the same time, the reverse is not true because a recovery in economic activity can follow a cyclical slowdown without going through a phase of negative growth.

0.2.3 The Growth Rate Cycle

More recently, before the real estate and sovereign debt crises, the scarcity of recessions, especially in the eurozone, has led to the growth rate cycle being introduced in the literature as a new category of economic cycle belonging to the growth rate of the overall economic activity. Thus, the acceleration cycle is essentially the alternation between decreases and increases in growth rates. In other words, the phases of acceleration or increase of the growth rate periodically give way to the phases of slowdown or decrease in the rate of growth.

The turning points in growth rates are marked by the appearance of a local minimum (or maximum) at a trough (or peak). When recessions are scarce, it is easy to observe a relative similarity between growth and acceleration cycles from a classical perspective. However, the interpretation of turning points differs significantly. A low growth rate signals the beginning of an acceleration phase, while a peak in the growth rate indicates a decel-

eration phase. While the NBER and OECD studies rely on the definitions of business and growth cycles, respectively, the Economic Cycle Research Institute (ECRI⁶), an independent research institute based in New York, is interested in dating acceleration cycles. When making forecasts, it is appealing to alternate the turning points in the growth rate cycles. Specifically, during a period of economic recession (in the business cycle) or a slowdown in growth (in the growth cycle), the point at which economic activity begins to accelerate again after reaching a low point indicates a future economic recovery.

0.3 The thesis

This thesis aims to test various methodologies for analyzing business cycles in West Africa. I will demonstrate how ECOWAS member states can monitor economic conditions in real time through improved data collection and modern econometric tools. This thesis aims to establish a toolkit for more appropriate regional economic analysis. The following section is organized as follows: [sub-section 1](#) outlines the problem, [sub-section 2](#) highlights the contribution of this thesis, and [sub-section 3](#) provides an overview of the different chapters in this thesis.

0.3.1 The economic issues

The structure of business cycles undergoes significant changes over time in response to evolving economic environments, such as the Great Recession of 2008-2009, the public debt crisis in 2010, and the COVID-19 pandemic. As a result, the classical, growth, and acceleration cycles alternate, and turning points in the economy may differ in number and volatility. Therefore, sophisticated methods beyond traditional forecasting or dating of business cycles are required for relevant analysis of economic fluctuations. Advanced algorithms facilitate the application of such methods in a multivariate framework, although business cycle analysis remains challenging.

⁶ECRI is an independent research institute based in New York

In parallel, new data collection forms, particularly Big Data, coupled with Machine Learning technology, improve the performance of real-time forecasting methods, including the “now-casting” technique borrowed from meteorology. These advances have significantly reduced the time needed to publish advanced economies’ Gross Domestic Product (GDP) growth rate. Additionally, advances in information technology enable the generation of real-time estimates of business cycle turning points from coincident economic variables. Mathematical analysis from signal and image processing, known as econometrics, measures the degree of synchronization between economic cycles. Wavelet transform allows for an in-depth examination of the synchronization of economic cycles and helps assess the feasibility of a single currency.

Modern business cycle analysis techniques have been used to answer economic, fiscal, and monetary policy questions in advanced countries. However, to our knowledge, they have yet to be fully utilized in the economies of ECOWAS for forecasting purposes. Therefore, this thesis proposes introducing modern tools that utilize proven algorithms linked to recent econometric methods widely used in industrialized countries to enable more relevant macroeconomic analysis in ECOWAS.

0.3.2 Our Contribution

The recent surge in major financial market indices may not reflect proven economic health and could result from a bubble. When such a bubble goes unnoticed by various risk assessments, its eventual bursting can lead to significant corrections similar to the impact of the COVID-19 crisis. The effects of such crises on real economic activity can be frustrating for central bankers, whose job is to ensure that growth does not cause tensions or embarrassments in the form of price fluctuations. Despite numerous tools available for analyzing macroeconomic conditions in real time in advanced economies, difficulties in measuring the business cycle are forcing policymakers to explore novel concepts such as artificial intelligence and other unconventional policies.

In the context of ECOWAS member states, we use some of the latest algorithms from the empirical literature to achieve three methodological goals in macroeconomic analysis: Firstly, we examine the common stylized facts of economic cycles in ECOWAS member states. Secondly, we forecast future growth based on the present state of the Ivorian economy. Finally, we date the turning points of economic activity in Ivory Coast. By accomplishing these three objectives, our contribution to macroeconomic analysis in West Africa is primarily methodological.

Our first contribution shows that a single currency in ECOWAS is feasible based on stylized data analyzed using the wavelet transform method. Furthermore, the wavelet coherency analysis indicates that twelve ECOWAS member states display significant levels of synchronization.

Our second contribution is the creation of a macroeconomic conditions index (MCI) for Côte d'Ivoire, utilizing the now-casting algorithm. This technique reduces the period between the end of a fiscal quarter and the official release of the growth rate for that quarter. Nowcasting is an advanced tool using real-time data to estimate early economic growth. The purpose of the MCI is to predict growth based on the current state of the Ivorian economy. We utilized the now-casting version of the New York Federal Reserve model. We followed the methodology presented by [Bok, Caratelli, Giannone, Sbordonne, and Tambalotti, \(2018\) \[1\]](#), which is accessible on the NYFED website. We also customized the model to suit the Ivorian economic environment, where quarterly GDP data are published six to nine months later.

Our third contribution suggests a monthly reference cycle for the historical turning points of economic fluctuations in Côte d'Ivoire between 1996 and 2019. We utilized two algorithms to estimate the reference cycle: the Bry-Boschan and mixture multiple-change point models. The Bry-Boschan model typically examines only one variable and is a commonly used method in the literature. In contrast, the mixture multiple-change point model is a recently developed algorithm by [Camacho, Gadea, and Loscos, \(2020\) \[2\]](#),

which considers multiple coincident variables. Depending on the economic environment, we combine the outputs of these algorithms with a narrative to identify the critical turning points. We also demonstrate how political crises frequently coincide with the economic cycle turning points in Côte d'Ivoire.

The use of advanced econometric tools and improved data-gathering techniques have facilitated the incorporation of more analytical elements into the debate concerning the proposed single currency of ECOWAS. Through our work, we have effectively experimented with real-time growth estimation and developed a baseline chronology of business cycle turning points in Côte d'Ivoire.

0.3.3 Chapters presentation

This thesis includes three chapters investigating recent econometric models' use for analyzing business cycles in West Africa. The goal is to provide tools for the region's economic, monetary, and fiscal policy decision-making. The thesis aims to contribute to three main areas. Firstly, it seeks to add to the ongoing discussion about creating a single currency, called the "eco," for ECOWAS member states ([Chapter 1](#)). Secondly, it offers a real-time way to monitor economic growth, which can reduce uncertainty and prevent undesirable price fluctuations. [Chapter 2](#) proposes an index for real-time monitoring of economic conditions in Côte d'Ivoire based on growth rate estimates. Finally, the thesis provides a reference chronology of the turning points in the economic cycle in Côte d'Ivoire. This tool will assist in analyzing economic fluctuations and anticipating potential issues in public finances ([Chapter 3](#)).

Chapitre 1

For over 35 years, the possibility of establishing a single currency in ECOWAS has been a topic of discussion, with the process encountering challenges. The region must ad-

dress several issues, such as factor mobility and regional integration, to create an optimal currency zone. West African economies' production systems must align and support complementarity with industrialized economies in Europe, America, and Asia. Despite these challenges, the **first chapter** of this study shows that a common monetary policy is feasible using the wavelet model. By evaluating the economic cycles of ECOWAS member countries, the study aims to minimize conflicts of interest and divergent economic policy objectives, enabling a standard monetary policy to operate more successfully in the region.

The study uses the wavelet transform and hierarchical clustering methods on the growth rate of the natural log of real GDP series to investigate the nature of comovement in business cycles for ECOWAS. The research has found that the ECOWAS member states lack a structure for elongating business cycles compared to other African regions. However, the study observes two distinct regional groups based on currency and economic status. The first group, referred to as "Eco-12," comprises the major economies in ECOWAS, while the second group, named "eco-peripheral," includes Sierra Leone and Guinea-Bissau. The *Eco-12* is made up of five non-UEMOA countries (Cabo Verde, Ghana, Gambia, and Nigeria) and seven economies of the CFA Franc zone, namely Benin, Burkina Faso, Mali, Côte d'Ivoire, Niger, Senegal, and Togo.

Our findings suggest that a single currency policy could significantly impact the economies of ECOWAS member states, and most ECOWAS economies could abandon their monetary sovereignty. However, to implement a common monetary policy across the region, we need to have the ability to accurately forecast the real-time growth rate of the economies in the region. Therefore, the next chapter assesses policymakers' capability to make informed decisions about global economic activity.

Chapitre 2

In West Africa, each country typically uses a national institute of statistics (INS) to collect data and publish quarterly gross domestic product (GDP) growth rates. However,

unlike advanced economies, the official growth rate is not released until nine to twelve months after the reference quarter. This delay hinders economic policy decisions, as central banks aim to ensure that economic growth generates predictable price fluctuations. At the same time, governments plan to combat poverty and inequality.

To address this, the **second chapter** creates an index for forecasting the rate of GDP growth relatively early by examining 18 monthly economic variables. In addition, the Dynamic Factor Model (DFM) in a state-space framework forecasts monthly GDP growth in Côte d'Ivoire, enabling real-time data reading and early economic growth estimates.

Our Macroeconomic Conditions Index (MCI) estimates GDP growth rates between January 2000 and June 2020, and the backtesting exercise shows that it can approach best practices in macroeconomic forecasting. While real-time tracking of GDP growth rates can help us understand the current state of the economy, it is also essential to know the historical turning points of an economy to forecast future trends and anticipate potential changes. In the next chapter, we chronologically estimate the turning points of Côte d'Ivoire's economic activities.

Chapitre 3

This chapter presents a chronology of the Ivorian economy's boom and recession stages, using various statistical and economic approaches to compute a reference cycle that captures the turning points. These include the Bry-Boschan approach for recession measures, the mixture multiple-change point (MMCP) model for analyzing ten coincident indicators, and averaging individual pairs of peaks and troughs to calculate turning points. Additionally, a narrative is used to determine the final turning points, considering the economic circumstances of the period.

From January 1996 to December 2019, the Ivory Coast economy experienced seven episodes of recession, each lasting an average of eleven months, compared to around two years for expansion phases. The analysis shows that political crises were associated with

most of the business cycle's turning points in Côte d'Ivoire, except for the 2008 recession, which was rooted in the global financial crisis. While the earlier estimates given by our now-casting model are consistent with the official GDP data, understanding the historical turning points of an economy can be useful for forecasting future trends and making strategic decisions.

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Chapter 1

Business Cycle Analysis in ECOWAS: Wavelet Transform and Monetary Integration Implications.

1.1 Introduction

Many currencies have experienced destabilization due to currency speculation strategies, particularly the "carry trade" strategy, which involves borrowing low-interest-rate currencies and investing in higher-interest-rate ones. For instance, in Africa, the CFA Franc, a common currency of seven countries, including Côte d'Ivoire and Senegal as the largest economies, was devalued in the 1990s due to speculative attacks. The Ghanaian cedi was subject to similar attacks in 2016 due to concerns over the country's fiscal deficit, as reported by [Accominotti \(2016\)](#) [1]. Moreover, the Zimbabwean dollar provides another example of the potentially destabilizing effects of currency speculation. In the late 2000s, hyperinflation caused the currency's value to drop rapidly, leading to a sharp increase in prices and a decline in the purchasing power of consumers. This example highlights how hyperinflation, triggered by currency speculation, can lead to severe economic destabilization.

The debate over a common currency in West Africa is multifaceted. It encompasses a range of issues, including concerns about destabilizing speculation of national currencies and a desire for greater economic integration and solidarity. To this end, the Economic Community of West African States (ECOWAS)¹ aims to replace national currencies with a common regional currency shared by all 15 member countries. However, this is a complex undertaking that involves potentially merging an existing monetary union, the West African Economic and Monetary Union (WAEMU)², with the West African Monetary Zone (WAMZ)³. [Debrun, Masson, and Pattillo \(2005\)](#) note these complexities in their

¹The Economic Community of West African States comprises 15 countries, including Cape Verde, Gambia, Ghana, Guinea, Liberia, Nigeria, and Sierra Leone, forming the West African Monetary Zone (WAMZ) in preparation, and seven countries from the West African Economic and Monetary Union (WAEMU).

²The West African Economic and Monetary Union includes eight member states, including Benin, Burkina Faso, Côte d'Ivoire, Guinea-Bissau, Mali, Niger, Senegal, and Togo, which share a common currency—the CFA Franc. The Central Bank of West African States has issued this currency and pegged it to the Euro since 1999. The CFA franc's convertibility is unlimited relative to the Euro and guaranteed by France. In return, the CFA zone countries deposit at least 65% (50% for the WAEMU, since 2005) of their foreign reserves in a special operating account held by the French Treasury.

³The West African Monetary Zone includes seven member states, including Gambia, Ghana, Guinea,

issue analysis [19].

ECOWAS comprises 32% of Africa's population and is one of the world's poorest communities, with twelve of its fifteen member states ranking among the worst regarding human development indices. Nonetheless, the region has been resilient despite falling commodity prices, maintaining an average growth rate of over 4% in the four years leading up to the COVID-19 pandemic. Moreover, by joining the AfCFTA⁴, ECOWAS has become part of one of Africa's most dynamic economic communities, with a combined GDP of US\$3 trillion, providing a potentially robust foundation for regional industrialization.

The ECOWAS member countries have been working on creating a single currency called "ECO" since 1983 to promote economic solidarity and integration that could increase financial stability and foster economic sustainability. However, this complex project involves fifteen member countries with diverse economic structures. This paper evaluates whether the economies of the West African Economic and Monetary Union (WAEMU) and the West African Monetary Zone (WAMZ) are growing together through the synchronization of business cycles. Furthermore, we assess whether these economies meet the requirements for adopting a single currency, as outlined by the Optimum Currency Area (OCA) argument, and whether there is potential for meeting these requirements in the future. We focus on measuring the similarity of business cycles of ECOWAS member states and also consider the recently discovered business cycles elongation principle from [Crowley and Hallett \(2017\)](#) [38]. In doing so, we aim to provide insights into the feasibility of the ECO project and its potential benefits for the region.

In the 1960s, the renowned economist Robert Mundell, with his Optimum Currency Areas (OCA) theory, opened up an entirely new world of possibilities for the countries seeking to establish a unified currency system. The OCA theory fundamentally centers around identifying the ideal conditions for a group of countries to adopt a common cur-

Liberia, Nigeria, and Sierra Leone, each with its currency.

⁴The African Continental Free Trade Area attempts to establish a single market for goods and services manufactured in Africa and addresses non-tariff barriers such as customs delays. Free trade officially began in the AfCFTA on January 1, 2021, after a six-month delay due to the COVID-19 outbreak.

rency. It meticulously analyzes the pros and cons of such a transition, highlighting the benefits of shared currency systems while cautioning against the pitfalls of blindly adopting them.

Mundell proposed that a group of countries must consider several critical factors to establish an OCA. For instance, there must be a high degree of economic integration, a relatively unrestricted labor market, and a strong resemblance in the participating nations' economic structures and business cycles. Only then can they consider sharing a common currency. Mundell postulated that meeting these conditions would eliminate exchange rate fluctuations and reduce transaction costs, ultimately leading to significant benefits for the group by adopting a single currency.

However, implementing a common currency can be advantageous and disadvantageous depending on the level of integration among the countries involved. While it could lead to increased economic stability by eliminating exchange rate fluctuations and reducing transaction costs, it could also hinder the ability of member states to cope with unexpected economic shocks. Despite these challenges, Mundell's work has significantly impacted the formation of currency unions worldwide, particularly the European Union's adoption of the Euro.

Mundell's OCA theory is a valuable tool for evaluating the advantages and disadvantages of implementing a shared currency. It is particularly relevant to ECOWAS, whose member states have been exploring the adoption of a common currency, the Eco, for over 35 years. However, the region faces significant obstacles to meeting the requirements for a shared currency, such as limited economic integration and significant economic structure disparities. To determine where ECOWAS member states stand about these challenges, we can apply Mundell's OCA criteria to the region's economies:

- i) According to the theory of OCA, an increase in factor mobility can help facilitate the implementation of monetary policy by offsetting the asymmetry of shocks (Crowley, 2008 [15]). However, in the case of ECOWAS, although there have been

attempts to encourage mobility, progress has been slow. As a result, there are significant adjustment requirements through exchange rate changes within the region.

- ii) The economies of ECOWAS specialize in agriculture and commodity exports, and their business cycles depend on their primary exports. Such specialization limits their development capacity and competitiveness (Frankel and Rose, 1998 [22]) while promoting an economy that is subject to negative external shocks. The global economic crisis has reduced trade flow in the region, negatively impacting fiscal balance and investment (Banik and Yoonus (2012) [6]). Moreover, the narrowness of the domestic market and high customer protection barriers exacerbate the insufficient contributions of the industry's value added to ECOWAS real GDP.
- iii) The economies of ECOWAS specialize in agriculture and commodity exports, and their business cycles depend on their primary exports. Such specialization limits their development capacity and competitiveness (Frankel and Rose, 1998 [22]) while promoting an economy that is subject to negative external shocks. The global economic crisis has reduced trade flow in the region, negatively impacting fiscal balance and investment (Banik and Yoonus (2012) [6]). Moreover, the narrowness of the domestic market and high customer protection barriers exacerbate the insufficient contributions of the industry's value added to ECOWAS real GDP.
- iv) In addition to the challenges previously mentioned, the limited domestic demand in the ECOWAS economies worsens the impact of demand shocks, as pointed out by Nkwatoh (2018) [34]. Furthermore, the production process in these economies is structured to complement economies outside the region rather than promoting inter-regional trade. Another issue is the inflation differential, as Nigeria and Ghana have experienced high inflation rates (10% to 13% on average) compared to the WAEMU countries, which have a target of 3%. This differential highlights the divergence in economic trends between ECOWAS countries, as Nitsch, 2004 [33] noted.

- v) The degree of similarity between domestic business cycles is optional. Still, a sufficient condition for desired integration, as shown by [Frankel and Rose \(1998\) \[22\]](#) and [Aguiar-Conraria and Soares \(2011\) \[3\]](#) using panel data. This study uses a wavelet approach, as discussed in [Crowley \(2007 \[14\]\)](#) and Mundell's theory (1961), to analyze the potential of an optimal currency area for ECOWAS. Similar growth rates across member states should mitigate issues related to the asymmetric impact of monetary policy. In contrast, growth rates with similar frequencies should alleviate the problems of implementing monetary policy in ECOWAS.

ECOWAS member states have ratified several agreements aligned with the Optimum Currency Area (OCA) framework. According to [Nkwatoh \(2018\) \[34\]](#), these agreements could lead to increased economic integration and the creation of a single currency, even if member countries have different economic cycles. While this study does not focus on the quality of trade links or solidarity among ECOWAS countries, we aim to examine the feasibility of the proposed single currency, the ECO, by analyzing the synchronization of business cycles within the region. We aim to determine whether the economies of the West African Economic and Monetary Union (WAEMU) and the West African Monetary Zone (WAMZ) are growing together or if there is a two-speed synchronization of business cycles in the broader ECOWAS region while considering different levels of inflation aversion. By answering this question, we aim to demonstrate the viability of the ECO for promoting regional economic integration.

To examine the nature of comovement in business cycles for ECOWAS, we use the wavelet transform and the Hierarchical clustering methods on the growth rate of the natural log of real GDP series. Our research contributes various methodological approaches to the literature on business cycle synchronization in ECOWAS, such as:

1. The decomposition of the ECOWAS business cycles into growth and the discussion of the principle of business cycle elongation in the region.

2. The consideration of correlations and coherencies within these decomposed cycles.
3. The use of cluster methods to compare the decomposed processes and assess business cycle groupings in ECOWAS since 1968.

Our research has found that compared to other African regions, the ECOWAS member states lack a structure for elongating business cycles, which sets them apart. However, we observe two distinct regional groups based on currency and economic status. The first group, referred to as "Eco-12," comprises the major economies in ECOWAS, while the second group, named "eco-peripheral," includes Sierra Leone and Guinea-Bissau.

We have organized the paper into five sections, with [Section 3](#) presenting a literature review of business cycle synchronization in the ECOWAS region. [Section 3](#) describes the techniques used in the analysis, including using the time-frequency domain for wavelet multi-resolution decomposition and wavelet coherency analysis. Additionally, this section explains the approach taken to group business cycle data in ECOWAS. [Section 4](#) presents the results, and [Section 5](#) concludes the paper by discussing the analysis findings.

1.2 A brief literature of business-cycle synchronization

Most modern economists readily accept that business cycles are regular patterns observed in the comovements between different aggregated time series with high coherence, as noted by [Lucas Jry, 1997 \[31\]](#). Therefore, the study of business cycle essential is crucial because it allows us to verify the properties of an optimum currency area and assess the feasibility of a common monetary policy, as observed by [Aguiar-conraria and Soares, \(2011 \[39\]\)](#). While empirical research on business cycle synchronization is abundant for developed economies, the measure of synchronization used can greatly affect the results. However, identifying similarities between economies in the ECOWAS area through the time-frequency approach still poses significant challenges.

1.2.1 Modeling business cycle comovements

One of the main stylized facts in economics is the study of comovements or correlations between economic cycles. Economists can use a linear combination of unpredictable correlated processes for standard cycles to measure comovements, as [Vahid and Engel, 1993](#)) [42] demonstrated. The concept of a standard cycle generally relies on rank reduction and adheres to cointegration. [Croux, Forni, and Reichline, \(2001](#) [13] reported on this idea, following [Engel and Granger, \(1987\)](#) [20].

The concepts mentioned can be useful for analyzing the dynamic properties of multivariate time series. However, they have limitations in studying business cycle comovements because they need to allow for establishing the different degrees of association, as reported by [Croux, Forni and Reichline, 2001](#) [13]. To overcome this limitation, the authors propose a dynamic correlation tool to analyze economic time series at different frequencies. This tool “*can decompose the time series into frequency and frequency bands*” from the Fourier Transform approach. This approach assumes that the function’s frequency content is stationary along the time axis.

Fourier analysis, which studies time series in terms of frequency, has limitations for business cycle analysis. As [Aguilar-Conraria and Soares, \(2011](#) [4] pointed out, one of the main issues is that lost time information makes it difficult to identify structural changes. Fourier Transform analysis does not allow signal moments to change over time, making it unsuitable for non-stationary time series. Therefore, more than time-domain or frequency-domain methods may be needed to adequately capture business cycle synchronization ([Aguilar-Conraria, Azevedo and Soares, 2008](#) [2]). As an alternative, the wavelet approach can be considered.

The term “wavelets” refers to small waves that start and end at a finite point in time, as defined by [Crowley \(2007](#) [14]. These localized functions are particularly useful for approximating variables in both time and space. Wavelet analysis is an alternative to an

empirical analysis of business cycles, according to [Aguiar-Conraria and Soares, 2014](#) [4]. The following sub-section will provide empirical examples of wavelet analysis applied to Europe, the US, and sub-Saharan Africa.

1.2.2 Business cycles in industrialized economies

Previous studies on business cycle synchronization have primarily utilized correlation analysis based on filtered time series to examine comovement features among different economies. For example, researchers like [Christodoulakis, Domelis, and Kollintzas \(1995\)](#) [10] and [Backus and Kehoe, \(1992\)](#) [5] have used the Hodrick-Prescott (HP) filter to measure volatility persistence and comovements of output fluctuations within the European Community (EC) and compared prewar and postwar business cycles of ten OECD economies, respectively. Similarly, [Fidrmuc \(2004\)](#) [21] performed a simple correlation analysis of business cycle convergence for OECD countries. In addition, structural Vector Autoregressions (SVAR) have also been used to analyze business cycles while giving little attention to economic theory. However, the SVAR approach “*may misrepresent the true dynamic responses*”, argued [Cooley and Dwyer, \(1998\)](#) [11]. Moreover, correlation measures have limitations because their results depend on the length of the window, potentially ignoring medium-term changes ([Gayer, \(2007\)](#) [24]).

To expand on the traditional correlation analyses, more recent measures of dependence suggest calculating dynamic correlation coefficients through band-pass filtered time series to identify potential changes in the comovements. In this vein, Croux, Forni, and Reichline (2001) proposed a measure of “cohesion” between output fluctuations based on “dynamic correlations” to evaluate the degree of synchronization among US states, Europe, and between the two groups. Similarly, in their study, [Camacho, Caro, and Lopez-Buenache \(2020\)](#) [9] employed dynamic factor and Markov-switching models to calculate a measure of how synchronized business cycles are in the euro area over time.

Although the approach of dynamic correlation with band-pass filtered time series has

been useful in extracting the business cycle component in economic time series ([Harvey and Trimbur, \(2003\) \[27\]](#)), it may have limitations. Business cycles have phases that switch over time, and filtering in the time domain can eliminate existing interrelations between signals as argued by [Herrera Escalona, Lopez, and Müller, \(2016\) \[37\]](#). Therefore, band-pass filtering might include spurious synchronization, as reported in several studies, including [Wand and Liu, \(2013\) \[43\]](#) and [Sun, Zhang, Zhou Xu and Small, \(2008\) \[40\]](#).

To depart from the previously discussed empirical approach, [Koopman and Azevedo, \(2003\) \[30\]](#) analyzed the cyclical dynamics of the euro area using a phase-adjusted correlation coefficient analysis. This method represented a clear departure from using only frequency domain representations based on the Fourier Transform. Furthermore, while the Fourier Transform was only suitable for analyzing the frequency contents of periodic and stationary signals, the Wavelet Transform tool is a better alternative for both static and non-stationary signals. Therefore, the use of Wavelet goes beyond the Fourier Transform approach and leads to a new era of business cycle synchronization analysis.

Researchers have investigated business cycles as the aggregate cyclical movement of each component displayed at different time horizons to better understand the cyclical movements in economic activity. One popular method to study the changing patterns of business cycles and their synchronization is the wavelet methodology, which can examine different frequency bands while preserving temporal information. The empirical applications of this relatively new method have grown considerably for the US, Asian, and European economies. For instance, [Ramsey and Lampart, \(1998a and 1998b\) \[36\]](#) pioneered the use of wavelets to determine the timing of economic relations and their variation over different business cycles, shedding light on the nature of business cycle frequency.

[Gallegati and Gallegati, \(2007\) \[23\]](#) utilized the maximal overlap discrete wavelet transform (MODWT) in a time-frequency framework to examine the synchronization of growth cycles within the European Union. Meanwhile, [Aguiar-Sonraria and Soares, \(2011\) \[39\]](#) used wavelet analysis to measure and test business cycle synchronization across the

EU-15 and the Euro-12 countries. In this study, we build on their work by using annual data to focus on the co-movement of growth cycles in the ECOWAS.

1.2.3 The case of west African economies

Several studies have used various methods to organize multivariate time series and assess the synchronicity and convergence of candidate countries in sub-Saharan Africa, particularly in the ECOWAS area. These studies aim to establish a baseline for advocating monetary integration, often weighed against the cost of giving up monetary policy independence. [Quah, 2007 \[35\]](#) supported this framework by presenting a diagnostic approach to OCA analysis, which can provide insights into the potential economic costs and benefits of monetary integration.

Various studies have investigated the business cycle dynamics and synchronization in sub-Saharan Africa, particularly in the ECOWAS area. [Bénassy-Quéré and Coupet, \(2005\) \[7\]](#) employed cluster analysis on 17 sub-Saharan African countries to determine the business cycle dynamics. [Kishor and Ssozi, John \(2011\) \[29\]](#) used an unobserved component approach to assess business cycle synchronization in East Africa. [Zouri \(2020\) \[44\]](#) analyzed the determinants of business cycle synchronization in ECOWAS based on the absolute differential in real GDP growth rate between economies. Some studies based on cluster analysis consider panel data models to assess the feasibility of a monetary union in ECOWAS. For instance, [Coulibaly and Gnimassoun \(2013\) \[12\]](#) investigated the optimality of a currency union in the ECOWAS region based on the convergence and co-movements between exchange rate misalignments. Their findings suggest that Ghana and Gambia could join WAEMU. Furthermore, [Couharde, Grekou, and Mignon, \(2021\) \[25\]](#) used clustering and factor analysis to examine the appropriateness of the ECOWAS monetary union project with a study based on coordinated exchange rate paths that would allow candidate countries to achieve internal and external balances. The authors advocate for two "ECOs" areas.

To better understand the relationship between two-time series, cluster analysis can be added to assess their similarity and phase relationship. Several studies have employed wavelet methods in Africa to investigate the relations between macroeconomic time series. For instance, [Boako and Alagidede \(2017\) \[8\]](#) used the continuous Morlet wavelet transform methodology to analyze the regional and global co-movements of Africa's stock markets, while [Idrissu and alidade \(2021\) \[28\]](#) focused on analyzing the inflation and monetary policy nexus in South Africa. [Habimana, Sesay, and Umulisa \(2020\) \[26\]](#) used wavelet spectra clustering to analyze ECOWAS business cycle synchronization.

In addition to analyzing the synchronization of the economic cycles of the ECOWAS member countries, we aim to verify the elongation principle of economic cycles proposed by [Crowley and Hallett \(2018\) \[17\]](#). To the best of our knowledge, this is the first study to combine this principle with the study of cycle similarity for African countries. The proposed methodological approach involves using Maximum Overlap Discrete Wavelet Transform to decompose economic cycles into different time-frequency scales, Continuous Wavelet Transform to analyze how relationships evolve, and hierarchical clustering analysis to confirm the grouping of economies in the region. This approach aims to provide information on the dynamics of economic cycles at different time and frequency scales.

1.3 Methodology and Data

1.3.1 Wavelet Transform

Economic growth is not a smooth process and contains growth cycles at different frequencies. [Crowley and Mayes \(2009\) \[18\]](#) have used wavelet transform analysis to identify these cycles and found that similarities between economies are high for low frequencies but lower at traditional business cycle frequencies. This analysis can provide valuable insights into complex economic phenomena and inform policy and decision-making. However, sudden shifts in ECOWAS economies can challenge accurate analysis. Therefore, it is essential

to gather information about the state of the economy to gain insights into the underlying dynamics of business cycles, where small changes in the timing of economic data can have a significant impact. We can use Wavelet Transform (WT), which [Morlet, \(1983\) \[32\]](#) introduced, to perform this analysis. Wavelet Transform (WT) approach utilizes wavelets to decompose a signal into different frequency components. One can perform this decomposition using the Discrete Wavelet Transform (DWT) or the Continuous Wavelet Transform (CWT).

1.3.2 Maximum overlap discrete wavelet transform

The discrete wavelet transform breaks down a time series into two sets of approximate and "detail" coefficients. The detail coefficients, known as "crystal," capture the high-frequency components of the series, while the approximate coefficients capture the low-frequency components. Despite this, the method captures only a finite number of frequency components, resulting in a loss of information about the underlying dynamics of the series. [Crowley, Garcia, and Quah \(2013\) \[16\]](#) demonstrated the discrete wavelet transform in their research and provided an equation to explain it. They wrote the equation as follows:

$$\psi(t) = \frac{1}{\sqrt{s}} \psi \left(\frac{t - \tau}{s} \right) \quad (1.1)$$

where the function's size is represented by s , and its location along the time series is referred to as u . The term $\frac{1}{\sqrt{s}}$ ensures that the norm of $\psi(\cdot)$ equals one. The wavelet function is centered at u and s ; the translation of u results in the wavelet shifting on the timeline. A broader, low-frequency wavelet function is produced with larger s values, while smaller s values produce a narrower, high-frequency wavelet function. For any time series $x(t)$, a "father" wavelet function captures the trend movements and cycles. In contrast, a "mother" wavelet assesses deviations from the mean ([Crowley, Garcia, and Quah \(2013\) \[16\]](#)). We use indices j for the scale and k for the number of translations. The integrals for father and

mother wavelets can approximate the wavelet crystals as follows:

$$s_{J,k} \approx \int x(t)\phi_{J,k}(t)dt \quad (1.2)$$

$$d_{J,k} \approx \int x(t)\psi_{J,k}(t)dt \quad (1.3)$$

, where $J = 1, 2, \dots, J$ with J being the maximum scale corresponding to the length of business cycles data of interest. Thus, the multi-resolution decomposition of the data can be written for a time series $x(t)$ as:

$$x(t) = \sum_k s_{J,k}\phi_{J,k}(t) + \sum_k d_{J,k}\psi_{J,k}(t) + \sum_k d_{J,k}\psi_{J-1,k}(t) + \dots + \sum_k d_{J,k}\psi_{1,k}(t) \quad (1.4)$$

The functions $\phi_{J,k}(t)$ and $\psi_{J,k}(t)$ are orthogonal, which means that they enable the representation of the signal with only a few non-zero coefficients. The multi-resolution decomposition (MRD) of the variable $x(t)$ is represented by the set of crystals :

$$s_J, d_J, d_{J-1}, \dots, d_1.$$

We use the MRD technique to capture short-term and long-term fluctuations in the economic activities of ECOWAS member states. This method allows us to analyze the underlying dynamics of the signal at different frequencies. Since we have an annual dataset with only 35 observations, the business cycle is identified as 2 to 4 years.

Table 1.1: Wavelet Decompositions

Scale Crystals	Annually Frequency Resolution	Type
d1	0-1 Y	Noise
d2	1-2 Y	Noise
d3	2-4 Y	Business Cycle
d4	4-8 Y	Business Cycle
d5	8-16 Y	Business Cycle
s5	16 Y+	Trend

The implementation of MRD involves using Discrete wavelet Transform (DWT), which

enables us to gain insights into the underlying dynamics of the series at different frequencies. However, DWT has two main drawbacks: first, it captures only a large number of frequency components, and its analysis needs to be more flexible. Second, the position of the time series within the sample can impact the results from this process, making it difficult to interpret the outcomes.

To address some limitations of DWT, we use the MODWT approach with five decomposition levels, as described by Crowley, Garcia, and Quah (2013) [16]. MODWT is not orthogonal but can handle any sample size and is insensitive to time shifts in the input data. We apply the 8-parameter LA(8) wavelets for smoother results. MODWT preserves the original information while performing multi-scale analysis at different frequency scales through multi-resolution analysis. It applies the wavelet function down the series data observation by observation, allowing us to control the degree of overlap between wavelet coefficients and accurately capture relationships between different variables. However, MODWT is limited by the number of available data points when analyzing correlations.

For example, due to our limited dataset of 35 annual data points, MODWT cannot accurately capture correlations between business cycles, which typically require around 52 data points. MODWT does not offer information about the phase relationship between the two series. We employ wavelet transform coherence based on cross-wavelet transform to overcome these limitations and provide a more thorough analysis of business cycle correlation and phasing in the ECOWAS area. This approach offers a more comprehensive and detailed examination of business cycle correlation and phasing.

1.3.3 Cross Wavelet Transform

The discrete wavelet transform method is a common approach for performing wavelet analysis in economics. However, researchers have increasingly favored the continuous wavelet transform (CWT) for analyzing time series with localized irregular fluctuations. For example, [Aguiar-Conraria and Soares \(2011\) \[39\]](#) propose a CWT approach to “*mea-*

sure the degree of synchronization among countries”. Since our objective is to analyze business cycle synchronization for 34 years (beginning in 1987) in the ECOWAS region, we have chosen the CWT method. This method allows us to investigate consistent phase relationships between business cycles in time-frequency space with common power, indicating causal links between the cycles in the ECOWAS area.

Expanding on the capabilities of the continuous wavelet transform (CWT) for time series data, we use the Cross Wavelet Transform (XWT). Unlike the CWT, the XWT analyzes multiple time series concurrently to investigate relationships between variables in time-frequency space, granting us a comprehensive understanding of the data. Utilizing the XWT, we can explore potential cross-correlations among business cycles in the ECOWAS region.

We use the XWT to define Wavelet Coherence (WTC) between two business cycles. We focus on Wavelet Transform Coherence because it can identify a significant relationship between two (2) time series, even if they have low shared power. We use the Morlet wavelet function to determine frequency-time resolution as it offers a good balance among all possible “*mother wavelet*”. Equation 1.5 represents a normalized Morlet wavelet.

$$\psi_{\omega}(t) = \pi^{-1/4} e^{i\omega_0 t} e^{-t^2/2}. \quad (1.5)$$

, where a Morlet wavelet is defined by a frequency of $\omega_0 = 6$ and a time variable t . This wavelet extracts features with equal variance in both time and frequency domains. Thus, we can estimate a signal’s instantaneous amplitude and phase and convert it between scales and frequencies. This is achieved through a technique known as the Continuous Wavelet Transform (CWT), which is used to analyze a time series x_t concerning a given wavelet ψ . The CWT of a time series x_t concerning the wavelet ψ is a function of two variables $W(\tau, s)$, which provides valuable information about the signal’s behavior in both the time

and frequency domains such that :

$$W_x(\tau, s) = \int x_t \left[\frac{1}{\sqrt{|s|}} \bar{\psi} \left(\frac{t - \tau}{s} \right) \right] dt \quad (1.6)$$

, s is a scaling or stretching factor controlling the width, and τ controls the wavelet's location. From the analysis above, a power spectral measure can be derived as:

$$W(\tau, s) = E\{W(\tau, s)W(\tau, s)^*\} \quad (1.7)$$

, where $*$ represents the calculation of complex conjugate such that the magnitude of the coefficients remains constant under the transform. Given two variables x and y a cross wavelet transform (XWT) can be derived as:

$$XWT_{xy}(\tau, s) = E\{W_x(\tau, s)W_y(\tau, s)^*\} \quad (1.8)$$

This measure can lead to wavelet coherence (WTC) as a normalization of the XWT.

1.3.4 Wavelet coherence

Coherence is a common measure of linear interactions between two signals. Unlike traditional statistics, coherence is based on the Pearson correlation coefficient in the frequency and time domains. Coherence calculates the average length of the resultant vector, or coherence, of the cross-spectral density of two signals. We can effectively identify regions of high co-movement, the direction of phases, and lead-lag information in the time-frequency space using wavelet coherence. This tool provides useful insights into the behavior of the business cycle in the ECOWAS region. The squared correlation coefficient, $WTC_{xy}(\tau, s)$, ranges from 0 to 1, indicating weak to strong co-movement. The wavelet formulation of coherence between two signals in the frequency and time domains is as

follows:

$$WTC_{xy}(\tau, s) = \frac{|(XWT_{xy}(\tau, s))|}{\sqrt{|W_x(\tau, s)W_y(\tau, s) * |}}, \quad (1.9)$$

Crowley, Garcia, and Quah (2013) [16], also represent detection of the phasing, $\varphi(s)$, between the cycles as:

$$WTC_{xy}(\tau, s) = |XWT_{xy}(\tau, s)|e^{i\varphi(s)}, \quad (1.10)$$

1.3.5 Data

We used real GDP from the World Development Indicators (WDI) dataset of the World Bank to analyze regional co-movements in ECOWAS. The sample comprises 14 available countries (ECOWAS has 15 member states), for which we have all the series back to 1987. The selection includes Benin, Burkina Faso, Cabo Verde, Ivory Coast, Gambia, Ghana, Guinea, Guinea-Bissau, Mali, Niger, Nigeria, Senegal, Sierra Leone, and Togo. We needed more data points to conduct the multi-resolution decomposition and the wavelet coherence analysis for Liberia. Nonetheless, Sierra Leone, having a similar history and economy, can be used as a proxy for Liberia in the analysis. In addition, we considered annual and seasonally adjusted Gross Domestic Product (GDP) data until 2021. These are transposed into log annual change data (equivalent to economic growth).

1.4 Business cycle synchronization in the ECOWAS

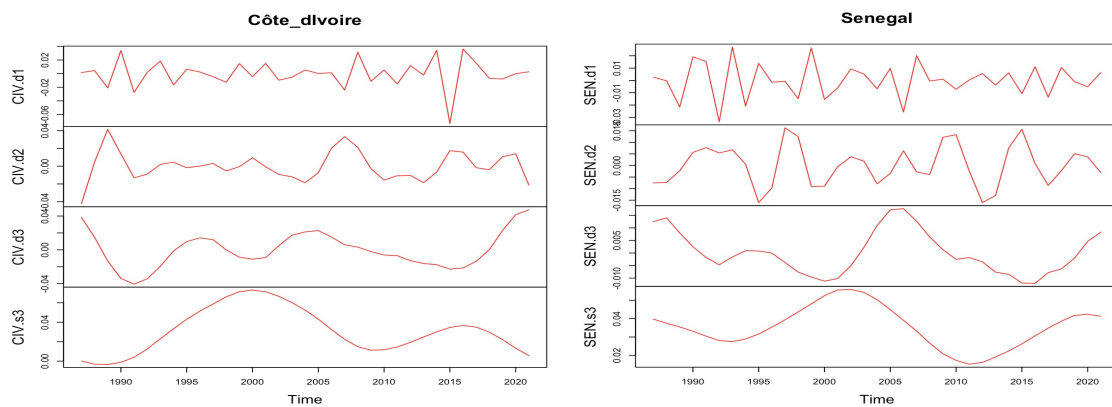
1.4.1 Results of MODWT multi-resolution decomposition

We based the wavelet multi-resolution decomposition analysis on the log annual real GDP growth series decomposition. In this analysis, we demonstrate the MODWT decomposition of the economic cycles of key ECOWAS member states. The variations at up to 1-year cycles, 1 to 2 years, and 2 to 4 years from 1987 to 2021 are represented by the detail crystals d1, d2, and d3. As we used annual data, the detail crystal d3 (2-4 years cycles) rep-

resents the business cycle level. The recessions in the 1990s, 2000s, and 2008 are evident in all detail crystals within ECOWAS.

Figures 1, 2, and 3 display the MODWT for Côte d’Ivoire, Senegal, Burkina Faso, Niger, Mali, and Benin. These plots suggest a recovery from 2020 at the d3 crystal, representing 2 to 4 years cycles. However, despite the observations shown in the crystals, there is no apparent volatility transfer from d1 to d3. Interestingly, the amplitude of these cycles seems to be widening, which implies that the business cycles are becoming larger instead of longer. This finding is unexpected since the CFA Franc area is inflation-averse by design. Thus these economies should have experienced business cycle elongation.

Figure 1.1: Cycles decomposition for Côte d’Ivoire, Senegal.



The MODWT plots for Nigeria and Ghana (Figure 4), Guinea-Bissau and Sierra Leone (Figure 5), and Cabo Verde, Guinea, Gambia, and Togo (Figure 6) do not indicate any lengthening of business cycles, except for Togo. This is because the WAMZ economies do not place as much emphasis on inflation aversion or output stabilization.

The MODWT analysis reveals that Togo is the only country in the ECOWAS region where business cycles have elongated, as the volatility of longer-term cycles (d3) has increased since 2013, while the volatility of shorter-term cycles (d1 and d2) has decreased.

Figure 1.2: Cycles decomposition for Burkina Faso and Niger.

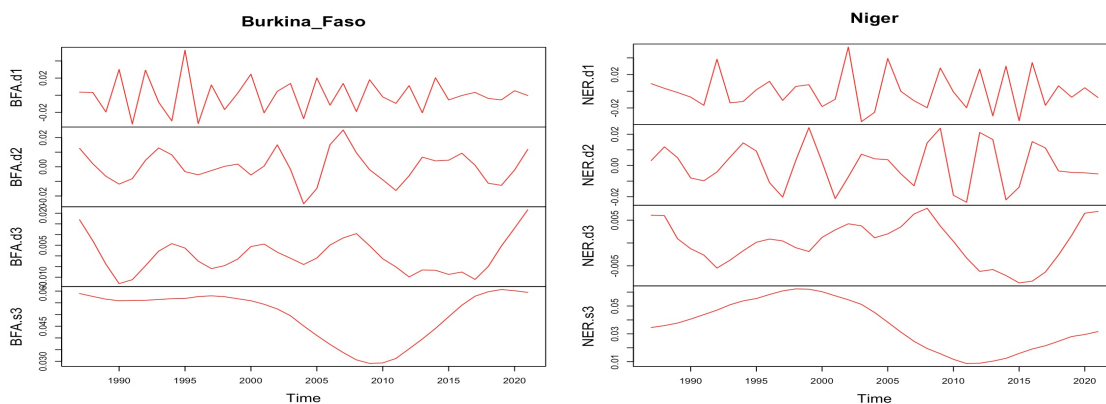


Figure 1.3: Cycles decomposition for Benin and Mali

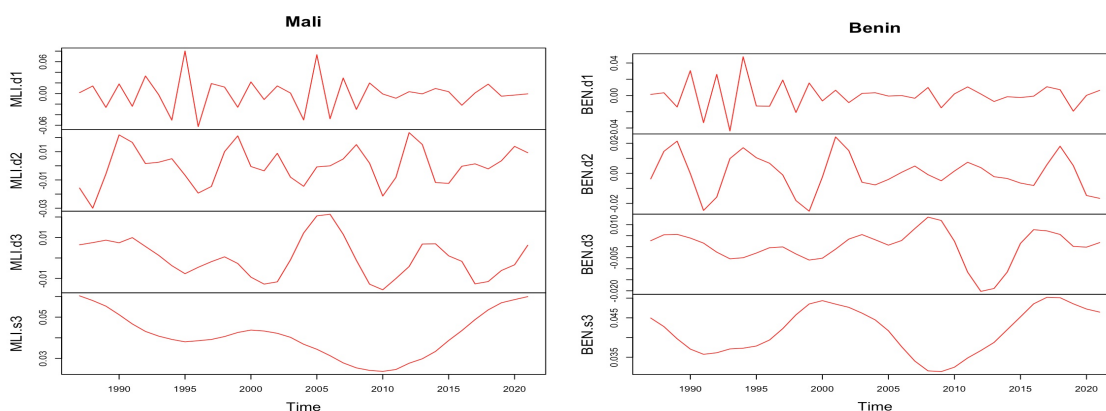
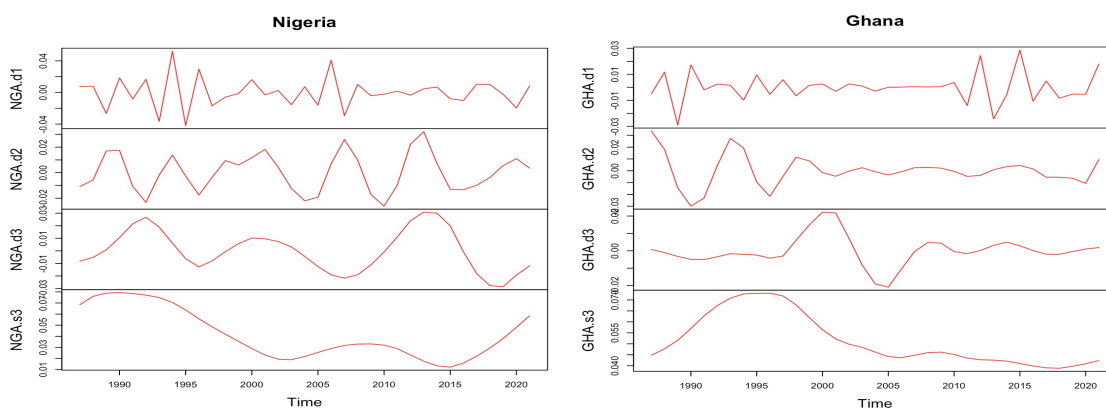
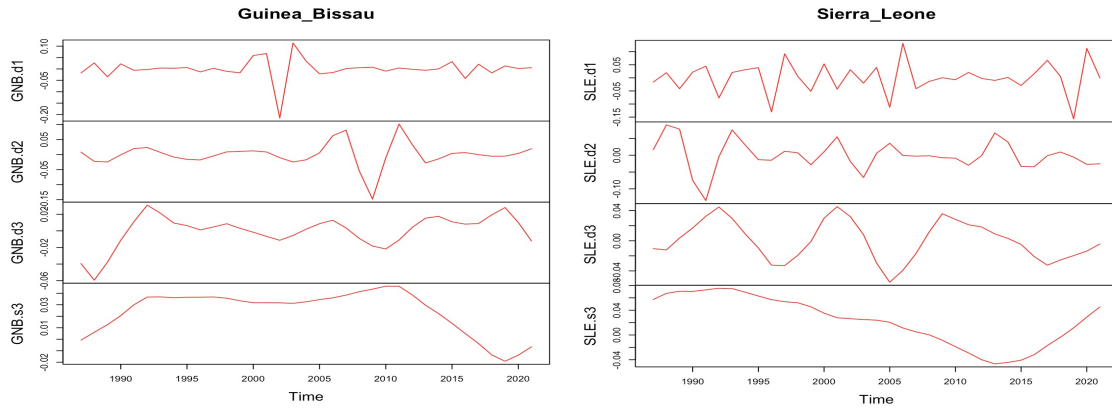


Figure 1.4: Cycles decomposition for Nigeria and Ghana.



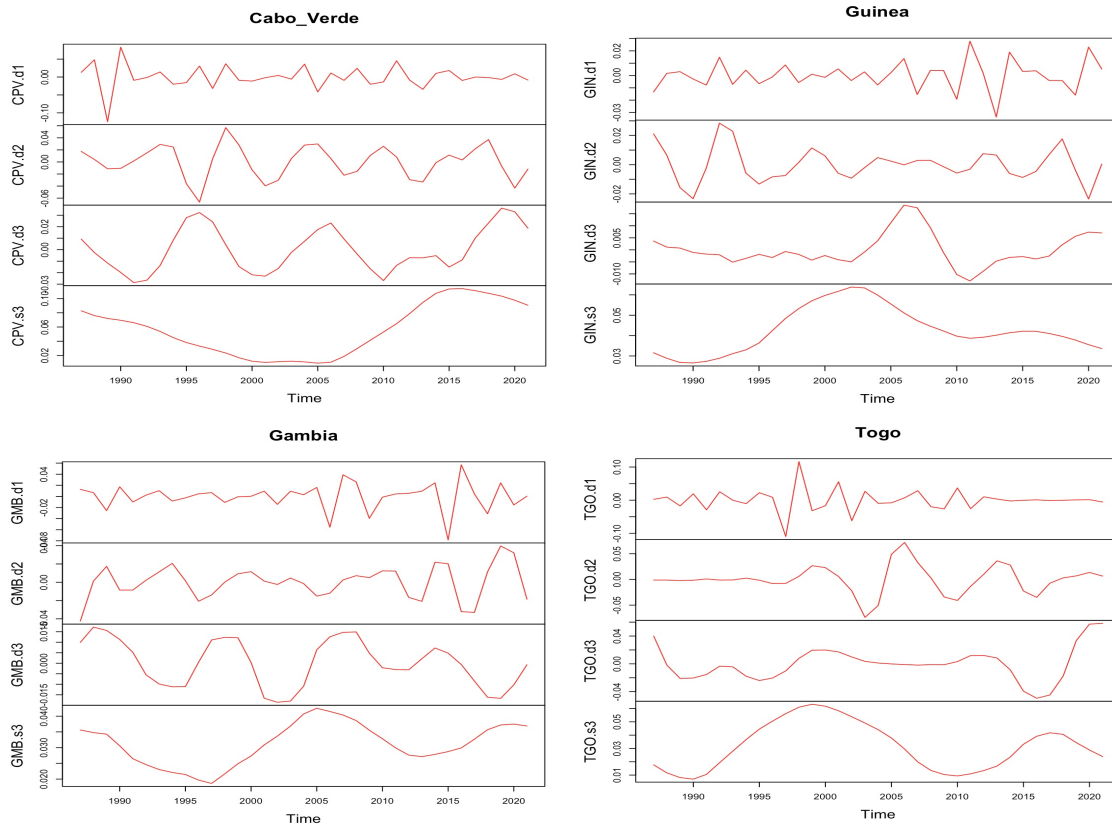
This unique case of Togo can be attributed to the country's ability to meet the convergence criteria necessary to adopt a single currency in 2020. These criteria require all ECOWAS member countries to maintain a deficit below 4% of their Gross Domestic Product, an in-

Figure 1.5: Cycles decomposition for Guinea-Bissau and Sierra Leone.



flation rate of less than 5%, and a debt-to-GDP ratio below 70%.

Figure 1.6: Cycles decomposition for Cabo Verde, Guinea, Gambia, and Togo.



Our analysis indicates that, except for Togo, there is no evidence of volatility transfer from high-frequency cycles to low-frequency ones in most ECOWAS economies. This

absence of elongated cycles contrasts with the findings of [Crowley and Hughes Hallett \(2018\)\[17\]](#), which demonstrated the presence of elongated cycles in almost all wavelet-based macroeconomic analyses. The authors showed that an increase in inflation aversion or a decrease in output stabilization efforts could lead to significant transfers of volatility, resulting in a period of "great moderation." These differences in findings may suggest that business cycles in ECOWAS have a unique experience in Africa.

As mentioned, the MODWT is limited in capturing correlations at the lowest frequency cycles due to the limited number of available data points. However, this issue is addressed by using wavelet transform coherence, which can capture correlations at all frequencies, regardless of the number of data points available.

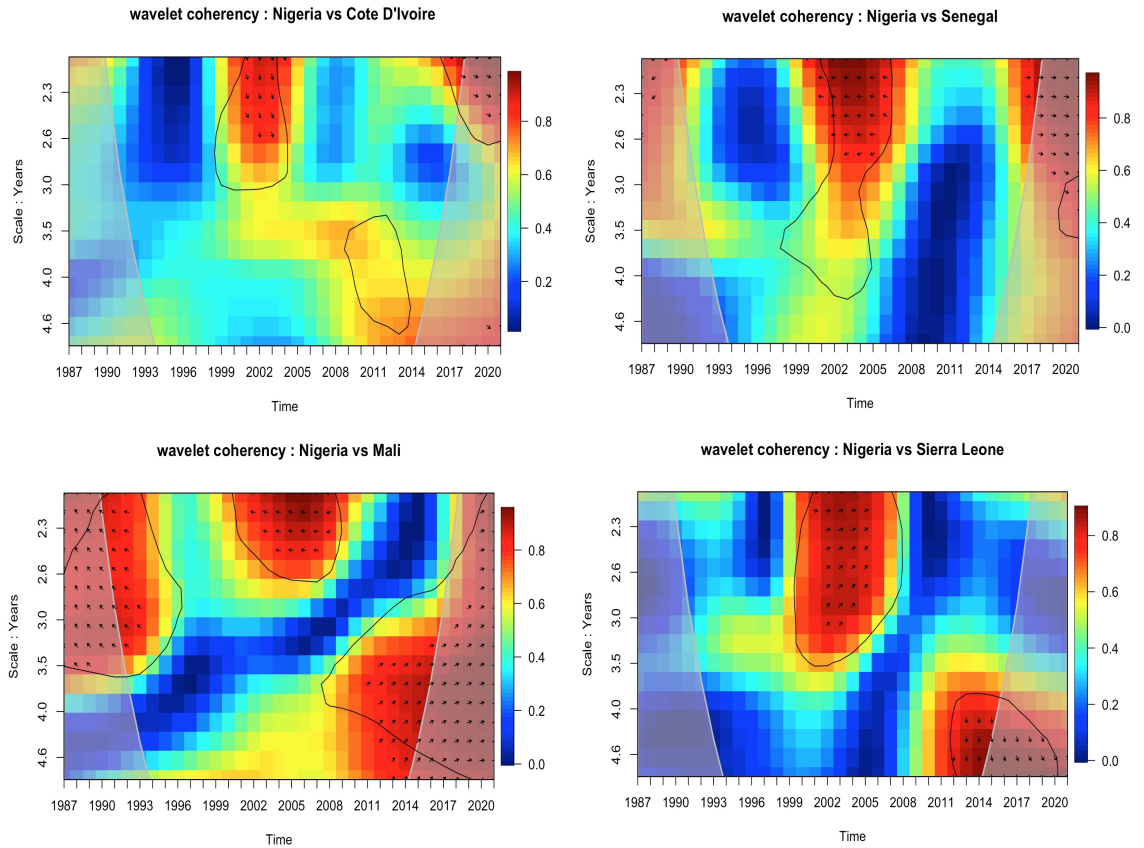
1.4.2 Results for Wavelet Coherency within ECOWAS

We use a color scheme to visually represent the degree of similarity among business cycles in the ECOWAS region. High coherence is denoted by red, while weak coherence is represented by blue. In addition, we use arrows to indicate the synchronization of business cycles at different frequencies. Right-pointing arrows show in-phase synchronization, while left-pointing arrows indicate anti-phase. Our study focuses primarily on the most prominent economies in the ECOWAS, namely Nigeria, Ghana, Côte d'Ivoire, Senegal, Gambia, Burkina Faso, and Benin. These economies accounted for around 96% of the ECOWAS GDP in 2020. Our study aims to determine the level of synchronization among these and other ECOWAS economies. We should note that our analysis has focused on the most dominant economies in the region.

Figure 7 illustrates the wavelet coherency plots for Nigeria compared to several ECOWAS countries. The plots indicate significant coherence between Nigeria and Côte d'Ivoire, Senegal, Mali, and Sierra Leone at 2 to 3-year cycle frequencies from 2000 to 2004 and mid-range frequencies with Mali from 2009 to 2015. Regarding the phasing of cycles, Nigeria is anti-phase with Mali and Senegal at high frequencies, except for Côte d'Ivoire,

where Nigeria lags in phasing.

Figure 1.7: Wavelet coherency for Nigeria

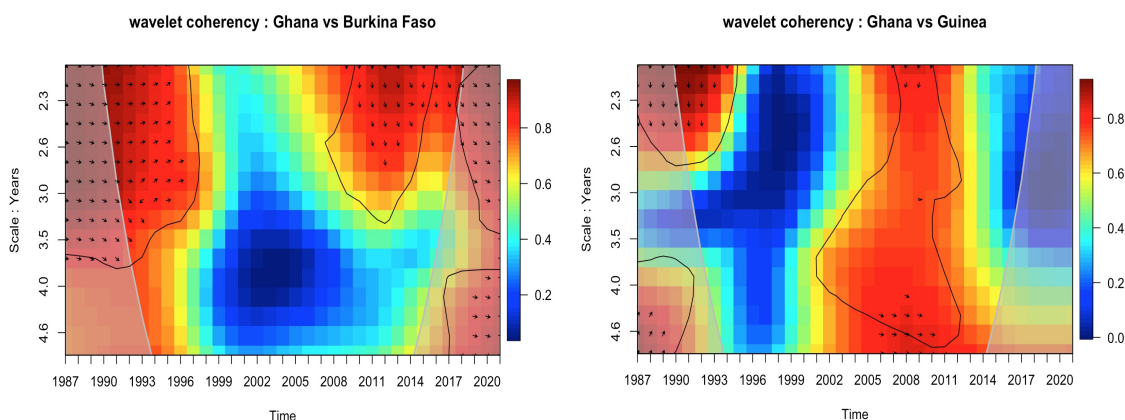


Note: Red represents high coherence, and blue represents weak coherence. The arrows show the phase between business cycles. Arrows pointing to the right (→) indicate that the two economies are in-phase, while arrows pointing to the left (←) indicate an anti-phase. In these cases, no economy leads the other. The arrows pointing right and up (↗) indicate that the first-listed economy leads the second. The arrows pointing right and down (↘) indicate that the second-listed economy leads the first. The thick black contours designate the 5% significance level against a red noise, and the thick grey line indicates the cone of influence (COI) inside, which we are assuming has accurate information.

Figure 8 presents the wavelet coherency plots for Ghana against several ECOWAS peers. The plots indicate a significant synchronization of Ghana's business cycles with Burkina Faso's cycles at up to 3.5-year cycle frequencies from 1992 to 1997 and 2010 to 2014. During the latter period, Burkina Faso leads Ghana in terms of phasing. Additionally, Ghana shows a high-frequency correlation with Guinea for a brief period between 2009 and 2011 and moderate relationships at mid-range frequencies from 2005 to 2011. However,

there is no noticeable phasing in these periods.

Figure 1.8: Wavelet coherency for Ghana

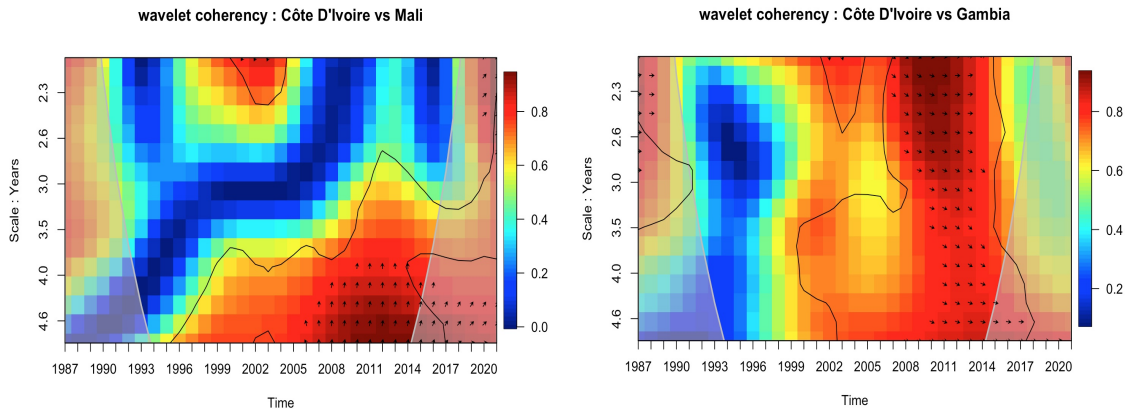


Note: Red represents high coherence, while blue represents weak coherence. The arrows show the phase between business cycles. Arrows pointing to the right (\rightarrow) indicate that the two economies are in-phase, while arrows pointing to the left (\leftarrow) indicate an anti-phase. In these cases, no economy leads the other. The arrows pointing right and up (\nearrow) indicate that the first-listed economy leads the second. The arrows pointing right and down (\searrow) indicate that the second-listed economy leads the first. The thick black contours designate the 5% significance level against a red noise, and the thick grey line indicates the cone of influence (COI) inside, which we are assuming has accurate information.

Figure 9 shows the coherency plots for Côte d'Ivoire and other ECOWAS countries. The plots reveal that Côte d'Ivoire's business cycles are synchronized with Gambia's at up to 3-year cycle frequencies from 2008 to 2015. Furthermore, the synchronization between the two countries intensifies at lower frequencies from 2003 to 2014. Gambia's cycles lead Côte d'Ivoire at all significant frequencies regarding the phasing of cycles.

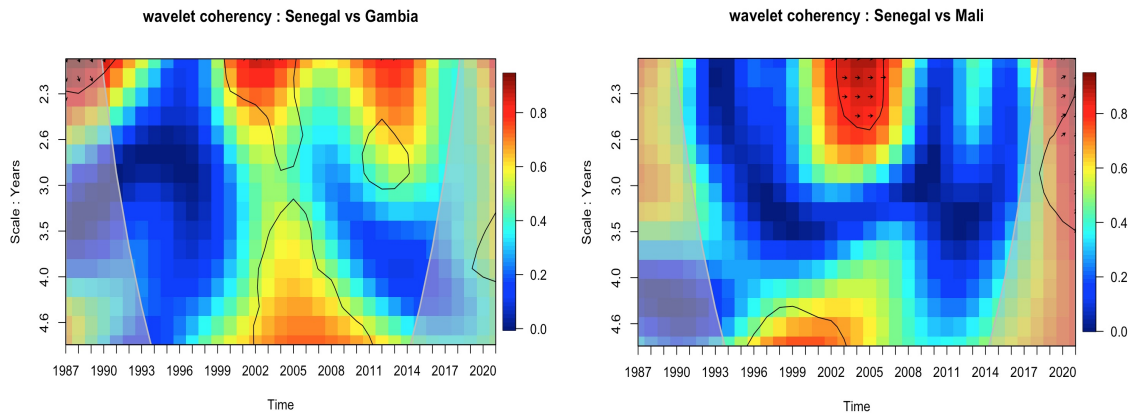
Figure 10 shows the wavelet coherency plots for Senegal against other ECOWAS countries, revealing a substantial synchronization of its business cycles with several other economies at higher frequencies. For example, Senegal led the cycles of Gambia from 2001 to 2004, synchronized with Mali's cycles from 2003 to 2005, Sierra Leone's cycles from 2001 to 2005, and Niger's cycles from 2008 to 2011. However, Senegal's cycles also display some relationship at lower frequencies with Gambia, Mali, and Sierra Leone, though

Figure 1.9: Wavelet coherency for Côte d'Ivoire



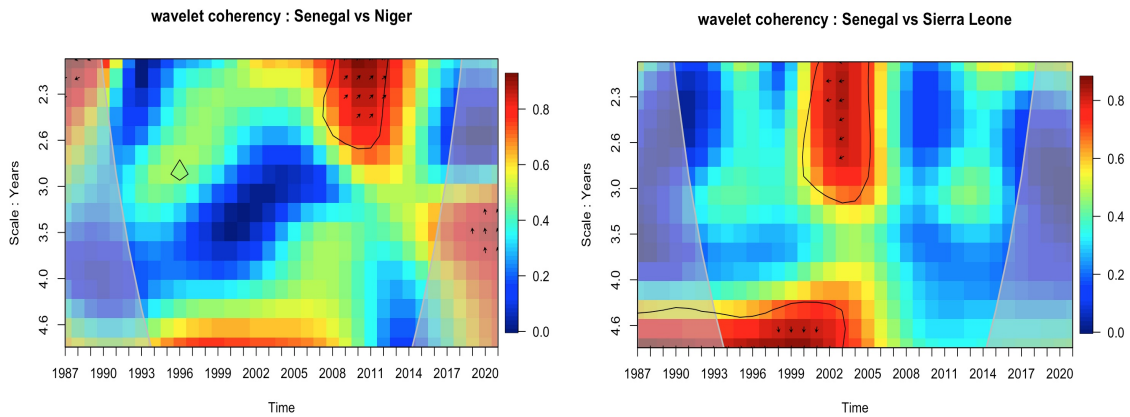
Note: Red represents high coherence, and blue represents weak coherence. The arrows show the phase between business cycles. Arrows pointing to the right (\rightarrow) indicate that the two economies are in-phase, while arrows pointing to the left (\leftarrow) indicate an anti-phase. In these cases, no economy leads the other. The arrows pointing right and up (\nearrow) indicate that the first-listed economy leads the second. The arrows pointing right and down (\searrow) indicate that the second-listed economy leads the first. The thick black contours designate the 5% significance level against a red noise, and the thick grey line indicates the cone of influence (COI) inside, which we are assuming has accurate information.

Figure 1.10: Wavelet coherency for Senegal



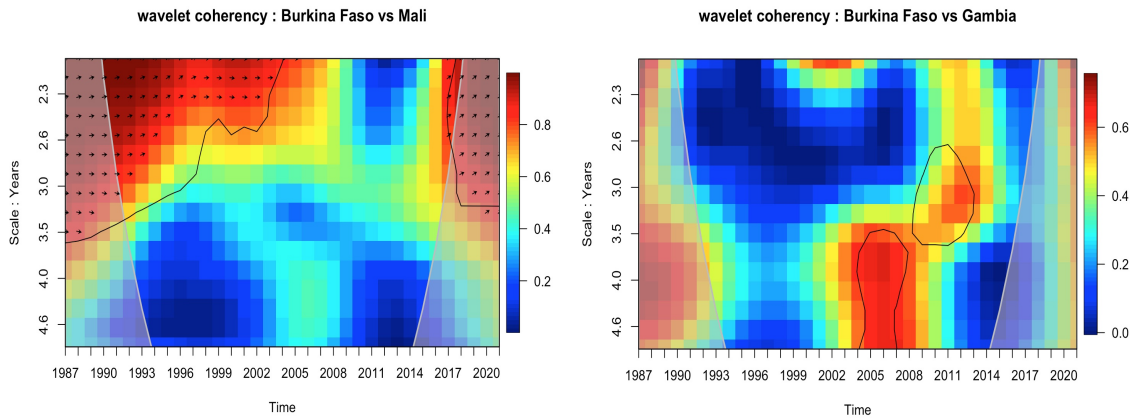
to a lesser degree.

Figure 11 presents the wavelet coherency plots for Burkina Faso against several ECOWAS countries, showing its synchronization with Mali's business cycles. Burkina Faso led Mali at 2.3-year cycles from 1991 to 2002 and showed synchronicity with Mali at 2.6-year cycles from 1992 to 1996. Additionally, from 2005 to 2007, Burkina Faso's business cycles were in phase with Gambia's at 3.5 to 4.6-year cycles.



Note: Red represents high coherence, while blue represents weak coherence. The arrows show the phase between business cycles. Arrows pointing to the right (\rightarrow) indicate that the two economies are in-phase, while arrows pointing to the left (\leftarrow) indicate an anti-phase. In these cases, no economy leads the other. The arrows pointing right and up (\nearrow) indicate that the first-listed economy leads the second. The arrows pointing right and down (\searrow) indicate that the second-listed economy leads the first. The thick black contours designate the 5% significance level against a red noise, and the thick grey line indicates the cone of influence (COI) inside, which we are assuming has accurate information.

Figure 1.11: Wavelet coherence for Burkina Faso

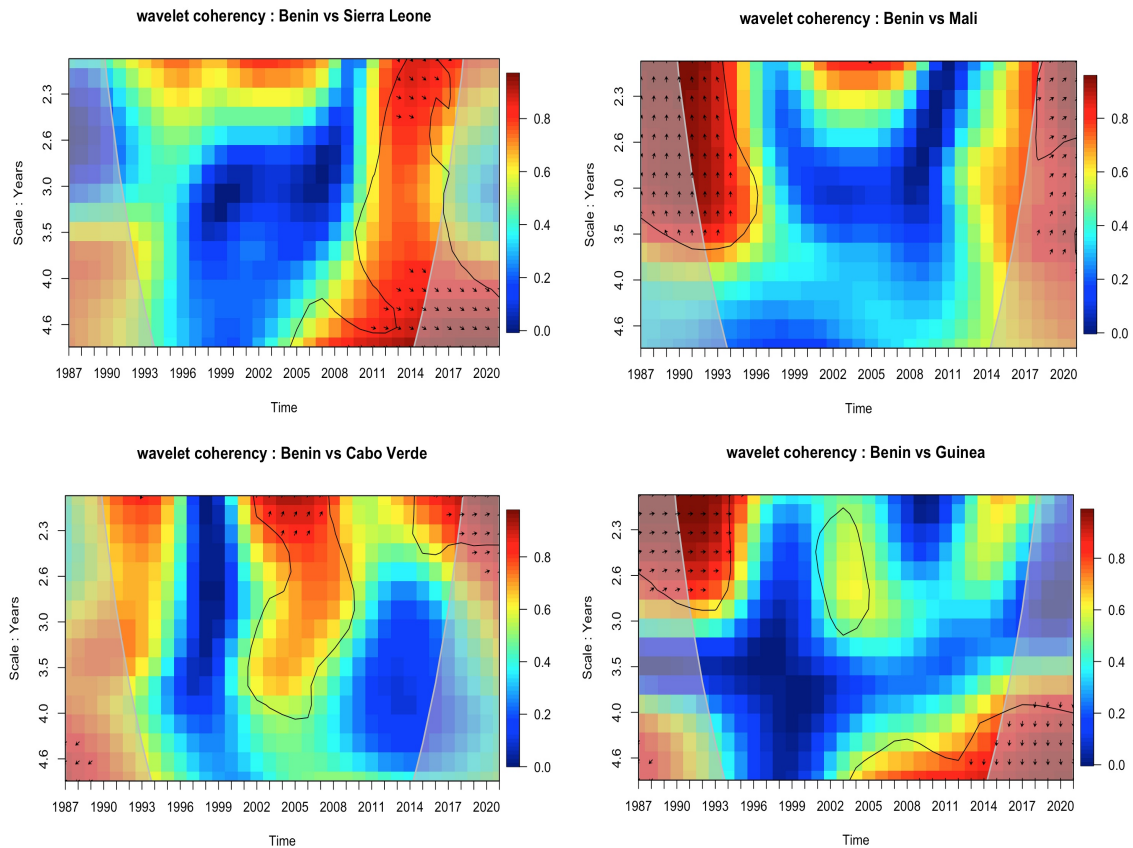


Note: Red represents high coherence, while blue represents weak coherence. The arrows show the phase between business cycles. Arrows pointing to the right (\rightarrow) indicate that the two economies are in-phase, while arrows pointing to the left (\leftarrow) indicate an anti-phase. In these cases, no economy leads the other. The arrows pointing right and up (\nearrow) indicate that the first-listed economy leads the second. The arrows pointing right and down (\searrow) indicate that the second-listed economy leads the first. The thick black contours designate the 5% significance level against a red noise, and the thick grey line indicates the cone of influence (COI) inside, which we are assuming has accurate information.

Figure 12 shows the wavelet coherence plots for Benin, illustrating the degree of synchronization of its business cycles with other ECOWAS countries. The plot indicates that Benin had significant coherence with Sierra Leone across all frequencies but only briefly

between 2013 and 2015. In addition, there was a noticeable relationship at 2 to 3.5-year cycle frequencies between 1992 and 1994 with Mali and at 2.6 years with Guinea during the same period.

Figure 1.12: Wavelet coherency for Benin

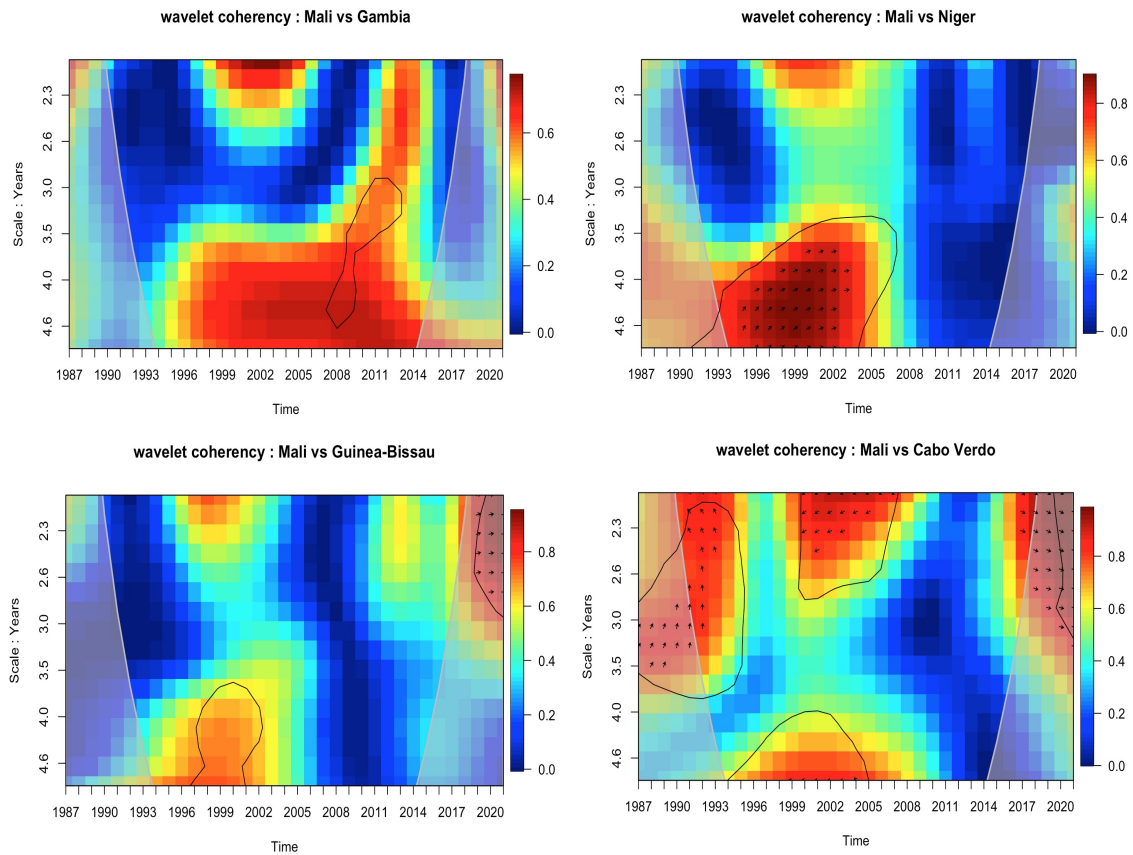


Note: Red represents high coherence, while blue represents weak coherence. The arrows show the phase between business cycles. Arrows pointing to the right (→) indicate that the two economies are in-phase, while arrows pointing to the left (←) indicate an anti-phase. In these cases, no, the economy leads the other. The arrows pointing right and up (↗) indicate that the first-listed economy leads the second. The arrows pointing right and down (↘) indicate that the second-listed economy leads the first. The thick black contours designate the 5% significance level against a red noise, and the thick grey line indicates the cone of influence (COI) inside, which we are assuming has accurate information.

In Figure 13, the wavelet coherency plot for Mali shows the degree of synchronization of its business cycle with multiple ECOWAS peers. Mali exhibited significant synchronization with Cabo Verde at higher frequencies (2 to 3 years cycles) between 1991 and 1993 and 2000 and 2007. The strongest coherence was observed at a frequency of 3.8 years

cycles and above with Niger's business cycles. Mali also demonstrated weaker but statistically significant coherence with Guinea-Bissau between 1999 and 2000, at 4.5 to 5 years cycles.

Figure 1.13: Wavelet coherency for Mali



Note: Red represents high coherence, and blue represents weak coherence. The arrows show the phase between business cycles. Arrows pointing to the right (\rightarrow) indicate that the two economies are in-phase, while arrows pointing to the left (\leftarrow) indicate an anti-phase. In these cases, no economy leads the other. The arrows pointing right and up (\nearrow) indicate that the first-listed economy leads the second. The arrows pointing right and down (\searrow) indicate that the second-listed economy leads the first. The thick black contours designate the 5% significance level against a red noise, and the thick grey line indicates the cone of influence (COI) inside, which we are assuming has accurate information.

Our analysis has identified 12 economies with synchronized business cycles, which we will refer to as Eco-12. These economies are in the ECOWAS zone and could form a common currency union. The Eco-12 is made up of subgroups with interconnected business cycles. Specifically, we found that

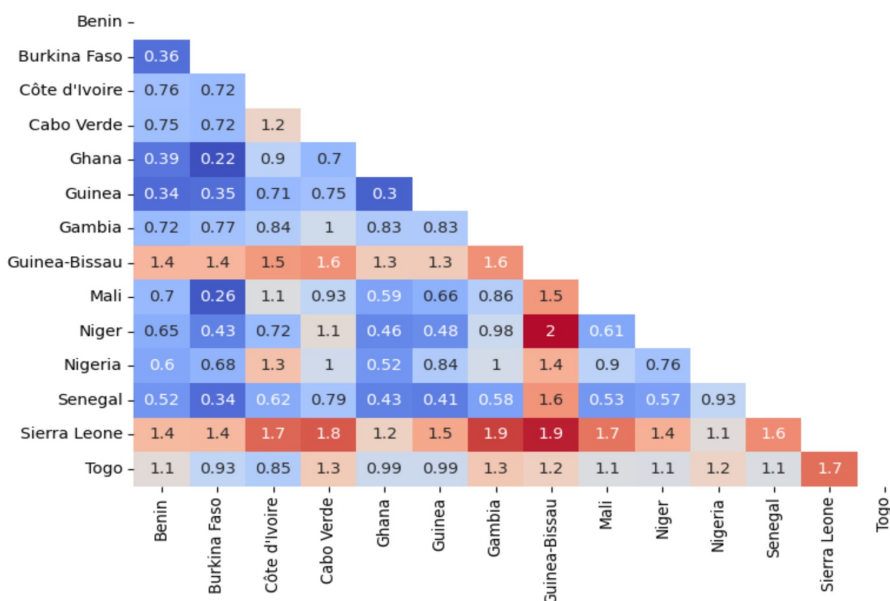
- Mali and Nigeria have synchronized business cycles and are in phase with Senegal. Senegal is also connected to several other economies, including Niger and Sierra Leone.
- In addition, Ghana is significantly linked with Burkina Faso and is synchronized with Gambia.
- Finally, Côte d'Ivoire is linked to the Gambia, synchronized with Burkina Faso and Senegal.

The Eco-12 includes the following countries: Benin, Burkina Faso, Côte d'Ivoire, Mali, Niger, Senegal, Togo, Ghana, Nigeria, Gambia, Guinea, and Cabo Verde. Based on our criteria for an optimum currency area, we suggest that several WAMZ economies, such as Ghana, Guinea, and Nigeria, could join the established CFA Franc area of the WAEMU member states and adopt a single currency. We employed wavelet coherence analysis to evaluate the strength and direction of relationships between business cycles across various frequencies. However, this method does not directly reveal which cycles are the most similar or dissimilar across these frequencies. Consequently, we used cluster analysis to identify cycles that move together.

1.5 ECOWAS Business cycle Clustering

Economists use cluster analysis to group and differentiate similar observations from dissimilar ones. The process involves creating distinct clusters that contain similar observations. Clustering can be performed through crisp clustering, which assigns each observation to a unique cluster, or soft clustering, which assigns observations to multiple clusters to varying degrees. In previous studies, such as [Tsangarides and Qureshi \(2008\) \[41\]](#), cluster analysis has been employed to analyze ECOWAS data. To accomplish this, a distance matrix is created by calculating the Euclidean distance between all pairs of business cycles.

Figure 1.14: Distance matrix for ECOWAS business cycles



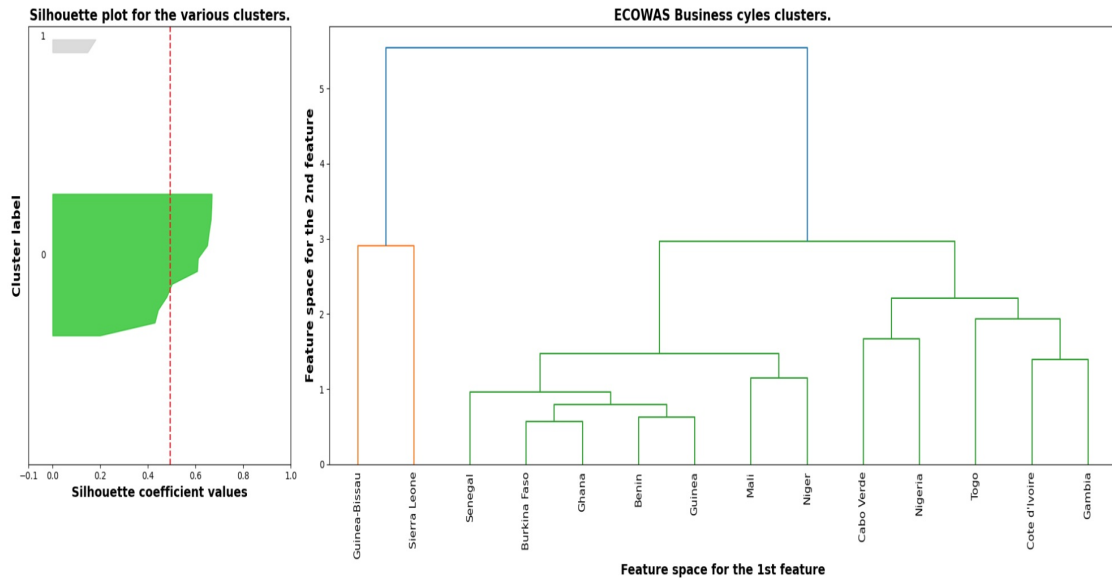
Note: The red color represents high coherency, and the blue represents weak coherency.

This distance matrix serves as a measure of dissimilarity and guides the clustering process.

We conducted a hierarchical clustering analysis with hard partitioning to identify which countries in ECOWAS are best suited to adopt a single currency and determine if a core business cycle exists. This approach entails dividing the data into a series of partitions based on similarities in the distance matrix. We utilized the "Agglomerative" method for hierarchical clustering. By employing cluster analysis, we can determine which countries are best suited to join a single currency by identifying clusters with similar business cycles.

To assess the quality of the clusters, we employed the silhouette score, a metric that measures how well a data point fits into its assigned cluster compared to other clusters. The silhouette score ranges from -1 to 1 , where a score of -1 indicates that the data point is incorrectly assigned to a cluster, and a score of 0 suggests that it is equally similar to two clusters. Conversely, a score of 1 implies that it is well-suited to its assigned cluster and poorly matched with other clusters.

Figure 1.15: ECOWAS Business cycles clusters



Note: All distances between business cycles within ECOWAS.

Table 1.2: Silhouette score for cycles clusters

Number of clusters	Silhouette score	Calinski Harabasz score	Davies Bouldin score
2	0.51	10.18	0.72
3	0.23	7.91	1.31
4	0.22	8.37	0.92

The silhouette score quantifies how well an object corresponds to its assigned cluster relative to other clusters, ranging from -1 to 1. A score of -1 indicates a poor fit, 0 implies the object is on the boundary between two clusters, and 1 indicates a strong fit. High silhouette scores indicate well-defined clusters. In contrast, the Davies-Bouldin score gauges the compactness of the clusters. A low score indicates tightly packed and well-separated clusters, while a high score suggests overlapping and spread-out clusters. If two clusters have a similar silhouette and Davies-Bouldin scores, the Calinski-Harabasz score can determine the superior set. This score is determined by the ratio of between-cluster variance to within-cluster variance, with a higher score indicating well-defined clusters.

Our clustering study has effectively distinguished between the business cycles of

ECOWAS member states using two clusters. This approach identified a primary group of 12 business cycles, known as the "Eco-12." Within the Eco-12 group, we found that the business cycles of Côte d'Ivoire and Togo, which belong to the CFA Franc area (WAEMU area), strongly synchronize with Cabo Verde, Gambia, and Nigeria, which belong to the West African Monetary Zone (WAMZ). In contrast, most of the economies in the CFA Franc area, including Benin, Burkina Faso, Mali, Niger, and Senegal, were primarily synchronized with several economies in the WAMZ region, such as Ghana and Guinea. Therefore, identifying the main group of 12 business cycles can provide insights into the clustering patterns of inflation within ECOWAS member states. This information can then inform the criteria analysis for the optimum currency area.

1.5.1 ECOWAS inflation Clustering

We analyzed inflation clustering in ECOWAS and found that similar to our business cycle analysis, using two clusters is the most effective way to distinguish inflation series. First, WAEMU member states, which share a common currency and have an official inflation target of 3%, are clustered with several non-WAEMU economies in the WAMZ region, including Cabo Verde and Guinea-Bissau. In contrast, the second cluster consists of high-inflation economies such as Ghana (9.89% in 2020) and Nigeria (13.25% in 2020), along with Sierra Leone (13% in 2020) and Guinea (10.60% in 2020). Identifying these inflation clusters can provide insights into the effectiveness of the monetary policy regimes in the region and inform the analysis of the optimum currency area criteria.

Table 1.3: Silhouette score for inflation clusters

Number of clusters	Silhouette score	Calinski Harabasz score	Davies Bouldin score
2	0.62	31.54	0.44
3	0.40	26.43	0.84
4	0.38	26.92	0.69

Figure 1.16: Distance matrix for inflation

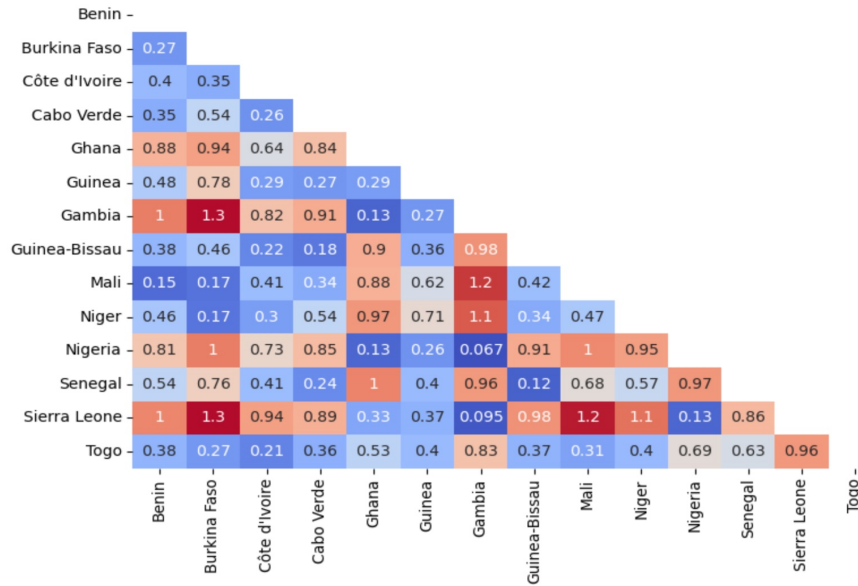
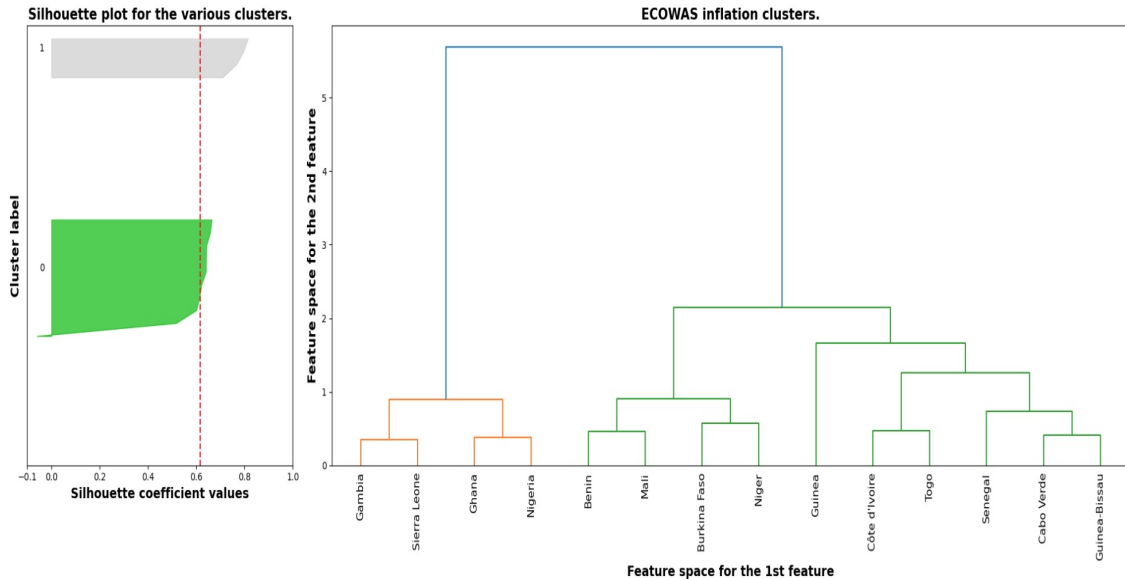


Figure 1.17: Inflation clustering



Our analysis of inflation clustering in the Economic Community of West African States (ECOWAS) revealed that key member states of the West African Monetary Zone (WAMZ), including Ghana, Nigeria, Sierra Leone, and the Gambia, exhibit similar inflation patterns. Additionally, certain WAMZ economies, such as Guinea-Bissau and Cabo Verde, exhibit similar inflation patterns to member states of the CFA Franc zone, which has

committed to maintaining an inflation target of 3%. We can attribute this similarity to the fact that the former countries have consistently kept their inflation rates below 10% over the past two decades.

1.6 Discussion and Conclusion

We used the Maximum Overlap Discrete Wavelet Transform approach to analyze the decomposition of ECOWAS business cycles and the continuous Morlet wavelet analysis to investigate the co-movements of regional business cycles. We also conducted a clustering analysis to determine which business cycles exhibit similar or dissimilar patterns across different frequencies. Given the significant economic disparities, we aimed to provide insights into the potential emergence of a currency union in the ECOWAS region.

The wavelet coherence analysis provides information about the strength and direction of relationships between business cycles at different frequencies. However, it does not indicate which cycles are most similar or dissimilar. Our multi-resolution decomposition reveals that, except for Togo, there needs to be more evidence of business cycle elongation in the ECOWAS region. This finding suggests that while low inflation rates indicate stable business cycles, other factors, such as fiscal policies and external shocks, must also be considered when analyzing the relationship between inflation and business cycles. We have identified a group of twelve countries called Eco-12, which could form a common currency zone within the ECOWAS region. This group consists of five countries from the WAMZ (Cabo Verde, Ghana, Gambia, Guinea, and Nigeria) and seven economies from WAEMU (CFA Franc area), namely Benin, Burkina Faso, Côte d'Ivoire, Mali, Niger, Senegal, and Togo. However, our analysis suggests integrating inflation-averse economies with high-inflation economies in a currency area which may pose considerable challenges.

One of the main challenges in creating a currency area with a combination of inflation-averse and high-inflation economies is the potential for conflicts in monetary policy. Low-inflation economies prioritize low inflation and may sacrifice some economic growth to

achieve this goal. On the other hand, high-inflation economies may prioritize economic growth and job creation over inflation control. Therefore, when these economies are combined, disagreements about the appropriate level of inflation and how to achieve it may arise. When the central bank has limited independence from political pressures, accommodating the preferences of high-inflation economies at the expense of the low-inflation ones can result in a problematic situation. Specifically, the largest economies in the region, Nigeria and Ghana, may exert pressure on the central bank leading to higher inflation and lower economic growth for WAEMU member states. In this scenario, maintaining an independent monetary policy would likely have yielded better outcomes for these member states.

Another issue in forming a common currency area is the potential for asymmetric shocks, which can affect some economies more severely than others. For instance, high-inflation economies may be more vulnerable to negative shocks than low-inflation economies. In such situations, the former may advocate for a more relaxed monetary policy to stimulate growth, while the latter may resist such measures to avoid potential inflationary effects. While this study focuses on the ongoing debate about the proposed single currency, "Eco," in the ECOWAS region, it highlights the need for further research on business cycle synchronization in the region. Future studies could explore synchronization patterns by separating amplitude and phase information, enabling better assessment of responses to a common stabilization policy. Additionally, more research is required to fully comprehend the drivers of business cycle synchronization in the region and design an effective currency union considering these complex dynamics.

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Appendices

Appendix A: Discrete Wavelet Transform

Although the uncertainty principle does not allow to specify both the position and the amplitude, [Meyer, 1985](#) defines an intermediate representation from an orthonormal base in Hilbert's space ($L^2(R)$) and proposes the following wavelet function :

$$\psi_{j,k}(t) = 2^{j/2}\psi(2^j t - k) \quad j, k \in Z \quad (11)$$

Here, the continuous variables **a** and **b** are replaced by relative integers **j** and **k**. Assuming that $a = k2^{-j}$ and $b = 2^{-j}$, the scaling factor is multiplied or divided by two at each scale change so that the WT does not produce a huge amount of data. This is the so-called Discrete Wavelet Transform (DWT) written as follows in [Gallegati and Gallegati \(2007\)](#):

$$\psi(J, k) = 2^{-J/2}\psi\left(\frac{t - 2^J k}{2^J}\right) \quad (12)$$

where $j = 1, \dots, J$ in J-level wavelet decomposition and J represents the scale index and k is the wavelet transform signal index. The authors define the wavelet representation of the discrete signal $f(t)$ in $L^2(R)$ as:

$$f(t) = \sum_k s_{J,k}\Phi_{J,k}(t) + \sum_k d_{J,k}\Psi_{J,k}(t) + \dots + \sum_k d_{j,k}\Psi_{j,k}(t) + \dots + \sum_k d_{1,k}\Psi_{1,k}(t) \quad (13)$$

here, $J = 1, 2, \dots, J$ represents the number of scales and k ranges from 1 to the number of specified scales. The coefficients $d_{j,k}$ and $s_{J,k}$ of the wavelet in [equation 5](#) above represent the details and smooth wavelet transform coefficients respectively. The smooth wavelet transforms coefficient $s_{J,k}$ represents the underlying smooth behavior of the data at the largest scale. The details coefficients $d_{1,k}, \dots, d_{j,k}, \dots, d_{J,k}$ instead, captures the deviations from the smooth behaviour. Thus, the decomposition of the original signal $f(t)$ can be written as :

$$f(t) = S_J + D_J + D_{J-1} + \dots + D_j + \dots + D_1 \quad (14)$$

with $S_J = \sum_k s_{J,k} \Phi_{J,k}(t)$ and $D_j = \sum_k d_{j,k} \Psi_{j,k}(t)$, where $j = 1, \dots, J$. The terms $S_J, D_J, \dots, D_j, \dots, D_1$ are the source of the signals at the different resolution levels 1 to J , and the detail signals D_j generate additions at each scale.

Appendix B: Wavelet multi resolution decomposition

Since we are assuming that a average overall business cycles is about five and half years, the decomposition of the GDP series does not span beyond a decade. We follow Gallegati and Gallegati (2007) to perform a j-level decomposition of GDP series for the ECOWAS economies using the maximum overlap discrete wavelet transform (MODWT). The decomposition levels from 164 quarterly GDP observations.

Table 4: Result of multi resolution decomposition.

Scale	Period	Corresponding frequency
d1	2-4 weeks	high frequency/short run
d2	4-8 weeks	short term
d3	8-16 weeks	Medium term
d4	16-32 weeks	low frequency/Business cycle level

Note: TheThe first wavelet scale (d_1) corresponds to 2 to 4 quarters period dynamics and the scales (d_2), (d_3) and (d_4) correspond to 4 to 8, 8 to 16 and 16 to 32 quarters periods respectively. The lower the period, the higher the frequency.

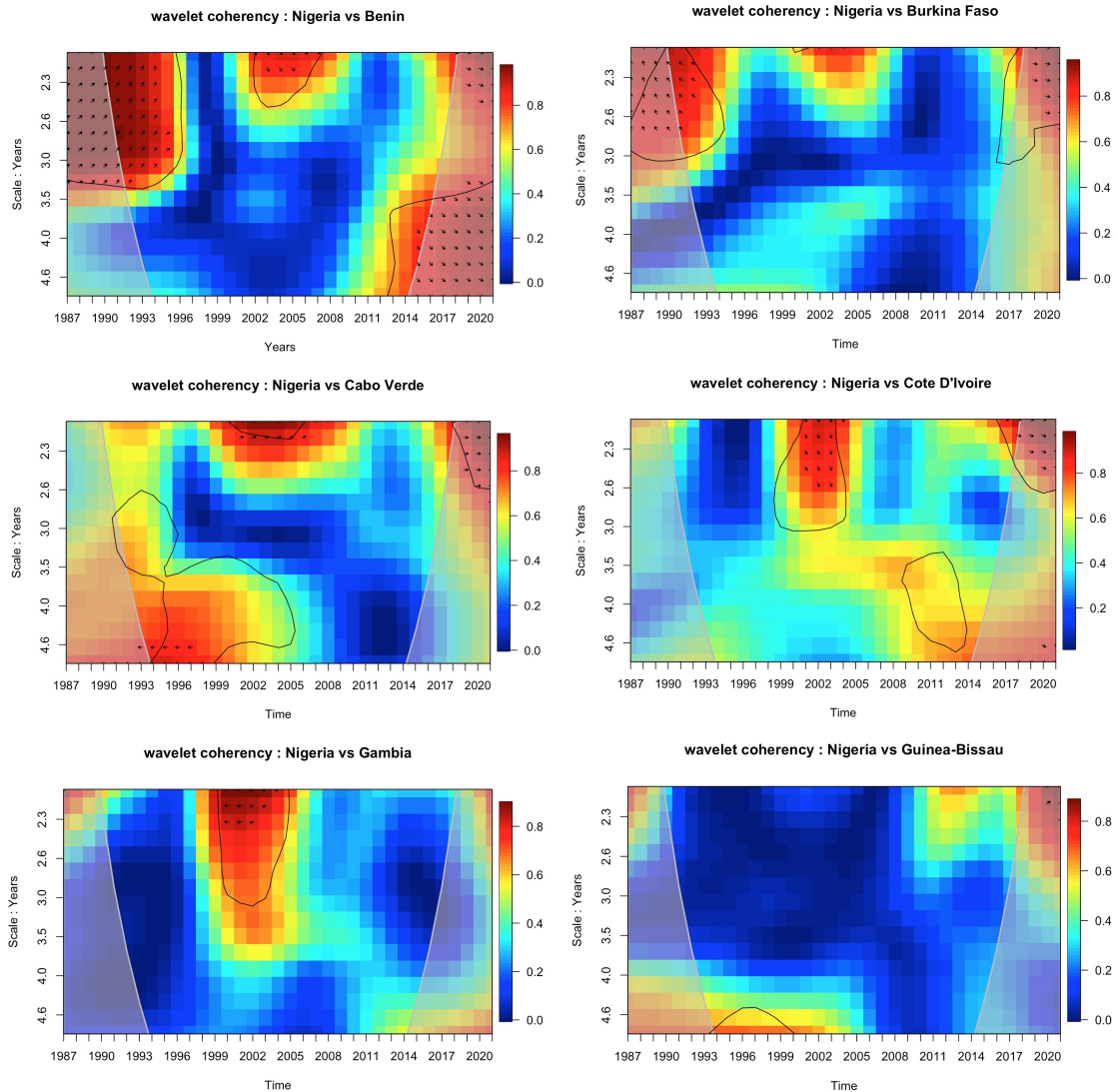
Appendix C: Business Cycles synchronization within the ECOWAS economies

Twelve (12) country-led pairwise coherency figures are shown for each ECOWAS member country. This is the full detail of phase directions, lead-lag position of the business cycle of each country versus their peers within the ECOWAS.

Figures **18** and **18** depict the synchronization of the **Nigerian** economy with its Ecowas peers. At the business cycle level, the Nigerian economy shows significant comovement with Ghana, which briefly led the former from 1997 to 1999. This period corresponds to the 1990 military coup attempt and starting of conflict in the Niger Delta. Nigeria regains the power to lead the region's second-largest economy in the 2000s. When a significant relationship occurs at the business cycle level, Nigeria experienced relatively strong relationships with WAEMU economies, including Mali and Togo. While no direction was noticed in its relation with Togo, Nigeria generally led Mali. We also find evidence of a stable common cycle in the later part of the sample with Cabo-Verde from 2008, Niger from 1995, Burkina Faso from 2004, and Benin and Gambia from 2005, respectively, respectively Cote d'Ivoire from 2006, and Senegal from 2005.

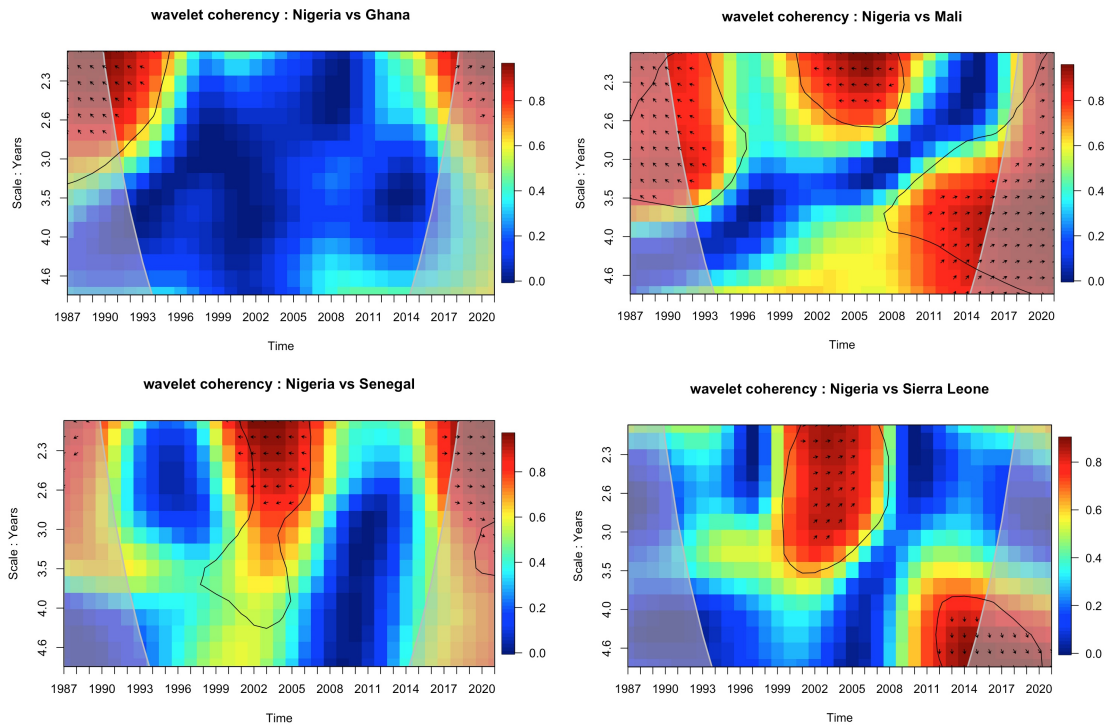
Figure **20** shows strong comovements between **Ghana** and several WAEMU members, including Benin, Burkina Faso, Mali, and Senegal. While Benin, Mali, and Senegal enjoyed the leading position most of the time over Ghana, the latter led Cabo-Verde most of the time. Indeed, the Ghanaian economy was underperforming its WAEMU peers from the 1990s until 2007, according to World Bank data. Later in the sample, Ghana shows a comovement with Ivory Coast, Niger, and Togo.

Figure 18: Nigeria led pairwise Wavelet coherency (1)



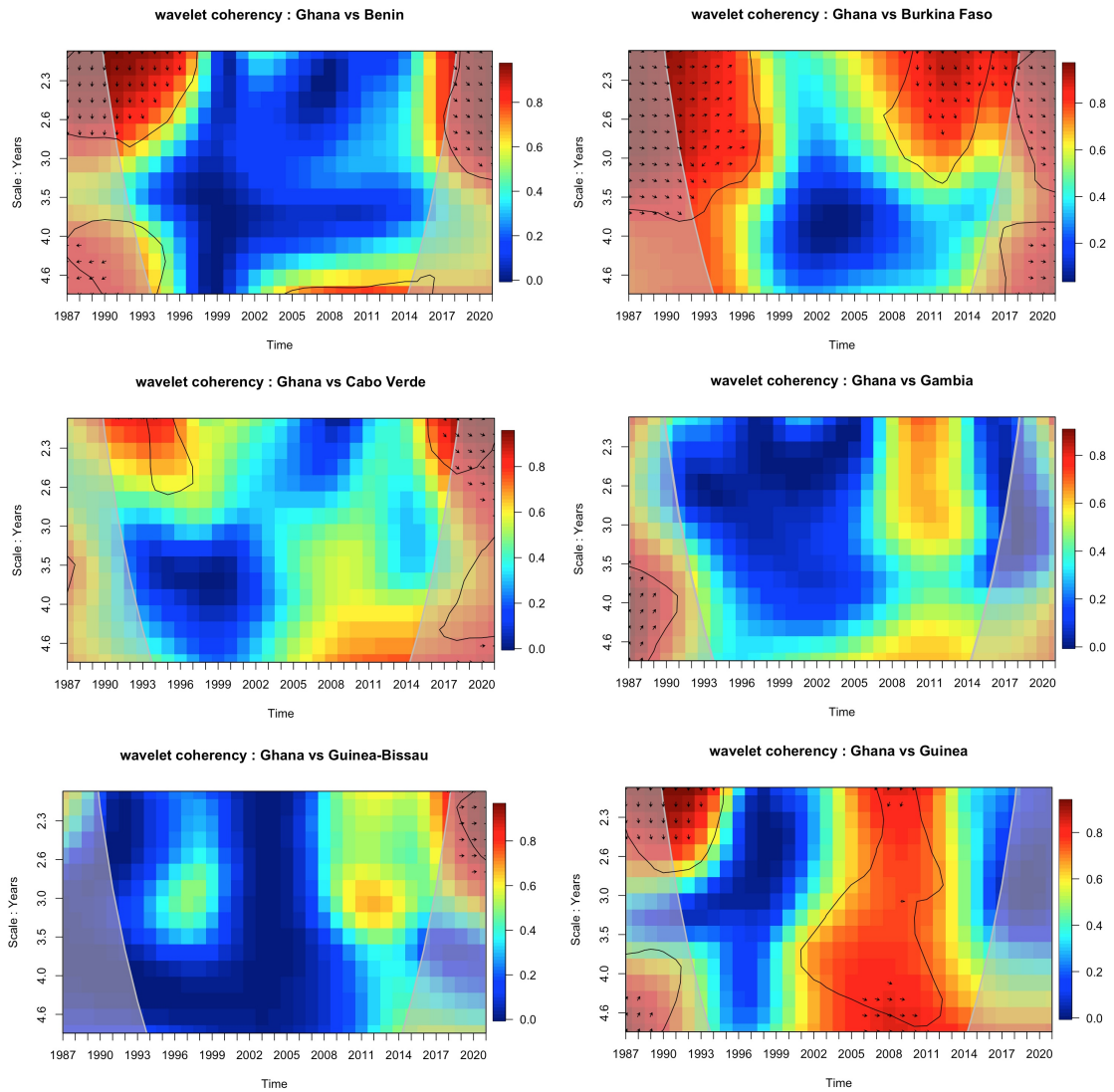
Note: Red represents high coherency, and blue represents weak coherency. The arrows pointing to the right (\rightarrow) indicate that the two economies are in-phase, while arrows pointing to the left (\leftarrow) indicate an anti-phase. In these cases, no economy leads the other. The arrows pointing right and up (\nearrow) indicate that the first-listed economy leads the second. The arrows pointing right and down (\searrow) indicate that the second-listed economy leads the first. The thick black contours designate the 5% significance level against a red noise, and the thick white line indicates the cone of influence (COI) inside, assuming we have accurate information.

Figure 19: Nigeria led pairwise Wavelet coherency (2)



Note: Red represents high coherency, and blue represents weak coherency. The arrows pointing to the right (→) indicate that the two economies are in-phase, while arrows pointing to the left (←) indicate an anti-phase. In these cases, no economy leads the other. The arrows pointing right and up (↗) indicate that the first-listed economy leads the second. The arrows pointing right and down (↘) indicate that the second-listed economy leads the first. The thick black contours designate the 5% significance level against a red noise, and the thick white line indicates the cone of influence (COI) inside, assuming we have accurate information.

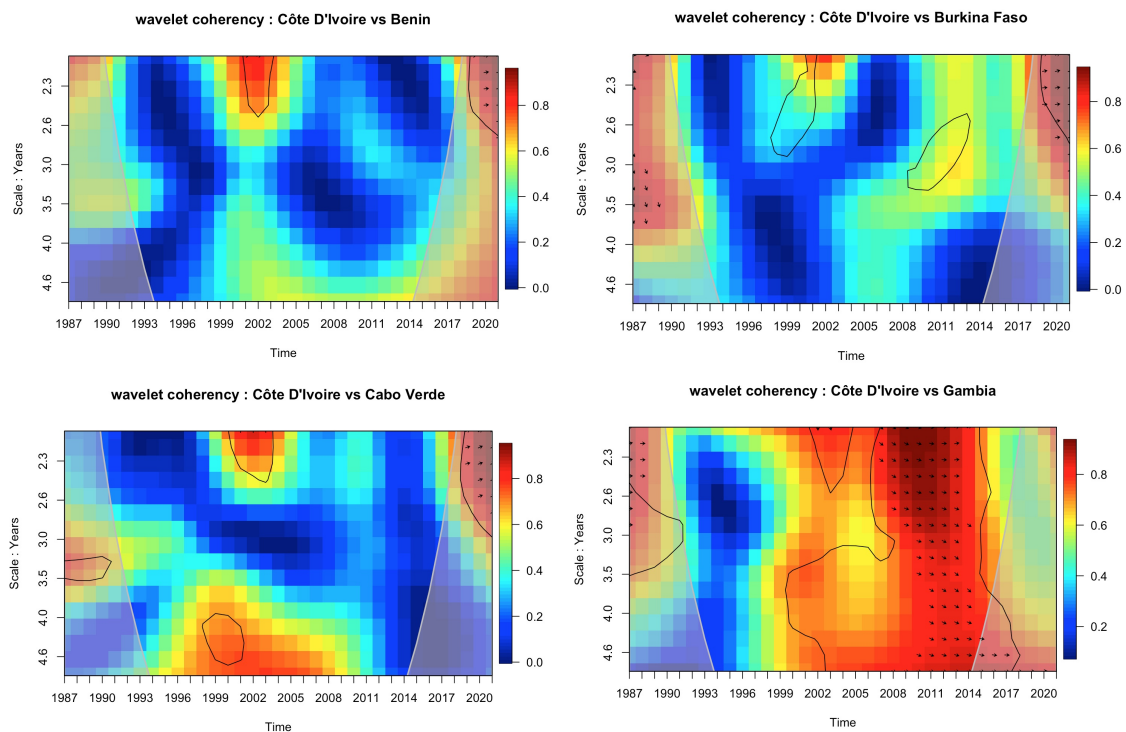
Figure 20: Ghana led pairwise Wavelet coherency (1)



Note: Red represents high coherency, and blue represents weak coherency. The arrows pointing to the right (\rightarrow) indicate that the two economies are in-phase, while arrows pointing to the left (\leftarrow) indicate an anti-phase. In these cases, no economy leads the other. The arrows pointing right and up (\nearrow) indicate that the first-listed economy leads the second. The arrows pointing right and down (\searrow) indicate that the second-listed economy leads the first. The thick black contours designate the 5% significance level against a red noise, and the thick white line indicates the cone of influence (COI) inside, assuming we have accurate information.

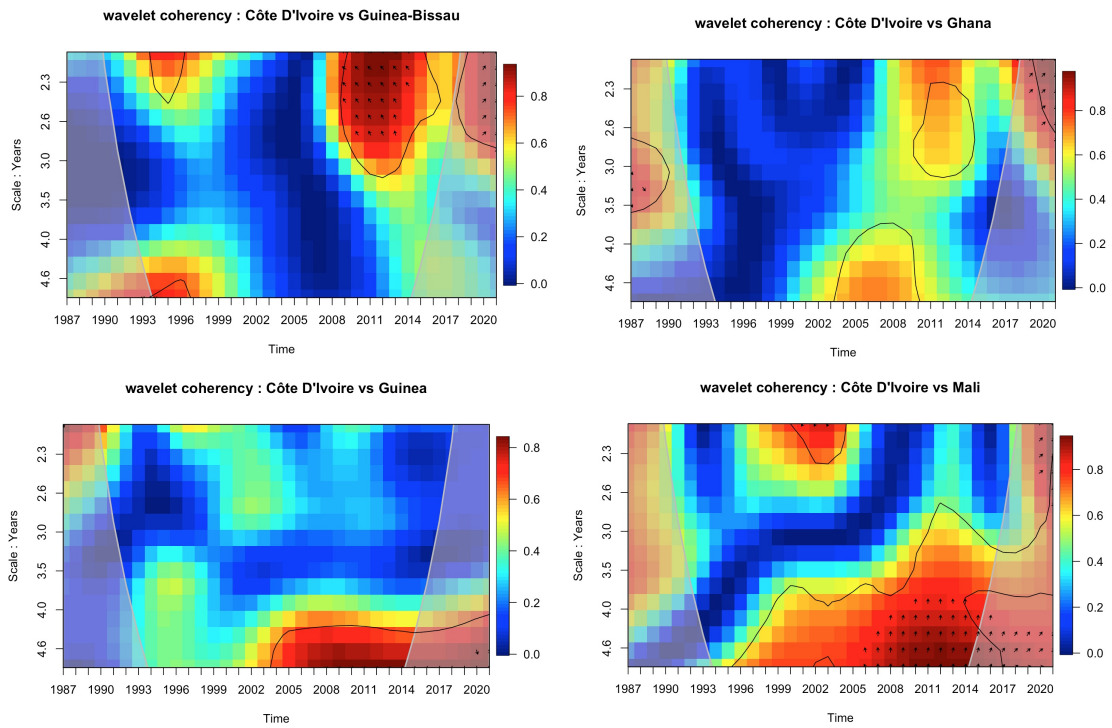
Figures 21 and 22 reveal that in Côte d'Ivoire, when significant coherency occurs mainly in the late part of the sample, the country experiences a relatively good synchronization with its ECOWAS peers. Notably, Côte d'Ivoire led several economies, including Benin in 2008, Burkina Faso in 2001, Niger in 2005, Senegal in 2001, and Cabo Verde in 2005. However, Côte d'Ivoire's economy shaded the leading position to Mali in 2008, Gambia in 2004, and Nigeria in 2008. Overall, the business cycles of Ivory Coast exhibits relatively poor relationship with its peers. This can be associated with the pressure due to political unrest in the country from 1990 with a civil war for a decade from 2002.

Figure 21: Côte d'Ivoire led pairwise Wavelet coherency (1)



Note: Red represents high coherency, and blue represents weak coherency. The arrows pointing to the right (\rightarrow) indicate that the two economies are in-phase, while arrows pointing to the left (\leftarrow) indicate an anti-phase. In these cases, no economy leads the other. The arrows pointing right and up (\nearrow) indicate that the first-listed economy leads the second. The arrows pointing right and down (\searrow) indicate that the second-listed economy leads the first. The thick black contours designate the 5% significance level against a red noise, and the thick white line indicates the cone of influence (COI) inside, assuming we have accurate information.

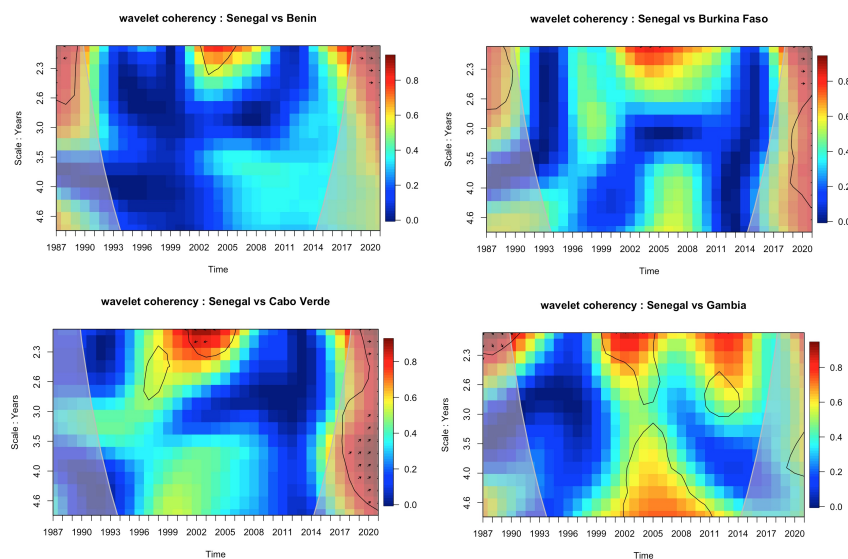
Figure 22: Côte d'Ivoire led pairwise Wavelet coherency (2)



Note: Red represents high coherency, and blue represents weak coherency. The arrows pointing to the right (\rightarrow) indicate that the two economies are in-phase, while arrows pointing to the left (\leftarrow) indicate an anti-phase. In these cases, no economy leads the other. The arrows pointing right and up (\nearrow) indicate that the first-listed economy leads the second. The arrows pointing right and down (\searrow) indicate that the second-listed economy leads the first. The thick black contours designate the 5% significance level against a red noise, and the thick white line indicates the cone of influence (COI) inside, assuming we have accurate information.

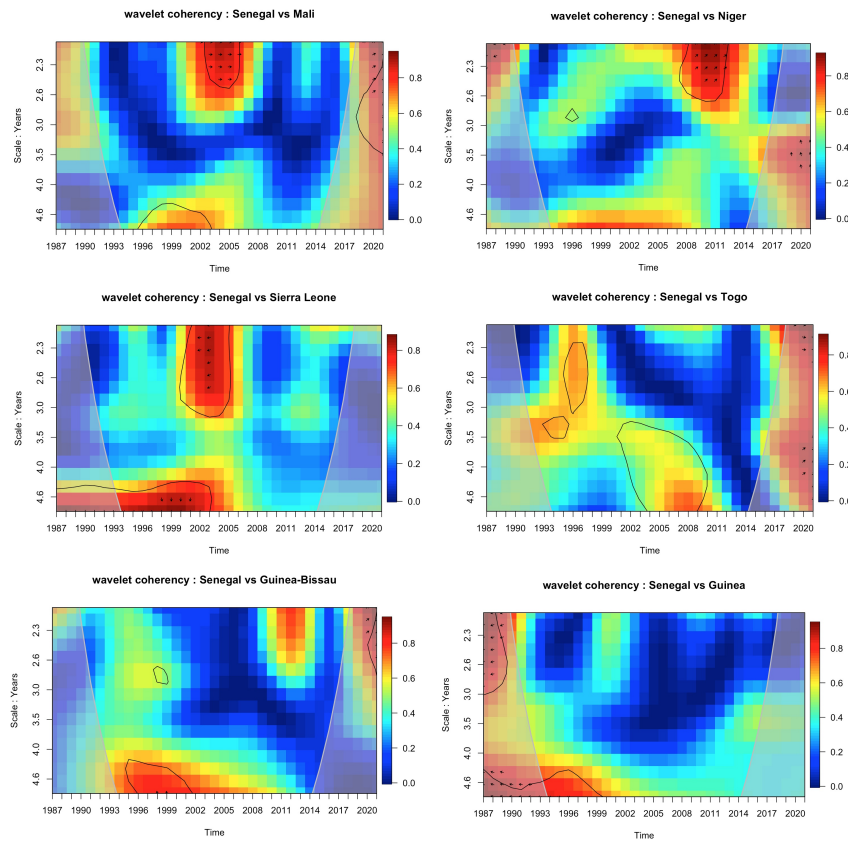
In **23** and **24**, at the business cycle level (period from 20 quarters), **Senegal**, the second largest economy of the WAEMU, shows ties in a leading position with many WAEMU economies, including Benin and Mali, while Burkina Faso was leading most of the time. The Senegalese economy also led those of Cabo Verde, Gambia, and Ghana over the full sample. Finally, Senegal led the relationship with Ivory Coast (from 2001), Niger (from 1994), and Nigeria (from 2004). We notice that Senegal has been enjoying a relatively stable political environment.

Figure 23: Senegal led pairwise Wavelet coherency (1)



Note: Red represents high coherency, and blue represents weak coherency. The arrows pointing to the right (\rightarrow) indicate that the two economies are in-phase, while arrows pointing to the left (\leftarrow) indicate an anti-phase. In these cases, no economy leads the other. The arrows pointing right and up (\nearrow) indicate that the first-listed economy leads the second. The arrows pointing right and down (\searrow) indicate that the second-listed economy leads the first. The thick black contours designate the 5% significance level against a red noise, and the thick white line indicates the cone of influence (COI) inside, assuming we have accurate information.

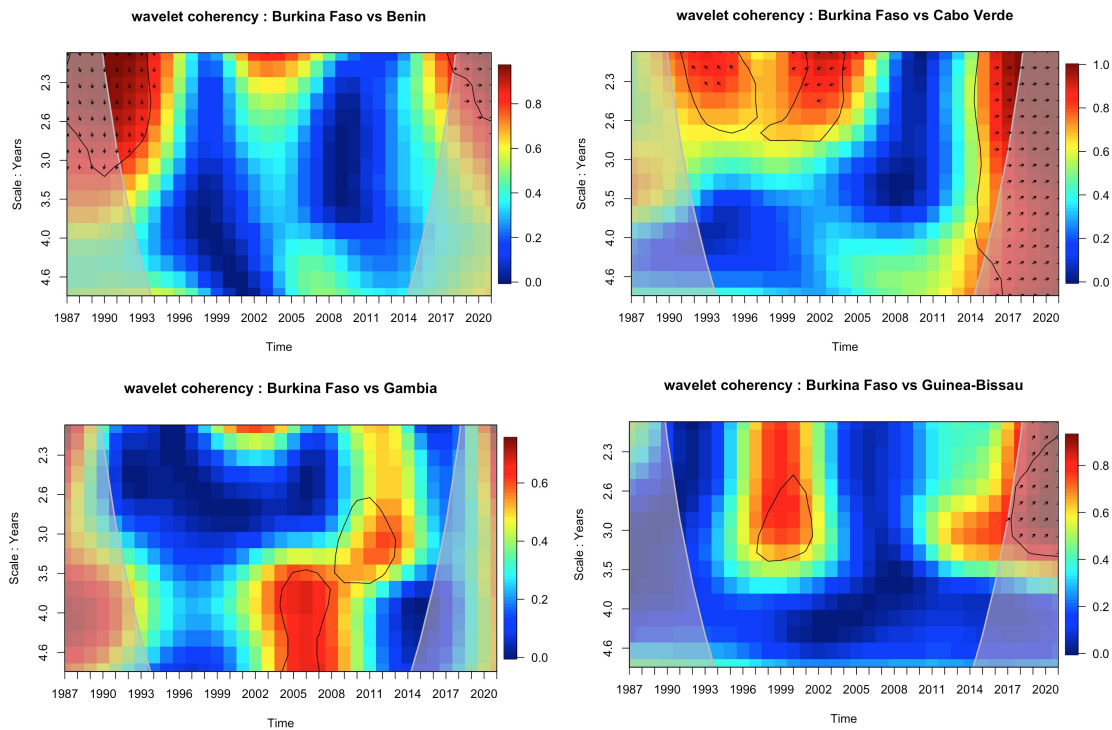
Figure 24: Senegal led pairwise Wavelet coherency (2)



Note: Red represents high coherency, and blue represents weak coherency. The arrows pointing to the right (\rightarrow) indicate that the two economies are in-phase, while arrows pointing to the left (\leftarrow) indicate an anti-phase. In these cases, no economy leads the other. The arrows pointing right and up (\nearrow) indicate that the first-listed economy leads the second. The arrows pointing right and down (\searrow) indicate that the second-listed economy leads the first. The thick black contours designate the 5% significance level against a red noise, and the thick white line indicates the cone of influence (COI) inside, assuming we have accurate information.

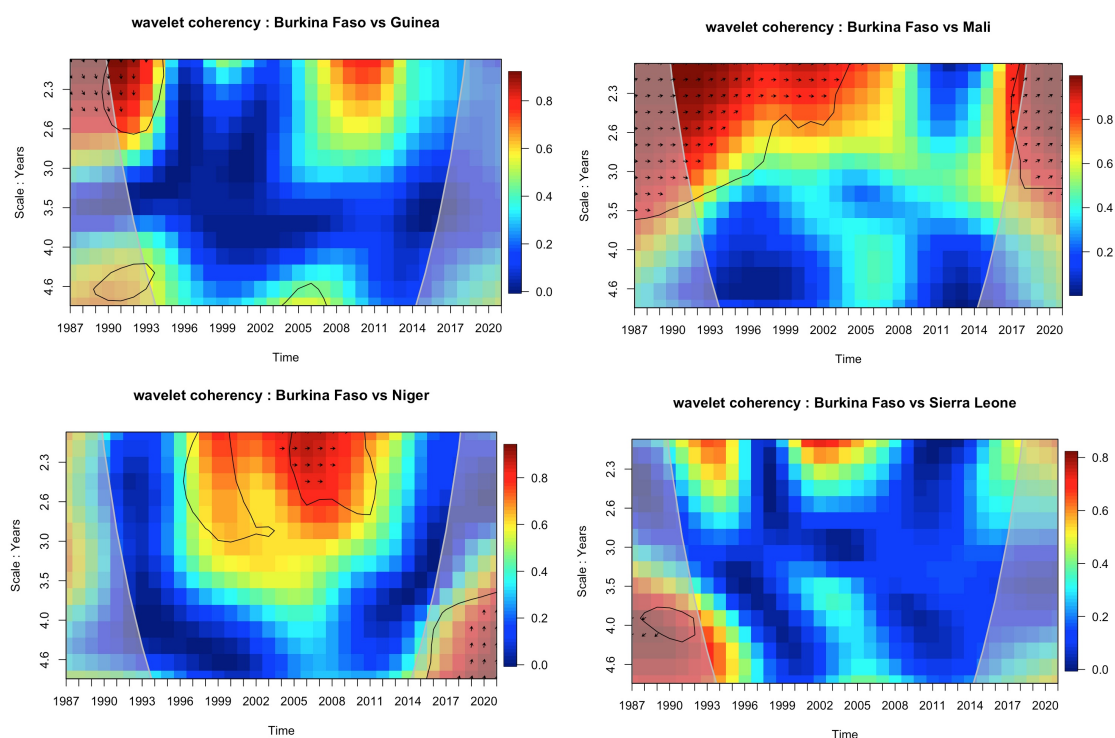
Figures 25 and 26 reveal that the Business cycle of **Burkina Faso** was in phase with its WAEMU peers, including Benin, Mali, and Senegal on the full sample in the leading position. This occurs instead with Niger and Togo in the later part of the sample, with Cote d'Ivoire in the leading position. The country also exhibits excellent correlation, in a leading position, with non-WAEMU member countries, including Cabo-Verde, Ghana, and The Gambia, on the full sample but was led by Nigeria mainly from 2004.

Figure 25: Burkina Faso led pairwise Wavelet coherency (1)



Note: Red represents high coherency, and blue represents weak coherency. The arrows pointing to the right (\rightarrow) indicate that the two economies are in-phase, while arrows pointing to the left (\leftarrow) indicate an anti-phase. In these cases, no economy leads the other. The arrows pointing right and up (\nearrow) indicate that the first-listed economy leads the second. The arrows pointing right and down (\searrow) indicate that the second-listed economy leads the first. The thick black contours designate the 5% significance level against a red noise, and the thick white line indicates the cone of influence (COI) inside, assuming we have accurate information.

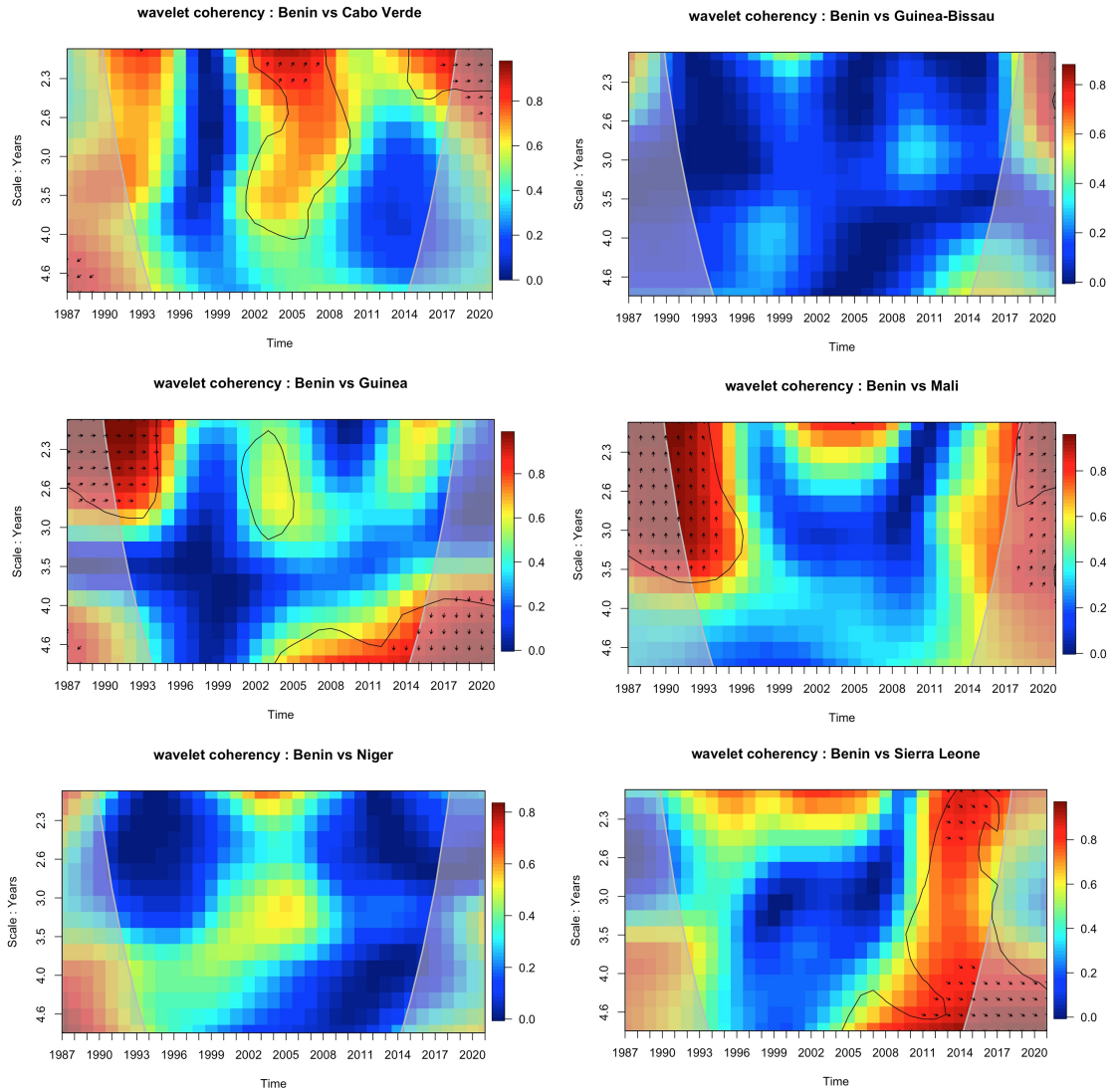
Figure 26: Burkina Faso led pairwise Wavelet coherency (2)



Note: Red represents high coherency, and blue represents weak coherency. The arrows pointing to the right (\rightarrow) indicate that the two economies are in-phase, while arrows pointing to the left (\leftarrow) indicate an anti-phase. In these cases, no economy leads the other. The arrows pointing right and up (\nearrow) indicate that the first-listed economy leads the second. The arrows pointing right and down (\searrow) indicate that the second-listed economy leads the first. The thick black contours designate the 5% significance level against a red noise, and the thick white line indicates the cone of influence (COI) inside, assuming we have accurate information.

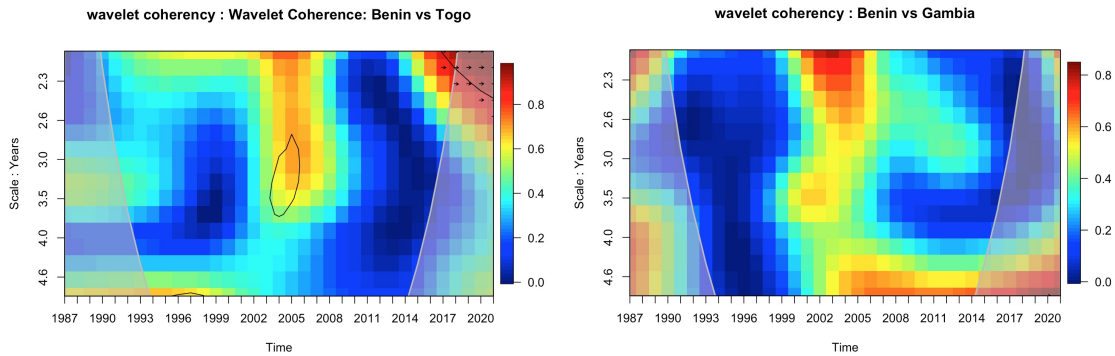
Besides the relatively significant co-movements with its WAEMU peers, including Burkina Faso, Mali, and Senegal, we observe in Figures 27 and 28 that the business cycle of **Benin** has ties with the business cycles of non-WAEMU countries. Indeed Benin was led by Cabo-Verde and Ghana over the full sample, and the country led Nigeria from 2005. The relationship between Benin and Gambia can be seen as a two parts one since Gambia led Benin from 1988 until 1996, while the latter emerged as the leader from 2003.

Figure 27: Benin led pairwise Wavelet coherency (1)



Note: Red represents high coherency, and blue represents weak coherency. The arrows pointing to the right (\rightarrow) indicate that the two economies are in-phase, while arrows pointing to the left (\leftarrow) indicate an anti-phase. In these cases, no economy leads the other. The arrows pointing right and up (\nearrow) indicate that the first-listed economy leads the second. The arrows pointing right and down (\searrow) indicate that the second-listed economy leads the first. The thick black contours designate the 5% significance level against a red noise, and the thick white line indicates the cone of influence (COI) inside, assuming we have accurate information.

Figure 28: Benin led pairwise Wavelet coherency (2)



Note: Red represents high coherency, and blue represents weak coherency. The arrows pointing to the right (\rightarrow) indicate that the two economies are in-phase, while arrows pointing to the left (\leftarrow) indicate an anti-phase. In these cases, no economy leads the other. The arrows pointing right and up (\nearrow) indicate that the first-listed economy leads the second. The arrows pointing right and down (\searrow) indicate that the second-listed economy leads the first. The thick black contours designate the 5% significance level against a red noise, and the thick white line indicates the cone of influence (COI) inside, assuming we have accurate information.

Looking at Figures 29 and 30, Mali, apart from strong relationships with Benin, Burkina Faso, and Senegal, we observe significant ties with non-WAEMU member economies. Indeed, while Mali is leading Ghana and Gambia (from 2000), it generally lags Cabo-Verde and Nigeria at the business cycle level over the full sample. The country also experiences some relationships later in the sample with Guinea Bissau, Cote D’Ivoire, and Togo. Mali has, most of the time, enjoyed a relatively peaceful environment before a military coup in 2012.

Figure 29: Benin led pairwise Wavelet coherency (2)

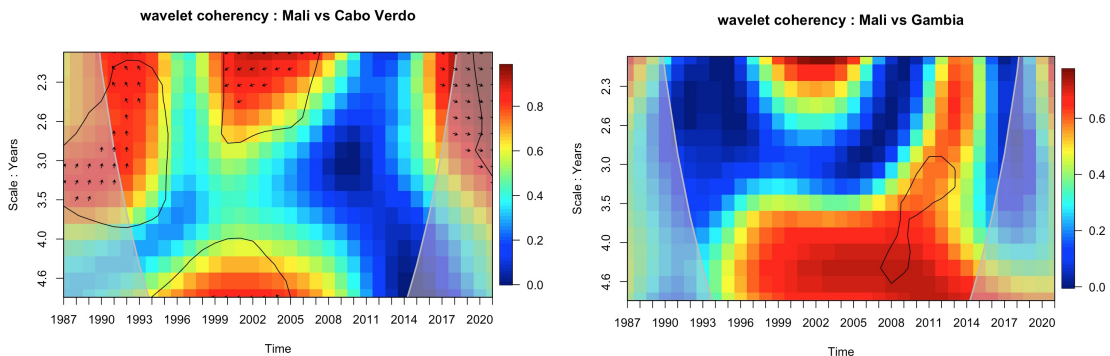
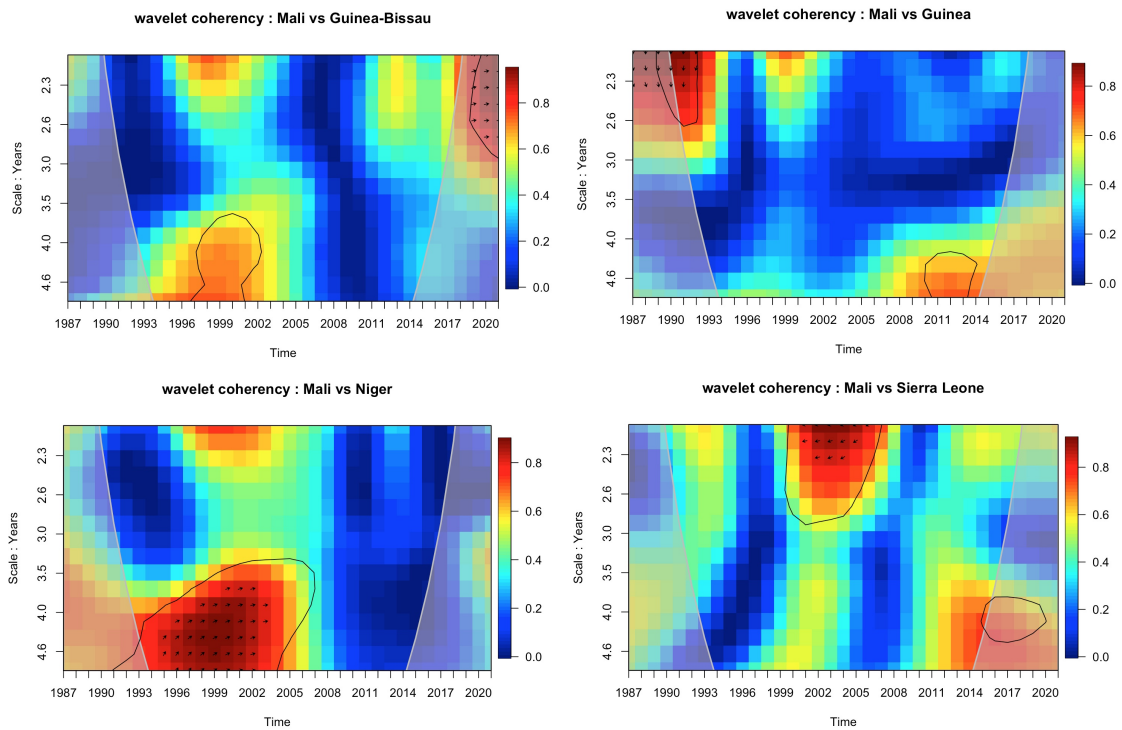


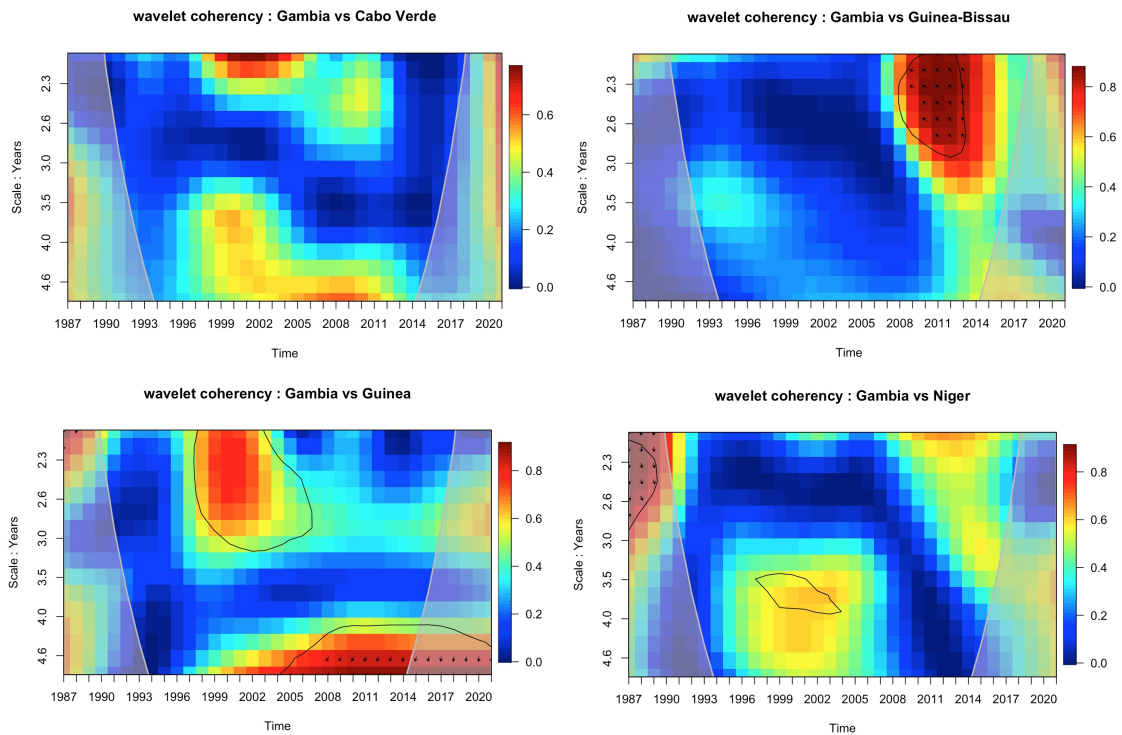
Figure 30: Mali led pairwise Wavelet coherency (1)



Note: Red represents high coherency, and blue represents weak coherency. The arrows pointing to the right (\rightarrow) indicate that the two economies are in-phase, while arrows pointing to the left (\leftarrow) indicate an anti-phase. In these cases, no economy leads the other. The arrows pointing right and up (\nearrow) indicate that the first-listed economy leads the second. The arrows pointing right and down (\searrow) indicate that the second-listed economy leads the first. The thick black contours designate the 5% significance level against a red noise, and the thick white line indicates the cone of influence (COI) inside, assuming we have accurate information.

Figures 31 reveal that **Gambia** has a strong relationship with Benin, Burkina Faso, Ghana, Mali, and Senegal. We observe that its relationship has been decreasing with Cabo Verde and Ghana since 1995. The country exhibits some relationship in the later part of the sample with Cote d'Ivoire, Nigeria.

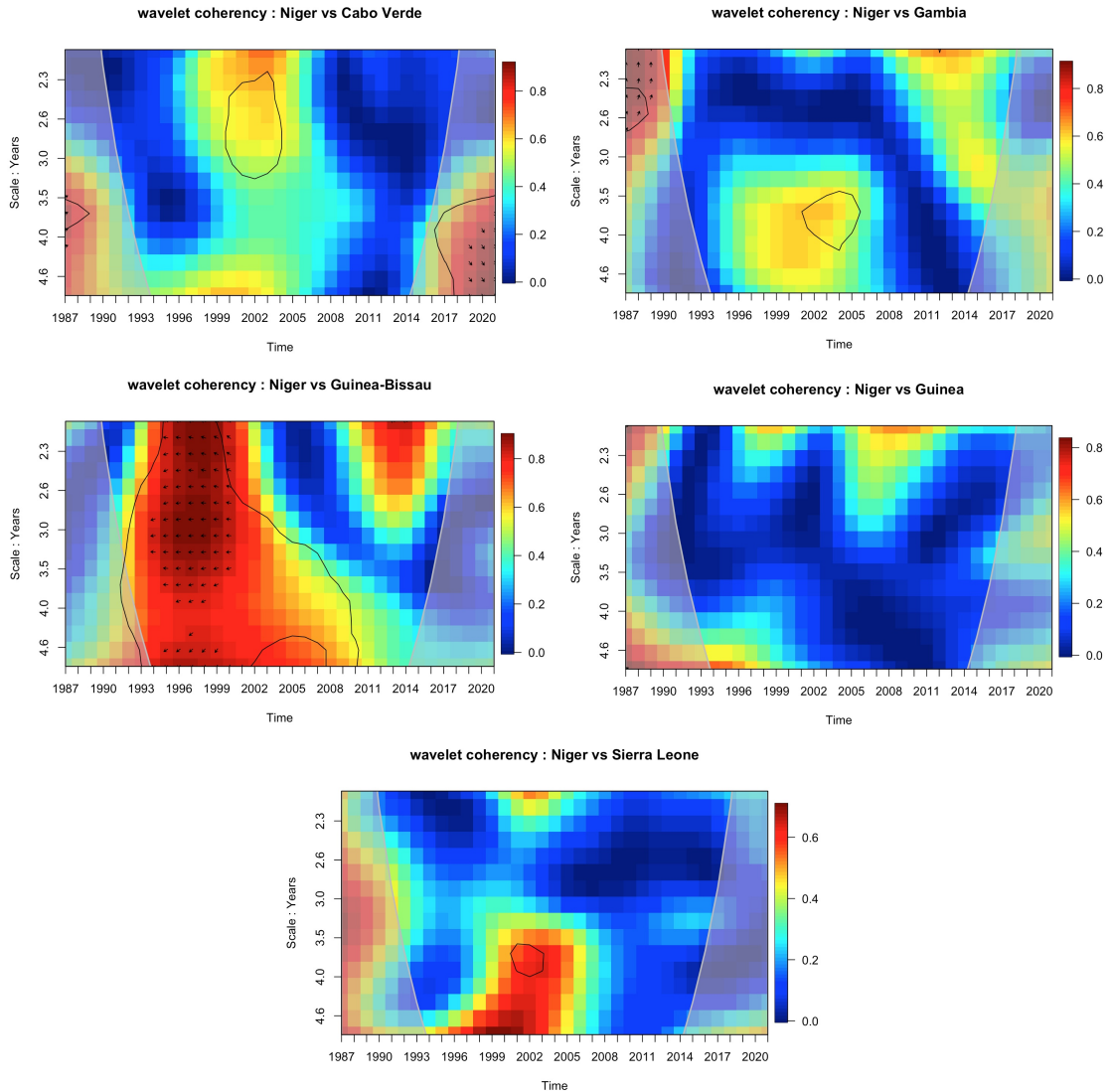
Figure 31: Gambia led pairwise Wavelet coherency (1)



Note: Red represents high coherency, and blue represents weak coherency. The arrows pointing to the right (\rightarrow) indicate that the two economies are in-phase, while arrows pointing to the left (\leftarrow) indicate an anti-phase. In these cases, no economy leads the other. The arrows pointing right and up (\nearrow) indicate that the first-listed economy leads the second. The arrows pointing right and down (\searrow) indicate that the second-listed economy leads the first. The thick black contours designate the 5% significance level against a red noise, and the thick white line indicates the cone of influence (COI) inside, assuming we have accurate information.

Figure 32 shows that most of the relationship of **Niger** started in the later part of the sample, mainly from 2005 when considering the 17 and 32 quarters band.

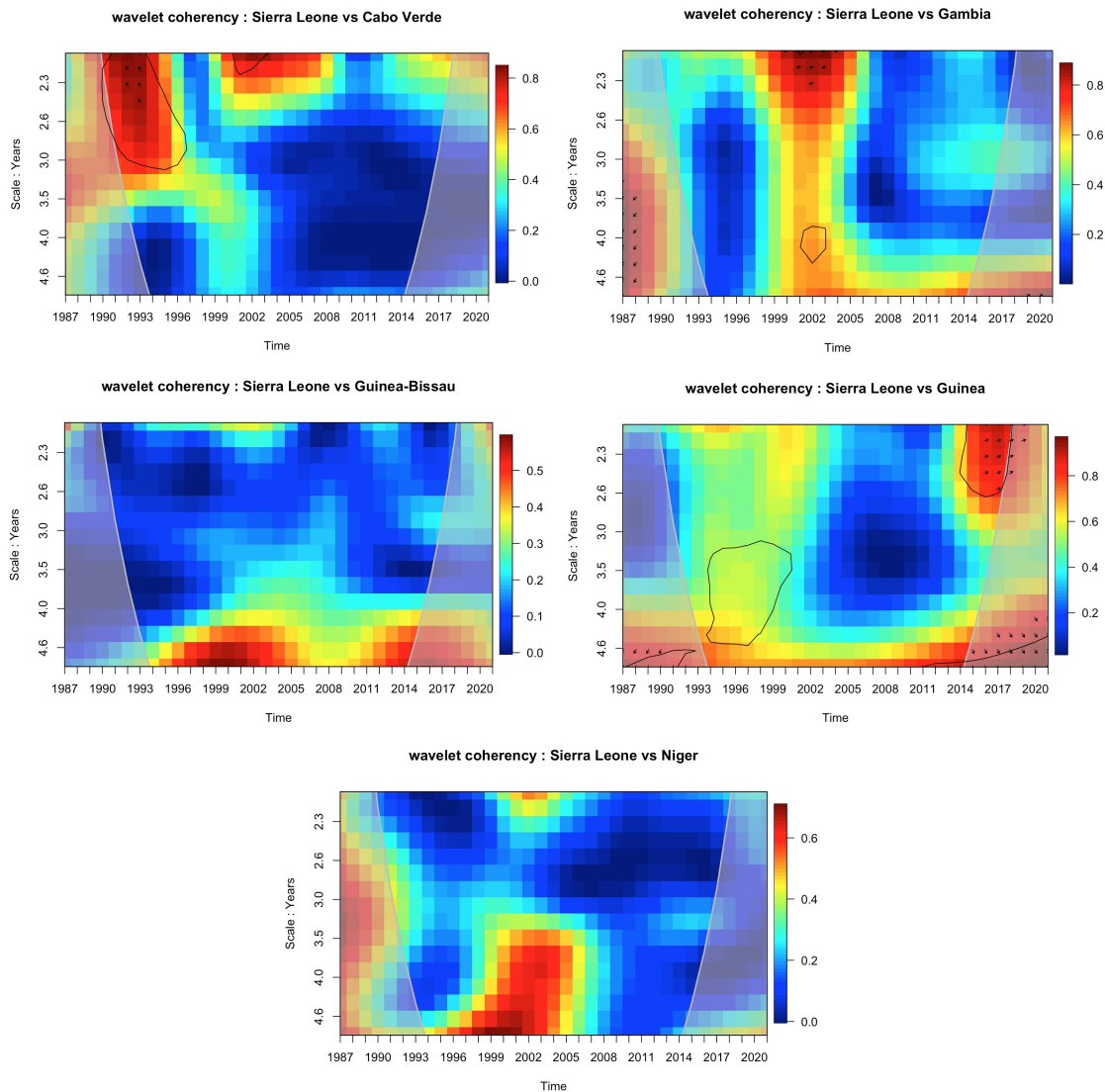
Figure 32: Niger led pairwise Wavelet coherency (1)



Note: Red represents high coherency, and blue represents weak coherency. The arrows pointing to the right (\rightarrow) indicate that the two economies are in-phase, while arrows pointing to the left (\leftarrow) indicate an anti-phase. In these cases, no economy leads the other. The arrows pointing right and up (\nearrow) indicate that the first-listed economy leads the second. The arrows pointing right and down (\searrow) indicate that the second-listed economy leads the first. The thick black contours designate the 5% significance level against a red noise, and the thick white line indicates the cone of influence (COI) inside, assuming we have accurate information.

Figure 33 shows **Sierra Leone**, which seems to have no relationship at the business level with the other Ecowas economies. However, we observe a weak correlation with Niger from 2005.

Figure 33: Sierra Leone led pairwise Wavelet coherency (1)

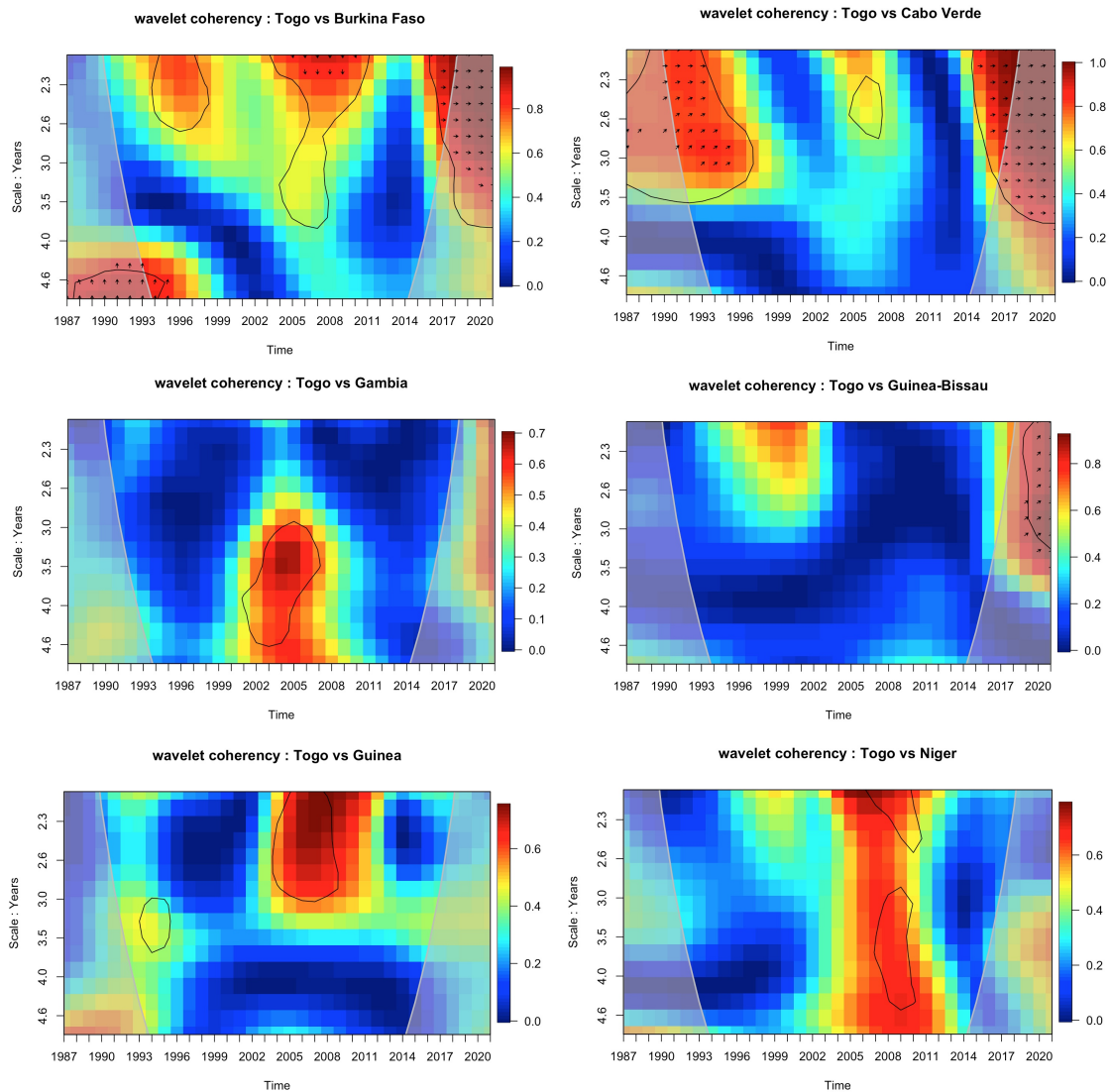


Note: Red represents high coherency, and blue represents weak coherency. The arrows pointing to the right (\rightarrow) indicate that the two economies are in-phase, while arrows pointing to the left (\leftarrow) indicate an anti-phase. In these cases, no economy leads the other. The arrows pointing right and up (\nearrow) indicate that the first-listed economy leads the second. The arrows pointing right and down (\searrow) indicate that the second-listed economy leads the first. The thick black contours designate the 5% significance level against a red noise, and the thick white line indicates the cone of influence (COI) inside, assuming we have accurate information.

Finally, in Figure 34, we observe that **Togo** is synchronized with Guinea Bissau (be-

tween 24 and 32 quarters band) over the full sample. The country experienced a correlation with Nigeria from 1998 until 1995 and again from 2001. Most of its relationships occurred later in the sample with Benin, Burkina Faso, Cote d'Ivoire, Senegal, Ghana, and Mali.

Figure 34: Togo led pairwise Wavelet coherency (1)



Note: Red represents high coherency, and blue represents weak coherency. The arrows pointing to the right (\rightarrow) indicate that the two economies are in-phase, while arrows pointing to the left (\leftarrow) indicate an anti-phase. In these cases, no economy leads the other. The arrows pointing right and up (\nearrow) indicate that the first-listed economy leads the second. The arrows pointing right and down (\searrow) indicate that the second-listed economy leads the first. The thick black contours designate the 5% significance level against a red noise, and the thick white line indicates the cone of influence (COI) inside, assuming we have accurate information.

Chapter 2

An attempt to track the Ivorian economy in real-time: A nowcasting approach.

2.1 Introduction

The Great Recession of 2008 abruptly ended the Great Moderation period's calm economic conditions. Since then, real-time forecasting models have piqued the curiosity of academics, governments, and other economic agents alike. Knowing the current level of economic activity when making economic policy decisions is evident in industrialized economies, where governments, central banks, and private groups evaluate real-time data. However, is the same said for West African economies that are resilient?

West African economies have consolidated their gains over the past decade. Despite shocks from commodity prices and successive political crises, West African economies proved resilient until the COVID-19 pandemic. While the contraction of GDP by -2.0 percent in 2020 versus 3.6 percentage points in 2019 seemed inevitable, it is hard to believe that the negative impact of the pandemic on tourism receipts, trade, and financial flows, and thus on GDP, was tracked in real-time. In other words, ECOWAS economies could not make early forecasts of national wealth in such a period of uncertainty.

However, key WAEMU¹ countries now view the destabilizing impact of the pandemic

¹The West African Economic and Monetary Union (WAEMU) is made up of eight member countries that

as an opportunity to adapt their economic growth strategies for greater resilience. Hence, policymakers must formulate efficient forward-looking policies to make better economic decisions. However, the authorities' ability to monitor macroeconomic conditions in real time will determine the effectiveness of such capabilities.

The delayed release of the key metric of economic activity poses a significant challenge for WAEMU economies to provide real-time economic snapshots. However, advanced economies have addressed this issue by employing the “nowcasting” approach. This method uses specialized algorithms to estimate the current state of the economy by compiling economic indicators and components of real GDP published at higher frequencies. Some commonly used methods for nowcasting include dynamic factor models (DFM), Bayesian VAR models, mixed-frequency models, and artificial intelligence (AI) techniques. These methods analyze large datasets, identify common factors that explain the variation in the data, and learn from historical data to make predictions about the current state of the economy. Overall, the nowcasting approach provides an indicative value of the growth rate of real GDP before its official release date, which can inform policymakers and guide economic decision-making.

[Banbura, Giannone, and Reichline, \(2011\) \[2\]](#) have defined nowcasting as a method of predicting the current and near-future state of the economy. The technique uses higher-frequency and more timely economic data to estimate low-frequency target variables. The nowcasting model processes this data to provide a timely estimate of the current economic state. This model is an extension of the bridge-type regression that associates quarterly GDP with quarterly aggregates of monthly economic indicators. While nowcasting and bridge models both use quarterly and monthly series, nowcasting is more complex due to its features, including the ability to update GDP estimates throughout the target quarter as new information becomes available, commenting on the source and impact of estimate revisions, and running estimations with missing observations due to publication lags ([Giannon,](#)

are located in the Western African region, namely Benin, Burkina Faso, Cote D'Ivoire, Guinea Bissau, Mali, Niger, Senegal, and Togo.

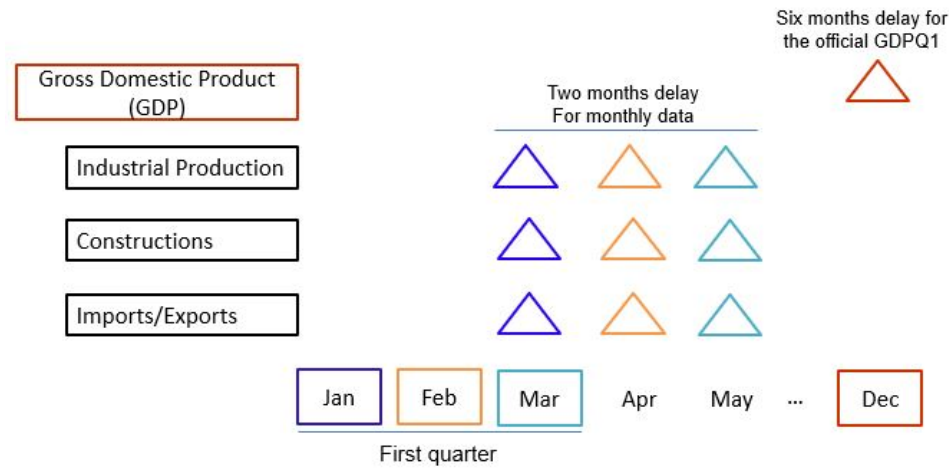
Reichline, and Small, (2008) [24]). Nowcasting extracts "news," part of monthly data that comes as a surprise, to revise GDP estimates in real-time. Therefore, understanding the real-time behavior and evolution of the economy would be of significant gain.

Official GDP data in OECD economies are published a few weeks after the end of the reference quarter. However, there is a longer delay in releasing official GDP growth figures in small open economies like West Africa. This delay, coupled with the fact that GDP is subject to revision, reduces its usefulness for investors, central bankers, or government authorities. Moreover, the delay creates obstacles to timely decision-making since the current state of the economy has yet to be discovered. This makes it difficult to plan investments efficiently to make substantial profits, make better monetary policy decisions to ease investments across the economy, or forecast a recession.

Côte d'Ivoire experiences a delay of six to twelve months between the reference quarter and the publishing of GDP data. For example, the authorities released the GDP for the fourth quarter of 2020 in December 2021. [Figure 1](#) shows the timing of publishing GDP and monthly economic data in Côte d'Ivoire. Monthly economic indicators, such as industrial production, construction, exports, and imports, actively track GDP in real time. For example, although the authorities release the first quarter's GDP in December, nine months after the end of the reference quarter, they publish monthly economic indicators for January, February, and March in March, April, and May, respectively, with a two-month delay. Consequently, investors can estimate the first quarter's GDP growth rate with a delay of two to three months rather than six months or more.

The nowcasting approach is particularly useful for computing real-time GDP growth rates for small open economies where publication delays are more significant than in emerging and advanced economies. However, while advanced economies use the nowcasting approach to monitor business cycles daily, there needs to be more efforts to consider real-time frameworks for monitoring economic conditions in sub-Saharan Africa, particularly in the francophone zone. This chapter attempts to shrink the gap in the literature by

Figure 2.1: The official GDP growth rates release dates



Note: The authorities released the official first quarter GDP (GDPQ1) in December, nine months after the end of the reference quarter. To get an early estimate of GDP, analysts use monthly economic indicators. The triangles in Figure 1 indicate when these indicators become publicly available, with a two-month delay. For example, January, February, and March data are released in March, April, and May, respectively. However, the authorities release the GDP growth rate at least six months after the end of the reference quarter.

testing the nowcasting methodology with a different data structure, enriching the nowcasting framework for WAEMU economies. The study focuses on Côte d’Ivoire, the largest economy in the region, in identifying consistent real-time GDP growth trajectories.

The study tests a version of the nowcasting model developed by Bok, Caratelli, Giannone, Sbordone and Tambalotti, (2017) [11] to generate a macroeconomic condition index (MCI) for Côte d’Ivoire. This index provides early estimates of the country’s GDP. First, the dynamic factor model is calibrated on various economic indicators to create a single unobserved index that encapsulates the movements in the data. This method involves the use of a Kalman filter. Then, when a series release does not match the model’s predictions, economic expectations are adjusted accordingly.

The study uses Stock and Watson, (1989)[30] approach to construct an index of coincident economic indicators with four series: industrial production, real personal income less transfer payment, real manufacturing and trade sales, and employee hours in non-agricultural areas. The MCI considers eighteen high-frequency economic indicators cov-

ering the real economy to predict GDP growth rates. Unlike traditional nowcasting implementations, this study does not use judgment-based variables, leaving out unavailable survey forecasts in Côte d'Ivoire. Instead, we consider only a significant correlation between GDP and higher frequency explanatory variables to ensure meaningful results.

The backtest analysis reveals that the nowcasting model performs relatively well, mimicking the national institute of statistics estimates over three years from 2017 to 2019 while outperforming the WAEMU's central bank. As a result, the MCI provides an index of early estimates of the macroeconomic conditions for Côte d'Ivoire, which could be a policy guide for the economic and monetary authorities. The MCI could also be used to estimate the current state of several economic sectors, helping investors and other agents make real-time decisions more efficiently.

The chapter is organized as follows: In [Section 2](#), we review the literature on nowcasting GDP in sub-Saharan Africa, focusing on the franc CFA zone. [Section 3](#) describes the nowcasting model used by the New York Fed. We discuss the data in [Section 4](#). We present our analysis of the results in [Section 5](#), while [Section 6](#) offers our concluding remarks.

2.2 A brief literature of nowcasting economic conditions

Gross domestic product (GDP) measures the national economy's size. It calculates the monetary value generated by production, earnings, and spending on goods and services and adjusts for general price increases to measure real GDP growth over time. However, developing economies experience a considerable delay in the availability of quarterly GDP data, and it is subject to revisions, making macroeconomic decision-making a volatile exercise. Therefore, there is increasing attention in the literature on real-time prediction of the economy's state. Researchers have analyzed real GDP, from detecting the economic cycle turning points ([Burns and Mitchell, \(1946\) \[15\]](#)) to predicting the size of the economy in real-time ([Giannone, Reichline, and Small, \(2008\) \[24\]](#)).

[Burns and Mitchell, \(1946\) \[15\]](#) analyzed monthly and quarterly time series to identify systematic co-movements across different sectors and activities of the economy, revealing cyclical changes in the overall economic activity in the United States. Mathematical methods have been used to extend this pattern recognition method for better analysis and evaluation of the attributes of business cycles.

In their seminal work, [Stock and Watson, \(1989\) \[30\]](#) summarized many economic variables that move the same way into a few factors. They constructed a coincident economic indicator index from the information a group of data conveys, such as industrial production, real personal income, sales, and employment. Their single-index dynamic factor model (DFM) made the analysis more formal and accurate, displaying judgment.

[Giannone, Reichline, and Small, \(2008\) \[24\]](#) recently predicted U.S. macroeconomic conditions through an automatic statistical procedure using the dynamic factor model (DFM). This nowcasting model uses many high-frequency coincident and leading indicators to predict the present, near future, and recent past economic conditions summarized within key economic aggregates such as real GDP growth. In addition, they combined models for big data and filtering techniques to build an automated platform to monitor macroeconomic conditions in real time without judgment.

As [Bhadury, Ghosh, and Kumar, \(2019\), \[9\]](#) described, nowcasting models involve estimating an unobserved common factor from numerous high-frequency economics series, mainly using a multivariate dynamic factor model written in a state space representation over a training sample. Next, Kalman filter techniques generate projections for every variable considered and estimate each data release, a surprise based on the model, and labeled "news." The weighted average of the news determines the level of nowcast revisions. The last step involves using the factor projections in an appropriate bridge equation to "nowcast" GDP growth.

2.2.1 From Traditional Factor Models to Real-Time Forecasting

[Barhoumi et al. \(2012\) \[7\]](#) recognize that economic forecasts generated by conventional factor models can be difficult to interpret. In such cases, bridge equations provide a credible alternative by allowing for the interpretation of forecasts based on changes in the explanatory variables. [Bulligan et al. \(2010\) \[14\]](#) further suggest that bridge models can be advantageous for quantifying the impact of sudden and rapid changes and gaining insight into their origins.

The structure of bridge models is similar to Mixed Data Sampling Models (MIDAS), another family of forecasting models. However, there are some differences between them. For instance, the latter does not need to approximate frequency ([Banbura et al., 2010](#)) or performance ([Clement and Calvão, \(2008\) \[17\]](#)). According to [Banbura et al. \(2010\) \[4\]](#), bridge models have limited knowledge of the economy's present state and its recent past.

Single equation models such as BMs and MIDAS are relevant. However, they may be less effective in capturing the impact of the information flow provided by explanatory variables over time. According to [Banbura et al. \(2010\) \[4\]](#), Bridge and MIDAS models can be robust in parameter instability. However, they have a significant disadvantage in nowcast interpretation as they must provide a system-based forecast for all variables. Therefore, the authors recommend using factor models based on systems of equations as they allow for a more accurate understanding of forecast revisions since they account for the information encoded in the release of each variable in the system over time.

[Geweke, \(1977\) \[23\]](#) and [Sargent et al. \(1977\) \[28\]](#). pioneered the work that led to the development of Dynamic Factor Models (DFM). Econometricians and researchers regularly use DFM in constructing coincident indicators. When dealing with large data, factor models can help avoid a proliferation of parameters. Additionally, factor models provide a parsimonious representation of information when the variables are correlated. In other words, factor models propose that a small number of unobservable latent factors can

describe the dynamics of many observed variables ([Bessec and Doz, \(2012\) \[8\]](#)).

Thus, monitoring the economic conditions requires modeling a dynamic system of several variables. Generally, state-space methods with Kalman filtering² are considered the optimal solution under a gaussian environment. The irregular structure of variables further justifies the need for the Kalman filter. Indeed, variables have different frequencies and sometimes show missing data. The filter uses the current observation to predict the next period's unobservable value and then uses the next period to update that forecast. The linear Kalman filter is optimal, assuming that the observed variable and the noise are jointly Gaussian. Hence, as soon as the set of parameters is estimated, the Kalman filter technique allows obtaining forecasts of the variable of interest (GDP in this case) automatically for any information available in the data set Ω_v . The DFM models have been widely considered in the literature, particularly for forecasting GDP growth for U.S ([Stock and Watson, \(2002\) \[31\]](#)), for the European area [Giannone et al. \(2008\) \[24\]](#)) and for the french economy ([Barhoumi et al. \(2010\) \[6\]](#)).

2.2.2 Nowcasting industrialized economies

The Dynamic Factor Model, which uses the nowcasting methodology pioneered by [Giannone, Reichline, and Small, \(2008\) \[24\]](#), has gained attention from policy-making institutions in advanced and emerging economies. Central banks increasingly rely on nowcasting models for short-term forecasts of economic variables, including GDP growth. [Bok, Caratelli, Giannone, Sbordone, and Tambalotti, \(2017\) \[11\]](#) from the Federal Reserve Bank of New York (FRBNY) has applied a nowcasting model to produce early estimates of US GDP growth. The model considers the dynamic interaction of many economic indicators within latent factors to forecast each economic series. If the actual release differs from

²The Kalman filter is an algorithm that allows recursive estimation of unobserved, time-varying parameters or variables in the system. Kalman filter differs from forecasting because forecasts are made for the future, whereas filtering obtains estimates of unobservables for the same period as the information set. The idea is to arrive at a conditional density function of the unobservables using Bayes' Theorem, the functional form of relationship with observables.

the forecast, the state of the economy is revised based on the marginal impacts of each economic series.

[Banbura, Giannone, and Reichline, \(2010\) \[4\]](#) applied the nowcasting process to the Euro area and credited the European Central Bank (ECB) for its monetary policy decisions. They produced a sequence of nowcasts about the impact of real-time data releases called "news." [Banbura and Modugno, \(2014\) \[5\]](#) successfully demonstrated the link between this news and actual GDP forecast revisions through a quasi-maximum likelihood estimation method, which has been proven consistent ([Doz, Giannone, and Reichline, \(2012\) \[22\]](#)) for a large panel of time series. They showed that weighted data releases could help evaluate nowcasting GDP growth through the Dynamic Factor Model. This model has been gaining attention from policy-making institutions in advanced and emerging economies.

The nowcasting method, first developed by [Giannone, Reichline, and Small, \(2008\) \[24\]](#), is being used as a workforce model. Central banks increasingly rely on nowcasting models to predict short-term changes in low-frequency economic variables, such as GDP growth. [Bok, Caratelli, Giannone, Sbordone, and Tambalotti, \(2017\) \[11\]](#) at the Federal Reserve Bank of New York (FRBNY) demonstrated how the nowcasting model could provide early estimates of GDP growth in the United States. The authors explained the dynamic interaction of many economic indicators within latent factors and how the model produces a forecast for each economic series. If the actual release differs from the model's forecast, the state of the economy is revised based on the marginal impacts of each economic series. [Banbura, Giannone, and Reichline, \(2010\) \[4\]](#), applied the nowcasting process to the Euro area, acknowledging the European Central Bank (ECB) for its monetary policy decisions. The authors produced a sequence of nowcasts about the marginal impact of real-time data releases called "news." [Banbura and Modugno, \(2014\) \[5\]](#) successfully demonstrated the link between this news and the actual revision of GDP forecasts.

The authors discovered that nowcasting models have advantages over institutional forecasts using a quasi-maximum likelihood estimation method, which has been proven

”consistent” by [Doz, Giannone, and Reichline, \(2012\) \[22\]](#) for a large panel of time series. In addition, Banbura and Modugno (2014) showed that weighted data releases could help evaluate global economic activity. Recently, [Hughes et al. \(2021\) \[25\]](#) used international futures to conduct a nowcasting exercise of Sustainable Development Goals (SDG) indicators for more than 180 countries. Therefore, the nowcasting model goes beyond simply producing early GDP estimates.

On a cross-country level, [Dahlhaus, Guénette, and Vasishtha, \(2017\) \[19\]](#) applied the dynamic factor model to forecast current real GDP growth in Brazil, Russia, China, and Mexico on a cross-country level. Their approach addressed data series issues like publication delays and short samples, and they found that the DFM methodology is suitable for emerging markets. Furthermore, to capture the impact of new information on each country’s nowcasts, they defined model-based ”news.” Finally, in a recent study, [Dauphin, Dybczak, Maneely, Sanjani, Suphaphiphat, Wang, and Zhang, \(2022\) \[20\]](#) used a combination of standard dynamic factor models (DFMs) and several machine learning (ML) tools to nowcast GDP growth across a group of European economies.

Several studies have analyzed the information provided by current GDP growth forecasts at a country level. For instance, in Norway, [Aastveit and Trovik \(2012\) \[1\]](#) employed dynamic factor models and a broad range of financial data to estimate the current quarter’s GDP. They discovered that asset prices are highly informative for predicting GDP growth in a small and open economy. In another study, [Bragoli, Metelli, and Modugno \(2014\) \[12\]](#) compared a nowcasting model for Brazil with institutional forecasts.

2.2.3 Applying Nowcasting Techniques in sub-Saharan Africa

In South Africa, [Kabundi et al., \(2016\) \[26\]](#) utilized a nowcasting methodology to predict the current quarter’s GDP growth for a brief period (2010 to 2014). In addition, it evaluated the impact of new data releases on the revisions of real GDP growth. The authors discovered that the model’s performance is on par with that of professional forecasters.

Meanwhile, in central Africa, [Bikai and De Resende, \(2019\) \[16\]](#) from BEAC³ used a dynamic factor model (DFM) to estimate Cameroonian quarterly GDP growth forecasts, yielding similar results. In addition, the DFM framework outperformed simple univariate models, and its reliability in forecasting current GDP growth for advanced and emerging economies was confirmed. Overall, these studies demonstrate the effectiveness of nowcasting in extracting relevant information from data-rich environments while disregarding noise.

Nowcasting is primarily associated with meteorology in most West African economies, including Côte d'Ivoire, where it is primarily used for temperature forecasts ([Savage \(2013\) \[29\]](#)). However, [Buell et al. \(2021\)\[13\]](#) demonstrated the predictive power of machine learning and parametric factor models by extracting alternative data, such as mobile money, from Google Trends searches to track economic activity in sub-Saharan Africa. This study focuses on standard indicators and uses the classic nowcasting model for real-time GDP estimates in Côte d'Ivoire. The Expectation-Maximization estimation method employed in [Ba'nburu, Marta, and Modugno \(2014\)](#) is used to analyze mixed-frequency, ragged-edge, and missing data samples, building upon the work of [Bok, Caratelli, Giannone, Sbordone, and Tambalotti \[11\]](#) from the staff of the New York Federal Reserve Bank. In contrast to temperature predictions and storm tracking, nowcasting is increasingly becoming an effective tool for real-time economic forecasting in sub-Saharan Africa.

2.3 Methodology

[Giannone, Reichline, and Small \(2008\)](#) proposed a dynamic factor model within a space-state environment [\[24\]](#). The DFM is qualified to handle mixed-frequency and missing data through maximum likelihood estimation, as described by [Banbura, Giannone, and Reichlin \(2010\) \[4\]](#). The state-space formulation of the DFM model consists of a mea-

³Created in 1972, the Bank of Central African States (BEAC) is the central bank common to the six states that make up the Economic and Monetary Community of Central Africa (CEMAC). These are Cameroon, Central African Republic, Congo, Gabon, Equatorial Guinea, and Chad

surement equation and a transition equation. The measurement equation relates observable variables to an unobserved latent state process characterized by the dynamics of economic activity, while the transition equation describes the dynamics of the state process. Monitoring economic conditions in real-time are challenging due to the frequency and irregularity of data in time series. The problem of the nowcasting process is presented in [subsection 1](#), while [subsection 2](#) solves the issue with the concept of “news” within the dynamic factor model (DFM). Finally, we use the maximum likelihood method in [Subsection 3](#) to estimate the DFM.

2.3.1 The problem of tracking GDP in real-time

Real-time assessment of the current state of the economy and its expected developments relies on a set of macroeconomic indicators (Ω_v) with varying publication dates v . To address the issue of how to use this information for nowcasting, [Banbura, Giannone, and Reichlin \(2010\)](#) [4] developed a rating system that makes it easy to understand nowcasts and their updates as new information becomes available. The authors define y_t^Q as quarterly GDP growth at time t . The problem of nowcasting GDP is then reduced to projecting y_t^Q using all available information Ω_v . This information can be summarized as a conditional expectation, such as:

$$P[y_t^Q | \Omega_v] = E[y_t^Q | \Omega_v] \quad (2.1)$$

where $E[y_t^Q | \Omega_v]$ represents the conditional expectation relative to the data set Ω_v . One of the prerogatives of the nowcasting model is reflected in its ability to combine monthly and quarterly series, such as:

$$x_{i,ti}, ti = 1, 2, \dots, T_{i,v}, i = 1, 2, \dots, n; y_{3k}^Q, 3k = 3, 6, \dots, T_{Q,v}$$

where $T_{i,v}$ is the last observation for each series i .

Successive projections $E[y_t^Q | \Omega_v], E[y_t^Q | \Omega_{v+1}], E[y_t^Q | \Omega_{v+2}] \dots$, are subject to revision

as new information becomes available over time $v, v + 1, \dots$. Thus forecasts updating is a problem that can be defined as follows:

$$\Omega_v \subseteq \Omega_{v+1} \quad (2.2)$$

$$\Omega_{v+1} \setminus \Omega_v = \{X - j, T_{j,v+1}, J \in J_{v+1}\} \quad (2.3)$$

The current forecast $E[y_t^Q | \Omega_{v+1}]$, is then described as the sum of the previous forecast $E[y_t^Q | \Omega_v]$ and the revision $E[y_t^Q | I_{v+1}]$ due to the availability of new information I_{v+1} from Ω_{v+1} whose elements are assumed orthogonal to those of Ω_v :

$$E[y_t^Q | \Omega_{v+1}] = E[y_t^Q | \Omega_v] + E[y_t^Q | I_{v+1}] \quad (2.4)$$

Therefore, $I_{v+1,j} = x_j, T_{j,v+1} - E[x_j, T_{j,v+1} | \Omega_v]$. In other words, $I_{v+1,j}$ is the only source for updating the forecast. The authors refer to this source as “*news*”, which carries the difference between the current forecast and the previous one. Ultimately, the arrival of new information requires a forecast revision. The authors associate the value of the revised forecast ($E[y_t^Q | \Omega_{v+1}] - E[y_t^Q | \Omega_v]$), with an intrinsic value of the new forecast ($x_{j,T_{j,v+1}} - E[x_{j,T_{j,v+1}} | \Omega_v]$), also with the weight $b_{j,t,v+1}$ of the latter concerning the variable of interest, i.e., the GDP. Thus, the revision can be written as follows: One of the prerogatives of the nowcasting model is reflected in its ability to combine monthly and quarterly series, such as

$$E[y_t^Q | \Omega_{v+1}] - E[y_t^Q | \Omega_v] = \sum_{j \in J_{v+1}} b_{j,t,v+1} (x_{j,T_{j,v+1}} - E[x_{j,T_{j,v+1}} | \Omega_v]) \quad (2.5)$$

Hence, the revisions are based on the weighted sums of the “*news*”.

2.3.2 The Dynamic Factor model (DFM)

The Kalman filter technique is adopted with the maximum likelihood estimation method as it integrates missing data characteristics and mixed frequencies. It is assumed that $y_t = (y_{1,t}, y_{2,t}, \dots, y_{n,t})$ represents a vector of the monthly growth rate of observed variables. In a dynamic factor model, each observed variable is modeled as the sum of two orthogonal components (Banbura et al. (2013) [3]): the first component represents the unobserved factors that explain the joint dynamics, while the second component represents the idiosyncratic residuals. In other words, the set of monthly indicators y_t is a function of r monthly factors f_t through a weighting matrix Λ and an idiosyncratic component ε_t . Therefore, the factor model can be represented as follows:

$$y_t = \mu + \Lambda f_t + \varepsilon_t \quad (2.6)$$

where f_t is an $r \times 1$ vector of common unobserved factors and ε_t is a vector of idiosyncratic white noise components. ε_t represents the weight of the factors. f_t and ε_t are null mean, which implies that the constants $(\mu = \mu_1, \mu_2, \dots, \mu_n)'$ represent the unconditional means. The above dynamic factor model assumes that the factors follow a p -order vector autoregressive process p such that:

$$f_t = A_1 f_{t1} + \dots + A_p f_{tp} + \mu_t, \quad \mu \text{ i.i.d } N(0, Q) \quad (2.7)$$

, where A_1, \dots, A_p represents rr matrices of autoregressive coefficients. The idiosyncratic component ε_t obeys an autoregressive process of order 1 (ou AR(1)). It can therefore be written as

$$\varepsilon_t = \alpha - i\varepsilon_{i,t-1} + e_{i,t}, \quad e_{i,t} \text{ i.i.d } N(0, Q^2) \quad (2.8)$$

One must follow a few steps to extract the common factor, including adjusting restrictions to fit the maximum likelihood method. This process generates local factors for each block

of indicators. The blocks consist of global (G), real (R), and nominal (N), which consider any local cross-correlation within them. Ultimately, this mechanism improves the extraction of the global factor. Furthermore, this structure allows an increase in the number of factors within each block. In matrix form, we can express the constraints on the Dynamic Factor Model (DFM) as follows:

$$\Lambda = \begin{bmatrix} \Lambda_{N,G} & \Lambda_{N,N} & 0 \\ \Lambda_{R,G} & 0 & \Lambda_{R,R} \end{bmatrix},$$

$$f_t = \begin{bmatrix} f_t^G \\ f_t^N \\ f_t^R \end{bmatrix}, \quad A_i = \begin{bmatrix} A_{i,G} & 0 & 0 \\ 0 & A_{i,N} & 0 \\ 0 & 0 & A_{i,R} \end{bmatrix}, \quad Q = \begin{bmatrix} Q_G & 0 & 0 \\ 0 & Q_N & 0 \\ 0 & 0 & Q_R \end{bmatrix}$$

This procedure is commonly used in the literature with various combinations of mixed frequencies, as described in the previous section for the variable of interest. This study estimates the global factor by considering all the explanatory variables.

2.3.3 Estimation of the Nowcasting model

Dynamic factor models condense the information from multiple economic variables into a few factors that apply to all these variables. For example, the expectation-maximization estimation method is commonly used because it can accommodate arbitrary missing values and mixed frequency data, as discussed in [Bańbura, Marta, and Modugno \(2014\)](#) [5]. An excellent illustration is the New York Federal Reserve Bank nowcast algorithm, as demonstrated in [Bok et al. \(2017\)](#).

Matlab code is modified to deal with economic variables due to various limitations, including the shortage of soft (survey) indicators. As a result, the NYFED Matlab algorithm is readily available online and is easier to comprehend and use. In practice, the Dynamic Factor model is presented in a state-space format (see [Appendix A2](#) for more information). This format enables the application of the Kalman filter, simplifying the filling in missing

past values and quickly utilizing mixed-frequency data. For $y_t^M = (y_t^I, y_t^Q)'$ and $\varphi = (\mu^I, \mu_Q)'$, we can define a state-space representation as follows:

$$\left\{ \begin{array}{l} y_t^M = \varphi + V(\theta)\alpha \\ \text{Equation of measure} \\ \alpha_t = T(\theta)\alpha_{t-1} \quad \eta \sim i.i.d \quad N(0, \Sigma_\eta(\theta)) \\ \text{Equation of state} \end{array} \right. \quad (2.9)$$

where the parameters of the model's maximum likelihood estimators are collected in θ while the common factor components and idiosyncratic components are included in the α_t state vector as for $p = 2$:

$$\alpha_t = (f_t^I, f_{t-1}^I, f_{t-2}^I, \epsilon_{1,t}, \dots, \epsilon_{n,t}, \epsilon_t^Q, \epsilon_{t-1}^Q, \epsilon_{t-2}^Q)'$$

The New York Federal Reserve Bank's nowcasting parameters (θ), unobserved common factors, and missing data are estimated using the Expectation Maximization (EM) algorithm. The EM algorithm involves iterating between the expectation step ("step E") and the maximization step ("step M") until convergence is achieved. In "step E", the likelihood function's conditional expectation is computed using the static parameter estimates (θ) from the previous iteration, θ_j . In "step M", the new parameters, θ_{j+1} , are estimated by maximizing the likelihood function from the previous step concerning θ .

The Expectation Maximization (EM) algorithm estimates the parameters (θ), the unobserved common factors, and the missing data. Then, it iterates between the E and M steps until convergence. The E-step uses estimates from the previous step, the state-space form, and the Kalman filter to fill in missing factors and observations through the Kalman smoother. Finally, it updates the likelihood function based on this augmented dataset. Using principal component analysis (PCA), [Giannone, Reichline, and Small, \(2008\) \[24\]](#) obtain the initial parameters (θ_0), a method successfully used in previous studies. The EM algorithm has been successfully tested on large datasets and automated for real-time forecasting ([Doz et al. \(2006\) \[21\]](#)). However, [Banbura et al. \(2010\) \[4\]](#) note this approach

may be most relevant for datasets with fewer than 30 variables. Further details of the EM algorithm are in [Appendix B2](#).

2.4 Data

This study used economic variables such as production, trade, services, and prices. We included only seventeen indicators to represent major economic activity. Unlike [Giannone, Reichline, and Small, \(2008\)](#) [24], we did not use survey indicators due to their non-existence. The data covered the period from January 1996 to September 2020. They were obtained from various sources, including the national institute of statistics (INS), the World Bank, and the West African states' central bank (BCEAO).

A time series decomposition technique by [Denton-Cholette, \(2006\)](#) [18] is used to create a quarterly series from annual GDP. This technique enables one to circumvent the lack of sufficient historical data. The IMF manual supports such a solution ([Bloem, Dippelsman, and Mæhle, \(2001\)](#) [10]). All indicators are seasonally adjusted. Following [Mariano and Murasawa \(2003\)](#) [27], [Appendix C2](#) explains the process of predicting the quarterly GDP growth rates using monthly variables in practice.

2.5 Results and Discussion

The nowcasting parameters are estimated using vintage data from 1996 over the sample period from January 2000 to June 2020. The accuracy of these nowcasts is evaluated back to 2017 by comparing them with the GDP growth rates provided by the national institute of statistics (INS) and the WAEMU's central bank (BCEAO). The Macroeconomic Conditions Index (MCI), which summarizes the nowcasts, is in relatively good agreement with the official GDP growth rates, especially regarding regime changes, although it tends to be conservative. Specifically, Côte d'Ivoire's economy performed well in the first quarter

Table 2.1: Nineteen Economic variables from 1996 to 2020.

Series	Source	Start Date	Lags	Transf.
Gross Domestic Product	WBK	Q1:1996	3	%QoQ ar.
Industrial Production	INS	Jan 1996	2	%MoM
Construction index	INS	Jan 1996	2	%MoM
Imports	INS	Jan 1996	2	%MoM
Exports	INS	Jan 1996	2	%MoM
Electricity sale	INS	Jan 1996	2	%MoM
Electricity production	INS	Jan 1996	2	%MoM
Electricity consumption	INS	Jan 1996	2	%MoM
Cocoa beans	INS	Jan 1996	2	%MoM
Cement	INS	Jan 1996	2	%MoM
Export Agriculture index	INS	Jan 2015	2	%MoM
Extractive industry index	INS	Jan 2015	2	%MoM
Food industries index	INS	Jan 1996	2	%MoM
Harmonized Price index	INS	Jan 2008	2	%MoM
Gov Rev. and donations	INS	Jan 2000	2	%MoM
Gov Tax revenues	INS	Jan 2000	2	%MoM
Customs duties	INS	Jan 2000	2	%MoM
Net credit	BCEAO	Jan 2004	2	%MoM
Money supply - M2	BCEAO	Jan 2004	2	%MoM

Note: QoQ AR refers to the quarter-on-quarter growth rate, % MoM refers to a simple percentage change. The lags column shows the delay period. Data is collected from the WAEMU's central bank (BCEAO), the World Bank (WBK), and the National Institute of Statistics (INS).

of 2017. However, the preventive measures and restrictions due to COVID-19 had a severe impact on the national economy, resulting in a significant decline in GDP growth (-0.1%) in the second quarter of 2020.

The overall downward trend in Ivory Coast's economy from 2017 through the second quarter of 2020 is captured by the MCI. The analysis is done over three significant periods, including, first of all, a steady decline of the Ivorian economy between the first quarter of 2017 and the first quarter of 2018, then a revival from quarter 2 of 2018 until the last quarter of 2019, and finally the period of steep decline from the first quarter of 2020.

Throughout 2017, the economy remained generally strong with a mean growth rate above 6 percentage points. However, the first quarter of 2018 saw a drop of more than 3%

Table 2.2: Real GDP growths.

Dates	GDP growths		
	INS	BCEAO	MCI
2017Q1	8.5	8.1	7.1
2017Q2	9.6	8.1	7.8
2017Q3	6.2	7.7	6.4
2017Q4	6.0	7.4	6.2
2018Q1	3.2	7.5	3.3
2018Q2	6.7	7.5	6.1
2018Q3	6.5	7.4	6.0
2018Q4	6.3	7.3	5.8
2019Q1	5.3	7.2	5.7
2019Q2	7.7	7.3	6.8
2019Q3	8.1	6.1	7.4
2019Q4	5.0	4.9	5.8
2020Q1	2.9	3.7	3.0
2020Q2	-5.3	-1.6	-0.1

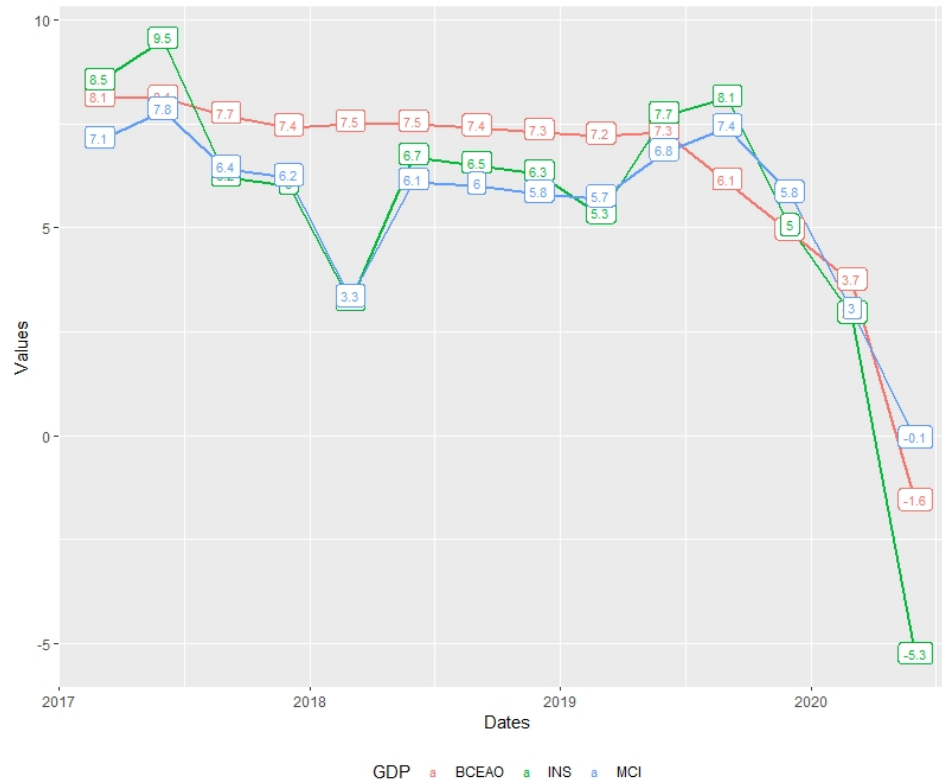
Note: Real GDP growth rates are estimated by the MCI, the national institute of statistics (INS), and the WAEMU central Bank (BCEAO)

captured by the MCI (3.3%), a 0.1 point above the official figure (3.2%). This contraction can be explained in particular by a mixed evolution of export agriculture, a contraction of the extractive industry, and the poor performance of public finances with a lower mobilization of tax revenues. The remaining quarters of 2018 see a relatively good economic performance, also well captured by the MCI, with figures lagging no more than 0.7 points compared to the official GDP growth rates.

In 2019, the economy performed well due to the momentum in export agriculture, increased construction activity, and good tax revenue collection. The Macroeconomic Conditions Index (MCI) closely tracked the official figures, lagging by less than 1 point behind the figures reported by the national institute of statistics (INS) in the second and third quarters of 2019. Specifically, the MCI recorded growth rates of 6.8% and 7.7% respectively, compared to the INS figures of 7.4% and 8.1%.

In 2020, the economy experienced a deeper decline than in the fourth quarter of 2019

Figure 2.2: MCI Nowcasts, BCEAO GDP estimates and published GDP growth rates compared.



Note: The green line reflects the government’s real GDP growth rate figures. The blue line represents the MCI nowcasts based on the DFM. The orange line depicts the central bank’s GDP growth rates.

due to the effects of the coronavirus pandemic. The measures implemented to control the spread of COVID-19 worsened the decline observed in the first quarter, which showed a decline of 2.9% according to the INS, compared to the MCI’s 3% decline. As a result, in the year’s second quarter, the GDP decreased by 5.3%, partly due to reduced tax revenues and donations, decreased foreign trade, and lower industrial production. The MCI, with a conservative estimate of -0.1% compared to the official estimate of -5.3% GDP decline, failed to capture the severity of the economic downturn.

Model prediction accuracy tests

Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) are commonly used as evaluation metrics to assess the accuracy of a model’s predictions. These metrics

provide a complete picture of how well our model is performing. For example, the MAE gives an idea of the magnitude of the errors. At the same time, the RMSE can indicate whether the model is making significant errors that could substantially impact its usefulness in practical applications.

The mean absolute error is calculated as the average of the absolute differences between actual and predicted values. It measures how far off the predictions are from the actual values on average. A smaller MAE indicates a more accurate model, while a larger one indicates a less accurate one. The formula for MAE is:

$$MAE = (1/n) * |y - \bar{y}| \quad (2.10)$$

, where n is the number of observations, y is the actual value of the i th observation, and \bar{y} is the predicted value.

RMSE is calculated by taking the square root of the mean squared error (MSE), the average of the squared differences between the predicted and actual values. RMSE is often used to evaluate the accuracy of regression or time series forecasting models, where lower values indicate better performance. RMSE is expressed in the same units as the predicted and actual values, making it easy to interpret practically.

$$RMSE = \text{sqrt}((1/n) * \sum_{i=1}^n (y_i - x_i)^2) \quad (2.11)$$

, where n represents the number of observations in the dataset, y_i is the observed value of the dependent variable, x_i stands for the predicted value of the dependent variable, \sum is the summation operator, and sqrt is the square root function.

Table 2.3 shows that our Macroeconomic Condition Index outperforms the central bank in forecasting GDP growth rates for Côte d'Ivoire, as evidenced by the lower MAE and RMSE values obtained.

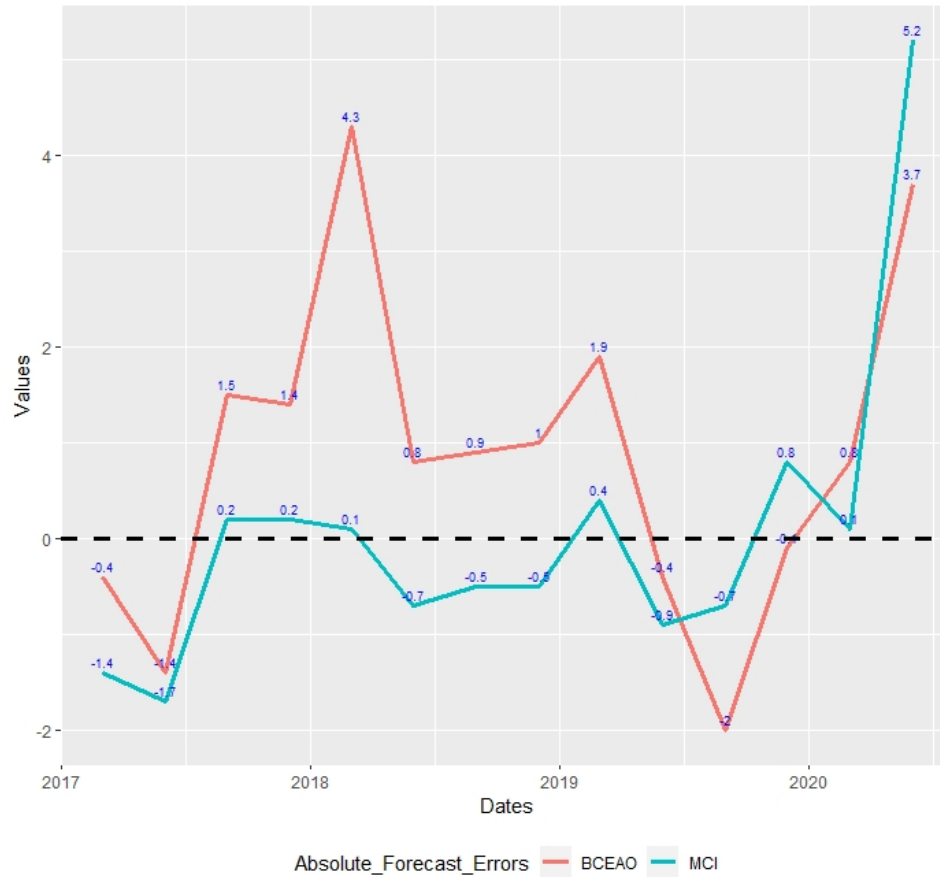
Table 2.3: MAE and RMSE

	Predicted (BCEAO, MCI) against actual GDP growth rates (INS)	
	BCEAO	MCI
Mean Absolute Error (MAE)	1.33	0.971
Root Mean Square Error (RMSE)	1.598	1.583

Note: MAE is the average prediction error, and RMSE can be interpreted as the weighted average performance of the model, where more weight is added to outliers.

Figure 2.3 shows the difference between actual GDP growth rates (INS) and the MCI forecasts. Before the COVID-19 pandemic, this difference ranged from 0.1 to 0.7; during the downturn caused by the pandemic in the first and second quarters of 2020, the difference reached 5.2, which is quite significant. Although the MCI estimates do not always match the reference GDP growth rates from the INS, they reflect the business cycle performance from 2017Q1 to 2020Q2. Moreover, the MCI estimates sometimes show closer proximity to the official figures than those of the central bank (BCEAO). For instance, from 2017Q2 to 2018Q1 and 2020Q1, the difference between the INS and the MCI GDP growth rates did not exceed +/- 0.2 points from the official figure. However, during the COVID-19 pandemic downturn in the second quarter of 2020, the MCI could not capture the INS's deep negative move. As a result, official GDP growth declined by -5.3 percentage points. At the same time, the MCI forecasted a GDP growth rate of -0.1%, resulting in an absolute forecasting error of 5.2 points, the largest over the period considered. This result demonstrates that the MCI's forecast accuracy tends to decrease in the face of a large adverse shock leading to negative territory. In conclusion, an alternative should be considered when forecasting the business cycle dynamics.

Figure 2.3: Absolute forecast errors:



Note: The absolute forecast errors are the difference between actual GDP growth rates from the INS and the MCI (blue line) and the WAEMU’s central bank (orange line) estimates. The dashed black line represents the level of the official GDP growth rates from which MCI and BCEAO deviate.

2.6 Concluding remarks

It is important to keep track of economic conditions in real-time to make better decisions and predictions. Experts in Europe and the United States have created a ” nowcasting ” model to address this need. This research aims to use a Dynamic Factor Model (DFM) in a state-space framework to forecast the monthly GDP growth in Ivory Coast. This DFM is useful for estimating how different time series move together and for predicting economic growth with mixed-frequency data.

This study’s nowcasting model is adapted to provide a real-time toolkit for predicting

Ivory Coast's current economic conditions. This country is one of the largest economies in the Franc CFA zone and the fourth largest in the ECOWAS. The resulting Macroeconomic Conditions Index (MCI hereafter) uses 18 monthly economic indicators. The MCI is estimated from January 1996 to June 2020. The backtesting exercise from 2017 until the second quarter of 2020 shows that the index can approximate best practices in macroeconomic forecasting. The MCI reproduces monthly GDP growth rates closer to the official figures, i.e., those of the National Statistical Institute. Ivory Coast's GDP growth slowed from 2017 to June 2020, driven by the mixed performance of tax revenue collection, foreign trade, construction, and industrial production. The MCI has captured this overall move.

The study's main objective is not to provide accurate estimates of the GDP growth rates of Ivory Coast's economy. The aim is to track economic activity in near real-time. The occurrence of gaps in comparison with the official estimates is common. Indeed, accurately measuring the output of a complex national account system is a challenge, even for large institutions in advanced economies. Nevertheless, the results of this study have a couple of policy implications. For instance, the nowcasting methodology can help design efficient investment processes and economic and monetary policy decisions for WAEMU economies. In addition, given the relatively high predictive power of tax revenues and the construction sector for GDP growth, policymakers could consider increasing the capacity of public finances by improving tax revenue collection and especially by facilitating private sector involvement in Ivory Coast.

As the MCI nowcast accuracy tends to decrease during large adverse shocks, future work could help to capture the characteristics of modern business cycles where steep recoveries may follow dramatic falls. In addition, interest in high-frequency data, such as mobile money transfers and restaurant reservations from big data platforms such as Google Trends, could provide timely information about the magnitude of shocks. Thus, growth dynamics that differ from classical recessions require a comprehensive modeling framework that may include, "machine learning" and parametric factor models-based tools that

are flexible enough to accommodate varying data frequencies.

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Appendices

Appendix A2 : DFM in state space representation

Suppose that y_t and Y_T^Q are respectively monthly and quarterly variables and Λ and Λ_Q the respective weights of the monthly and quarterly series. For $p = 1$ and $r = 3$, the system of equations ((A7 to A8) can be stated in the following state-space form:

$$\begin{bmatrix} y_t \\ y_t^Q \end{bmatrix} = \begin{bmatrix} \mu \\ \mu_Q \end{bmatrix} + \begin{bmatrix} \Lambda & 0 & 0 & 0 & 0 & I_n & 0 & 0 & 0 & 0 & 0 \\ \Lambda_Q & 2\Lambda_Q & 3\Lambda_Q & 2\Lambda_Q & \Lambda_Q & 0 & 1 & 2 & 3 & 2 & 1 \end{bmatrix} \begin{bmatrix} f_t \\ f_{t-1} \\ f_{t-2} \\ f_{t-3} \\ t \\ t^Q \\ t-1^Q \\ t-2^Q \\ t-3^Q \\ t-4^Q \end{bmatrix}$$

$$\begin{bmatrix} f_t \\ f_{t-1} \\ f_{t-2} \\ f_{t-3} \\ t \\ t^Q \\ t-1^Q \\ t-2^Q \\ t-3^Q \\ t-4^Q \end{bmatrix} = \begin{bmatrix} A_1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ I_r & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & I_r & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & I_r & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & I_r & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & \text{diag}(\alpha_1, \dots, \alpha_n) & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & \alpha_Q & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \end{bmatrix} \begin{bmatrix} f_{t-1} \\ f_{t-2} \\ f_{t-3} \\ f_{t-4} \\ f_{t-5} \\ t-1 \\ t-1^Q \\ t-2^Q \\ t-3^Q \\ t-4^Q \\ t-5^Q \end{bmatrix} + \begin{bmatrix} u_t \\ 0 \\ 0 \\ 0 \\ 0 \\ e_t \\ e_t^Q \\ 0 \\ 0 \\ 0 \\ 0 \end{bmatrix}$$

où $\varepsilon_t = (\varepsilon_{1,t}, \varepsilon_{2,t}, \dots, \varepsilon_{n,t})'$ and $e_t = (e_{1,t}, e_{2,t}, \dots, e_{n,t})'$

Taking into account any local cross-sectional correlation using blocks, for a better

extraction of the common factor, implies that:

$$\Lambda = \begin{pmatrix} \Lambda_{N,G} & \Lambda_{N,G} & 0 \\ \Lambda_{R,G} & 0 & \Lambda_{R,R} \end{pmatrix}, \Lambda_Q = \begin{pmatrix} \Lambda_{Q,G} & 0 & \Lambda_{Q,R} \end{pmatrix}, f_t = \begin{pmatrix} f_t^G \\ f_t^N \\ f_t^R \end{pmatrix}$$

$$A_i = \begin{pmatrix} A_{1,G} & 0 & 0 \\ 0 & 0 & A_{1,N} \\ 0 & & \\ 0 & 0 & A_{1,R} \end{pmatrix}, Q = \begin{pmatrix} Q_G & 0 & 0 \\ 0 & Q_N & 0 \\ 0 & 0 & Q_R \end{pmatrix}$$

Appendix B2 : The EM algorithm

We detail the EM algorithm by adopting the notations of Bańbura, Giannone and Reichlin (2010), they are even based on the results of Bańbura and Modugno (2010). Indeed, the EM algorithm consists of the estimation of the set of parameters of the space-state representation (System of equations 28). Thus, the EM algorithm is nothing other than the expression of the likelihood of the parameters in terms of observable and latent variables on the one hand, and depending on the data available, obtaining estimates of the maximum likelihood by iteration through steps E and M on the other hand. The initial parameters (0) , are obtained by principal component analysis (PCA). This method has been used in the work of Doz, Giannone and Reichlin (2006b). In step E, the expected log-likelihood, based on the available data, is a function of the estimates obtained from the previous iteration (j) . It is calculated using the Kalman straightener. In step M, the expected log-likelihood of the previous iteration is maximized to obtain new parameters $(j + 1)$. In detail, the iteration process $j + 1$ (steps E and M) involves at prerequisite, a selection of diagonal matrices D_t and D_{Q_t} of respective sizes n and 1 in order to take into account missing data. Thus the missing values of the series monthly y_t and quarterly y_{Q_t} have the value 1. The rest of the appendix presents the specifications necessary for the elaboration of stages E and M, relative to the weighting matrices associated with different parameters.

.0.1 Unrestricted weighting matrices

Firstly, Bańbura, Giannone and Reichlin (2010) do not impose any restrictions on the weights ω , Q , Γ and Q considering a specification of factors by blocks. Consequently, in step M we obtain:

1. Les matrices de pondération des variables mensuelles:
2. Les matrices de pondération des variables trimestrielles

Appendix C2 : Interpolation of low frequency data

In this study, we consider the monthly factor model described above, in which the variable of interest is quarterly. This approach is used by Rünstler et al.[?], Banbura and Modugno [?], and Banbura et al.[?] growth based on the work of Mariano and Murasawa[?]. Indeed, these authors propose to approximate a quarterly variable by constructing its partially observed monthly counterpart. In this perspective, the inflation-forecasting model proposed by Modugno[?] uses daily, weekly, and monthly stock market data for real-time inflation forecasting.

Our study thus focuses on the formulation of Banbura et al.[?] for GDP forecasts for the economies of the WAEMU zone, considering monthly and quarterly frequencies. This sub-section shows how to construct the monthly counterpart partially observed from a quarterly variable. From this point of view, GDP at the PIB_t^Q level can be defined as the sum of the unobserved monthly contributions PIB_t^M :

$$PIB_t^Q = PIB_t^M + PIB_{t-1}^M + PIB_{t-2}^M, \quad t = 3, 6, 9, \dots \quad (12)$$

Let $Y_t^Q = 100 \times \log(PIB_t^Q)$ and $Y_t^M = 100 \times \log(PIB_t^M)$. The authors assume that the unobserved GDP growth $y_t = \Delta Y_t^M$ can be modeled from the factor model as a real monthly variable such as:

$$y_t = \mu_Q + \Lambda_Q f_t + \varepsilon_t^Q \quad (13)$$

$$\varepsilon_t^Q = \alpha_Q \varepsilon_{t-1} + e_t^Q, \quad e_t^Q \sim i.i.d. \quad N(0, \sigma_Q^2) \quad (14)$$

where $\Lambda_Q = (\Lambda_{Q,G} \ 0 \ \Lambda_{Q,R})$.

Monthly GDP can therefore be linked with observed GDP by constructing partially observed monthly series such as: $y_t^Q = \begin{cases} y_t^Q - y_{t-3}^Q & t = 3, 6, 9, \dots \\ \text{unobserved} & \text{otherwise} \end{cases}$

By approximation [Mariano and Murasawa](#)[?] obtains the following result:

$$\begin{aligned}y_t^Q &= Y_t^Q - Y_{t-3}^Q \approx (Y_t^M + Y_{t-1}^M + Y_{t-2}^M) - (Y_{t-3}^M + Y_{t-4}^M + Y_{t-5}^M) \\y_t^Q &= y_t + 2y_{t-1} + 3y_{t-2} + 2y_{t-3} + y_{t-4} \quad t = 3, 6, 9, \dots\end{aligned}\tag{15}$$

Chapter 3

**A reference chronology of Côte
d'Ivoire's Business cycles in real time: A
finite Markov Mixture approach.**

3.1 Introduction

Since the global financial crisis of 2007-2009, advanced economies have experienced slower growth. Despite this, the extended period of weak growth highlights the importance of long-term growth while minimizing economic fluctuations, which remains a significant objective for stabilization policies. Therefore, decision-makers need to accurately identify economic cycle turning points to anticipate regime changes and ensure financial stability. There are several business cycle dating organizations in industrialized countries, including the Organisation for Economic Co-operation and Development (OECD), the Economic Cycle Research Institute (ECRI), the Centre for Economic and Policy Research (CEPR) for Europe, and the National Bureau of Economic Research (NBER) for the United States. The AFSE (Association Française des Économistes) also provides an informal chronology of the business cycle for France. However, an official reference chronology of business cycle turning points in the West African Economic and Monetary Union (WAEMU¹) does not exist yet. WAEMU is a West African organization created in 1994 to achieve economic integration of member states with unified external tariffs. Member states of WAEMU are Benin, Burkina Faso, Côte d'Ivoire, Guinea-Bissau, Mali, Niger, Senegal, and Togo. Therefore, this study monitors business cycle turning points with real-time characteristics.

To create business cycle reference chronologies, one must identify cyclical turning points. The literature identifies two main approaches to achieving this goal. [Burns and Mitchell, \(1946\)](#) [5] pioneered the first approach. It involves identifying turning points for each economic variable in a panel before finding a turning point common to all variables. "BB algorithm (1971)" expanded on this idea. They developed the "BB algorithm," which estimates the turning points of a business cycle using the gross domestic product (GDP) as a representative time series for global economic activity. In 2020, [Camacho, Gadea, and](#)

¹The West African Economic and Monetary Union (also known by its French acronym, UEMOA), is a West African organization created on January 10, 1994, whose mission is to achieve the economic integration of member states with unified external tariffs. Member states of WAEMU are Benin, Burkina Faso, Côte d'Ivoire, Guinea-Bissau, Mali, Niger, Senegal, and Togo.

[Loscos \[6\]](#) introduced a new approach that uses a multivariate model. This model includes several coincident time series, such as the GDP, to identify turning points. This approach represents an improvement over the BB algorithm because it considers the simultaneous movement of multiple economic variables.

This research uses a three-step process to identify when the Ivory Coast's economy changes direction. First, the **BB algorithm** estimates when the monthly real GDP changes direction. This technique involves analyzing the GDP time series using a weighted moving average technique, similar to the NBER's approach. Then, the mixture multiple-point change model (MMCP) developed by **mixture multiple-point change model (MMCP)** of [Camacho, Gadea, and Loscos, \[6\]](#) in 2020 is used to identify clusters of turning points from a set of coinciding economic variables. This model was built on the work of [Harding and Pagan, \(2016\) \[14\]](#). Finally, the results of these two models are adjusted using a narrative approach that considers the economic, political, and social context of the period under review.

The BB algorithm's turning points are relatively more accurate based on the estimation results. However, the MMCP model can provide valuable information on the impact of the economic variables that make up GDP on its performance. For example, the analysis identified seven (7) economic cycles in Côte d'Ivoire between 1996 and 2019. The resulting chronology of turning points could serve as a basis for a local dating committee to analyze the current state of the economy each month. While the methods used have limitations, they could be improved by analyzing the phase and amplitude separately for better analysis, as suggested by [Addo, Martey and Billio, and Guégan, \(2014\) \[1\]](#).

As far as we know, this is the first recorded chronology of business cycle turning points for the WAEMU. The remainder of this study is organized as follows: [Section 2](#) presents the relevant literature. [Section 3](#) explains the Bry-Boschan (BB) algorithm, which is then expanded to a multivariate framework in [Section 4](#) through a mixture of multiple-change point models. The data set used in the study is introduced in [Section 5](#), while [Sections 6](#)

and 7 use the BB algorithm and the mixture multiple-point change method, respectively. These sections also analyze the results obtained. Finally, section 8 concludes the study.

3.2 Literature review

3.2.1 Business cycle turning points, a univariate approach

Burns and Mitchell [5] formalized the concept of economic cycles in 1946. They noticed the persistence of cyclical imbalances. Their work was initially graphical but later automated through an algorithm developed by Bry and Boschan [4] in 1971. This algorithm censors certain data and imposes constraints on the length and phase of cycles. Harding and Pagan (2002) [12] later modified this algorithm to accommodate quarterly data.

In practice, the Bry-Boschan algorithm identifies business cycles by selecting local extrema in the raw data based on constraints regarding the length and amplitude of the expansion and recession phases. The algorithm allows for coherently identifying peaks and troughs in different cycle phases. In addition, parametric models, such as regime-switching models pioneered by Hamilton in 1989, can provide optimal inference about the business cycle phases. These models have been widely used to detect economic turning points. For example, Bismans and Le Roux (2013)[2] used a dynamic regression Markov-switching model to establish a chronology of South African business cycles, identifying six complete cycles between 1960 and 2011. Damette and Rabah (2010)[10] used a similar probabilistic approach to identify four recessions in France between 1970 and 2009.

Although the BB algorithm is a popular tool for dating business cycles, it has limitations highlighted by researchers like Chen, Mils, and Flasaquier, (2009)[7]. They argue that relying solely on a univariate analysis is inadequate since the co-movement of multiple variables is a crucial factor in economic cycles that a univariate framework cannot capture. Therefore, we will explore more appropriate multivariate approaches for dating business cycles in the following section.

3.2.2 Business cycle turning points, a multivariate approach

Several studies have explored the multivariate approach to dating business cycles by assuming that the chronology of a reference cycle can be derived from coincident economic indicators. For example, [Harding and Pagan, \(2006\)](#) [13] proposed a non-parametric algorithm that goes beyond the visual inspection of [Burns and Mitchell's, \(1946\)](#)[5] work. Their algorithm identifies clusters of turning point dates and extracts reference cycles from them, which are then averaged. This clustering framework provides a natural way to improve the accuracy of reference cycle identification, which is a significant advancement in business cycle analysis.

In 2010, [Stock and Watson](#) proposed a method that is similar to Harding and Pagan's approach in exploring the multivariate approach. They used ordinary least squares to average turning points and then estimated the parameters based on the known occurrence of phase changes throughout the business cycle. Although this method has some limitations, it has important features that account for missing data and irregular time series. [Stock and Watson, \(2014\)](#)[16] introduced the concept of population as an opportunity to innovate. They assume that a population of economic indicators can represent the turning points' central tendency of the distribution of these indicators. This enables statistical inferences to be made about the estimated reference cycle.

Building upon the population concept mentioned earlier, [Camacho, Gadea and Loscos, \(2020\)](#)[6] propose an algorithm to minimize the number of distributional assumptions while simultaneously determining regime changes and their exact dates. Their model accomplishes three goals: classifying observations, accounting for clustering, and modeling unobserved heterogeneity. Finite mixed modeling, assuming that observed data belongs to unobservable population groups and probability density mixtures, has been used in many fields, including internet traffic clustering. For instance, [Sjørl, Loft, and Jørgensen, \(2004\)](#) [15] utilized finite mixed models for clustering internet traffic, while [Wedel, De-](#)

[Sarbo, Bult, and Ramaswamy, \(1993\)\[17\]](#) applied them to investigate perceived consumer risk.

[Camacho, Gadea, and Loscos, \(2020\)\[6\]](#) conducted research using several Monte Carlo simulations to discover patterns in economic fluctuations using disaggregated economic variables. They utilized a Markov-switching mixed model that addressed several issues. Firstly, the authors minimized the assumptions about the distribution by using a pair of turning points to determine the reference cycle timing. They assumed each pair of turning points resulted from an unknown number of bivariate normal distributions. Secondly, they defined the overall reference cycle chronology as the means of these distributions. Thirdly, they employed a Markov chain with a measurable state space to capture regime changes across the cycles with non-recurrent transition probabilities. This process resulted in multiple turning points, which were selected using a Mixture Multiple-Point Change (MMCP) model based on the reference chronology of peaks and troughs.

The abovementioned specification is an alternative to the conventional BB algorithm used in a multivariate setting with missing and jagged data. This contribution is noteworthy as no official reference chronology of business cycles exists in the WAEMU countries.

3.3 Specification of the Bry-Boschan Procedure

The Bry-Boschan approach focuses primarily on determining the location of every turning point in the business cycle. In practice, this method involves using seasonally adjusted time series and follows five successive steps:

- **First Step : Identification of local extremums**

The BB algorithm identifies peaks and troughs over five (5) months. The adaptation was made by [Harding and Pagan, \(2002\) \[12\]](#), rather configures the local extremes on a periodicity of two quarters (or six months).

- **Second step: Respect of the alternation of peaks and troughs**

The higher peak is selected for successive peaks, while the lower one is chosen for consecutive troughs. Thus, the necessary alternation of turning points is ensured.

- **Third step: Minimum duration of the cycle**

Cycles that are too short to be valid are removed by applying the Spencer curve to the resulting series from step 2. Indeed, the minimum cycle duration of 15 months includes at least three turning points, which are configured as follows: peak-trough-peak or peak-trough-trough.

- **Fourth step: Minimum duration of a phase**

Considering information from the third step, any contraction (peak to peak) or expansion (trough to trough) must respect the minimum duration of five months required for a complete phase. We eliminate all turning points associated with a phase of fewer than five months.

- **Fifth step: Some rules of censorship**

1- If the first inflection point is a peak (trough), its value must be higher (lower) than the first point of the studied series. Otherwise, the phase is eliminated.

2- If the last turning point is a peak (trough), its value must be higher (lower) than the first point of the studied series. If not, the phase is eliminated.

3- Finally, any phase whose peak value is less than the trough is eliminated.

Thus, the BB algorithm selects peaks and troughs, candidates to be turning points, and then applies a series of operations to eliminate the points that do not meet the cycle criteria. The BB algorithm can be summarized in table 1 as follows:

Table 3.1: Summary of the BB algorithm

Specification	Business Cycle
Peak	$y_{t-k} > y_t < y_{t+k}$
Trough	$y_{t-k} < y_t > y_{t+k}$
Minimum duration of a phase	5 months
Minimum duration of a cycle	15 months

Note: These are the BB algorithm censoring rules which constrain phase and cycle lengths in estimating a reference chronology of business cycles' turning points.

3.4 Mixture multiple-point change model specification

Camacho, Gadea and Loscos, (2020)[6] developed the mixture multiple-point change (MMCP) model as an econometric tool that builds upon the population concept of Stock and Watson, (2014)[16]. The model aims to identify turning points in the business cycle and introduces some interesting innovations. One of the main innovations involves representing the idea of turning point clusters by separate normal distributions, allowing for a more accurate representation of the different phases of the business cycle. The authors contribute to the field by estimating the business cycle phases rather than assuming them, departing from previous models. Another significant innovation is using confidence intervals to identify turning points, providing a more rigorous and statistically sound approach to evaluating the reference cycle. Overall, the MMCP model significantly contributes to econometrics, improving the accuracy and statistical reliability of identifying turning points in the business cycle.

To divide the entire reference business cycle into distinct expansion and contraction phases, \mathbf{k} pairs of peak and trough dates are used for a given period. According to Camacho, Gadea and Loscos, (2020)[6], each reference turning point date pair, denoted as $w_k = (w_k^p, w_k^c)$, represents a peak (**P**) or a trough (**C**). These turning point pairs are calculated from a set of \mathbf{R} coincident economic indicators. Specific pairs of turning point dates are

collected from subsets of size n_r for each indicator \mathbf{r} , where $r = 1, \dots, R$. Therefore, there are $N = n_1 + n_2 + \dots + n_R$ individual pairs of turning point dates, denoted as τ_j^r where $j = 1, \dots, n_r$ and $r = 1, \dots, R$. In summary, the set of all turning points is denoted as $\tau = (\tau_1, \dots, \tau_N)$, with individual pairs represented as $\tau_i = (\tau_i^P, \tau_i^C)$ and $i = 1, \dots, N$. This process is carried out using the BB algorithm.

In this context, [Camacho, Gadea, and Loscos, \(2020\)\[6\]](#) make a couple of assumptions for modeling the reference cycle turning points, including:

1. the authors of the study found that the distribution of turning point clusters is different across the entire reference cycle, but it is consistent within each individual phase. They concluded that this difference implies that the specific groups of turning point dates cluster around different reference turning points, causing the distribution to be heterogeneous. Additionally, they suggest that τ has a different probability distribution around each reference turning point, further contributing to the heterogeneous distribution of turning point clusters.
2. when considering these two facts together, the turning points at each phase k are generated from a family of bivariate normal distributions with means w_k and covariance matrices \sum_k .
3. specific turning point dates are generated from a mixture of K normal distributions
4. making a case for a Markov regime change process, the authors indicate that the reference cycle turning points are inferred from an unobserved state variable s , taking values from 1 to K . These state variables are collected in $S = (s_1, \dots, s_N)$. Hence, the process s follows a first-order Markov process implying that the probability of transitioning to the current state at time t depends only on the state at time $t-1$:

$$Pr(\tau = K | s_{t-1} = l, \dots, s_1 = v, \tau^{i-1}) = Pr(s_i = k | s_{t-1} = l) = p_{lk} \quad (3.1)$$

where $\tau^i=(\tau_1,\dots,\tau_i)$ represents a set of consecutive pairs of turning points dates. The process involves a $(K \times K)$ matrix P with rows summing to 1.

5. because the turning point dates τ_i are displayed in an ascending order and the pairs of reference turning points dates w_k do not overlap, $w_k^P < w_k^T < w_{k+1}^P$, for all $k = 1, \dots, K$, consequently, $s_i = s_{i+1}$.

It is reasonable to consider a non-ergodic Markov chain, meaning the probability distribution is not recurring. Thus, when the process first reaches a reference turning point date k , it will remain there with a probability of p_{kk} until the next reference turning point date $k + 1$, with a probability of $1 - p_{kk}$ for all k ranging from 1 to $K - 1$. These probabilities create a transition probability matrix \mathbf{P} that depends on the probability p_{kk} :

$$P = \begin{bmatrix} p_{11} & 1 - p_{11} & 0 & \dots & 0 \\ 0 & p_{22} & 1 - p_{22} & \dots & 0 \\ \vdots & \ddots & \ddots & \ddots & \vdots \\ 0 & 0 & 0 & p_{k-1k-1} & 1 - p_{k-1k-1} \\ 0 & \dots & \dots & 0 & 1 \end{bmatrix} \quad (3.2)$$

where p_{kk} are collected in the vector $\theta = (\theta_1, \theta_2, \dots, \theta_K, \theta_P)$ with $\theta_k = (w_k, \Sigma_k)$ representing the parameters of the distribution for each pair k and the following finite Markov mixture model captures the density of the distribution of turning points dates:

$$p(\tau_i|\theta, \tau^{i-1}) = \sum_{k=1}^K Pr(S_i = k|\theta, \tau^{i-1})p(\tau_i|\theta_k, \tau^{i-1}) \quad (3.3)$$

where $p(\tau_i|\theta, \tau^{i-1})$ is the Gaussian density, $N(w_k, \Sigma_k)$, reflecting the fact that the majority of the observed values of different means and covariance matrices are contained in a restricted interval around the mean. $Pr(S_i = k|\theta_k, \tau^{i-1})$ is the filtered probability of sampling from group k with $0 \leq Pr(S_i = k|\theta_k, \tau^{i-1}) \leq 1$ and $\sum_{k=1}^K Pr(S_i = k|\theta_k, \tau^{i-1}) = 1$.

The mixture multiple-point change (MMCP) model mentioned above needs Bayesian

inference to obtain a complete posterior probability distribution on coincident economic indicators. This means that based on the available information, unknown and unobservable quantities can be estimated.

3.4.1 Bayesian inferences

Bayesian inference is a method of using probability theory to draw conclusions and learn from data. For example, in analyzing business cycles, the goal is to determine the distribution of turning point dates, which are unknown quantities. This process requires three steps. First, a prior probability distribution represents what the MMCP model knows before seeing the data. Second, the prior distribution is updated, and finally, the posterior probability distribution is used to describe what the MMCP model knows after seeing the data.

However, computing the mean and variance can be challenging in this process. Sampling algorithms based on Markov Chain Monte Carlo techniques (MCMC) can be useful for inference. MCMC sampling involves simulating N samples from the distribution, which can be used to calculate any statistic of a posterior distribution. Gibbs sampling is one of the MCMC techniques best suited for this context. It generates posterior samples by scanning each variable to sample its conditional distribution while fixing the remaining variables at their present values. The bayesian analysis first deduces a parameter's posterior distribution and then summarises the complete distribution. With Gibbs sampling, the distribution of the parameters of the MMCP model can be transformed into quantity distributions.

3.4.2 The Gibbs sampling

Gibbs sampling is a commonly used Markov Chain Monte Carlo algorithm that generates a random sample of variables (X_1, \dots, X_n) without knowing the density $f(x)$. Simulating a sufficiently large sample makes it possible to calculate the mean, variance, or

other characteristics of $f(x)$ with the desired degree of accuracy. To determine the distributions of turning point dates, the parameters $(\theta = (\theta_1, \theta_2, \dots, \theta_k, \theta_P))$ of the distributions and the inference about the state variable S need to be estimated. This is done using a Markov Chain Monte Carlo (MCMC) method through a Gibbs sampler, which requires a preliminary classification. The Gibbs sampler can be set using the approach put forward by [Frühwirth-Schnatter, \(2006\)\[11\]](#) so that each pair k of reference turning point dates has several preliminary observations $N_k(S^{(0)})$ and sample means $w_k^{(0)}$. Then, the k-means clustering algorithm can be used to identify groups of reference turning point dates and assign individual pairs of turning points to the correct group. From this perspective, [Camacho, Gadea and Loscos, \(2020\) \[6\]](#) approximate the distribution of the parameters through a prior distribution of simulated values by taking $m = 1, \dots, M_0, M_{0+1}, \dots, M_0 + M$ steps, where M_0 is not considered in obtaining the best possible posterior from the Gibbs sampler. Note that the MCMC can be achieved in two steps.

1. First step: Sampling parameters $\theta^{(m)}$ based on classification.

In finite mixture modeling, the parameters $\theta_1, \dots, \theta_K$ are set to be independent of the θ_P . Following [\[6\]](#), this implies that:

$$p(\theta) = p(\theta_1, \dots, \theta_K)p(\theta_P) \quad (3.4)$$

As in [\[8\]](#), the transition probabilities p_{kk} are assumed to follow Beta distributions and to be independent both a priori ($p_{kk} \sim \text{Beta}(e_{k1}, e_{k2})$) and a posteriori ($p_{kk}|S \sim \text{Beta}(e_{k1}(S), e_{k2}(S))$) with:

$$e_{k1}(S) = e_{k1} + N_{kk}(S) \quad (3.5)$$

$$e_{k2}(S) = e_{k2} + N_{kk+1}(S) \quad (3.6)$$

for $k = 1, \dots, K - 1$ and $N_{ij}(S)$ standing for the number of transitions from state i to state j . Given the assumed transition probability matrix P in (3.2), $N_{kk+1}(S) = 1$. Accordingly, the vector parameters $\theta_P^{(m)}$ can be sampled from posterior distribution $p(\theta_P | S^{(m-1)})$.

To clarify, the reference turning point dates and their covariance matrices are independent of each other. When dealing with a multivariate distribution like this, it can be difficult to calculate integrals. However, a Wishart distribution can be used as a conjugate prior to multivariate normality, which makes it easier to approximate this type of distribution through sampling. In this case, a conjugate prior is used for each covariance matrix $\sum_k^{-1} \sim W(c_{0k}, C_{0k}^{-1})$, with fixed bivariate means w_k for each cluster of turning point dates. [Camacho, Gadea and Loscos\[6\]](#) argue that the posterior density can be determined using this approach :

$\sum_k^{-1} | w_k, S, \tau \sim W(c_k(S), C_k(S)^{-1})$, where

$$c_k(S) = c_0k + N_k(S) \quad (3.7)$$

$$C_k(S) = C_k + \sum_{i:s_i=k} (\tau_i - \mu_k)(\tau_i - \mu_k)' \quad (3.8)$$

Hence, it is easier to sample $\sum_k^{(m-1)}$ given $S_k^{(m-1)}$ and $\mu_k^{(m-1)}$. Indeed, Using a conjugate prior is helpful in situations where it is impossible to obtain a posterior distribution of a certain variable, such as the variance of a normal distribution with a beta distribution. A conjugate prior can remedy this issue by allowing us to make an approximation and obtain a posterior distribution.

The same logic holds while maintaining the covariance of each group of turning point dates. Thus, under the prior for each mean, one can write the posterior density

as $w_k | \sum_k, S, \tau \sim N(b_k(S), B_k(S))$ such that:

$$B_k(S) = \left((B_0 k^{-1} + N_k(S) \sum_k^{-1}) - 1 \right) \quad (3.9)$$

$$b_k(S) = B_k(S) \left((B_0 k^{-1} b_0 k + \sum_k^{-1} \sum_{i:s_i=k} \tau_i) \right) \quad (3.10)$$

Precisely as in the previous case, sampling $w_k(m)$ becomes naturally straightforward, given $S^{(m-1)}$ and \sum_k^{m-1} .

While implementing the Gibbs sampler, [Camacho, Gadea and Loscos, \(2020\)\[6\]](#) set the priors $e_{k1} = 6$ and $e_{k2} = 0.1$ as in [\[8\]](#) while non informative priors $b_0 k = 0$, $c_0 k = 0$, $B_0 k = 1000I_2$, and $C_0 k = I_2$ are used.

2. Second step: Sampling the classification $S^{(m)}$ given the parameters $\theta^{(m)}$

Once the conditional posterior distribution is known through the parameters $\theta^{(m)}$, sampling the entire path S becomes the main focus in the Gibbs process. To this end, the first-order Markov chain properties help [Camacho, Gadea and Loscos, \(2020\)\[6\]](#) to note the procedure as:

$$Pr(S|\theta, \tau^N) \prod_{i=1}^{N-1} Pr(s_i | s_{i+1}, \theta, \tau^i) \quad (3.11)$$

where, $\tau^i = (\tau_1, \dots, \tau_i)$.

The above procedure is based on the filtered probability of each state $Pr(s_i = k | \theta, \tau^i)$. Such a filter is detailed in [Hamilton \(1989\)](#). Thus, a two-step recursive procedure takes an initial probability value $Pr(s_0 = k | \theta, \tau^0) = 0$ It consists of a one-step-ahead prediction, updated in a second step.

- **One-step ahead prediction.** Given $i = 1, \dots, N$, the one-step ahead prediction

is computed in as:

$$Pr \left(S_i = k | \theta, \tau^{i-1} = \sum_{l=1}^k pl Pr(s_{i-1} = l | \theta, \tau^{i-1}) \right) \quad (3.12)$$

- **Updated filtered probability**

The above-filtered probability is updated as below once a consecutive turning point is added.

$$Pr (S_i = k | \theta, \tau^i) = \frac{p(\tau_i | S_i = k, \theta, \tau^{i-1}) Pr(s_i = k | \theta, \tau^{i-1})}{Pr(\tau_i | \theta, \tau^{i-1})} \quad (3.13)$$

where $Pr(S_i = k | \theta, \tau^i) = \sum_{k=1}^K p(\tau_i | S_i = k, \theta, \tau^{i-1}) Pr(s_i = k | \theta, \tau^{i-1})$

In order to sample the entire path S as indicated in equation (3.11), [Camacho, Gadea and Loscos, \(2020\)\[6\]](#) start by sampling the last observation s_N which coincides with the last filtered probability $Pr(s_N | \theta, \tau^N)$. In the detail, the authors set out couple of assumptions including:

- (a) a random number u with a uniform distribution between 0 and 1
- (b) w the number of times that $\sum_{k=1}^{k^*} Pr(S_N = k | \theta, \tau^N)$
- (c) S_N is sampled as $1 + W$.

Thus it becomes relatively easier to sample s_i , $i = N - 1, N - 2, \dots, 1$ as the result of comparing the random numbers generated with the conditional distribution $Pr(S_i | s_{i+1}, \theta, \tau^i)$. In this context, assuming $s_{i+1} = 1$, the conditional distribution of $s_i = j$, can be set as:

$$Pr (S_i = j | s_{i+1} = l, \theta, \tau^i) = \frac{p_{jl} Pr(s_i = j | \theta, \tau^{i-1})}{\sum_{k=1}^k P_{kl} Pr(s_i = k | \theta, \tau^{i-1})} \quad (3.14)$$

To avoid an identification problem that could arise from many different modes resulting from the posterior mixture model, the authors propose an "identification

constraint.” This constraint requires that the segmentation of the entire period respects the assumption that the episodes K do not overlap. In other words, for each $k = 1, \dots, K$, the reference cycle turning points must be displayed in ascending order: $\mu_k^{P(m)} < \mu_k^{T(m)} < \mu_{k+1}^{P(m)}$. Any drawing that does not meet this constraint is excluded from the sampling procedure. This procedure helps ensure that the resulting model is properly identified and accurate.

3.4.3 Estimating the number of the turning point dates

Once the various turning points are identified, it is important to determine how many distinct groups make up the reference business cycle for the entire period under consideration. To accomplish this, a method based on likelihood is used, which involves identifying the number of clusters, denoted as K , that have the highest marginal likelihood, represented by $\log p(\tau|\theta_K M_K)$ from a set of clusters $1, \dots, K$.

Following [Camacho, Gadea and Loscos, \(2020\)\[6\]](#), I note that:

1. K^* is user specified
2. M_K is a mixture model of K elements
3. θ_k^* is the d_K dimensional vector of its maximum likelihood estimated parameters.

The choice of the appropriate model is based, on the one hand, on the value of K that minimizes the Akaike criteria. ($AIC_K = -2\log p(y|\theta_K^*) + 2d_K$) and the Schwartz ($BIC_K = -2\log p(y|\theta_K^*) + d_K \log(N)$) On the other hand, the value of the components K maximizes the classification quality through the entropy criterion.

$$EN_K = - \sum_{i=1}^N \sum_{k=1}^K p(s_i = k|\tau_i, \theta) \log p(s_i = k|\tau_i, \theta) \quad (3.15)$$

Thus, the ideal data partition will have an entropy value of 0. Conversely, the positive and increasing importance of entropy characterizes misclassification. In this context, the

best model is the one that presents both the optimal number of components and an efficient partition. [Camacho, Gadea and Loscos, \(2020\)\[6\]](#) consider the model with the number of K , which minimizes $BIC_k + EN_k$.

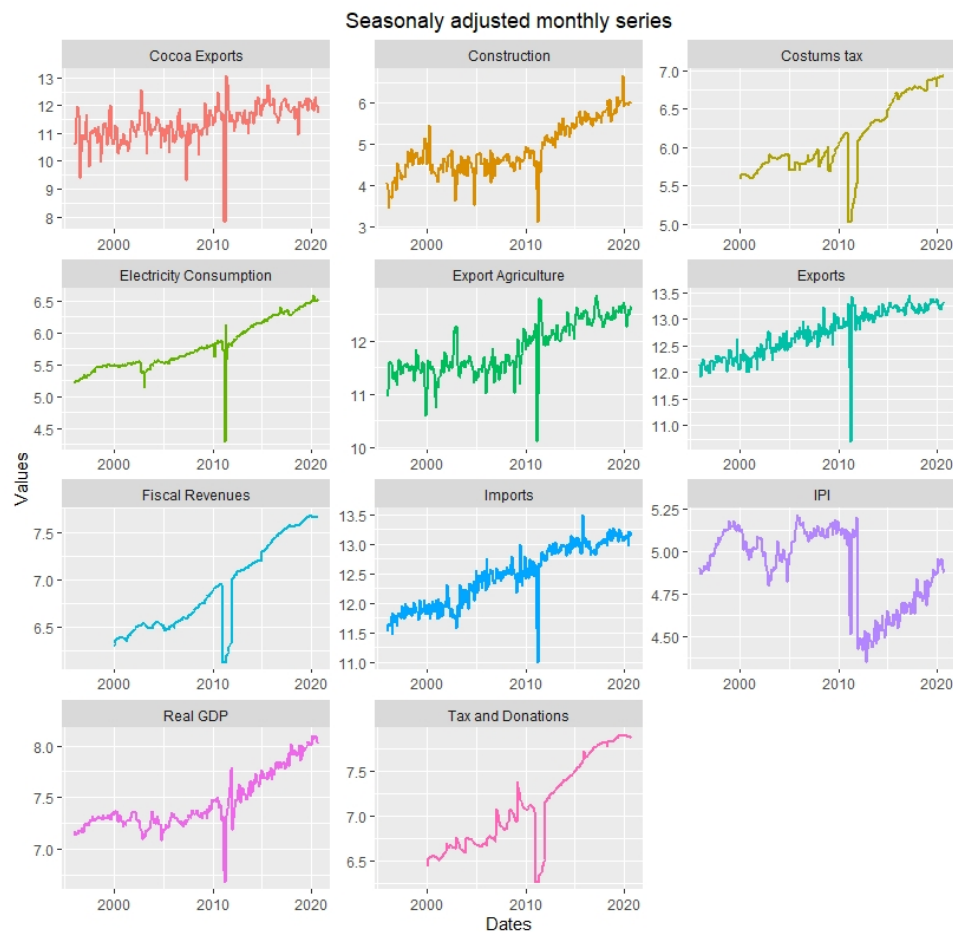
3.5 The Data

Monthly Gross Domestic Product (GDP) is a country's primary economic activity measure. We use real GDP² at purchase price from the World Bank. In addition, other monthly economic indicators are used to provide a chronology of Côte d'Ivoire's economic reference cycle. However, some of these indicators have missing observations, while others are only available briefly. Without survey data, our data set is limited to several groups of indicators, namely: industrial production index, imports, exports, construction, electricity consumption, tax revenues, cocoa beans export, other agricultural exports, revenues, and donations.

Our study uses real GDP as the primary measure of a country's economic activity and has found that other economic indicators are relatively correlated. We apply the **X13-ARIMA** method to the monthly GDP series to account for seasonal variations. Additionally, we use the Denton-Cholette process with temporal disaggregation, based on [Dagun and Cholette, \(2006\) \[9\]](#) methodology, to convert the real annual GDP into a monthly series. Although this process is purely mathematical, it enables us to use additional indicators to provide economic value to the resulting series. The Denton-Cholette method transfers the movement of the indicator to the resulting series, so the monthly Industrial Production (IP) series serves as a movement indicator of the GDP series. We obtain the IP series, and the remaining data from the national institute of statistics of Côte d'Ivoire provides the remaining variables see [Figure 3.1](#)).

²Source: World Bank staff estimates based on World Bank national accounts data archives, OECD National Accounts Statistics, and IMF World Economic Outlook database.

Figure 3.1: Monthly seasonally adjusted series



Note: Monthly seasonally adjusted series with real GDP desegregated from annually to monthly through the Denton-Cholette method.

3.6 Bry-Boschan routine applied to the Ivorian economy

3.6.1 Results

We use the standard BB algorithm to measure the absolute declines in the real GDP series. This analysis shows seven (7) periods of contraction between January 1996 and December 2019, with an average duration of 24.8 months. However, we do not consider short periods of contraction followed by expansion, as the BB algorithm does not measure growth and acceleration phases. [Table 3.2](#) presents the results of the *Bry-Boschan* pro-

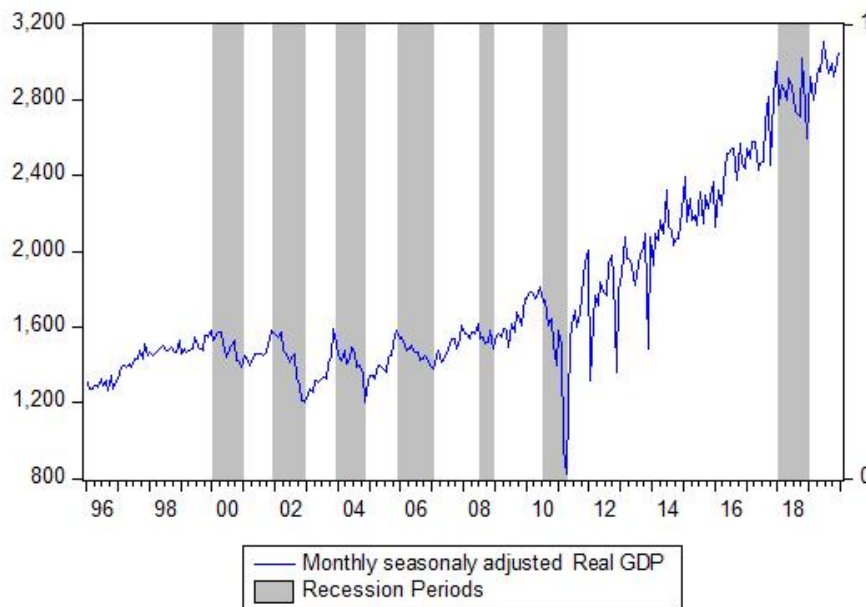
cedure, and Figure 3.2 provides a visual representation of the results. We discuss these outputs in the next section.

Table 3.2: A chronology of Business Cycle turning points from the BB algorithm

Peak	Trough	T-P Duration (months)	P-T Duration (months)
1999:12	2000:12	-	12
2001:11	2002:12	11	13
2003:11	2004:11	11	12
2005:11	2007:01	12	14
2008:06	2008:12	17	06
2010:06	2011:04	18	10
2017:12	2018:12	80	12
Average		24,8	11,29

Note: Turning point dates from the Bry-Boschan algorithm calibrated on monthly GDP series with the industrial production series as a movement indicator (Denton-Cholette).

Figure 3.2: Turning points dates between 1996 and 2019 from the BB algorithm



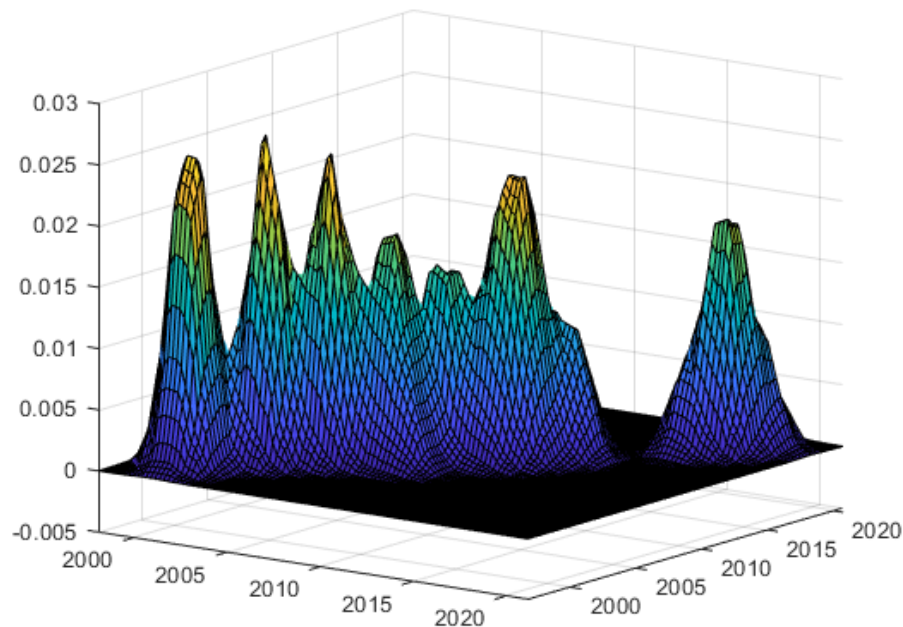
Note: Grey bars are turning point dates from the Bry-Boschan algorithm calibrated on the monthly GDP series with the industrial production series as a movement indicator (Denton-Cholette).

3.7 The application of the mixture multiple-point model

3.7.1 Results

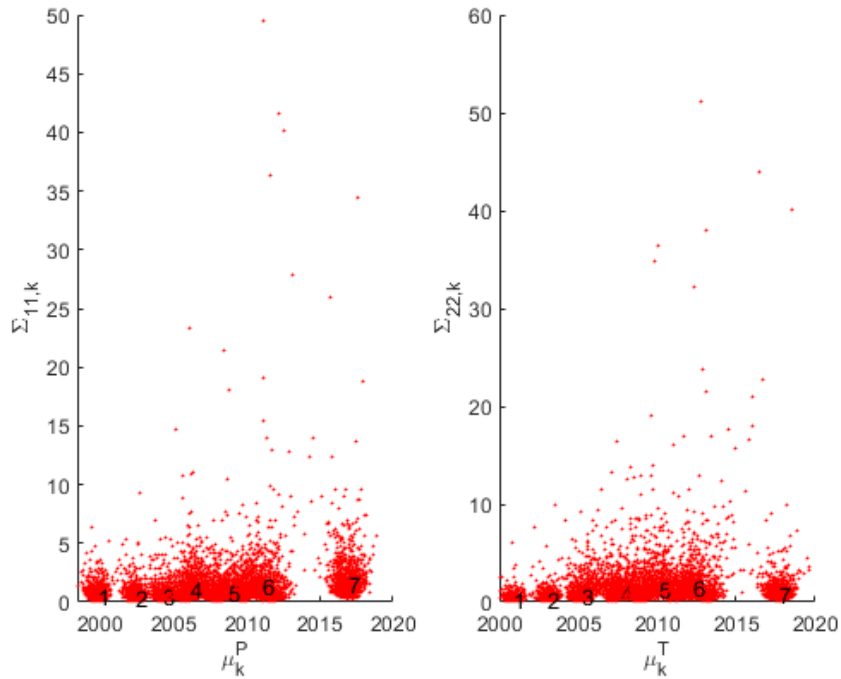
The mixture multi-point change model identifies individual turning points. In [Figure 3.3](#), a bivariate kernel distribution displays seven (7) groups of business cycle turning points. Additionally, the algorithm reveals seven (7) clusters of turning point dates from multiple Monte Carlo simulations, as shown in the scatter plot of means and variances in [Figure 3.4](#). The Matlab code implements model selection in [Table 3](#) to determine the optimal number of significant clusters. These peaks and troughs are further discussed in a dedicated section.

Figure 3.3: Kernel density estimates of the Bivariate Distribution



Note: The bivariate distribution shows seven conical shapes representing the many turning points of the economic cycles between 1996 and 2019 in Ivory Coast.

Figure 3.4: Scatter plots of means and variances



Note: Two groups of turning points are derived from the mixture multiple change-point model. Peaks on the left and troughs on the right. Peaks and trough durations have relatively similar strengths, except in the last phase, with an 80-month peak.

Model selection

In this section, we describe the process of determining the date groups of turning points using the Monte Carlo simulation discussed earlier. To evaluate the performance of the MMPC model, we combine all the simulated pairs of change point dates into specific groups. Table 3 reports the penalties introduced in the model selection and presents the values of the best MMPC model. The model is selected based on several criteria, including Log-likelihood, AIC, BIC, Entropy, BIC+Entropy, and Bayes factor.

The Mixture Multi-point Change (MMPC) Model results show seven (7) complete business cycles. This finding is confirmed by the Bayes factor sequence, which compares two models with k_1 and k . According to the estimates provided in Table 3.3, the highest log likelihood (-81.20) and the minimum values of AIC (244.4) correspond to a small value

of entropy (0.97) and $K = 6$. Therefore, from 1996 to 2019, the economy of Ivory Coast has encountered six (6) reference turning points.

Table 3.3: Model selection.

K	Log Likelihood	AIC	BIC	Entropy	BIC Entropy	Bayes Factor K-1/K
1	-405.21	820.41	828.85	-	-	-
2	-139.79	301.58	320.16	0.41	320.97	508.70
3	-119.27	272.53	301.24	0.41	302.07	18.91
4	-105.24	256.47	295.32	0.64	296.59	5.93
5	-94.06	246.13	295.11	0.84	296.78	0.21
6	-87.98	245.96	305.07	0.82	306.71	-9.96
7	-81.20	244.10	313.64	0.97	315.59	-8.57
8	-84.19	262.37	341.75	2.21	346.18	-28.11

Note: The first column refers to the marginal log-likelihoods; the second and third columns refer to the Bayesian AIC and BIC selection criteria; the third column shows the entropy; the fourth column shows the BIC corrected for misclassification; the last column reports twice the log of the Bayes factor for K-1 versus K clusters, with $K = 2, 3, \dots, 7$.

Selected turning points dates

The algorithm provides a confidence interval for each peak and trough (Table 3.4) from which the final seven turning points are identified (Table 3.5).

Table 3.4: Confidence intervals from the MMCP model.

Confidence intervals for :			
Peaks		Troughs	
1999:03	2000:06	2000:06	2001:05
2001:11	2002:12	2002:08	2003:08
2003:09	2004:12	2004:07	2006:05
2005:04	2007:09	2006:10	2008:10
2007:07	2010:03	2008:06	2011:07
2009:09	2012:07	2011:02	2013:12
2015:12	2017:12	2016:12	2018:06

Note: Confidence intervals for each turning point dates estimate from the Mixture Multiple-point Change model.

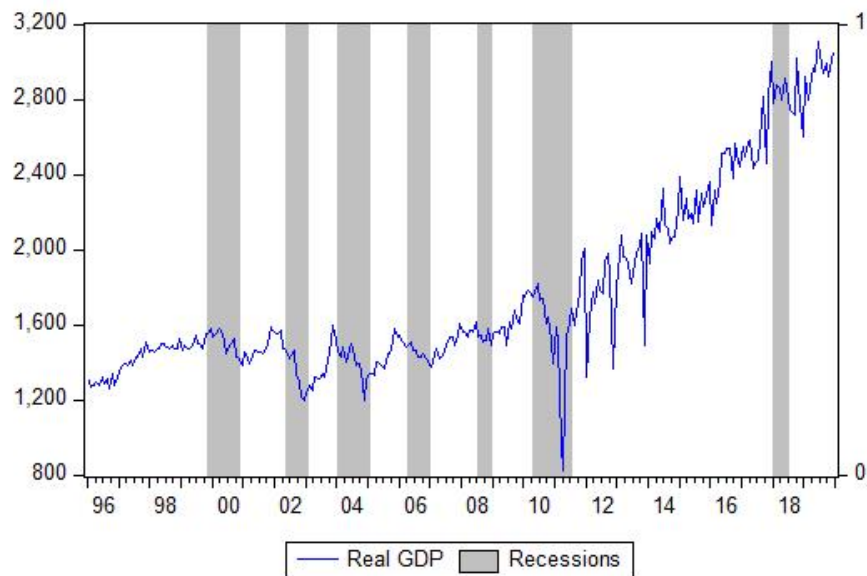
The dates of the final business cycle turning points are presented in [Table 3.5](#), based on the bands of peaks and troughs. The MMCP algorithm automatically selects average peaks and troughs, and we choose the final turning points within the confidence intervals. Our decisions are guided by a narrative that considers the influence of political and social factors on macroeconomic conditions during the period examined. [Figure 5](#) shows these turning points.

Table 3.5: A chronology of Peaks and Troughs estimates from the MMPC model.

Mixture Multiple-point Change model		
peaks	troughs	Durations of Recessions
1999:10	2000:11	13
2002:04	2003:01	09
2004:01	2005:01	12
2006:03	2006:12	09
2008:06	2008:12	06
2010:03	2011:07	16
2017:12	2018:06	06
Average duration		10

Note: Estimates of peaks and troughs from the MMPC model. The turning point dates in blue are actual peaks, and the troughs picked up from the confidence intervals match the behaviour of the monthly real GDP.

Figure 3.5: Turning points of business cycles in Ivory Coast (MMCP model).



Note: Grey bars represent business cycles’ turning points from the Mixture Multi-Point model calibrated on several monthly economic time series. The algorithm reveals seven business cycles between 1996 and 2019.

3.7.2 Discussion from the BB algorithm and the MMPC model results

We use two methods to measure periods of recession: the standard Bry-Boschan algorithm using the “@Bry-Boschan” procedure in WinRats 9.2 and a Matlab code for the mixture multiple-point change (MMCP) model. Both approaches confirm that the Ivorian economy experienced seven (7) recessionary phases between January 1996 and December 2019. However, while the Bry-Boschan routine and the MMCP model generally agree on the occurrence of business cycles for Ivory Coast, the two approaches differ on the start and end dates of the cyclical phases, except for the trough starting in July 2008 and January 2018. However, considering the political, social, and economic environment, a view emerges on the length of business cycles. Additionally, a better understanding of the similarities between the BB routine and the MMCP algorithm shows that the latter provides information on the impact of the main components of real GDP on the occurrence of turning points in business cycles.

Table 3.6: Peaks and Troughs estimates from the Bry-Boschan and the MMCP model.

Standard Bry-Boschan algorithm (months)				Mixture Multiple-point Change model (months)			
Peaks	Troughs	Exp	Rec	Peaks	Troughs	Exp	Rec
1999:12	2000:12	-	12	1999:10	2000:11	-	13
2001:11	2002:12	11	13	2002:04	2003:01	17	09
2003:11	2004:11	11	12	2004:01	2005:01	12	12
2005:11	2007:01	12	14	2006:03	2006:12	14	09
2008:06	2008:12	17	06	2008:06	2008:12	18	06
2010:06	2011:07	18	10	2010:03	2011:07	15	16
2017:12	2018:12	80	12	2017:12	2018:06	77	06
Average duration		24.8	11.29	Average duration		25.5	10

Note: The left side of the graph shows the results of the Bry-Boschan algorithm applied to the seasonally adjusted GDP series. The analysis shows that there were, on average, 11-month contractions in the GDP series seven times between 1996 and 2019. The Mixture Multiple-point Change (MMCP) model results are shown on the right side of the graph. The model also reproduces seven phases with recessions lasting an average of ten months.

Between 1999 and 2018, the BB routine and MMCP algorithm identified seven periods of economic decline and six periods of growth. The BB algorithm identified the **first period of decline** in 2000 without providing further details. However, the MMCP algorithm attributed this initial decline in tax revenues, industrial production, and private-sector activities to political tensions. The BB routine and MMCP algorithm also identified an expansion period lasting over a year. Unfortunately, this growth was short-lived due to the country's economic fragility, further exacerbated by an attempted coup in September 2002.

A **second economic downturn** occurred in 2002 due to disrupted investor confidence. Both the BB routine and MMCP algorithm recorded this downturn to varying degrees. While the BB routine identified this downturn well before the destabilization attempt, the MMCP algorithm states that the decline in GDP began a few months later, in May 2002. The MMCP algorithm added that the second recession lasted less than a year, and the expansion that marked the turning point lasted twelve months. The BB routine and MMCP algorithm reported that the expansion ended in November 2003 and January 2004, respec-

tively. Such an economic improvement can be attributable to investors' confidence due to political negotiations at the international level, such as the Marcousis and Accra agreements.

Amidst a time of continuing tension, there were unfortunate incidents, such as the destruction of a French cantonment by an Ivorian warplane that led to the death of 12 individuals. This unrest harmed the Ivorian economy, causing its **third recession** in 2004, which halted the strong economic performance of the previous year. The BB routine and MMCP algorithm both recorded this recession. However, the Ivorian economy showed improvement and performed well for a minimum of 12 months between late 2004 and 2005.

During 2005, the BB algorithm detected a **fourth economic contraction**, despite some political progress. However, this contraction ended in early 2007 and was followed by at least twelve months of economic expansion until the second quarter of 2008. The positive economic performance during this period is probably due to the delayed effects of the 2007 political agreement between the conflicting parties that tackled power-sharing. Additionally, United Nations resolution 1721 created a secure environment for businesses to operate, allowing the President to stay in power.

The economy experienced a **fifth recession** in the second half of 2008, primarily due to the subprime mortgage crisis. Indeed, the subprime mortgage crisis impacted global economic growth, trade, and capital flows. In addition, the crisis reduced demand for African exports, reduced foreign investment, and reduced remittances from African workers abroad. Many African countries, including Côte d'Ivoire, have slowed economic growth due to these factors. Both algorithms agreed that the recession lasted at least six months, starting June 2008. Following this, the BB algorithm identified an expansion period of over eighteen months from 2009 to March 2010. This positive economic performance resulted from businesses regaining confidence after signing the fourth political agreement, widely known as the "Accord Ouagadougou."

The economy had been showing signs of recovery, but it experienced a **sixth recession** at the beginning of 2010 due to mounting political tensions before the presidential election. During the post-election crisis in early 2011, the private sector suspended its activities for at least four months. This setback caused the MMCP algorithm to identify a trough, which lasted for sixteen months between June 2010 and July 2011. Following this, the MMCP model identified a relatively long period of growth lasting 77 months, supported by significant government investment programs.

The economy performed favorably in 2017, exhibiting a growth rate exceeding 6%. However, the extractive industry and tax revenues experienced a downturn in 2018. Consequently, the economy faced its **seventh recession** in December 2017, lasting six months.

Both methods of measuring business cycle turning points are complementary, with the BB method being relatively precise in identifying the initiation and conclusion of cyclical phases and easier to apply. Conversely, the Mixture Multiple Change Point model (MMCP) provides more comprehensive insights into the sources of business cycle regime shifts, relating GDP performance to changes in each component. This feature can be advantageous in directing government policies to enhance GDP performance. For example, both models concur that political concerns were the principal cause of the recession in Côte d'Ivoire from 1996 to 2019. These findings align with several studies, including [Block, \(2002\) \[3\]](#), which suggests that developing countries' weak political and governance institutions contribute to politically induced economic fluctuations.

3.8 Conclusion

Major recessionary episodes, such as the financial crisis of 2007-2008, have spurred a renewed interest in analyzing cyclical fluctuations. As a result, researchers and economists have developed new statistical and econometric tools to establish a reference chronology of turning points in economic cycles. Several organizations, including the French Association of Economic Sciences (AFSE) in France, the Center for Economic Policy Research (CEPR)

for Europe and America, and the National Bureau of Economic Research (NBER) for the United States, have conducted reference chronologies of economic cycles.

Table 3.7: Selected reference economic turning point dates

Selected reference chronology of Business cycle turning point dates	
Tuyning Points	Dates
Peak	1999:10
Trough	2000:11
Peak	2002:04
Trough	2003:01
Peak	2004:01
Trough	2005:01
Peak	2006:03
Trough	2006:12
Peak	2008:06
Trough	2008:12
Peak	2010:03
Trough	2011:07
Peak	2017:12
Trough	2018:06

Note: The reference business cycle turning point dates for the economy of the Ivory Coast. The dates are selected from a combination of econometric tools and a narrative depending on the economic context

We use a multivariate approach to present a monthly reference cycle of turning points in the Ivorian economy. We determine the reference chronology of turning points through three steps. Firstly, we apply a traditional NBER-type recession measure to the monthly real GDP series using the WinRats 9.2 standard “@Bry-Boschan procedure”. Secondly, we employ the Matlab algorithm of Camacho and Loscos’ Mixture Multiple-Change point model to analyze ten coincident indicators to automatically estimate turning point dates as averages of individual pairs of peaks and troughs. Lastly, we use a narrative approach, depending on the economic context of the period, to assist in determining the final reversal turning point dates.

The Bry-Boschan algorithm was applied to the real GDP series, while the MMCP model was used to analyze ten higher-frequency coincident indicators. We found that from 1999 to 2019, the Ivorian economy underwent seven (7) recession phases, lasting an average of ten months, while the expansion phases lasted twenty-four (24) months. While providing more insights, the MMCP model was consistent with the Bry-Boschan approach in capturing key turning points. The analysis also revealed that political issues were the primary cause of the recessions in Côte d'Ivoire, except for the 2008 global financial crisis.

While this study can serve as a starting point for a business cycle dating committee for the Ivory Coast or other ECOWAS member states, more research is needed to improve the analytical methods' accuracy. In particular, relying on ex-post-cyclical turning points requires a thorough effort to ensure the accuracy of dates. Additionally, conventional business cycle analysis methods cannot uncover hidden information about time series behavior. In addressing this drawback, future research could explore the use of complex Morley wavelets to gather phase information and identify the cycle of the time series based on the associated frequency and magnitude. This framework could provide additional insights and enhance the analysis of GDP fluctuations.

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Appendices

Appendix A3 : The Monte Carlo Simulation

Different Monte Carlo simulation experiments can be used to determine the exact number of separate turnaround-point date groups. With each turning point in the group that suits it, the Monte Carlo simulation thus makes it possible to estimate the chronology of the reference cycle for the economy of Cote d'Ivoire. Seven scenarios can be used to simulate the dates of specific turning points from 1000 mixtures of three bivariate normal distributions.

1. Scénario 1

We generate, for each mixture, specific dates around three pairs of reference cycle dates that are generally the means of the Gaussian distributions corresponding to the average characteristics of the reference cycle highlighted by the BB algorithm. Thus the first reference peak is fixed at μ_1^P in March 2003. We establish at 15 months the distance between each reference peak and the corresponding reference trough and at 60 months the distance between the reference trough and the next reference peak.

For each of the three reference dates, a sample of 300 specific dates of bivariate Gaussian distributions is established, whose means μ_k represent the reference dates and whose covariance matrices \sum_k , are the mean of the covariance matrices estimated when the MMC model is applied to all the indicators. In this scenario, the covariance is equal to zero.

For each of the 1000 simulations, 2500 prints are generated from the subsequent distributions. However, the first 500 simulations are ignored if they satisfy the initial conditions.

2. Scenario 2

As in Scenario 1, we simulate a reference cycle that is relatively longer than normal.

3. **Scenario 3**

This scenario allows us to simulate a double-dip recession cycle. In other words, this time we take into account possible periods of recession followed by brief expansions. This case appears in 2010 in Cote d'Ivoire, whose reference cycle contains a brief 7-month expansion. The 3 following scenarios take into account the low quality of the coincident indicators.

4. **Scenario 4**

Here, we capture the fact that the reference turning points are difficult to identify due to the very high dispersion of date groups of specific turning points. Consequently, this scenario is a case of a data generation process whose variances are twice as large as the mean of the estimated variances of the empirical application.

5. **Scenario 5**

We deal with incomplete series with missing data at the beginning of the sample. This involves calculating inferences from a smaller set of observations. In this case, we generate only 50 observations for the first cluster.

6. **Scenario 6**

In this scenario, specific dates are obtained from a small set of indicators. The total number of specific dates simulated is, therefore, 50 in this case.

7. **Scenario 7**

The final scenario is outside the theoretical framework where we are able to capture overall economic activity from certain indicators. However, the leading or lagging trends of some indicators can lead to asymmetry around groups of turning points. These differences in symmetries can be studied by simulating the specific turning points from a distribution spread to the right (**Scénario 7a**) and a distribution spread to the left (**Scénario 7b**), using a mixture of the two distributions. The first is a

normal distribution with the true mean parameters and the second is a normal distribution that shifts the mean parameters by -3 months in (**Scénario 7a**) and +3 months in (**Scénario 7b**). The proportion of the two distributions is 90% and 10% respectively.

General Conclusion

A significant mismatch between private savings and private investment resulted in long-term stagnation during the 1930s Great Depression. Because of the prevailing uncertainty and pessimism, private investors were hesitant to invest, despite the availability of significant savings. However, the period from 1946 to the mid-1970s was marked by a prolonged period of exceptional and consistent economic growth, dubbed the "Golden Age of Capitalism." Nonetheless, recent events such as the Ukraine war and the 2021-2022 energy crisis may cause an economic downturn and high inflation similar to the 1970s, characterized by stagflation - the simultaneous occurrence of high inflation and economic stagnation. Despite efforts to identify and forecast economic cycles, it remains challenging due to the irregularity and unpredictability of these cycles. Economic activity alternates between periods of growth, crisis, recession, and recovery, with varying durations and intensities, making it challenging to predict accurately.

Econometricians have developed powerful tools to quickly identify and forecast business cycles by analyzing high-frequency data. These techniques are essential for policymakers seeking to respond effectively to economic developments. However, despite the availability of these tools, real-time economic analysis is lacking among policymakers in the Economic Community of West African States (ECOWAS), which has been considering introducing a single currency for its member states for many years. In light of this, the present thesis proposes several tools to facilitate a more relevant analysis of economic regime changes in the ECOWAS region. Furthermore, this thesis aims to contribute to the

ongoing debate about the preparedness of ECOWAS member states to relinquish their monetary sovereignty in exchange for a single currency. By applying these tools, policymakers will be better equipped to make informed decisions regarding introducing a single currency, which could have far-reaching implications for the economic and political stability of the region.

The first chapter evaluates the business cycle synchronization of ECOWAS member states to design an effective currency union. The study uses the Maximum Overlap Discrete Wavelet Transform approach and the continuous Morlet wavelet analysis to investigate the co-movements of regional business cycles. In addition, we conducted a clustering analysis to determine which business cycles exhibit similar or dissimilar patterns across different frequencies. The results indicate the need for more evidence of business cycle elongation in the ECOWAS region, except for Togo. In addition, the study identifies a group of twelve countries called **sayEco-12** that could form a common currency zone within the ECOWAS region. This group comprises five WAMZ economies, including Nigeria and Ghana, and the seven CFA Franc economies. Thus, the **sayEco-12** could integrate low-inflation, and high-inflation economies, a mixup that could pose considerable challenges, such as potential conflicts in monetary policy and asymmetric shocks. The study highlights the need for further research on business cycle synchronization in the region to design an effective currency union considering these complex dynamics. For example, future studies could explore synchronization patterns by separating amplitude and phase information, enabling better assessment of responses to a common stabilization policy. Additionally, more research is required to fully comprehend the drivers of business cycle synchronization in the region.

Ivory Coast has experienced a series of inconsistent economic growth performances since the 2000s, followed by a strong and stable performance since 2012, before experi-

encing a significant decline in 2020. Therefore, understanding what is happening now is essential for estimating growth and looking ahead. In this context, the second chapter lays out a mechanism for real-time monitoring of economic conditions to assess what is happening in the Ivorian economy. We used **saynow-casting** technique for real-time prediction for evaluating the present and near future of the Ivorian economy between the first quarter of 2017 and the second quarter of 2020. The results, recorded in the macroeconomic conditions index (MCI), show that the quarterly growth rates of gross domestic production (GDP) are relatively close to the official figures. Furthermore, the MCI helps explain the influence of the cycle phases on the components of GDP and provides the ability to make informed judgments based on early projections of the business cycle. For example, between January 2017 and June 2020, Ivory Coast continually declined in activity. Deterioration in several areas, including tax revenue collection, foreign trade, construction, and industrial production, are the primary sources of the observed downturn. The COVID-19 pandemic, among other things, prompted this scarcity.

While the main objective of the index is not to provide an accurate estimate of the GDP growth rate, the results of this chapter have some policy implications. Indeed, this chapter shows that the now-casting methodology can help to anticipate cycles and thus make effective investment, economic, and monetary policy decisions in ECOWAS economies. For example, given the relatively high weight of public finance in calculating GDP growth, policymakers could consider increasing their capacity to collect tax revenues and facilitate private sector involvement. Despite its strengths, for example, in tracking the monthly evolution of the GDP growth rate, the MCI needs to provide a historical reference time frame for the business cycle. **Chapter 3** proposes an ex-post dating of the succession of downturns and upturns in the level of economic activity, which is helpful for forecasting exercises.

The third chapter proposes a multivariate approach to present a monthly reference cy-

cle of turning points in the Ivorian economy. We determine the reference chronology of turning points through three steps. Firstly, we apply a traditional NBER-type recession measure to the monthly real GDP series using the WinRats 9.2 standard “@Bry-Boschan procedure”. Secondly, we employ the Matlab algorithm of Camacho and Loscos’ Mixture Multiple-Change point model to analyze ten coincident indicators to automatically estimate turning point dates as averages of individual pairs of peaks and troughs. Lastly, we use a narrative approach, depending on the economic context of the period, to assist in determining the final reversal turning point dates.

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While this study can serve as a starting point for a business cycle dating committee for the Ivory Coast or other ECOWAS member states, more research is needed to improve the analytical methods’ accuracy. In particular, relying on ex-post-cyclical turning points requires a thorough effort to ensure the accuracy of dates. Additionally, conventional business cycle analysis methods cannot uncover hidden information about time series behavior. In addressing this drawback, future research could explore the use of complex Morley wavelets to gather phase information and identify the cycle of the time series based on the associated frequency and magnitude. This framework could provide additional insights and enhance the analysis of GDP fluctuations.

Although this thesis provides a significant contribution, there are several areas where it can be improved:

1. It would benefit from examining the amplitude and phase of the business cycle sep-

arately, allowing for a more detailed analysis of cyclical behavior in the case of a significant adverse shock. This process would enable a more coordinated stabilization policy.

2. The New York FED's version of the now-casting model has a limited forecasting capacity during major recessionary shocks. This drawback could be corrected by considering BIG Data available in real-time at higher frequencies. For instance, data on money transfers and restaurant reservations could provide information on the magnitude of shocks. In this context, machine learning could assist economic agents in making more accurate decisions, as it is flexible enough to adapt to varying data frequency and availability contexts.
3. The real-time monitoring of the business cycle and the ex-post dating of turning points in this thesis are limited to GDP. However, tracking business cycles by sector of activity would provide more extensive readability to economic agents.

In conclusion, the progress in data collection and the development of relevant economic analysis tools in industrialized countries can serve macroeconomic analysis in ECOWAS countries. Furthermore, new sophisticated models, including machine learning and deep learning applied to BIG Data, can push back the limits of business cycle analysis in now-casting, forecasting, and dating.