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Abdelhamid Addi

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Quatre essais sur le risque systémique

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Introduction générale

Les crises financières successives ont montré les faiblesses inhérentes au système financier conventionnel. Plus particulièrement, la crise de 2008 a révélé l'importance de repenser en profondeur le fonctionnement de la finance bancaire. En effet, le phénomène 3D (désintermédiation, déréglementation, décloisonnement) a transformé le monde de la finance, favorisant davantage la libéralisation économique et la globalisation financière. Cela a conduit à une accélération des transactions financières, à une fluidité des flux de capitaux et à la création de nouveaux produits financiers. Si cette libéralisation financière a permis un développement économique et financier remarquable, elle a également conduit à l'éclatement de la bulle spéculative, qui s'est accompagné d'une augmentation des inégalités au niveau mondial. C'est dans cette perspective qu'il est désormais nécessaire de développer et de promouvoir une finance alternative, viable et résiliente aux crises : une finance qui offre la possibilité de lier performance économique et performance éthique. L'intérêt grandissant pour l'investissement socialement responsable (ISR) et l'essor réservé aux énergies propres vont dans le sens d'une prise de conscience mondiale de l'importance du développement durable. La finance islamique, grâce à son modèle distinctif, pourrait correspondre à ces attentes.

Par ailleurs, la crise financière de 2008, tout comme la récente crise liée à l'épidémie de COVID-19, ont montré que la complexité des liens, que ce soit entre pays ou entre acteurs financiers, conduit à une propagation facile des chocs. Ce sont effectivement les propriétés structurelles (intrinsèques et extrinsèques) du réseau financier qui définissent

l'élasticité du système face au risque systémique, qui pourrait déstabiliser l'ensemble du système financier. Face à ce risque, se concentrer sur la surveillance d'une institution financière individuelle a des conséquences sur la garantie de la stabilité des autres institutions. En effet, une institution financière n'est pas autarcique. Bien au contraire, elle interagit en permanence avec tous les acteurs qui composent le système financier. Lesdites interactions entre institutions produisent des interconnexions et renforcent ainsi la nature systémique du système financier. Même si le risque individuel d'une institution est contrôlé, un degré élevé d'interconnexion peut non seulement conduire à la défaillance d'une seule institution, mais aussi se propager à un grand nombre d'institutions, déstabilisant ainsi le système financier dans son ensemble. Dans ce contexte, la question du risque systémique et ses canaux est devenue un sujet d'une grande importance. D'où l'intérêt d'accorder une attention particulière à la définition et la mesure du risque systémique. L'intérêt est ainsi passé des approches microprudentielles aux approches macroprudentielles, afin d'assurer la stabilité globale du système financier, plutôt que la stabilité d'une institution individuelle.

De nombreux efforts ont été déployés pour définir et mesurer le risque systémique. Les chercheurs divergent encore quant à la définition de cette notion mais tendent à s'accorder sur sa complexité. Les propositions de définition sont différentes et ne cernent souvent qu'une dimension du risque systémique. Parallèlement, et en ce qui concerne la mesure de risque systémique, les différentes approches développées ne ciblent également qu'une facette particulière de ce dernier. Les mesures qui ont été suggérées appréhendent le risque systémique dans un cadre univarié, en tenant compte de l'importance de l'institution financière individuelle. Ces mesures quantifient donc essentiellement la contribution et l'exposition des institutions financières au risque systémique global. Tobias and Brunnermeier (2016) ont développé la ΔCoVar (Conditional value-at-risk), qui mesure la contribution d'une institution au risque global du système financier. En d'autres termes, elle mesure la perte du système financier conditionnée à la détresse d'une institution financière. Dans une approche inverse, Acharya et al. (2012) proposent

le Marginal Expected Shortfall (MES) qui mesure la contribution de l'ensemble du système financier au risque systémique d'une institution financière. Autrement dit, l'exposition au risque systémique d'une institution est liée au fait que le système financier soit en détresse. Brownlees et al. (2012) suggèrent l'indice SRISK, qui mesure l'insuffisance de capital d'une institution, à travers un indice qui évalue la proportion de capital qu'une banque doit réunir pour résister à une crise systémique.

En parallèle, il existe un deuxième courant de mesure du risque systémique, tenant cette fois-ci compte l'ensemble du système financier. Afin de quantifier le risque systémique dans une dimension réseau, la théorie relative à cette dernière a mis en évidence le lien étroit entre la structure du réseau et le risque systémique à travers les nœuds¹ et les liens bidirectionnels entre ceux-ci. Dès qu'un nœud est affecté par un choc, il peut rapidement transmettre le risque à d'autres nœuds, ce qui pourrait généraliser la propagation à l'ensemble du système financier. De ce fait, il apparaît nécessaire d'étudier en profondeur les interconnexions afin de maîtriser le risque systémique. Plus précisément, il s'agit d'examiner les interconnexions entre les banques comme étant une source d'émission et de réception de risque systémique dans le réseau financier. Les modèles découlant de cette approche ont pu comprendre la complexité des interconnexions qui structurent les réseaux financiers et apportent ainsi avec succès des réponses à des interrogations relatives à la transmission de la contagion et aux phénomènes de débordements.

Parmi ces modèles économétriques figurent ceux qui sont basés sur la causalité au sens de Granger (Hong et al. (2009); Billio et al. (2012); Candelon and Tokpavi (2016); entre autres). Ces derniers utilisent le test de causalité en analysant la dynamique de la transmission de l'information pour mesurer le risque systémique. Ensuite, il y a les modèles qui se basent sur les événements extrêmes de queue (Hautsch et al. (2015); Härdle et al. (2016); Torri et al. (2021); entre autres). Ces modèles estiment le risque par la sensibilité d'une institution aux événements extrêmes qui impactent les autres

¹Les nœuds reflètent les acteurs financiers dans le réseau, ils peuvent être un pays ou une institution.

institutions. Enfin, il y a les modèles de débordements de rendement et de la volatilité (Billio et al. (2012); Diebold and Yilmaz (2014b); entre autres). D'une manière générale, ces modèles quantifient les structures de réseaux des différents contextes financiers en identifiant les connectivités directionnelles entre les acteurs, pour montrer les récepteurs et les émetteurs de risque systémique et, par conséquent, discerner ceux qui influencent le plus le risque systémique.

S'inscrivant dans ce cadre, cette thèse étudie le risque systémique. Dans une première partie, nous nous attachons à examiner ce dernier en comparant banques islamiques et conventionnelles. Les résultats obtenus révèlent des différences entre les deux types de banques, au sein des pays dotés d'un système financier dual. Il convient toutefois de rappeler que ce groupe de pays ne permet pas de cerner en profondeur les particularités des banques conventionnelles au sein d'un système financier homogène. Ainsi est apparu l'intérêt d'une deuxième partie focalisée sur le risque systémique du système financier de la zone euro, qui représente un groupe homogène de pays pesant sur la scène financière mondiale. Nous présentons succinctement ci-dessous les motivations et les contributions à la littérature de chacun des essais qui composent les deux parties de cette thèse.

Dans la première partie, nous abordons la question de la différenciation entre la finance islamique et la finance conventionnelle. Cette partie est déclinée en deux chapitres. Un premier porte sur l'impact de la taille des banques sur le risque systémique, en comparant les banques islamiques et conventionnelles. Un second chapitre analyse la structure des interconnexions et la pertinence systémique des banques des pays du Golfe.

La finance islamique a été développée sur la base de la doctrine islamique, qui privilégie une finance solidaire, éthique et socialement responsable. Compte tenu de ces principes, la finance islamique peut représenter un levier ou un moyen dans la quête d'une économie durable, qui respecte l'aspect éthique et moral. La finance islamique

repose sur une multitude de principes que l'on peut présenter comme suit : l'interdiction de toute forme d'intérêt² sur les prêts, le partage des profits et des pertes (3P)³, l'interdiction de la spéculation et des jeux d'hasard⁴, l'adossement à un actif tangible et réel, le paiement d'un impôt religieux⁵, la supervision de la banque islamique par un conseil religieux⁶ et le caractère éthique des actifs, des investissements, avec pour conséquence l'interdiction d'investir dans des secteurs non conformes aux exigences islamiques. C'est à travers ces principes que la finance islamique se distingue de la finance conventionnelle.

La crise financière a clairement démontré que la détresse de certaines banques est susceptible de déstabiliser l'ensemble du système financier, en raison de leur importance individuelle dans la transmission des défaillances financières aux autres (López-Espinosa et al. (2013); Laeven et al. (2014); Zhang et al. (2015); Bostandzic and Weiss (2018); Varotto and Zhao (2018); Qin and Zhou (2019); entre autres). Cela a déclenché des débats houleux sur les fondamentaux qui rendent une banque plus systémique qu'une autre. Parmi les facteurs qui ont été identifiés comme majeurs, rendant certaines banques déstabilisantes pour le système financier, figure la taille de la banque.

Il est à rappeler que les banques islamiques ont connu une expansion remarquable au cours des dernières années. Selon le rapport 2019 de l'IFSB⁷, le total des actifs des banques islamiques dans le monde s'élève à 1 765 milliards de dollars en 2019, dont 854 milliards de dollars concentrés dans les pays du Golfe, soit une part de 44%.

²Le *Riba* : ce principe interdit toute rémunération fixée ex ante et tout taux d'intérêt prédéterminé.

³Mécanisme financier appliqué à toutes les transactions financières adossées à un actif tangible afin de partager selon une clé de répartition définie les pertes et les profits.

⁴Respectivement *Qimar* et *Maysir*, qui incluent toutes les formes de contrats aléatoires, comme la spéculation et les produits dérivés.

⁵La Zakat, qui est un pilier de l'Islam. Littéralement, le mot *Zakat* a plusieurs significations : purification, croissance et bénédiction. Elle est considérée comme un instrument de justice sociale, à travers la redistribution des richesses.

⁶Le conseil de *Sharia Board* : ce conseil est adopté par la banque islamique en parallèle du conseil d'administration traditionnel. Son rôle est de contrôler la conformité des produits financiers proposés, afin de s'assurer qu'ils sont compatibles avec les principes de la finance islamique..

⁷Islamic Financial Services Board (IFSB).

En dépit de la croissance remarquable de la banque islamique et du caractère distinctif de ses principes et de son modèle économique, la question du risque systémique reste importante, en particulier l'effet de la taille sur ce dernier. Il est à remarquer que le modèle en vogue est la coexistence des banques islamiques et conventionnelles. Compte tenu de leurs différences structurelles, cette coexistence soulève plusieurs questions. La première se situe au niveau individuel de la banque islamique et de sa capacité à résister au risque systémique. La seconde concerne sa contribution au risque global, comparativement aux banques conventionnelles.

Dans le premier chapitre, nous étudions ainsi l'effet de la taille des banques sur le risque systémique pour un échantillon de 34 banques islamiques et de 70 banques conventionnelles, de 12 pays de la région MENA, sur une période allant de 2006 à 2017. Pour commencer, nous mesurons la contribution et l'exposition au risque systémique de chaque banque, en utilisant respectivement l'approche ΔCoVaR proposée par Tobias and Brunnermeier (2016) et l'approche Marginal Expected Shortfall (MES) développée par Acharya et al. (2012). L'approche ΔCoVaR mesure le risque conditionnel à un événement extrême, où le risque est défini comme étant la valeur à risque (VaR)⁸. La ΔCoVaR d'une banque est définie comme étant la sensibilité de la VaR du système financier, conditionnellement aux changements de la VaR de la banque en question. Par conséquent, la ΔCoVaR d'une banque capture sa contribution marginale au risque systémique global de l'ensemble du système financier. Le MES mesure l'exposition d'une banque mais dans des conditions bien particulières, à savoir que le marché est soumis à un événement extrême. Dans un deuxième temps, nous étudions l'effet de la taille des banques sur leur contribution et leur exposition au risque systémique dans un cadre linéaire, en appliquant le modèle de panel dynamique et plus particulièrement la méthode des moments généralisés en système, et dans un cadre non linéaire en utilisant

⁸La VaR estime la perte maximale qu'un actif peut subir sur un horizon donné. Par exemple une VaR de -7% au niveau de confiance de 5% indique qu'il existe une probabilité de 5% d'un rendement inférieur ou égal à -7%.

le modèle PSTR (Panel Smooth Threshold Regression). Une analyse dans un cadre semi-paramétrique est aussi proposée.

Les résultats du panel dynamique révèlent qu'il existe une relation positive entre la taille et le risque systémique pour les banques islamiques et conventionnelles. Parallèlement, l'analyse non linéaire suggère l'existence d'effets de seuil dans cette relation. La taille n'affecte positivement le risque systémique qu'à partir d'un certain seuil. En-dessous de celui-ci, l'effet de la taille devient négatif. Toute augmentation de la taille accroît à la fois la contribution et l'exposition au risque systémique des banques islamiques et conventionnelles. Les seuils obtenus à partir du modèle PSTR ont révélé un effet différentiel entre les banques islamiques et conventionnelles. Les banques conventionnelles montrent une certaine vulnérabilité au risque systémique, en se transformant en régime fort à un seuil plus bas que les banques islamiques. En revanche, les banques islamiques sont plus sensibles aux chocs systémiques, en se transformant en régime fort à un seuil plus bas que les banques conventionnelles. Le modèle semi-paramétrique a largement confirmé l'existence de deux régimes pour les banques islamiques et conventionnelles. La relation entre le risque systémique et la taille dans le cas des banques islamiques est très proche d'une relation convexe. Dans le cas des banques conventionnelles, cette relation est complexe et loin d'être de forme quadratique. Ainsi, nous pouvons conclure de manière générale que sur la base de la mesure MES, les banques islamiques sont plus sensibles aux chocs du marché que les banques conventionnelles. En revanche, sur la base de ΔCoVaR , les banques conventionnelles sont plus vulnérables.

Notre premier chapitre contribue à deux volets de la littérature. Le premier volet étudie les effets linéaires et non linéaires de la taille sur la contribution et l'exposition au risque systémique des banques islamiques et conventionnelles. Etant donné l'expansion remarquable du secteur bancaire islamique au cours des dernières années, il paraît nécessaire de mettre en évidence les effets potentiels de la taille sur le risque systémique

pour ces banques. En ce qui concerne le deuxième volet de notre contribution, bien que la littérature ait mis en avant les déterminants du risque systémique en se concentrant principalement sur la taille, elle s'est limitée à supposer l'existence d'une relation potentiellement non linéaire entre la taille et le risque systémique. Notre étude élargit la littérature en testant la non-linéarité entre la taille et le risque systémique.

D'un point de vue méthodologique, notre approche PSTR prend en compte la progressivité de la croissance de la taille pour déterminer le seuil à partir duquel cette dernière passe d'un régime faible à un régime fort. Le modèle PSTR permet de tenir compte de cette spécificité dans la détermination du seuil optimal. Qui plus est, l'approche semi-paramétrique n'impose pas une forme fonctionnelle entre la taille et le risque systémique, comme dans le cas d'un modèle quadratique qui est, par définition *ad hoc*.

Les incertitudes économiques et géopolitiques jouent un rôle prépondérant dans la propagation des effets de contagion des chocs à l'ensemble du système. Il est ainsi important d'étudier leurs effets sur le risque systémique dans une dimension réseau. La région du Golfe est caractérisée par des incertitudes à la fois économiques et géopolitiques. Cette région dépend principalement de la production pétrolière ; les réserves de pétrole s'élevant à 29% et celles de gaz naturel à 22%⁹. Suite à la chute des prix du pétrole, les pays du Golfe ont subi une perte de 287 milliards de dollars de revenus pétroliers en 2015¹⁰. Cette dépendance expose continuellement les marchés financiers de la région aux chocs pétroliers, ce qui, *in fine*, impacte l'économie réelle. En outre, la région reste confrontée à des risques géopolitiques persistants, notamment le printemps arabe, la guerre en Syrie et au Yémen, et récemment le blocus du Qatar et la concurrence avec l'Iran. Une telle situation affecte largement le sentiment des investisseurs régionaux et mondiaux et redéfinit constamment la situation économique et les enjeux stratégiques

⁹Agence internationale pour les énergies renouvelables (IRENA).

¹⁰Agence internationale pour les énergies renouvelables (IRENA).

de la région, ce qui influence considérablement la volatilité des marchés financiers des pays qui la composent (Charfeddine and Al Refai (2019); Mensi et al. (2019); Selmi and Bouoiyour (2020); entre autres). Apparaît ainsi l'intérêt d'étudier les interconnexions entre les banques islamiques et conventionnelles dans une dimension réseau, afin de mettre en évidence les structures des interconnexions du secteur bancaire des pays du Golfe.

Pour ces raisons, nous étudions dans un deuxième chapitre la structure des interconnexions de 53 banques cotées en bourse de 5 pays du Golfe (Arabie Saoudite, Bahreïn, Emirat Arabe Unis, Kuwait et Qatar). Nous analysons la structure des interconnexions et la pertinence systémique d'un panel de 20 banques islamiques et de 33 banques conventionnelles à l'aide du modèle TENET (Tail-Event driven NETWORK risk) proposé par Härdle et al. (2016). Ce modèle étend l'approche ΔCoVaR en mesurant la dépendance conditionnelle de queue entre les banques islamiques et conventionnelles. Il mesure le degré de dépendance à partir duquel un événement de queue dans une banque se répercute sur un événement de queue dans une autre banque. Contrairement aux modèles univariés, ce modèle considère la dimension réseau en tenant compte de l'interconnexion d'une banque avec l'ensemble des banques du système financier (Härdle et al. (2016)). Le modèle TENET permet aussi la détection du canal de transmission, qui trace la directionnalité des effets de débordements entre les banques.

L'analyse empirique du deuxième chapitre met en exergue l'existence d'une dépendance asymétrique entre les secteurs bancaires islamique et conventionnel. Les résultats suggèrent que la connectivité totale des banques dans les pays du Golfe augmente conjointement avec des moments extrêmes, notamment la crise financière de 2008 et le choc pétrolier de 2015. La structure des interconnexions entre les banques islamiques et conventionnelles est formée par trois types de liens : les interconnexions inter et intra-sectorielles entre les banques islamiques et conventionnelles et les interconnexions bilatérales au niveau des pays. En outre, les effets de débordements du secteur bancaire conventionnel vers le secteur bancaire islamique sont relativement élevés.

La contribution de ce chapitre est multiple. Nous analysons un réseau bancaire double, qui combine les banques islamiques et conventionnelles en utilisant la théorie des réseaux. Ce chapitre étudie les connectivités directionnelles des secteurs bancaire islamique et conventionnel en montrant les récepteurs et les émetteurs de risque systémique. Premièrement, nous étudions l'évolution dynamique de la connectivité totale et sectorielle, ce qui nous permet de visualiser les changements dans la structure de la connectivité et les secteurs qui l'influencent. Deuxièmement, nous analysons les structures topologiques qui existent entre les banques islamiques et conventionnelles. Nous proposons une cartographie du réseau en mettant en évidence les différentes interconnexions du réseau et la directionnalité des effets de débordements entre les deux secteurs bancaires, islamique et conventionnel. Enfin, nous classons les différentes banques en fonction de la réception et de l'émission du risque systémique, ce qui nous permet d'identifier les banques d'importance systémique nécessitant une supervision plus stricte de la part des autorités de régulation. Grâce au contenu informationnel sur la nature de la structure de réseau des banques islamiques et conventionnelles, les décideurs politiques et les autorités de régulation peuvent surveiller les canaux de transmission des chocs afin de proposer des mesures efficaces pour atténuer le risque systémique et prévenir les crises.

La seconde partie, qui étudie le risque systémique dans le système financier européen, s'articule autour de deux chapitres. Dans le premier, nous étudions le risque extrême en fonction des différents niveaux d'externalités de queue dans la distribution des rendements des acteurs financiers de la zone euro. Dans le deuxième chapitre, nous nous focalisons sur les débordements de la volatilité avant et pendant la crise sanitaire de la COVID-19 des banques européennes.

Depuis le début de la crise sanitaire due à l'épidémie de COVID-19, le monde est immergé dans une incertitude profonde, aussi bien sur le plan économique que social. La propagation rapide de la pandémie a eu un impact marqué sur les marchés

financiers, plus particulièrement en accélérant la fréquence des chocs. Contrairement à la crise financière de 2008, la crise actuelle est une crise sans précédent qui a pris un caractère universel en paralysant toutes les économies mondiales. La crise épidémique s'est en effet traduite par un double choc économique de l'offre et de la demande, engendrant ainsi des conséquences considérables. Pour limiter les dégâts humains, économiques et sociaux liées à la crise sanitaire, les Etats ont été obligés de prendre des mesures drastiques, en particulier, des mesures de confinement qui ont conduit à une réduction de la production et ont entraîné une destruction d'emplois ainsi qu'une montée du niveau de chômage dans certains secteurs. Une telle situation n'épargne pas les banques qui peuvent subir le risque de défaut de paiement. Ce dernier est susceptible d'augmenter le risque de crédit chez les banques et, par conséquent, leurs risques systémiques. Par ailleurs et contrairement au choc de la crise financière de 2008, le choc lié à la COVID-19 est exogène. Par conséquent, les conclusions précédentes sur les mécanismes de contagion des crises passées ne peuvent pas être généralisées (Duan et al. (2021)). Le choc de la pandémie est susceptible de laisser des séquelles sur les acteurs financiers et en particulier les banques, dont on ne connaît pas encore la réaction. Dans ce contexte, plusieurs interrogations peuvent être soulevées. La première concerne le risque systémique et ses effets potentiels sur le système bancaire pendant la pandémie de la COVID-19. La seconde interrogation porte sur la capacité des mesures mises en place à la suite de la crise de 2008 à absorber le choc de la crise sanitaire. Le contexte des pays européens est un terrain fertile qui peut être mobilisé afin de répondre à ces deux interrogations. En effet, l'Europe a été fortement touchée par la crise de 2008, la crise de la dette souveraine de 2011 et finalement par la crise de la COVID-19, d'où l'intérêt de s'intéresser à la résilience des systèmes financiers dans les pays européens.

Au cours des dernières années, la modélisation des interdépendances entre les différents acteurs financiers est devenue un domaine de recherche largement examiné (Hué et al. (2019); Yang et al. (2020); Wang et al. (2021a); Torri et al. (2021); entre autres). Les crises financières (États-Unis et zone euro), les divers événements politiques

(comme le Brexit) ainsi que la pandémie de la COVID-19, ont révélé à quel point la connexion entre les institutions financières tient un rôle prépondérant et déterminant dans la transmission des chocs. De fait, la forte connectivité qui règne entre les acteurs financiers concourt à une propagation rapide des risques dans le système, ce qui se traduit par une certaine instabilité financière (Battiston et al. (2016); Abad et al. (2017); Daly et al. (2019)). Le niveau élevé d'incertitude sur les marchés financiers a révélé la nécessité de déployer des mesures destinées à évaluer de manière rigoureuse l'importance systémique des institutions ainsi que la stabilité du système financier, mais aussi de formuler des politiques macroprudentielles appropriées afin de maîtriser l'ampleur de la contagion et du risque systémique (Rizwan (2021)).

Dans le premier chapitre, nous appliquons un nouveau cadre pour étudier les débordements du risque (à la baisse et à la hausse) entre les entreprises financières de la zone euro, en suivant les travaux de Li et al. (2020). Cette analyse sera basée sur le modèle de risque de causalité de Granger de Candelon and Tokpavi (2016). Notre objectif consiste à mesurer les débordements du risque entre les institutions financières lorsque le marché est à la baisse, mais aussi lorsqu'il est à la hausse, de manière à obtenir une représentation plus fine de la contagion potentiellement présente entre les acteurs financiers.

Dans ce chapitre¹¹, nous visons à examiner les débordements du risque extrême entre 183 institutions financières de la zone euro sur la période 2005-2020. Nous employons le test de causalité de Granger à travers les quantiles afin de pouvoir appréhender l'interdépendance des risques extrêmes entre les acteurs financiers dans les différentes situations de marché. Ainsi, nous sommes en mesure d'étudier et d'estimer l'effet de débordements du risque dans différents mécanismes de propagation durant les bonnes et mauvaises conditions enregistrées sur le marché financier. Nos résultats montrent

¹¹Ce chapitre a été co-écrit avec Matteo Foglia, Gang-Jin Wang et Eliana Angelini et publié dans *Journal of International Financial Markets, Institutions Money*. <https://doi.org/10.1016/j.intfin.2022.101522>.

un effet de débordement du risque qui diffère en fonction des conditions du marché. Ce résultat suggère le rôle important des conditions baissières dans la propagation sectorielle des débordements du risque. Enfin, nous élargissons l'étude pour examiner la relation entre le risque et la politique monétaire. Une telle prolongation nous a permis de présenter un nouvel éclairage quant à l'effet de l'orientation monétaire de la Banque Centrale Européenne sur la stabilité financière.

Notre apport, à travers ce chapitre, est quadruple. Le premier consiste à développer une approche qui vise à construire différents types de réseaux de débordements pour estimer les débordements de risque dans des cas spécifiques. Certes, de nombreuses études antérieures ont analysé les débordements du risque entre les institutions financières (Billio et al. (2012); Diebold and Yilmaz (2012, 2014a); Hautsch et al. (2015); entre autres). Cependant, il est tout à fait possible de concevoir qu'une analyse non conditionnelle du marché est susceptible de masquer l'hétérogénéité qui peut être détectée en considérant des cas distincts. En effet, comme nous l'avions mentionné, nous considérons deux cas, à savoir la queue gauche (une période de ralentissement ou de crise), et la queue droite (une période de reprise) des distributions des rendements boursiers des institutions. Cela nous a amené à une meilleure connaissance de la dynamique au sein des institutions financières suivant les conditions du marché. Deuxièmement, notre ensemble de données est composé de 183 institutions financières cotées, situées dans un panel de 10 pays. A notre connaissance, cette étude est la première à utiliser un tel échantillon d'entreprises financières dans le contexte des pays de la zone euro. Ainsi, nous sommes en capacité d'étudier la contagion du risque provenant d'une vaste étendue du système financier.

De plus, nous apportons une contribution à la littérature, certes limitée mais émergente, consacrée à l'étude de la propagation du risque de contagion entre les différents opérateurs du système financier européen (Billio et al. (2013); Abad et al. (2017); Foglia and Angelini (2020b); Fong et al. (2021); entre autres). Nous alimentons ce volet de la littérature en approfondissant l'étude des débordements du risque entre différents types

d'institutions financières de la zone euro (banques, compagnies d'assurance, sociétés financières diversifiées et sociétés immobilières). Il est ainsi possible de brosser un portrait détaillé de la propagation des risques au sein du marché financier. En quatrième lieu, nous apportons une contribution à la littérature traitant de la relation entre le risque et la politique monétaire (Roache and Rousset (2013); Altunbasa et al. (2014); entre autres). Nos résultats apportent un nouveau schéma d'analyse de l'impact de l'orientation monétaire sur la stabilité financière.

La multiplicité des événements de grande ampleur qui ont secoué les marchés financiers mondiaux a mis en péril la stabilité financière et bancaire (ECB (2020b); Aldasoro et al. (2020a)). De tels événements ont révélé comment les interconnexions entre les acteurs financiers ont participé à la propagation des risques (Brogi et al. (2021)). Au-delà de ces grands épisodes ayant affecté la structure du marché financier comme la crise financière de 2008 et la crise de la dette souveraine de la zone euro de 2011, il convient de considérer la crise sanitaire actuelle. Celle-ci a eu des incidences notables sur la sphère financière en augmentant de manière très nette le risque de crédit. La relation entre les risques de crédit, les prêts non performants et la stabilité financière est largement documentée dans la littérature (Imbierowicz and Rauch (2014); Vazquez and Federico (2015); entre autres). Dans cet ordre d'idée et compte tenu de la nature de la crise sanitaire, nous nous attendions à ce qu'une chute des revenus des entreprises accompagnée d'une destruction substantielle d'emplois et d'une augmentation des engagements financiers de la part des ménages aient des effets importants sur la stabilité bancaire et sur le risque systémique au sein de la zone euro.

L'objectif du dernier chapitre¹² est double. Dans un premier temps, il s'agit d'identifier quels sont les acteurs qui transmettent le plus de risques et donc quelles sont les banques qui font l'objet du plus de volatilité. Ensuite, il s'agit de quantifier l'impact

¹²Ce chapitre a été co-écrit avec Matteo Foglia et Eliana Angelini et publié dans le *Global Finance Journal*. <https://doi.org/10.1016/j.gfj.2021.100677>.

de la pandémie de la COVID-19 sur la stabilité bancaire. L'atteinte de ces deux objectifs nous permet de cerner comment les principales banques de la zone euro contribuent à l'évolution du risque systémique. Pour ce faire, nous mesurons la connectivité de la volatilité de 30 valeurs bancaires de la zone euro entre juin 2005 et août 2020 en nous appuyant sur le cadre de Diebold and Yilmaz (2012, 2014a) qui nous permet d'identifier comment un choc idiosyncratique tel que la crise de la COVID-19 peut se propager au système bancaire à travers le temps.

Notre analyse permet de dégager les résultats suivants. Dans un premier temps, nous montrons que toutes les banques contribuent de manière significative à la contagion. Cependant, cette contribution s'avère être plus importante pour les banques d'importance systémique (G-SIB)¹³. Dans un second temps, nos estimations montrent, comme on pouvait s'y attendre, un impact considérable de la crise sanitaire de la COVID-19 sur la connectivité de la volatilité. Cet effet se traduit par une augmentation qui se situe aux alentours des 20%. Dans un troisième temps, notre analyse dynamique illustre comment la connectivité a pu augmenter durant les crises, en particulier la crise financière de 2008, la crise de la dette souveraine européenne et finalement la crise sanitaire de la COVID-19. De surcroît, nos résultats mettent en avant le rôle prépondérant joué par les banques d'importance systémique (G-SIB) et ce, en matière de transmission de la volatilité. Ce résultat corrobore la thèse qui admet que le système bancaire de la zone euro est « trop grand pour faire faillite ». Finalement, nous montrons que les banques de petite et moyenne taille peuvent constituer des sources potentielles de la transmission de la volatilité, soutenant la thèse selon laquelle le secteur bancaire de la zone euro est « trop interconnecté pour faire faillite ». L'analyse empirique nous permet également d'examiner l'effet hétérogène de la crise de la COVID-19 dans le système bancaire de la zone euro. Cette hétérogénéité peut, en effet, constituer à l'avenir une source d'instabilité financière au sein de cette zone.

¹³Global Systemically Important Banks (G-SIBs)

Nous contribuons à la littérature existante en apportant un nouvel éclairage sur la connectivité de la volatilité entre les banques de la zone euro et l'effet de la crise épidémique de la COVID-19 sur le secteur bancaire. Plusieurs travaux antérieurs ont analysé l'interconnectivité de la structure financière au sein de la zone euro (Billio et al. (2012); Glasserman and Young (2015); Betz et al. (2016); Dreassi et al. (2018); entre autres). Or, aucune de ces études ne s'est basée sur le modèle de connectivité de la volatilité de Diebold and Yilmaz (2012, 2014a). Ce modèle constitue un outil pertinent pour pouvoir analyser les débordements du risque de volatilité, tout en tenant en compte des chocs idiosyncratiques et communs au sein du système de réseau. La deuxième contribution de ce travail s'inscrit dans la continuité de la littérature qui a émergé avec la crise sanitaire et qui a étudié l'effet de la COVID-19 sur les marchés financiers (Rizwan et al. (2020); Corbet et al. (2020); Nițoi and Pochea (2020); Ortmann et al. (2020); Broadstock et al. (2020); Le et al. (2020); Seven and Yilmaz (2020); entre autres). Plus particulièrement, nous examinons l'effet de contagion lié à la COVID-19 sur le système bancaire de la zone euro. Finalement, nous contribuons à la littérature qui supporte le fait qu'une institution financière peut non seulement être « trop grande » mais aussi « trop interconnectée » pour faire faillite (Acharya and Yorulmazer (2007); Zhou (2009); Beccalli et al. (2015); entre autres). Nous participons à cette littérature en soulignant que lorsque le système est fortement interconnecté et dispose de grandes banques, cela ne fera que participer à une forte propagation de la volatilité.

Nous clôturons notre thèse par une conclusion générale qui rappelle le contexte, les objectifs visés, les principaux résultats, les principales implications, les limites de notre recherche et les perspectives qui nous semblent intéressantes.

The impact of banks' size on systemic risk : Evidence from Islamic and conventional banks

Abstract

In this study, we aim to understand the relationship between systemic risk and bank size. To achieve this, we first investigate the relationship between systemic risk and bank size in a linear framework on a sample of 34 Islamic banks and 70 conventional banks over the period from 2006 to 2017 using the dynamic panel model approach (GMM). In a second step, we explore non-linearity based on a Panel Smooth Transition Regression (PSTR) model. Our results suggest a positive relationship between systemic risk and size for both Islamic and conventional banks and in particular, the existence of threshold effects. If size is below these thresholds, any rise in size will decrease systemic risk. Beyond these thresholds, any increase in size will lead to an increase in systemic risk. This is true for both Islamic and conventional banks. Finally, we also provide robustness using a semi-parametric model and the results remain similar to the main ones.

Keywords: Islamic banks; conventional banks; systemic risk; bank size; Generalized method of moment; Panel smooth transition regression model; semiparametric model

JEL Classification: G21, G01, G28, C23

1.1 Introduction

For several decades, the concern for a stable, responsible and ethical financial model has been paramount and omnipresent among different economic stakeholders, including policy makers and financial institutions. The 2008 financial crisis constituted the relevant instance that led to far-reaching rethinking about the working as well as the content of the current banking models (Alaabed et al. (2015)). In particular, the so-called financial crisis sparked a real reflection on ethical approaches such as socially responsible investment (SRI) and corporate social responsibility (CSR) (citedelpachitra2020islamic). SRI and CSR have a common basis that seems to be close to the premises of Islamic finance. Arguably, Islamic finance is the religious side of ethics, while SRI and CSR stand for its secular side. According to Reddy et al. (2017) and Charfeddine et al. (2016), the Islamic finance fosters sustainability by means of social responsibility, something that is not far from the secular approaches.

From a theoretical point of view, the Islamic financial system is based on principles and prohibitions such as no interest, Profit and Loss Sharing (PLS) in financial transactions, prohibition of speculation, backing on an intangible asset, ethical investment and exclusion of assets and activities that contravene these principles¹(Mallin et al. (2014) and Charles et al. (2015)). Islamic finance, in terms of its properties, differs from conventional finance in its paradigm that reinforces the link between finance and social requirements, environmental sustainability and alternative energy (Paltrinieri et al. (2020) and Qoyum et al. (2020)).

As a further consequence of the 2008 financial crisis, a deep reflection on micro-prudential regulations in terms of the conceptualisation of financial risks has also emerged. In fact, by neglecting the macro-systemic dimension, microprudential regulations are content to measure the risk of a single bank, neglecting its interactions and consequences on the financial system as a whole, thus preventing the correct prediction of the occurrence of a systemic crisis (Allen et al. (2012) and O'Halloran and Nowaczyk

¹Compliance with the principles of Islamic finance is ensured by a council of jurisprudence called the Sharia Board (Mallin et al. (2014) and Charles et al. (2015)).

(2020)). Similarly, the individual measure of bank risk does not account for a systemic event that could spread and destabilize the entire financial system (Huang et al. (2009); Abbas et al.; Laeven et al. (2014) and Bostandzic and Weiss (2018)). The limitation of micro-measuring the risk of an institution has the effect of reorienting banking regulations by highlighting the critical importance of macroprudential approaches (Laeven et al. (2014)). In such a crisis context, the measurement of systemic risk and the identification of the factors influencing it represents actually a fundamental concern of regulators. Therefore, the objective would be to control cross-cutting risks and identify systemically important institutions in order to limit the resulting macroeconomic effects.

Among the best known measures of systemic risk is the Marginal Expected Shortfall (MES) introduced by Acharya et al. (2012). The latter assesses systemic risk in terms of the distress of the financial system. In particular, it quantifies the degree of exposure of an institution in the event of a systemic shock. In contrast to the first approach, there is the conditional value-at-risk ΔCoVaR developed by Tobias and Brunnermeier (2016), that allows for the contribution to the overall systemic risk of a financial institution in the event of distress.

Understanding aspects of systemic risk has been the concern of different empirical studies (López-Espinosa et al. (2013); Zhang et al. (2015); Bostandzic and Weiss (2018) and Qin and Zhou (2019)). The objective of our study is to investigate the determinants of systemic risk with a view to proposing appropriate rules to enhance financial stability and prevent risks. Among the important findings of the existing literature is the importance of bank size as a relevant factor in identifying systemically important banks. In fact, large banks have shown high levels of contribution to systemic instability leading to instability in the financial system as a whole (Pais and Stork (2011); Brunnermeier et al. (2012); Bostandzic et al. (2014); Laeven et al. (2014) and Varotto and Zhao (2018))². Similarly, other authors have attempted to examine the relationship between size and

²Despite the importance of size in systemic risk emphasised in most of the empirical studies conducted, some works lead to distant conclusions. For example, Varotto and Zhao (2018) find that systemic importance is not necessarily related to large size. Rather, it is attributed to highly risky projects that expose the bank's balance sheet to systemic risk.

systemic risk by considering a non-linear relationship (Pais and Stork (2013); Mayordomo et al. (2014); Tarashev et al. (2015) and Qin and Zhou (2019)).

It should be noted that, on the one hand, the relationship between size and systemic risk remains complex to define (van Oordt and Zhou (2019)). Despite the existence of several empirical investigations to analyse the impact on systemic risk, there is no clear and unambiguous consensus on this issue. On the other hand, even taking into account the non-linearity, the results obtained are far from answering definitively the problem, hence the interest of our paper which tries to bring new insights by investigating the association between size and systemic risk in a sample of Islamic and conventional banks. It is worth noting that the issue of systemic risk is rarely discussed in the context of Islamic banks except for a few rare studies (Hashem and Giudici (2016); Chakroun and Gallali (2017) and Abedifar et al. (2017)). Most studies indicate that Islamic banks were resilient in the face of the disruptions of the 2008 crisis, thereby stabilising the financial system (Caby et al. (2013); Hasan and Dridi (2010) and Beck et al. (2010)). In the same vein, other authors such as Chapra (2008) and Hilary and Hui (2009) highlight that maintaining the stability of the financial market lies in the integration of the Profit and Loss Sharing (PLS) system which aims to discipline the financial system. Incorporating the PLS makes the system more resilient to potential shocks (Ebrahim (1999) and Siddiqui (2008)). In contrast, other studies have shown that there is no significant difference between the two systems in terms of resilience (Kassim and Shabri Abd. Majid (2010); Bourkhis and Nabi (2013), and Abedifar et al. (2017)). Moreover, the empirical literature on the stability of Islamic banks has mainly relied on stand-alone bank risk measures such as the Z-score. The issue is that such measures do not take into account the systemic dimension. The latter is supposed to take into account the contribution and exposure to systemic risk.

With these considerations in mind, our paper aims to examine the effect of size on systemic risk by looking at the non-linear aspect. We consider a panel of 34 Islamic banks and 70 conventional banks for the period 2006-2017. In order to measure systemic risk, we rely on the MES which measures systemic risk exposure (Acharya et al. (2012))

and the ΔCoVaR introduced by Tobias and Brunnermeier (2016). The latter measures the contribution to systemic risk of a bank in case of distress. In order to explore the non-linearity of the relationship and to determine the optimal threshold at which the effect of size might differ, we used a recent PSTR approach, initiated by Gonzalez et al. (2005). We also used a semi-parametric model in order to provide robustness to the estimates.

Our main results suggest the existence of a positive relationship between systemic risk and size for both Islamic and conventional banks and the existence of threshold effects. The optimal threshold between the contribution to systemic risk measured by ΔCoVaR and the size of Islamic and conventional banks is estimated at around \$12.91 and \$5.44 billion, respectively. The systemic risk exposure measured by the MES and size is \$7.5 billion for Islamic banks and \$32.82 billion for conventional banks. If size is below these thresholds, any growth in size will decrease systemic risk. Above these thresholds, any increase in size will lead to an increase. This is true for both Islamic and conventional banks.

The paper consists of five sections. Section 2.2 will be dedicated to a presentation of the literature review on measures of systemic risk and the effect of size on it. Then, we present the methodology, data and econometric specifications in section 1.3. Section 1.4 will be devoted to the discussion of our empirical results. Finally, in section 2.5, we provide a conclusion with policy recommendations.

1.2 Review of the literature

In this section, we first present the related literature that focuses on the notion, determinants and the various approaches of systemic risk. Then, we discuss the studies that deal with the stability of Islamic finance.

1.2.1 What does the literature tell us about measuring systemic risk?

In economics as in finance, systemic risk is a protean concept. Among the first attempts to conceptualise systemic risk is the definition of the European Central Bank ECB Bank (2009) which considers systemic risk as a risk of financial instability that destabilizes the functioning of the financial system. The Financial Stability Board Board (2011) defines it as a distress or shock that would lead to the disruption of the financial system as a whole. Most authors agree that systemic risk is an event with significant socio-economic costs (Nier et al. (2007); Schwarcz (2008); Billio et al. (2012), Duan and Zhang (2013) and Trabelsi and Naifar (2017)).

More formally, according to Acharya (2009), systemic risk is the failure of a financial institution that leads to the failure of other institutions through contagion. It is, in fact, the propagation of an initial shock from one institution to the rest of the system. The existing literature distinguishes three main measures of systemic risk: (i) The capital deficiency index (SRISK) introduced by Brownlees et al. (2012) which measures the expected capital deficit of an institution during a systemic crisis. The greater the capital shortfall, the greater the likelihood of systemic risk (Benoit et al. (2013)); (ii) The Marginal Expected Shortfall (MES) approach measures the marginal loss of each institution to overall systemic risk provided the financial system is in distress. This measure defines the loss of an individual financial institution conditional on an increase in overall financial system risk (Lin et al. (2018)); (iii) ΔCoVaR is based on the concept of VaR and quantifies the contribution to systemic risk of an institution in the event of distress. Tobias and Brunnermeier (2016) defined it as the difference between the VaR of the financial system - provided that a systemic event would affect the financial institution - and the VaR of the financial system conditional on its median state. This measures the contribution of a financial institution in the event of distress to the overall systemic risk of the financial system (Borri and Di Giorgio (2021)).

1.2.2 Size and systemic risk

Several empirical studies have focused on the study of systemic risk and bank-specific determinants (Acharya et al. (2012); Zhang et al. (2015); Brunnermeier et al. (2012); Laeven et al. (2014) and Qin and Zhou (2019)). One of the most important drivers that has attracted the attention of researchers and financial stability supervisors is the size of banks. Regulators have labelled the large banks that contributed most to instability during the 2008 crisis as Systemically Important Financial Institutions (SIFIs). These banks have been subject to very special supervision in terms of requirements. In fact, Laeven et al. (2014) studied the systemic risk of large banks during the 2008 financial crisis. They found that systemic risk increases with bank size. This favors the imposition of capital requirements based on systemic risk. According to these authors, systemic risk increases if banks operate in potentially risky activities. Bostandzic and Weiss (2018) state that the functioning of large banks is complex. The latter represent high degrees of interdependence and their failures that may cause large losses compared to small banks. In this sense, Huang et al. (2009) confirm that a large bank does not necessarily depend on an increase in systemic risk, but on highly risky activities. This excessive risk-taking is justified by the reliance on state interventions, e.g., through bailouts, in case of failure in line with the "too big to fail" hypothesis (Gandhi and Lustig (2015)). In recent studies, Elyasiani and Jia (2019) by adopting the indicator (SRISK) that measures capital inadequacy, found that large banks suffered a significant decline in performance relative to small banks during the 2007-2009 financial crisis. These large banks also experienced a remarkable increase in systemic risk. Varotto and Zhao (2018) analyzed systemic risk of US and European firms level from 2004 to 2012. Varotto and Zhao (2018) observed that size is a common indicator of systemic risk. The nature of the relationship between size and systemic risk would therefore be mixed. Indeed, some authors have assumed a potentially non-linear relationship between size and systemic importance (Tarashev et al. (2015); Pais and Stork (2013) and De Jonghe et al. (2015)). More concretely, Moore and Zhou (2013) found that there is a threshold effect between the size and systemic importance of US banks, which differentiates the degree of systemic importance

of banks. Indeed, systemic importance is only positively related to size above a certain threshold. In the same vein, Qin and Zhou (2019) highlight a non-linear effect of size on the expected marginal deficit. Although a large body of empirical work has attempted to address the concern of systemic risk, it is worth noting that studies that have attempted to examine the non-linearity between size and systemic risk remain relatively limited (Pais and Stork (2013) and Qin and Zhou (2019)). These studies, in order to test for non-linearity, have used a quadratic model by introducing the variable height squared. However, such a model corresponds to an ad hoc specification that imposes the functional form of the relationship. This is the reason why we will treat in this article in a more detailed way this relation. In particular, we focus on Islamic and conventional banks in the MENA region³, which have not been sufficiently analyzed.

1.2.3 The stability of Islamic banks and systemic risk

In a comparative study combining Islamic and conventional banks, Čihák and Hesse (2010) found that small Islamic banks tend to be more financially stable than their conventional counterparts. In contrast, large conventional banks tend to be more financially stable than large Islamic banks. They also showed, in the context of Islamic banks, that small Islamic banks represent a greater stability than large ones. In another study, Ibrahim and Rizvi (2017) found the opposite, showing that large Islamic banks are more stable than small Islamic banks. In a similar approach, Abedifar et al. (2013) examined the risk and stability characteristics of Islamic banking. They find that small Islamic banks have low credit risk and are more stable in terms of insolvency risk vis-à-vis conventional banks.

Using a Distance to Default (DD) model by Merton (1974), which measures the probability of a bank's default when the market value of its assets decreases by its book value of its liabilities. Kabir et al. (2015) assessed the credit risk of 156 conventional and 37 Islamic banks in 13 countries between 2000 and 2012. They showed that Islamic banks have significantly lower credit risk than conventional banks when considering the

³Middle East and North Africa.

DD model. However, based on the Z-score, Islamic banks have a higher credit risk. In the same vein, based on a simultaneous structural equation approach, Hassan et al. (2019) found that credit risk and liquidity risk are negatively correlated and that liquidity risk and stability are negatively related only for Islamic banks. Beck et al. (2010) used the Z-score as an indicator of bank stability for a sample of 34 Islamic and 34 conventional banks from 16 countries. They show that there is no significant difference in terms of the impact of the financial crisis on the soundness of Islamic and conventional banks. Similarly, Doumpos et al. (2017) concluded that there is no difference in terms of financial soundness between Islamic and conventional banks. In contrast to these studies, Olson and Zoubi (2008) found that Islamic banks were more resilient to the financial crisis of 2007-2008 than conventional banks.

Regarding the measurement of systemic risk of Islamic banks, there are relatively few studies (Trabelsi and Naifar (2017); Hashem and Giudici (2016); Abedifar et al. (2017) and Chakroun and Gallali (2017)). Early essays focused on comparative studies between the conventional and Islamic financial systems. Şensoy (2015), by using the conditional dynamics approach, indicate that the systemic risk in Islamic stock markets is lower than in the conventional system. However, they found no difference in terms of statistical significance at the levels of systemic risk. Trabelsi and Naifar (2017) studied the exposure of Islamic stock indices to systemic risk by estimating the proposed CoVaR measure of Tobias and Brunnermeier (2016). They show the existence of significance in the dynamic conditional correlations between Islamic stock indices and the financial system. They also found that Islamic stock indices are less exposed to systemic risk. In a comparative approach between Islamic and conventional banks, Hashem and Giudici (2016) investigate the effects of contagion through financial network modeling based on Gaussian graphical models for stock returns. They highlight that the more diversified the activities of the Islamic banking sector are, the more financial stability is enhanced. The same authors pointed out that Islamic banks improve financial stability.

In a similar study, Abedifar et al. (2017) examine the stability of the dual financial system that combines Islamic and conventional banks by comparing 79 listed Islamic

and conventional banks over a period from 2005 to 2014. Abedifar et al. (2017) found that conventional banks, which also offer Islamic products, are vulnerable to systemic events and are more interconnected in the financial network in times of crisis. Chakroun and Gallali (2017) applied the expected marginal deficit measure (MES) on 46 listed banks from six Middle Eastern countries. They conclude that Islamic banks contribute significantly to systemic risk in times of crisis. In contrast, conventional banks represent a significant systemic risk compared to Islamic banks.

On the basis of the related literature, we remark that most studies have focused mainly on measuring individual bank risk. However, the individual dimension of bank risk differs from the systemic dimension in two ways. On the one hand, the systemic dimension makes it possible to measure the contribution and exposure of a bank to systemic risk, which could destabilize the entire financial system. On the other hand, beyond microprudential regulations, the systemic dimension leads to possible macroprudential regulations by focusing on potentially systemic banks.

1.3 Methodology, econometric specifications and data

In this section, we present the measures used to calculate systemic risk, the data used and the various econometric approaches.

1.3.1 Methodology

As discussed in an earlier section, the empirical literature proposes several measures that quantify and analyse the contribution and exposure to systemic risk. Tobias and Brunnermeier (2016) propose ΔCoVaR as a measure of a bank's contribution in the event of an extreme tail loss. This externality is based on the concept of VaR (Value at Risk) which measures the maximum loss due to a systemic shock of a bank on the financial system. It is the difference between the VaR of the financial system conditional on a bank in a difficult situation and the VaR of the financial system conditional on the same bank in a normal situation. This indicator is modeled by the dynamics of bank returns

and financial market returns. To estimate the systemic risk measures, we first calculated the daily return of each bank (R_{it}) according to the following formula:

$$R_{it} = Ln(P_t) - Ln(P_{t-1}) \quad (1.1)$$

P_t and P_{t-1} are the daily share prices of a bank at date t and date t-1, respectively. Next, we calculate the weighted market return (R_{mt}) of the financial system, which is composed of all banks in our sample according to the following formula:

$$R_{mt} = \sum_{i=1}^N \omega_{it} R_{it} \quad (1.2)$$

With: ω_{it} is the market capitalisation of each bank to take into account the bank's weight in the financial system.

The contribution of a financial institution to systemic risk under the Δ CoVaR approach is expressed by Eq. (2.3):

$$Pr(R_{it} \leq VaR_{it}^q) = q \quad (1.3)$$

With : VaR_{it}^q is defined as q quantile where R_{it} is the return of bank i.

The Δ CoVaR is expressed by Eq. (2.4).

$$Pr(R_{mt} \leq CoVaR_{m|i,t}^q | R_{it} = VaR_{it}^q) = q \quad (1.4)$$

The CoVaR measure is the qth quantile of the market return conditional on the distress event in which the return of institution i is less than or equal to its VaR. The contribution of an individual institution to systemic risk is presented by Eq. (2.5).

$$\Delta CoVaR_{m|i,t}^q = CoVaR_{m|R_{it}=VaR_{it}^q,t}^q - CoVaR_{m|R_{it}=VaR_{it}^{0.5},t}^q \quad (1.5)$$

The estimation of Δ CoVaR can be estimated by quantile regression or by GARCH modeling (Tobias and Brunnermeier (2016)). In our study, we use the dynamic condi-

tional correlation (DCC) model of Engle (2002) to model the individual bank’s contribution to systemic risk. In contrast to quantile regression, this model accounts for the variability over time between the dynamics of financial system returns and the returns of financial institutions (Tobias and Brunnermeier (2016)).

In a different approach, Acharya et al. (2012) introduce the notion of expected marginal loss, i.e. the MES. The latter measures the impact of a potential systemic event in the financial system on a given bank. It is a marginal loss when the market falls below a critical threshold in the event of a systemic crisis. Formally, the MES is expressed by Eq. (2.6):

$$MES_{it}(C) = E_{t-1}[R_{it} | R_{mt} \leq C] \quad (1.6)$$

With C the threshold value, which is defined as a decrease in the average expected market return (R_{mt}). A crisis event is defined when the market return $R_{mt} \leq C$. This approach measures the increase in overall risk generated by bank losses in the system. As the bank’s MES increases, the individual bank’s contribution to the overall risk increases (Benoit et al. (2013)).

1.3.2 Econometric specifications

Since our aim is to investigate the effect of banks’ size on their systemic risk, we first consider a linear relationship by estimating a dynamic GMM (Generalized Methods of Moments in Systems) panel model. Secondly, to test the non-linearity between risk contribution and exposure and bank size, we estimate a quadratic model. Moreover, we go beyond a quadratic specification by considering a PSTR model that does not impose any form on the relationship between variables. Finally, to provide some robustness to our main models, we specify a semiparametric model consisting of both a parametric and a nonparametric part.

1.3.2.1 Linear and non-linear quadratic model

In what follows, we will empirically study the impact of size on the systemic risk of Islamic and conventional banks. To achieve this objective, we will estimate a dynamic panel model (DPM) proposed by Arellano and Bond (1991), which has the advantage of taking into account the endogeneity problem. In particular, the GMM approach provides unbiased estimates in the presence of the endogeneity problem. Our benchmark model is shown in Eq. (2.7):

$$Systemicrisk_{it} = \alpha systemicrisk_{it-1} + \beta_0 size_{it} + \delta Bank_{it} + \theta M_{it} + \eta_i + \gamma_t + \epsilon_{it} \quad (1.7)$$

Where: $Systemicrisk_{it}$, represents the different dependent variables. It corresponds to the measures of systemic risk that are estimated as the annual average ($\Delta CoVaR_{it}$ and MES_{it}) for Islamic banks ($i=1...34$), and for conventional banks ($i=1...70$), over a period from 2006 to 2017; $systemicrisk_{it-1}$ is the lagged dependent variable that allows us to take into account the dynamic aspect and temporal persistence of systemic risk. $size_{it}$ is our variable of interest. It is represented by the logarithm of total assets of Islamic and conventional banks (in log); $Bank_{it}$ is the vector of bank-specific explanatory variables; M_{it} represents the vector of macroeconomic variables; η_i represents bank-specific fixed effects; γ_t represents time-specific effects; ϵ_{it} is the error term which is assumed to be independent and identically distributed (i.i.d).

In order to test for the presence of non-linearity between risk contribution and exposure and bank size, we estimate a quadratic model by introducing the variable size squared into our baseline model :

$$Systemicrisk_{it} = \alpha systemicrisk_{it-1} + \beta_0 size_{it} + \beta_1 size_{it}^2 + \delta Bank_{it} + \theta M_{it} + \eta_i + \gamma_t + \epsilon_{it} \quad (1.8)$$

In Eq. (2.8), the relationship between size and systemic risk is assumed to be non-

linear. We expect the sign of the coefficient to be different from that of β_1 's . If this is the case, it suggests the existence of a threshold effect at which the effect of bank size varies.

Let us start with the variable of interest, namely: Size represents the logarithm of the bank's total assets. This variable is considered a key factor in identifying the systemic importance of a bank. It is well accepted in the literature that large banks are likely to destabilize the financial system in case of failure, due to their complexities (Brunnermeier et al. (2012); Laeven et al. (2014) and Bostandzic and Weiss (2018)). We expect a positive relationship between size and systemic risk. Furthermore, we assume a potential non-linear relationship between size and systemic risk (Pais and Stork (2013); Moore and Zhou (2013) and Qin and Zhou (2019)).

For the control variables, we consider the following variables: Leverage : is the ratio of equity to total assets. This ratio is widely used in the literature as an indicator of insolvency risk (Acharya et al. (2012) and Brownlees et al. (2012)). The higher the ratio, the lower the risk of default. At the same time, leverage could encourage banks to increase excessive lending, which would subsequently lead to an increase in systemic risk (Beck et al. (2010) and Beltratti and Stulz (2012)). In addition, we there is an evidence (e.g., Olson and Zoubi (2011) and Abedifar et al. (2013)) that Islamic banks are better capitalized and represent significant levels of capital, implying a lower level of risk and better stability. We, therefore, expect a negative relationship between leverage and systemic risk. Liquidity : the liquidity ratio is represented by total loans over total deposits. We assume that there is a positive relationship between liquidity and systemic risk. As this ratio increases, liquidity risk increases, which favors an increase in systemic risk. Regarding the liquidity risk of Islamic banks, Olson and Zoubi (2011) find that there is no significant difference in liquidity between Islamic and conventional banks. Credit risk : with regard to the measures of credit risk. Cihák and Hesse (2008) used the ratio of net loans to total assets as an indicator of credit risk for Islamic banks. Beck et al. (2013) find a difference between Islamic and conventional banks and find that Islamic banks have better capitalization and higher asset quality than conventional banks. We

use the ratio of total loans to total assets of a bank to account for this variable. A bank with more loans would be more exposed to credit risk (Duan and Zhang (2013)). We expect a positive relationship between systemic risk and lending. Financial structure We also study the financial structure to investigate the relationship between the bank's funding structure and its systemic risk. We refer to the work of Tobias and Brunnermeier (2016) and Bostandzic and Weiss (2018), considering the ratio of total loans to total liabilities of a bank. According to these authors, banks with a higher deposit base are less exposed to systemic risk. In this sense, it is suggested that the functioning of Islamic banks differs from that of conventional banks through some characteristics, such as the non-practice of interest and the principle of profit and loss sharing (PLS). According to Cihák and Hesse (2008) these intrinsic characteristics allow Islamic banks to be less susceptible to vulnerabilities than conventional banks. Through the principle of profit and loss sharing (PLS), Islamic banks rebalance a negative shock from their assets to their liabilities. However, it exposes them to a significant withdrawal risk (Khan et al. (2001) and Sundararajan and Errico (2002)). Value at risk : The value at risk has been included in our model since the estimates of ΔCoVaR are closely related to its VaR. This variable is a measure of tail risk. Previous studies confirm a strong relationship between VaR and ΔCoVaR of banks (Tobias and Brunnermeier (2016)). The expected association between VaR and ΔCoVaR is positive. Beta : that measures the systematic sensitivity to market fluctuations. According to Benoit et al. (2013), there is a positive relationship between bank beta and the MES. We expect a positive relationship between our systemic risk measures and beta. We take into account GDP growth and inflation in order to capture the effect of macroeconomic variables on systemic risk. As our analysis covers banks from different countries, the idea is to capture the country-macroeconomic effects.

1.3.2.2 PSTR model: Panel Smooth Transition Regression

In Eq. (2.8) above, we require a functional form of the relationship between size and systemic risk. However, this is an ad hoc specification where we impose the form of

the relationship by assuming the existence of one threshold effect. In order to further explore the non-linear aspect of the effect, we use a recent approach, namely PSTR (Panel Smooth Transition Regression) which was proposed by Gonzalez et al. (2005), and is an extension of the panel threshold regression model PTR (Panel Transition Regression) proposed by Hansen (1999). The PTR model assumes that the transition between two regimes is abrupt, while the PSTR model assumes that this transition is rather smooth. The transition from one regime to the other is transformed in a gradual (and not abrupt) manner. Another advantage that could be mentioned is that the PSTR model contains an infinite number of regimes that are bounded between two extreme regimes (weak and strong). Furthermore, the PSTR model does not impose any specific functional form, unlike the quadratic model which assumes an ad hoc form. Moreover, the regime change of a bank's size is gradual. Indeed, a small bank does not become a large bank in a sudden way -except in exceptional cases, such as the purchase or absorption of another bank- but gradually, as its turnover increases.

Following the methodology of Gonzalez et al. (2005), our non-linear PSTR model for the relationship between systemic risk and size is written as Eq. (2.9):

$$Systemicrisk_{it} = \eta_i + \beta_1 size_{it} + \beta_2 size_{it} g(q_{it}, \gamma, c) + \gamma Controls_{it} + \epsilon_{it} \quad (1.9)$$

With η_i denotes the bank fixed effects. $Controls_{it}$ is the vector of explanatory variables. β_1, β_2 , denote the parameters of the linear and non-linear model respectively. $g(q_{it}, \gamma, c)$ is the transition function, which is a continuous function and depends on the transition variable (q_{it}), the smoothing parameter (γ) and the threshold parameter (c).

The transition function in the PSTR model with more than two regimes can be modeled according to Gonzalez et al. (2005), by Eq. (2.10) as follows:

$$G(q_{it}, \gamma, c) = [1 + \exp(-\gamma \prod_{j=1}^m (q_{it} - c_j)^{-1})], \gamma \geq 0, c_1 \leq \dots \leq c_m \quad (1.10)$$

Where $c = (c_1, \dots, c_m)$ is a vector of dimension grouping the threshold parameters and

represents the assumed positive smoothing parameter

The estimation of the PSTR model formally requires the verification of the linearity assumption between the dependent variable and the transition variable. Before using this model, it is essential to determine the regime number (r). The first step is to clarify whether there is a non-linear relationship between systemic risk and size. If non-linearity is present, the second step is to determine the number of regimes (i.e. the number of thresholds). Three tests are used, namely the Wald (LM), Fisher (LM_F) and Likelihood (LRT) tests, which allow the null hypothesis of a linear model ($H_0 : r = 0$) to be tested against a non-linear model ($H_1 : r = 1$), and the hypothesis of the existence of only one threshold and two regimes ($H_0 : r = 1$) to be tested against the hypothesis of the existence of at least two thresholds and at least three regimes in the model ($H_1 : r = 2$)

$$LM = \frac{TN(SCR_0 - SCR_1)}{SCR_0} \sim \chi_{mk}^2 \quad (1.11)$$

$$LM_F = \frac{\frac{SCR_0 - SCR_1}{mk}}{\frac{SCR_0}{TN - N - mk}} \sim F(mk, TN - N - mk) \quad (1.12)$$

$$LRT = -2[\log(\frac{SCR_{ur}}{SCR_0})] \sim \chi_{mk}^2 \quad (1.13)$$

Where SCR_0 and SCR_1 refer to the sum of the squares of the residuals of a linear model with individual effects and an m -regime non-linear PSTR model, respectively. The Fischer LM_F test ($F(m, k, TN, N)$) approximately follows the χ_k^2 distribution under the null hypothesis, where k , m , N and T are the number of independent variables, the maximum number of thresholds, and the banks and observation period, respectively⁴.

1.3.2.3 Preliminary analysis: basic model

As a reminder, our objective is to measure systemic risk in the Islamic and conventional banking sectors. We estimate the contribution of a bank to systemic risk in case of distress by the Δ CoVaR measure and the marginal loss a bank suffers in case of a systemic shock

⁴For more details of this methodology, please refer to Gonzalez et al. (2005) among others.

by the MES. The estimation of these two measures is daily for 34 Islamic banks and 70 conventional banks from 12 countries (Bahrain, Bangladesh, Egypt, Jordan, Kuwait, Malaysia, Pakistan, Palestine, Saudi Arabia, Turkey, United Arab Emirates and Qatar), for a period from 2006 to 2017⁵. The definitions of the variables as well as the descriptions of the data sources are given in the table 1.13 in appendix 2.6.

Tables 2.8 and 2.1 present the annual averages of our systemic risk measures and explanatory variables for Islamic and conventional banks over the period 2006-2017. The average estimate of the contribution to systemic risk measured by ΔCoVaR is 0.22% for Islamic banks and 0.25% for conventional banks. The average exposure to systemic risk measured by the MES is 1.12% for Islamic banks and 1.08% for conventional banks.

Table 1.1: Descriptive statistics for Islamic banks.

	ΔCoVaR (%)	MES (%)	Size en (\$ bn)	Leverage	Credit risk	Financial structure	Liquidity risk	Value at risque 95 (%)	Beta	GDP	Inflation
Mean	0.22	1.12	4.388	0.13	0.56	0.77	0.82	3.44	0.53	4.09	5.44
Median	0.15	1.08	5.222	0.11	0.59	0.84	0.8	3.15	0.43	4.37	3.57
Maximum	1.54	5.88	91.493	0.9	0.98	0.98	1.26	8.98	2.56	12.41	29.5
Minimum	0.01	0.09	3.372	0.01	0.06	0.02	0.05	0.11	-0.08	-7.08	-0.88
Std. Dev.	0	0.01	1.74	0.1	0.16	0.21	0.55	0.01	0.47	2.94	4.91

Furthermore, the average size of Islamic banks is \$4.3 billion (ranging from a minimum value of \$3.372 billion to a maximum value of \$91.49 billion). With an average of \$10.97 billion (with a maximum value of \$222.72 billion), conventional banks have a higher average than Islamic banks. As far as our control variables are concerned, there is little difference between the two types of banks.

⁵Despite the fact that the available data are daily, we have transformed them to annual measures. This was imposed by the annual nature of the explanatory variables included in our estimates.

Table 1.2: Descriptive statistics for Conventional banks.

	ΔCoVaR (%)	MES (%)	Size in (\$ bn)	Leverage	Credit risk	Financial structure	Liquidity risk	Value at risque 95 (%)	Beta	GDP	Inflation
Mean	0.25	1.08	10.975	0.12	0.56	0.78	0.83	3.19	0.57	4.02	5.79
Median	0.15	0.9	10.952	0.11	0.57	0.8	0.85	2.93	0.37	4.4	4.52
Maximum	1.33	4.83	222.723	0.36	0.91	0.98	1.49	21.16	3.35	12.41	29.5
Minimum	0.01	0.18	4.431	0.01	0.13	0.39	0.18	0.01	0	-7.08	-0.88
Std. Dev.	0.25	0.9	1.38	0.04	0.12	0.11	0.21	1.62	0.62	3.02	5

Regarding the correlation between the variables, according to Tables 2.2 and 2.3, we find a positive relationship between the contribution and exposure to systemic risk and the size of Islamic bank.

Table 1.3: Correlations of Islamic bank variables

	ΔCoVaR	MES	Size	Leverage	Credit risk	Financial structure	Liquidity risk	Value at risque 95%	Beta	GDP	Inflation
ΔCoVaR	1										
MES	0.869	1									
Size	0.369	0.286	1								
Leverage	0.214	0.261	-0.062	1							
Credit risk	0.157	0.079	-0.002	-0.135	1						
Financial structure	0.125	-0.046	0.042	-0.426	0.353	1					
Liquidity risk	0.108	0.124	0.115	0.399	0.063	-0.47	1				
Value at risque 95%	-0.015	0.165	-0.181	0.038	-0.298	-0.219	0.118	1			
Beta	0.787	0.857	0.415	0.146	0.138	0.016	0.14	-0.007	1		
GDP	-0.182	-0.236	-0.166	-0.069	-0.081	-0.036	0.019	0.065	-0.175	1	
Inflation	0.132	0.061	-0.203	-0.126	0.088	0.245	-0.11	0.131	0.015	0.151	1

For Conventional banks, the relationship between size and systemic risk is characterized by a strong positive correlation (0.61 for ΔCoVaR and and 0.51 for MES and size).

Table 1.4: Correlations of Conventional bank variables

	ΔCoVaR	MES	Size	Leverage	Credit risk	Financial structure	Liquidity risk	Value at risque 95%	Beta	GDP	Inflation
ΔCoVaR	1										
MES	0.89	1									
Size	0.61	0.51	1								
Leverage	-0.05	-0.07	-0.08	1							
Credit risk	0.06	0	0.16	0.06	1						
Financial structure	-0.22	-0.24	-0.35	0.12	0.04	1					
Liquidity risk	0.18	0.15	0.33	0.16	0.77	-0.56	1				
Value at risque 95%	0.16	0.37	-0.25	-0.18	0.03	0.05	-0.03	1			
Beta	0.76	0.88	0.59	-0.08	0.02	-0.31	0.21	0.21	1		
GDP	-0.01	0	-0.05	-0.14	-0.04	-0.01	-0.05	0.06	0.08	1	
Inflation	0.14	0.26	-0.11	-0.19	-0.17	-0.05	-0.11	0.33	0.18	0.17	1

Figures 2.3 and 2.4 illustrate the evolution of ΔCoVaR and the MES for the period studied, respectively. They reveal that, during the financial crisis, systemic risk was significantly increased for both Islamic and Conventional banks.

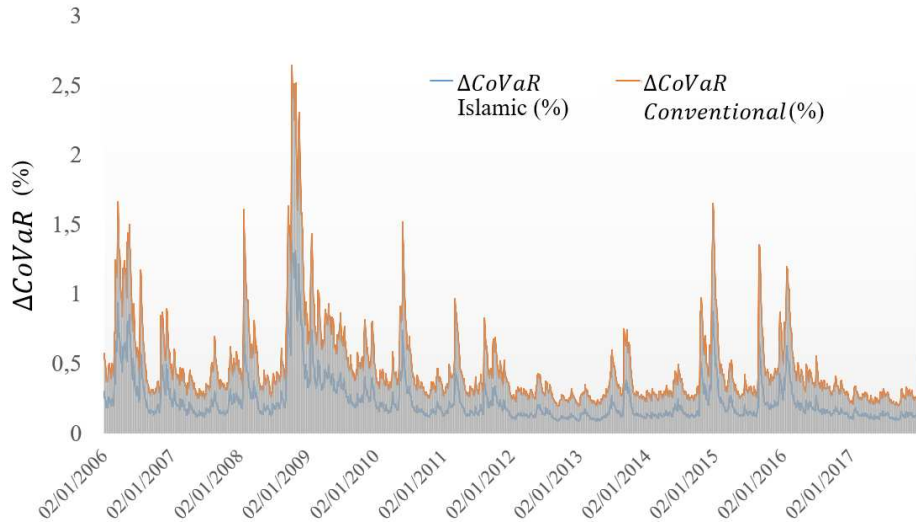


Figure 1.1: Evolution of the ΔCoVaR of Islamic and conventional banks from 2006 to 2017

Figures 2.3 and 2.4 also show that Islamic banks have a lower sensitivity to systemic risk than conventional banks. Moreover, we find that the measures of systemic risk evolve in a similar and closely related manner.

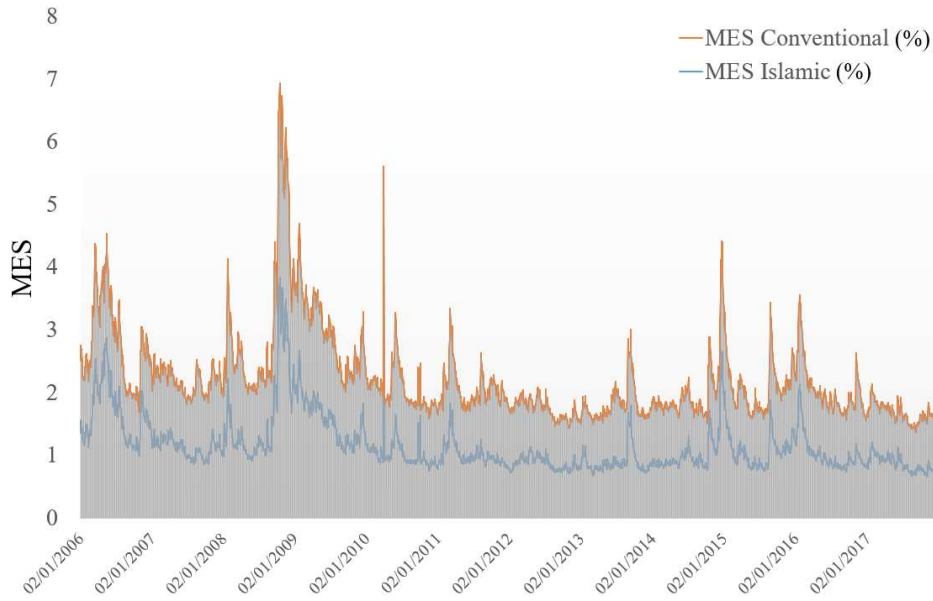


Figure 1.2: Evolution of the MES of Islamic and conventional banks from 2006 to 2017

1.4 Empirical results and discussion

1.4.1 Results of the Linear Model: Islamic and conventional banks

This section aims to provide the estimates of the linear model for the effect of size on systemic risk. Tables 2.4 and 2.5 provide us with the estimated results of different methods: ordinary least squares (OLS), fixed effects model (FE), random effects model (RE) and dynamic panel model using the system generalized moment method (system GMM).

The estimates obtained through the different methods are nearly similar. We find a positive and significant relationship between systemic risk exposure measured by the MES and the size of banks - both Islamic and conventional. The contribution to systemic risk measured by the ΔCoVaR is positively correlated with size, with a significance of around 1%, for both Islamic and conventional banks. These results corroborate many studies that have confirmed a positive relationship between size and systemic risk (Laeven et al. (2014) and Qin and Zhou (2019)).

Table 1.5: Linear regression between systemic risk and the size of Islamic banks

	All Islamic Banks							
	OLS		EF		RE		GMM	
Dependent variable:	ΔCoVaR	MES	ΔCoVaR	MES	ΔCoVaR	MES	ΔCoVaR	MES
Size	0.0155*** (0.00484)	-0.00408 (0.0153)	-0.0172 (0.0172)	-0.0583 (0.0436)	0.0156** (0.00768)	-0.0144 (0.0284)	0.238*** (0.0637)	0.0899*** (0.0249)
Leverage	0.409*** (0.0819)	1.311*** (0.259)	0.311*** (0.112)	0.748*** (0.283)	0.525*** (0.0921)	1.198*** (0.255)	1.632*** (0.227)	1.311*** (0.252)
Credit risk	0.0482 (0.0527)	0.257 (0.167)	0.122 (0.0749)	0.308 (0.190)	0.0664 (0.0666)	0.300 (0.188)	1.295*** (0.279)	0.379* (0.214)
Financial structure	0.127*** (0.0459)	-0.189 (0.145)	-0.0157 (0.0580)	-0.0452 (0.147)	0.127** (0.0533)	0.0135 (0.147)	0.0415 (0.214)	-0.304 (0.226)
Liquidity risk	-0.00684 (0.0159)	-0.142*** (0.0502)	-0.0389** (0.0187)	-0.0918* (0.0474)	-0.0126 (0.0183)	-0.0907* (0.0488)	-0.156*** (0.0529)	-0.103** (0.0479)
Value-at-risk 95%	0.374*** (0.0177)	1.676*** (0.0560)	0.116*** (0.0303)	1.219*** (0.0767)	0.292*** (0.0236)	1.423*** (0.0709)	1.738*** (0.220)	0.987*** (0.0779)
Beta	-0.000319 (0.00535)	0.102*** (0.0169)	0.0833*** (0.0100)	0.364*** (0.0254)	0.0295*** (0.00710)	0.282*** (0.0220)	0.416*** (0.0479)	0.173*** (0.0215)
GDP	-0.00512** (0.00255)	-0.0338*** (0.00808)	-0.000575 (0.00209)	-0.00496 (0.00530)	-0.00244 (0.00232)	-0.00983* (0.00569)	-0.00394 (0.00528)	0.00375 (0.00333)
Inflation	0.00738*** (0.00165)	0.00843 (0.00523)	0.00503*** (0.00174)	0.00392 (0.00441)	0.00750*** (0.00175)	0.00780* (0.00458)	0.0311*** (0.00706)	0.0303*** (0.00512)
$\Delta\text{COVAR} (-1)$							0.306*** (0.0385)	
MES (-1)								0.425*** (0.0298)
Constant	-0.393*** (0.0950)	0.0134 (0.301)	0.0475 (0.286)	-0.0467 (0.726)	-0.499*** (0.139)	-0.654 (0.492)	-11.99*** (0.914)	-5.616*** (0.651)
Observations	408 0.716	338 0.811	372 0.423	372 0.750	372 0.8062	372 0.6800	342	345
AR(1)							0.001	0.012
AR(2)							0.325	0.942
Hansen Test							0.103	0.188

***, **, * denote coefficients significant at the 1%, 5% and 10% level, respectively.

However, we find a difference in intensity between Islamic and conventional banks. A 1% increase in the size of Islamic banks is associated with an increase in ΔCoVaR and MES of 0.23% and 0.08%, respectively. While for conventional banks, an increase in size is associated with a 0.41% increase in the contribution to systemic risk measured

by $\Delta CoVaR$ and an increase in the exposure to systemic risk measured by the MES by 0.12%. The estimates reveal that the size effect is larger for conventional banks. This is due to the fact that conventional banks represent larger sizes than Islamic banks. With respect to the control variables, leverage is positively correlated with systemic risk in both the Islamic and conventional banking sectors. An increase in leverage increases both the expected marginal loss when the market is undercapitalized and the contribution to systemic risk in the case of bank distress. As expected, beta and VaR of both Islamic and conventional banks are positively related to systemic risk as measured by $\Delta CoVaR$ and MES.

Table 1.6: Linear regression between systemic risk and conventional bank size

		All Conventional Banks							
		OLS		EF		RE		GMM	
Dependent variable:		ΔCoVaR	MES	ΔCoVaR	MES	ΔCoVaR	MES	ΔCoVaR	MES
Size		0.0681*** (0.00618)	0.110*** (0.0151)	-0.0699*** (0.0136)	-0.389*** (0.0584)	0.0488*** (0.00819)	0.0546** (0.0259)	0.416*** (0.0134)	0.124*** (0.0149)
Leverage		0.818*** (0.221)	1.863*** (0.539)	0.0964 (0.247)	-0.0773 (0.910)	0.755*** (0.233)	1.630** (0.766)	4.698*** (0.354)	0.929*** (0.354)
Credit risk		0.871*** (0.240)	0.788 (0.587)	0.704*** (0.259)	0.318 (0.886)	0.860*** (0.253)	1.059 (0.838)	-0.125 (0.328)	0.486 (0.307)
Financial structure		-0.562*** (0.198)	-0.521 (0.484)	-0.911*** (0.211)	-1.260* (0.736)	-0.838*** (0.208)	-0.986 (0.688)	-1.433*** (0.361)	-0.699*** (0.210)
Liquidity risk		-0.636*** (0.170)	-0.770* (0.416)	-0.694*** (0.168)	-0.913 (0.571)	-0.682*** (0.173)	-0.994* (0.575)	-0.0595 (0.197)	-0.437** (0.196)
Value-at-risk 95%		0.232*** (0.0134)	1.111*** (0.0326)	0.0640** (0.0251)	0.590*** (0.0906)	0.186*** (0.0175)	1.065*** (0.0556)	0.0295 (0.0336)	0.486*** (0.0475)
Beta		0.0159*** (0.00429)	0.127*** (0.0105)	0.0431*** (0.00517)	-0.00342 (0.0187)	0.0342*** (0.00473)	0.0563*** (0.0156)	0.139*** (0.0102)	0.221*** (0.00777)
GDP		-0.00535*** (0.00194)	-0.0262*** (0.00475)	-0.00503*** (0.00143)	-0.0460*** (0.00511)	-0.00604*** (0.00160)	-0.0502*** (0.00539)	0.000233 (0.00133)	-0.000255 (0.00136)
Inflation		0.00533*** (0.00136)	0.0200*** (0.00333)	0.00545*** (0.00115)	0.000659 (0.00419)	0.00579*** (0.00119)	0.0111*** (0.00396)	0.0453*** (0.000949)	0.0155*** (0.00157)
$\Delta\text{COVAR} (-1)$								0.538*** (0.0122)	
MES (-1)									0.336*** (0.0149)
Constant		-0.652*** (0.183)	-1.343*** (0.447)	2.067*** (0.283)	8.842*** (1.154)	-0.128 (0.212)	0.354 (0.689)	-9.992*** (0.489)	-5.852*** (0.307)
Observations		717 0.668	717 0.842	735 0.305	735 0.216	735 0.7776	734 0.9258	731	725
AR(1)								0.003	0.011
AR(2)								0.662	0.146
Hansen Test								0.134	0.152

***, **, * denote coefficients significant at the 1%, 5% and 10% level, respectively.

Concerning the economic activity and financial structure of banks, our results show a differential impact on systemic risk for the two types of banks. We find a positive and statistically significant relationship between the contribution and exposure to systemic risk and credit risk for Islamic banks. The economic interpretation of this result is that the more Islamic banks engage in loan-based activities, the more systemic risk increases.

The relationship between credit risk and systemic risk is not significantly related to vulnerability and exposure to systemic risk for banks operating in conventional finance. The relationship between financial structure and systemic risk is negative and statistically significant for conventional banks. Any increase in deposits is accompanied by a reduction in systemic risk. This means that as conventional banks take more deposits, the risk decreases. For Islamic banks, this relationship is not significant.

The liquidity ratio represented by total loans to total deposits is negatively associated with systemic risk for both Islamic and conventional banks. This result is consistent with the results of Olson and Zoubi (2008) who find no difference between Islamic and conventional banks in terms of liquidity ratio. Finally, for macroeconomic variables, the relationship between inflation and the contribution and exposure to systemic risk is positive for both banking sectors. An increase in inflation rates could increase banks' vulnerability to systemic risk. Regarding economic growth, its effect is overall insignificant in most specifications.

1.4.2 Results of the Quadratic Model: Islamic and conventional Banks

After investigating the relationship between contribution and exposure to systemic risk in a linear framework, we extended the analysis by examining non-linearity in a quadratic model. Tables 2.6 and 2.7 present the estimates and reveal two main findings. The significance of the quadratic coefficients of our variable of interest suggests the existence of a non-linear effect between contribution and exposure to systemic risk for Islamic and conventional banks by any measure. In particular, there is a non-linear relationship that takes the U-form (convex) for Islamic banks and that takes the inverted U-form (concave) for conventional banks. Specifically, the quadratic shape provides evidence of a threshold effect, suggesting the presence of an inflection point at which the size effect changes. For Islamic banks, size would negatively affect systemic risk below a certain threshold. Above this threshold, any increase in the size of the Islamic bank would increase the contribution and exposure to systemic risk.

Table 1.7: Quadratic estimate between systemic risk and the size of Islamic and conventional banks

	All Islamic Banks		All conventional Banks	
	Quadratic Model		Quadratic Model	
Dependent variable:	ΔCoVaR	MES	ΔCoVaR	MES
Size	-1.035*** (0.169)	-1.621*** (0.296)	1.249*** (0.101)	2.901*** (0.257)
Size ²	0.0408*** (0.00626)	0.0645*** (0.0103)	-0.0345*** (0.00313)	-0.0818*** (0.00764)
Leverage	1.292*** (0.269)	2.889*** (0.536)	1.157*** (0.330)	3.172*** (0.542)
Credit risk	0.00611 (0.188)	0.605* (0.332)	-0.140 (0.292)	-0.266 (0.537)
Financial structure	0.242** (0.110)	0.188 (0.211)	-0.179 (0.231)	-0.765* (0.424)
Liquidity risk	-0.0528 (0.0424)	-0.295*** (0.0623)	-0.287 (0.198)	-0.752** (0.366)
Value-at-risk 95%	0.202*** (0.0311)	0.562*** (0.0355)	0.0977*** (0.00510)	0.293*** (0.0104)
Beta	-0.280*** (0.0647)	0.522*** (0.110)	-0.00315 (0.00962)	0.469*** (0.0194)
GDP	0.00336 (0.00254)	8.16e-05 (0.00525)	-0.00218*** (0.000648)	-0.00653*** (0.00143)
Inflation	0.00313 (0.00322)	-0.00127 (0.00491)	0.0180*** (0.000649)	0.0346*** (0.00150)
$\Delta\text{COVAR} (-1)$	0.364*** (0.0714)		0.310*** (0.0152)	
MES (-1)		0.165*** (0.0474)		0.319*** (0.00949)
Constant	5.411*** (1.097)	7.689*** (2.168)	-11.04*** (0.890)	-25.02*** (2.231)
AR(1)	0.001	0.002	0.001	0.002
AR(2)	0.681	0.737	0.681	0.737
Hansen Test	0.146	0.148	0.146	0.148

***, **, * denote coefficients significant at the 1%, 5% and 10% level, respectively.

However, the opposite is true for conventional banks, with size having a positive effect on systemic risk below a certain threshold. Above this threshold, any increase in the size of banks could decrease the contribution and exposure to systemic risk. As explained earlier, the thresholds obtained may be inappropriate, as the quadratic model imposes a specific form on the relationship. If this is the case, it could lead to a loss of information in contrast to other models, such as nonparametric models. To overcome this limitation, we estimate the non-linear PSTR model which we believe would be more suitable for determining the shape of the non-linearity and the determination of the optimal threshold at which the size could change regime.

1.4.3 Results of the PSTR Model: Islamic and conventional Banks

1.4.3.1 Linearity test and regime number determination: Islamic and conventional banks

As noted, the first step in specifying PSTR regime-switching models is to test the linearity hypothesis (see the Tables 2.7 and 1.9). The Wald (LM), Fisher (LMF) and Likelihood (LRT) linearity tests we conducted confirmed the rejection of the null hypothesis (H_0 : a linear model)⁶. Our results confirm the existence of a non-linear relationship between size, the contribution to systemic risk measured by ΔCOVAR and the exposure to systemic risk measured by MES for Islamic and conventional banks.

⁶Note that the alternative hypothesis is the following: H_1 : the model accepts at least one non-linear threshold.

Table 1.8: Linearity test and regime number for Islamic banks: ΔCoVaR

Linearity Tests		Testing The Number Of Regimes	
Threshold variable	m=1	Threshold variable	m=1
	Linearity test $H_0:r=0 H_1=r=1$		Remaining non linearity test $H_0:r=1 H_1=r=2$
	Wald Tests (LM) 87.527 *** 0.000		Wald Tests (LM) 18.144 0.034**
Size	Fisher Tests (LMF) 11.247 *** 0.001	Size	Fisher Tests (LMF) 1.772 0.073*
	LRT Tests (LRT) 99.791 *** 0.000		LRT Tests (LRT) 18.601** 0.029

***, **, * denote coefficients significant at the 1%, 5% and 10% level, respectively.

Table 1.9: Linearity test and regime number for Islamic banks: MES

Linearity Tests		Testing The Number Of Regimes	
Threshold variable	m=1	Threshold variable	m=1
	Linearity test $H_0:r=0 H_1=r=1$		Remaining non linearity test $H_0:r=1 H_1=r=2$
	Wald Tests (LM) 112.521 *** 0.000		Wald Tests (LM) 13.638 0.136
Size	Fisher Tests (LMF) 15.852 *** 0.001	Size	Fisher Tests (LMF) 1.315 0.228
	LRT Tests (LRT) 134.001 *** 0.000		LRT Tests (LRT) 13.894 0.126

***, **, * denote coefficients significant at the 1%, 5% and 10% level,

respectively.

The second step is to test the null hypothesis of a one-threshold, two-regime model against the alternative hypothesis of a model with at least two thresholds and three regimes. We rely on the Wald (LM), Fisher (LMF) and Likelihood (LRT) tests to validate these hypotheses. According to these three tests, the null hypothesis is preferred. Consequently, we conclude that our two models need to be estimated by a single threshold PSTR model with two regimes for Islamic and conventional banks (see the Tables 1.10 and 1.11).

Table 1.10: Linearity test and regime number for conventional banks: *DeltaCoVaR*

Linearity Tests		Testing The Number Of Regimes			
Threshold variable	m=1	Threshold variable	m=1		
	Linearity test H0:r=0 H1=r=1		Remaining non linearity test H0:r=1 H1=r=2		
	Wald Tests(LM)	84.488 ***	Wald Tests(LM)	6.502	
		0.000		0.689	
Size	Fisher Tests (LMF)	9.461 ***	Size	Fisher Tests (LMF)	0.639
		0.000		0.764	
	LRT Tests (LRT)	89.363***	LRT Tests (LRT)	6.529	
		0.000		0.686	

***, **, * denote coefficients significant at the 1%, 5% and 10% level, respectively.

Table 1.11: Linearity test and regime number for conventional banks: MES

Linearity Tests		Testing The Number Of Regimes			
Threshold variable	m=1	Threshold variable	m=1		
	Linearity test H0:r=0 H1=r=1		Remaining non linearity test H0:r=1 H1=r=2		
	Wald Tests(LM)	60.282 ***	Wald Tests(LM)	12.600	
		0.000		0.182	
Size	Fisher Tests (LMF)	6.525 ***	Size	Fisher Tests (LMF)	1.247
		0.000		0.263	
	LRT Tests (LRT)	62.715***	LRT Tests (LRT)	12.702	
		0.000		0.177	

***, **, * denote coefficients significant at the 1%, 5% and 10% level, respectively.

The results of the PSTR model for Islamic and conventional banks are presented in Table 12. The estimates indicate that the slope parameter, which estimates the transition speed, between the contribution to systemic risk measured by $\Delta CoVaR$ and the size of Islamic banks is 1.49 and with an estimated optimal threshold of \$12.91 billion. The systemic risk exposure measured by the MES and the size of Islamic banks indicate a transition speed of 1.57. The optimal threshold at which size changes regime with respect

to systemic sensitivity is \$7.50 billion. Below the threshold of \$12.91 billion, size growth will turn into a weak regime. In other words, any 1% increase in the size of the Islamic banks will decrease the contribution to systemic risk by 0.060%. Beyond this threshold, the model will transform into the high regime in which any increase in the size of the Islamic bank will lead to an increase in the contribution to systemic risk of 0.022%.

With regard to the systemic risk sensitivity of Islamic banks, it becomes low below the optimal threshold of \$7.50 billion (low regime). Any increase in size will decrease the sensitivity to systemic risk in case of a systemic shock by 0.22%. Above this threshold, the model will shift to the high regime, i.e. any increase in the size of the Islamic bank will lead to an increase in sensitivity to systemic risk exposure of 0.044%.

Table 1.12: PSTR estimate between systemic risk and the size of Islamic and conventional banks

Dependent variable	All Islamic Banks				All conventional Banks			
	PSTR: $\Delta CoVaR$		PSTR: MES		PSTR: $\Delta CoVaR$		PSTR: MES	
	Regime 1	Regime2	Regime 1	Regime2	Regime 1	Regime2	Regime 1	Regime2
	$\Delta CoVaR$	$\Delta CoVaR$	MES	MES	$\Delta CoVaR$	$\Delta CoVaR$	MES	MES
Size	-0.0608*** (0.0180)	0.0227** (0.0139)	-0.2273*** (0.0557)	0.0444* (0.0277)	-0.3031*** (0.0866)	0.1304** (0.0677)	-0.0733 *** (0.0179)	0.0451* (0.0297)
Leverage	0.2106*** (0.0903)	0.7894 (0.6696)	0.4298* (0.2644)	-0.8347 (0.9180)	-3.2703** (1.8519)	1.0721 (2.3475)	-0.0291 (0.0453)	0.2291** (0.1353)
Credit risk	0.0915* (0.0743)	0.2742 (0.3106)	0.3089* (0.2443)	0.5899 (0.5175)	-2.0394* (1.6073)	3.1248* (2.0641)	-0.0201 (0.2787)	2.6730*** (1.0503)
Financial structure	0.1219*** (0.0435)	-1.1272*** (0.2099)	0.2903*** (0.1133)	-1.8226*** (0.3901)	1.3733 (1.1270)	-2.5656** (1.4685)	-0.1134 (0.2728)	-2.5486*** (1.0227)
Liquidity risk	-0.0141* (0.0110)	-0.1359* (0.1057)	-0.0151 (0.0334)	-0.3923** (0.2103)	2.2300*** (1.0968)	-3.2642*** (1.3431)	0.0441 (0.2743)	-2.9155*** (1.0460)
Value-at-risk 95%	2.5482*** (1.1808)	22.2567*** (3.2692)	0.1559*** (0.0386)	0.5449*** (0.0721)	0.8726 (2.0091)	23.8341*** (2.9893)	0.8940*** (0.0370)	-0.0270 (0.0714)
Beta	0.2129*** (0.0553)	-0.4186*** (0.0934)	1.7343*** (0.1927)	-1.2325*** (0.2544)	0.6730* (0.4395)	-0.4806 (0.4460)	0.2885*** (0.0195)	0.2544*** (0.0512)
GDP	-0.0038* (0.0026)	0.0114** (0.0065)	-0.0050 (0.0067)	0.0028 (0.0123)	0.0475*** (0.0132)	-0.0548*** (0.0149)	-0.0001 (0.0017)	-0.0037 (0.0036)
Inflation	-0.0002 (0.0020)	0.0152*** (0.0039)	-0.0082* (0.0051)	0.0281*** (0.0077)	0.0089 (0.0122)	0.0084 (0.0149)	0.0030** (0.0016)	0.0053* (0.0039)
y	1.4996		1.5761		2.0171		2.9669	
c	12,91		7,50		5,44		32,82	

***, **, * denote coefficients significant at the 1%, 5% and 10% level, respectively.

The results of the PSTR model show that the smoothing parameter is equal to $\gamma = 2.01$ and the optimal threshold is \$5.44 billion. The smoothing parameter between systemic risk exposure and the size of conventional banks is 2.96, with an optimal threshold of \$32.82 billion. As the size is below the threshold of \$ 5.44 billion, the growth in the size of conventional banks turns into a low regime, i.e. any growth in size of 1 % will decrease the contribution to systemic risk by 0.303 %. Beyond this threshold (high regime), any increase in the size of the conventional bank will lead to an increase in the contribution to systemic risk of 0.130 %. Furthermore, the systemic risk sensitivity of conventional banks is low below the optimal threshold of \$32.82 billion. Any increase in size will decrease

the sensitivity to systemic risk in the event of a systemic shock by 0.073 %. Above this threshold, the model will shift to the high regime, where any growth in the size of the conventional bank leads to a growth in sensitivity to systemic risk exposure of 0.045 %.

Our results illustrate the non-linear relationship between size and systemic risk for Islamic and conventional banks. Furthermore, we note that there is a differential impact of size on the contribution and exposure to systemic risk. This highlights the existence of a decreasing relationship in a weak regime below the obtained threshold. Once the latter is exceeded, this relationship will transit to a high regime and the effect of size becomes positive over proportional to the systemic importance. Islamic banks are more sensitive to systemic shock than conventional banks. Islamic banks move into the high regime with a significantly lower threshold than conventional banks. Moreover, our findings reveal that conventional banks contribute more to systemic risk. Conventional banks are more vulnerable and move into the high regime with a lower threshold than Islamic banks. The contribution of conventional banks reaches 0.130% (compared to 0.022% for Islamic banks).

The sensitivity of Islamic banks to the systemic shock can be explained by their structures which are both different and less diversified compared to conventional banks. The growth in size of a bank would make its banking activities more complex. Islamic banks would benefit from implementing sophisticated risk management instruments that both respect the principles of Islamic finance and absorb systemic market shocks (Kassim and Shabri Abd. Majid (2010) and Chakroun and Gallali (2017)). The vulnerability of conventional banks compared to Islamic banks may be due to their sizes, which greatly exceed Islamic banks. Conventional banks are largely integrated into the financial system through large market shares. This large presence would increase their interdependence with the financial system and their vulnerabilities in case of distress. A very large diversification of activities could be adopted to better manage individual risk but could increase their systemic importance at the same time (Moore and Zhou (2013)).

In relation to the control variables, leverage is positively related to the contribution to systemic risk measured by ΔCoVaR in the first regime. This result is consistent with the

result of Adrian and Tobias and Brunnermeier (2016), who confirm that any increase in leverage will lead to an increase in systemic risk (measured by ΔCoVaR). This suggests that Islamic banks with a size of less than \$12.91 billion become less solvent in the event of difficulties which will increase their contributions to systemic risk. However, the impact on leverage and systemic risk is insignificant in the second regime for Islamic banks. For conventional banks, the relationship between leverage and systemic risk is negative and statistically significant in the first regime. However, in the second regime, the impact of leverage becomes positive and statistically significant with the sensitivity to systemic risk (measured by the MES). This suggests that as the level of leverage increases, the sensitivity to systemic shock is greater for conventional banks. The different signs of impact could be interpreted by referring to the work of Tasca et al. (2014) who admit that leverage is dependent on a critical level that discriminates between two safe and risky regimes. Indeed, in a safe regime, a high contribution to systemic risk characterized by high leverage could be compensated by an adequate diversification strategy. On the other hand, in the risky regime, a poor diversification strategy cannot compensate for the market impact.

For credit risk, there is a positive and significant relationship at the 10% level for both systemic risk measures in the weak regime for Islamic banks. In contrast, conventional banks have a negative relationship at the 10% statistical level with the ΔCoVaR and a positive relationship with the MES in the low regime. In the high regime, this relationship is positive and statistically significant at the 1% level with the systemic sensitivity of conventional banks. This result suggests that the higher the level of credit extension, the higher the sensitivity to systemic shock for conventional banks.

As for the deposit ratio, which reflects the financial structure of the bank, two main conclusions can be drawn. Indeed, we observe the existence of a significant positive relationship between this ratio and systemic risk in the first regime. In the second regime, this relationship becomes negative. This result suggests that Islamic banks with sizes below a certain threshold have a fragile funding. As soon as the size increases, the reliance on deposit funding is favored. This result is supported by the findings of

Bostandzic and Weiss (2018) who confirm that banks accepting more deposits contribute less to the overall systemic risk. The liquidity ratio is negatively related to systemic risk for both Islamic and conventional banks.

The value-at-risk (VaR) variable, which measures the tail risk of the bank relative to the market, is significantly and positively related to systemic risk for both banking sectors and in both regimes. The beta variable, measuring systematic risk, has a positive and statistically significant impact on the MES in the first and second regimes for conventional banks. This result is echoed in the work of Benoit et al. (2013). However, for Islamic banks, the relationship between systematic risk (beta) and systemic risk is positive in the first regime and negative in the second regime. This result suggests that the size of Islamic banks may have a differential impact on systematic risk. Indeed, as the size of the Islamic bank increases, its systematic risk decreases relative to the systemic risk.

Finally, with respect to macroeconomic variables, GDP growth is negatively associated with the contribution to systemic risk of conventional and Islamic banks in the first regime. On the other hand, economic growth of GDP has a positive effect on the contribution to systemic risk of Islamic banks in the second regime for large banks. This relationship loses significance with systemic risk sensitivity in both regimes in the case of both banks. The inflation variable positively affects systemic risk for both banks. This means that as inflationary pressures increase, the systemic risk of banks becomes more significant.

1.4.4 Semiparametric model

In the analysis we have conducted so far, we have found that the relationship between size and systemic risk is non-linear. This result has been derived first by a quadratic model and then by a threshold model, namely the PSTR approach. The objective of this section is to provide some robustness to these specifications by estimating a semiparametric model. In fact, by introducing a quadratic size term to examine the determinants of systemic risk, we impose a certain specification on our model. However, if this specification remains far from reality, the estimates obtained are approximate or even biased.

Secondly, one of the characteristics of the PSTR approach, such as the fact that the results are sensitive to the number of observations, pushes us to go further. In our case, we admit that the relationship between size and systemic risk is not known, a priori. To do this, we favor the use of a semi-parametric model. The latter has the advantage of being less demanding in terms of the number of observations, unlike the nonparametric approach (Ahamada et al. (2008)). More specifically, we use the double residual estimator proposed by Robinson (1988).

The semiparametric model allows for a more robust specification that combines a parametric (linear) and a nonparametric part. Such a specification often leads to more robust estimates than in the case of a linear model. The semi-parametric model of Robinson (1988) is expressed in Eq. (2.14).

$$Systemicrisk_{it} = \beta X_{it} + M(size_{it}) + \epsilon_{it} \quad (1.14)$$

Where X_{it} is a matrix of (k-1) previously defined explanatory variables. $M(.)$ is the nonparametric function. Size corresponds to the explanatory variable whose relationship with $Systemicrisk_{it}$ is unknown. ϵ_{it} corresponds to the error term. In our case, we use the semi-parametric model to confirm the non-linear relationship between the contribution to systemic risk measured by $\Delta CoVaR$ and the exposure to systemic risk measured by the MES and the size of Islamic and conventional banks.

The results of the estimation of the semi-parametric model are presented in Figures 2.5, 2.7, 2.6 and 2.8 for Islamic and conventional banks. They confirm the existence of a strong non-linearity between the contribution, the exposure to systemic risk and the size of the Islamic and conventional banks. We find that there is a negative correlation followed by a positive correlation between $\Delta CoVaR$, MES and size for both types of banks. This result confirms the non-linearity hypothesis and the regime shift between systemic risk and bank size.

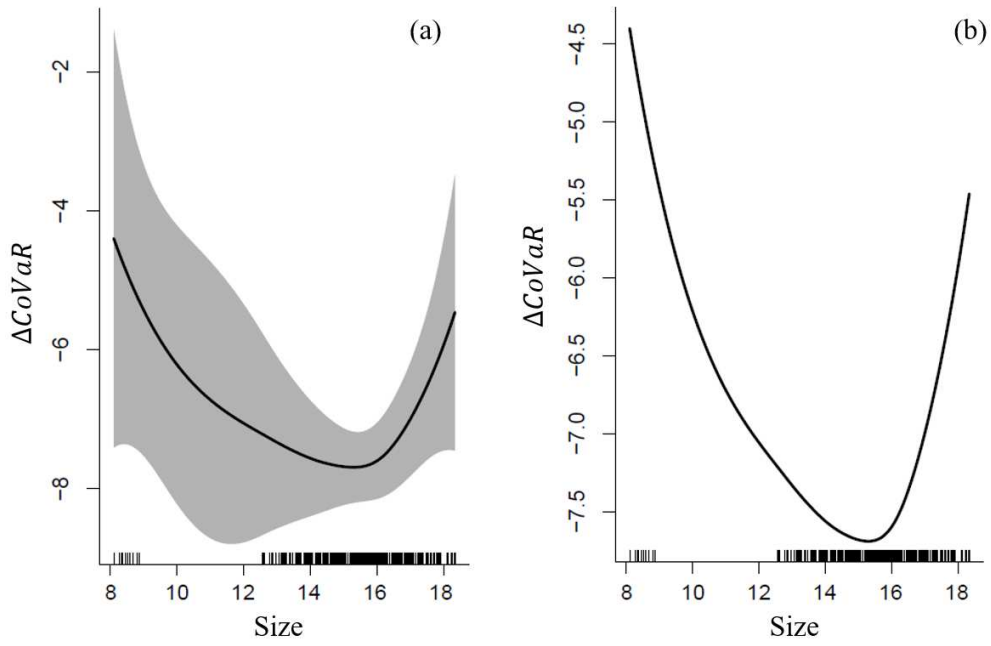


Figure 1.3: Semiparametric estimation between the ΔCoVaR and the size of Islamic banks

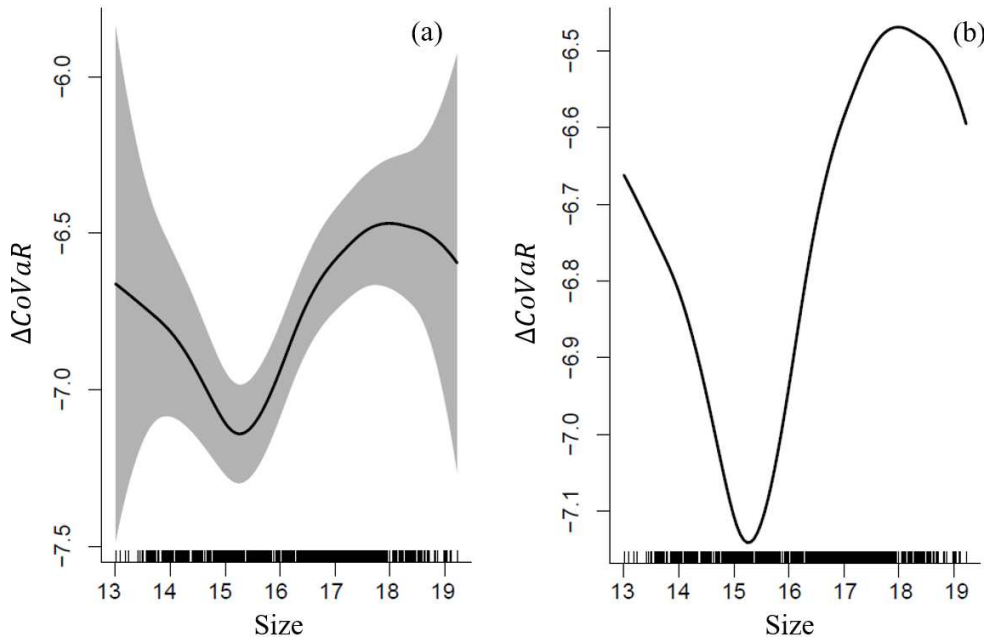


Figure 1.4: Semiparametric estimation between ΔCoVaR and conventional bank size

The transition from a negative to a positive relationship shows two thresholds for

Islamic banks. However, for conventional banks, the relationship is strongly linear and shows several thresholds between systemic risk and size. The results of the semi-parametric model confirm the non-linearity and the existence of several inflection points for conventional banks at which size transitions from one regime to the other. We distinguish globally two regimes for the two types of banks but the results seem nevertheless ambiguous for conventional banks. Indeed, at first, we observe the presence of a threshold effect. However, we also noticed the existence of other inflection points. This does not contradict the results of the PSTR model in the sense that the variation associated with these turning points is not considerable.

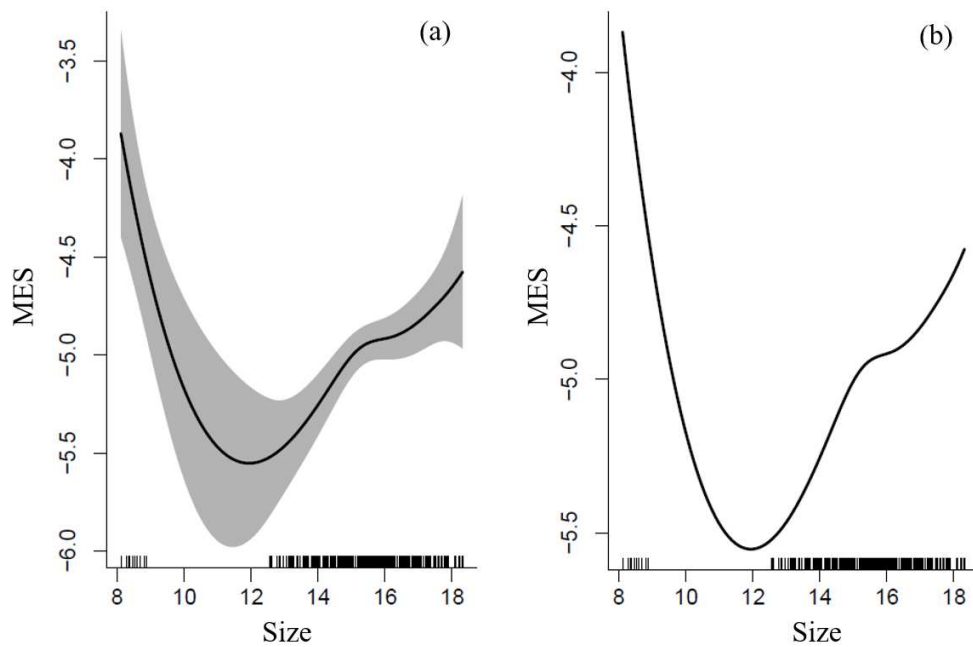


Figure 1.5: Semiparametric estimation between the MES and the size of Islamic banks

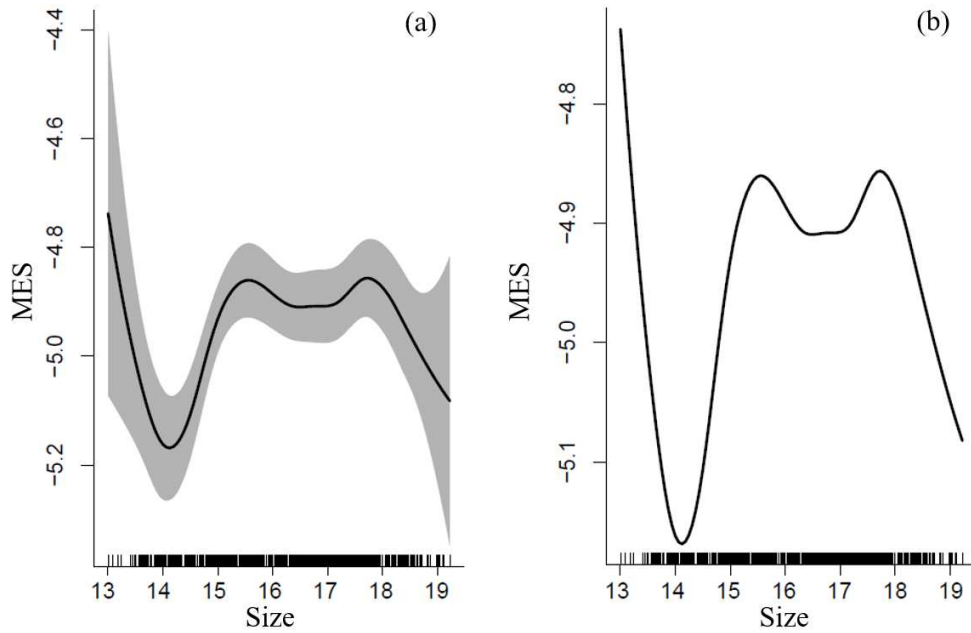


Figure 1.6: Semiparametric estimation between MES and conventional bank size

1.5 Conclusions

In this study, we study the impact of size on systemic risk as measured by the ΔCoVaR and the MES. Our paper is the first approach to have examined the relationship in a parametric and nonparametric framework. First, the relationship between systemic risk and size was examined in a linear framework using a dynamic model (GMM) and then in a non-linear framework using a PSTR model and a semi-parametric model for a sample of 34 Islamic banks and 70 conventional banks over the period 2006 to 2017.

Our findings reveal a positive relationship between systemic risk and size for both Islamic and conventional banks. The tests strongly reject the hypothesis of linearity between the contribution - measured by the ΔCoVaR -, the exposure -measured by the MES- to systemic risk and the size of Islamic and conventional banks. One of our main results suggests the existence of threshold effects in the relationship between systemic risk and size. The optimal threshold between the contribution to systemic risk measured by ΔCoVaR and the size of Islamic banks is estimated to be around \$13

billion. The systemic risk exposure measured by the MES and the size of Islamic banks is estimated at a threshold of around \$7.50 billion. The results of the PSTR modeling give optimal thresholds of \$5.44 billion and \$32.82 billion respectively for the contribution and exposure to systemic risk and the size of conventional banks. Provided that the size is below these thresholds, any growth in size will decrease the contribution and exposure to systemic risk and turn into a weak regime. Above these thresholds, the model will turn into a high regime : any increase in size will lead to an increase in the contribution and sensitivity to systemic risk of Islamic and conventional banks. The results of the semiparametric models confirm the existence of a negative correlation in the first regime followed by a positive correlation between systemic risk and bank size, are consistent with the results of the PSTR model. There is always a negative correlation in a first regime followed by a positive correlation between $\Delta CoVaR$, the MES and the size for both types of banks. The semi-parametric model broadly confirmed the existence of two regimes for both Islamic and conventional banks. The relationship between systemic risk and size in the case of Islamic banks closely approximates a convex shape. In the case of conventional banks, the relationship between systemic risk and size would be more of a mixed nature, complex and far from being a quadratic shape relationship. In general, based on the MES measure, Islamic banks are sensitive to market shock compared to conventional banks. On the other hand, based on the $\Delta CoVaR$, conventional banks are more vulnerable.

Although there is some work that has studied the relationship between systemic risk and size, the study of non-linearity has not been explored in depth. Our work is an important contribution to the literature on this issue. In terms of policy implications of our study, regulators should take into account the growth of bank size in their decision making and in their evolution. Systemic importance could depend on the size of the bank, but also on other characteristics such as capital, loans and deposits. A deeper understanding of the factors of systemic risk would promote the growth of banks and thus protect the financial system as a whole.

1.6 Appendices

Table 1.13: Definitions of variables and data sources

Variables	Definitions	Sources
Dependent variables		
ΔCoVaR	ΔCoVaR proposed by Tobias and Brunnermeier (2016), is defined as the difference between the Value-at-Risk (VaR) of a particular bank's distressed conditional market return and the VaR of the bank's median conditional market return.	Datastream, own. calc
MES	The expected marginal deficit, as defined by Acharya et al. (2012).	Datastream, own. calc
Bank characteristics		
size	Natural logarithm of bank total assets (in \$billion).	Datastream
Leverage		Datastream, own. calc
Credit risk	Ratio of total loans to total assets.	Datastream, own. calc
Financialstructure	Total deposits divided by total assets.	Datastream, own. calc
Liquidity	Ratio of total loans to total deposits.	Datastream, own. calc
Value at risque 95 (%)	The unconditional VaR of the system performance, used to define the conditional event as defined by Benoit et al. (2013).	Datastream, own. calc.
Beta	The systematic risk between the market return and the bank's return as defined by Benoit et al. (2013).	Datastream, own. calc.
Macroeconomic variables		
GDP	Annual real GDP growth rate (in %).	World Bank
Inflation	Inflation, defined as annual inflation rate.	World Bank

The structure of interconnectedness and the systemic relevance of Gulf banks

Abstract

The aim of this paper is to construct a banking network by applying the TENET model Härdle et al. (2016). We analyzed the interconnectedness properties and systemic relevance of a panel of 20 Islamic and 33 conventional banks from 2007 to 2017. Our results suggest: (i) strong interconnectedness of the Gulf banking system, especially during periods of instability; (ii) inter- and intra-sectoral interconnectedness between Islamic and conventional banks and bilateral interconnectedness at the country level; (iii) conventional banks are the main senders and receivers of systemic risk spillovers.

Keywords: Islamic banks; conventional banks; banking network; interconnectedness; tail event; systemic relevance

JEL Classification: G21, G28, G01, C31

2.1 Introduction

The structure of financial systems is now exceedingly complex. This is a consequence of the large number of actors that are constantly interacting with each other (Wang et al. (2017) and Hué et al. (2019)). Indeed, the interdependencies between different financial actors, especially through the use of joint investments, interbank lending, bilateral relationships and so on, have become concentrated to form a small financial network. Through these interdependencies, the transmission of shocks and the spread of financial contagion have become easier and faster, especially during crisis periods (Acharya and Yorulmazer (2008); Gupta and Guidi (2012); Cho et al. (2015); Braverman and Minca (2018); Gkillas et al. (2019) and Liu et al. (2021)).

A financial network is composed of several actors that interact within the financial system, but each actor can be distinguished from the others according to its level of systemic risk (Wang et al. (2017); Wang et al. (2018a); Foglia and Angelini (2020b) and Wang et al. (2021b))¹. It can, in fact, be a sender of systemic risk at one time and a receiver at another. This attitude depends not only on the macro-financial conditions of the financial market (periods of calm or crisis), but also on particularities such as, the size, the interconnection, and the idiosyncratic risk of the actor considered (Hué et al. (2019) and Torri et al. (2021)).

More formally, the contagion links in a financial network, which form the interconnectedness, can be described according to Acharya (2009) and Braverman and Minca (2018) by assuming that two institutions A and B hold common assets. In response to an exogenous shock, institution A is forced to liquidate its assets. The price of the common asset will be sensitive to this liquidation, and will therefore influence the price of the asset held by institution B. This justifies the interdependencies between institutions, which are detectable in the tail distribution of stock returns (Acharya and Yorulmazer (2008) and Hong et al. (2009)). Referring to network theory, several empirical model proposals have been developed. In order to model financial networks, financial actors

¹Who identified, respectively, the receivers and senders of systemic risk in the U.S., Chinese, and European contexts and showed that connectivity structures change in times of financial crisis.

(banks, insurance companies, and others) are modeled as nodes, and the links between these nodes are represented as edges (Hu   et al. (2019); Mazzarisi et al. (2020) and Torri et al. (2021)). Indeed, the graphical representations of interconnectedness provided by the network models allow to highlight the mechanisms of financial contagion, and to identify the most systemic financial institutions from the less systemic ones within the financial network (Hu   et al. (2019); Mazzarisi et al. (2020) and Torri et al. (2021)). From a macroprudential perspective, this allows regulators to gain insight into the channels of risk transmission within banking systems (Torri et al. (2021)).

In this context, it is interesting to know how Islamic and conventional banks in the Gulf countries are interconnected. In fact, we are particularly interested in the behaviour of Islamic banks, which are clearly different from conventional banks, especially in terms of operation, structure, business model and even technology (Safiullah, 2021). Most authors agree that Islamic banks are relatively stable compared to conventional banks (see, among others, Olson and Zoubi (2008);   ih  k and Hesse (2010); Beck et al. (2010); Caby et al. (2013); Kabir et al. (2015); Mollah et al. (2017); Pappas et al. (2017) and Safiullah (2021)). Indeed, Islamic banks differ from conventional banks principally by prohibiting any remuneration generated by the use of interest rates. The latter is, in contrast, a basic instrument for the conventional banks (Mollah et al. (2017)).

In order to generate profit margins, Islamic banks use other financing substitutions such as the purchase and resale agreement known as Murabaha², the contract of association, called Musharaka , and the partnership contract called Mudharaba³. In addition to these instruments, Islamic finance has other instruments such as the Saleem⁴, and Ijara⁵ etc.(Izzeldin et al. (2021)). In addition, Islamic finance is also based on other principles such as Profit and Loss Sharing (PLS). This principle requires that the risk should be

²Is a contract by which a customer orders the purchase of an asset from a bank. The latter buys the good and becomes its owner and then resells it to the customer who ordered the purchase in the first place. The difference between the purchase and resale price is the profit margin for the bank. This contract is called the Murabaha with purchase order.

³Is a contract that brings together an investor, who provides the capital, and an entrepreneur, who provides the know-how, to invest in a project and share the profits and losses.

⁴Is a forward sale contract. It allows for deferred delivery of the purchase item but requires immediate.

⁵This is the equivalent of a leasing contract. Through this contract, the bank rents an asset to a beneficiary, who will exploit its usufruct against a rental amount.

proportionally shared by the project participants, depending on the type of contracts mentioned above (Chapra (2008) and Siddiqui (2008)). Moreover, Islamic finance does not use short selling, gambling and complex derivatives (Mensi et al. (2019) and Izzeldin et al. (2021)). These are considered to be assets that are disconnected from the real economy. Moreover, Islamic finance requires that each contract must be backed by a tangible asset that exists in the real economy.

From an economic point of view, several papers have taken a strong interest in Islamic finance by examining its determinants, economic, financial and social impacts (see, among others, Makdisi et al. (2006); Furqani and Mulyany (2009); Imam and Kpodar (2013); Abdelsalam et al. (2014) and Boukhatem and Moussa (2018)). Our work is a continuation of this literature which, despite its richness, remains relatively incomplete compared to that on conventional finance. In particular, the analysis of interconnectedness as a determinant of systemic risk has been well examined in other contexts such as the US (Billio et al. (2012); Diebold and Yilmaz (2014b); Härdle et al. (2016) and Hernandez et al. (2020)), European (Foglia and Angelini (2020b) and Torri et al. (2021)), Chinese (Wang et al. (2018a) and Gong et al. (2019)), and Indian (Verma et al. (2019)) context. However, this literature has not focused on the connectivity structure of Islamic and conventional banks based on the network approach.

The 2008 financial crisis and the 2010 sovereign debt crisis, as well as other crises, were major events that left virtually no financial market unscathed. In addition to these events, the economies of the Gulf region are heavily dependent on oil production. The latter is a A sector that is constantly experiencing disruptions and volatility shocks which are further transmitted to the stock markets (Finta et al. (2019)). This is especially true since the region is characterized by geopolitical tensions such as the blockade of Qatar⁶It has been shown recently by Charfeddine and Al Refai (2019) and Selmi and Bouoiyour (2020), that the Qatar blockade has led to spillover effects between Qatar and other CCG⁷

⁶It took place from June 5, 2017. This blockade was formed by Saudi Arabia, the United Arab Emirates, Egypt and Bahrain. These four countries have officially decided to sever their diplomatic relations with Qatar (Selmi and Bouoiyour (2020)).

⁷The Gulf Cooperation Council. It is made up of six countries: Saudi Arabia, Oman, Kuwait, Bahrain, and the United Arab Emirates.

countries. Moreover, this region is a destabilized area due to various wars, notably in Syria and Yemen. Such instability increases geopolitical uncertainty, and consequently the stock market volatility (Charfeddine and Al Refai (2019)). In this vein, understanding the interconnectedness of Islamic and conventional banks remains paramount.

The objective of our paper is threefold. Firstly, we try to understand the structure of interconnectedness between Islamic and conventional banks in the Gulf countries. Secondly, attempt to show which banks transmit the most systemic risk and which banks receive the most. Finally, we measure the impact of extreme events (such as the 2008 financial crisis, the European debt crisis and the 2015 oil shock) and assess the level of systemic risk of each bank. The aim is to highlight the structural characteristics of the interconnectedness of the dual Gulf banking sector.

From a methodological point of view, to analyse financial networks several approaches have been developed (see, among others, Hong et al. (2009); Billio et al. (2012); Diebold and Yilmaz (2014b); Hautsch et al. (2015); Härdle et al. (2016) and Torri et al. (2021)). In our research work, we apply the TENET model proposed by Härdle et al. (2016). First, this model is an extension of the CoVaR approach proposed by Tobias and Brunnermeier (2016). The CoVaR approach measures the degree of interconnectedness of an institution with the financial system without taking into account its interaction with other institutions. The TENET approach proposes to extend the CoVaR approach into a network dimension. It thus allows to take into account the interconnection with all the institutions of the financial system (Härdle et al. (2016)). Second, and in contrast to the Granger causality model in average¹, the TENET model relies on extreme tail events as a transmission mechanism for extreme risk spillover effects in order to characterize the degree of interconnectedness. These are typically detected in extreme declines in the distribution of stock return tails (Hong et al. (2009); Candelon and Tokpavi (2016) and Basu et al. (2019)). Thirdly, the analysis of the structure of interconnectedness according to network approaches, allows both to capture spillover effects arising from the structure of connectivity and to detect the contribution of highly interconnected institutions (Hautsch et al. (2015); Wang et al. (2017) and Basu et al. (2019)). Indeed, large institu-

tions can be potential sources of contagion. Underestimating their systemic importance could therefore lead to a destabilization of the whole financial system (Hué et al. (2019) and Yang et al. (2020)).

The use of the TENET model was carried out on a representative sample of listed banks in the Gulf countries (Bahrain, Kuwait, Qatar, Saudi Arabia and the United Arab Emirates). The sample consists of 53 banks, 20 of which are Islamic banks and 33 conventional banks over a period from 2007 to 2017. Our findings reveal that total financial system connectivity increases significantly during periods of stress, notably in 2009 and 2016. After decomposing total connectivity, we find that inbound connectivity is dominated by the conventional banking sector. In contrast, the Islamic banking sector influences outbound connectivity from 2013 onwards. By analyzing the dynamics of the relative influence (RI) of each sector, we show that both sectors behave as sender and receiver of system risk spillovers. The analysis of the characteristics of the interconnectedness of the Gulf banking system suggests three types of linkages: close linkages between banks in the same sector (intra-sectoral extreme risk spillovers), close linkages between conventional and Islamic banks (inter-sectoral extreme risk spillovers) and close linkages between countries (cross-border extreme risk spillovers) that are either intra-sectoral or inter-sectoral. The study of banks' contribution to systemic risk according to the Systemic Risk Receiver (SRR) and Systemic Risk Emitter (SRE) indices showed that conventional banks contribute more to systemic risk mainly through banks in Saudi Arabia and the United Arab Emirates.

Our contribution to the literature is multiple. We join the literature interested in network analysis (see, among others, Hautsch et al. (2015); Härdle et al. (2016); Wang et al. (2018a); Foglia and Angelini (2020b) and Torri et al. (2021)), in particular that of Islamic banks, which are still unexploited. We study the dynamic evolution of connectivity to analyse the change in the dynamic connectivity structure of Islamic and conventional banks. We analyse the topological structures that characterize the interconnection of the Gulf countries. We propose a network mapping by highlighting the different spillover effects between the two Islamic and conventional banking sectors. We also classify the

different banks according to the reception and emission of systemic risk.

This paper is structured as follows: section 2.2 details the different models that are interested in measuring interconnectedness, section 2.3 describes the estimation methodology of the TENET model, section 2.4 presents and discusses the obtained and section 2.5 concludes our study.

2.2 Literature review

In order to be able to study the topology of financial networks, contagion mechanisms and spillover effects, multiple efforts have been made in the empirical literature. The causality concept of Granger ⁸ initiated by Granger (1980) has been used by several studies that seek to measure interconnectedness in financial systems.

Referring to the extreme tail covariations, Hong et al. (2009) developed a Granger causality test of risk at the low level of the tail distribution. The latter is considered to be the first model that takes into account Granger causality in tails. It allows, as a matter of fact, to study financial contagion by measuring risk by the extreme low end of the distribution (left tail). Following the model of Hong et al. (2009), Balboa et al. (2015) analyzed the causality in the tails of large international banks and suggested that large banks visibly exhibit significant levels of extreme covariations, thus increasing their financial contagion. Based on the same procedure, Corsi et al. (2018) attempted to analyse periods of financial market shocks and proposed an indicator of flight to quality. They found that the latter can serve as an early warning indicator to detect periods of instability in the financial market. In order to measure the contribution to systemic risk, Billio et al. (2012) proposed a Granger causality model to measure the spillover effects of returns. Indeed, this model constructs the directional structure of bilateral return spillover effects. By examining four actors in the US financial system (hedge funds, banks, brokers/traders and insurance companies), Billio et al. (2012) showed that

⁸Granger causality is used to measure the direction of a causal relationship in a network. It estimates whether information from past events from one institution can help predict information from future events of another institution (Billio et al. (2012)).

connectivity increases significantly during periods of turbulence. The Granger causality model proposed by Billio et al. (2012) has attracted a lot of interest to study the causal effects in performance spillovers (Gong et al. (2019); Zheng and Song (2018) and Lai and Hu (2021)). Using this model, Gong et al. (2019) explained the contagious effects by constructing the directional causal relationships of the Chinese financial system. They found that the number of connections increases during crisis periods, and that banks play a key role in transmitting risk throughout the Chinese financial system. Focusing on Granger causality in stock markets, Zheng and Song (2018) and Lai and Hu (2021) studied the topological characteristics of different stock markets. They concluded that Granger causality networks are relevant measures taken to prevent systemic risk.

In an extension of the procedure proposed by Hong et al. (2009), Candelon and Tokpavi (2016) proposed a Granger causality model that captures the different levels of tail distribution (left, centre, right). This extension makes it possible to identify the level of the distribution that influences risk more. Furthermore, through an approach that combined the time and frequency domain, Wang et al. (2021b) proposed a time-frequency Granger causality network. This model was applied in the Chinese context by considering banks, securities and insurance, and showed the importance of considering frequency (periodicity) in the analysis of risk interconnection and transmission.

Moreover, there are many other models that have enriched the empirical literature (Diebold and Yilmaz (2014b); Hautsch et al. (2015); Härdle et al. (2016); Chen et al. (2019); Torri et al. (2021) and others). In order to measure volatility shocks, Diebold and Yilmaz (2014b) generalized the variance decomposition to construct a volatility spillover network. Through this variance decomposition, Diebold and Yilmaz (2014b) differentiated between senders and receivers of spillover effects, and showed that the largest commercial banks are intensively interconnected. However, this model has been criticized because it is constrained to the sample size. To address this dimensionality constraint, Demirer et al. (2018) used the Least-Absolute Shrinkage and Selection Operator (LASSO) method to estimate volatility spillover effects in networks in a high-dimensional setting. However, the volatility spillover model proposed by Diebold and Yilmaz (2014b)

has been widely used in particular to study the connectivity between stock indices (see, among others, Maghyereh et al. (2016); Gamba-Santamaria et al. (2017); Wang et al. (2018b) and Hassan et al. (2020)). On the other hand, another part of the literature has focused on the tail risk to build the networks. Applying the LASSO method, Hautsch et al. (2015) quantified the individual marginal effect that measures the level of interconnectedness of an institution on the network while calling it the beta of systemic risk. Using a sample of large North American financial institutions, Hautsch et al. (2015) show a high level of interconnectedness and a large contribution to systemic risk throughout the 2007-2008 financial crisis.

In the same vein, a variety of models have been proposed. Härdle et al. (2016) extend the CoVaR approach introduced by Tobias and Brunnermeier (2016) by proposing the Tail Event Driven NETWORK (TENET) model. This model generalizes the CoVaR approach by taking into account the spillover effects of extreme events in a generalized quantile regression. Indeed, TENET allows for the measurement of the degree of systemic interconnectedness of each institution in the financial system. Based on this model, Härdle et al. (2016) proved that the banking sector is the largest emitter of systemic risk compared to other financial actors (depositories, insurance, brokers and others) in the US context. The TENET approach has been widely applied in different financial contexts. Wang et al. (2018a) looked at the Chinese context and concluded that large commercial banks and insurers have significant levels of systemic risk. However, there are also smaller companies that are systemically important because of their high connectivity (incoming) or outgoing.

In a recent study, Foglia and Angelini (2020b) found that interconnectedness are influenced mainly by the banking sector in terms of systemic risk transmission in the European context. More specifically, Verma et al. (2019) find that Indian banks are highly interconnected. Comparing between developed and emerging America, Hernandez et al. (2020) observe that spillover effects and connectivity are dominated by banks in developed America. The TENET technique has also been extended to study the interdependencies of other contexts including crypto-currencies in Xu et al. (2021) and large

caps in the Eurozone in Huynh et al. (2021). In another recently developed empirical approach, Torri et al. (2021) developed a conditional risk network model to construct euro area banking interconnectedness. They have found the existence of clustered banking interconnectedness at the level of European regions.

Regarding the Islamic and conventional banking sector, studies on interconnectedness and spillover effects in the field are almost scarce, except for the work of Abedifar et al. (2017) and Mensi et al. (2019). Using the DECO-FIGARCH model and the spillover index of Diebold and Yilmaz (2014b), Mensi et al. (2019) studied the dynamic risk spillovers and hedging efficiency between the commodity market (oil and gold) and stock indices of Islamic and conventional banks. The authors show the directionality of volatility spillover effects by distinguishing between net volatility senders and net volatility receivers. Abedifar et al. (2017) used measures (such as MES, SRISK, and CoVaR) and graphical networks to assess the systemic risk and interconnectedness of GCC Islamic and conventional banks, respectively. The authors suggested that conventional banks with Islamic windows are, from a systemic perspective, the most vulnerable to a systemic shock and the most interconnected, due to their strong synchronization with the banking sector. However, this work has not focused, on one hand, on the structural characteristics of network interconnectedness, such as the dynamics of total and sectoral connectivity and the degree of contagion; and on the other hand, on the individual characteristics of each bank in terms of systemic relevance.

2.3 Methodology and data

In this section we present the different steps of the estimation of the TENET (Tail-Event driven NETWORK) model. This model is an extension of the CoVaR approach proposed by Tobias and Brunnermeier (2016). In fact, the CoVaR approach is based on a pairwise quantile regression, allowing to estimate the interconnection between two financial institutions independently of the other institutions. The TENET model extends the CoVaR approach to a network dimension, which allows to consider all possible interconnected-

ness in the system. We first define the CoVaR concept, then the TENET model, and finally move on to the connectivity indicators that will allow us to analyse the structural properties of the network.

2.3.1 VaR et CoVaR concepts

The CoVaR method by Tobias and Brunnermeier (2016) is developed based on the concept of VaR (value at risk). VaR measures the extreme risk of a financial institution as the maximum loss of an institution i at time t at quantile $\tau \in (0, 1)$. The VaR of a financial institution is defined as follows:

$$P(X_{i,t} \leq \leq VaR_{i,t,\tau}) \stackrel{def}{=} \tau \quad (2.1)$$

With τ is the quantile level, $X_{i,t}$ is the logarithmic return of bank i at time t .

In order to estimate the VaR, we quantile regress the returns of each individual financial institution with the macro-financial variables, which reflect the state of the economy (Tobias and Brunnermeier (2016)). This equation is as follows:

$$X_{i,t} = \alpha_i + \gamma_i M_{t-1} + \varepsilon_{i,t} \quad (2.2)$$

$$\widehat{VaR}_{i,t,\tau} = \widehat{\alpha}_i + \widehat{\gamma}_i + M_{t-1} \quad (2.3)$$

Where, $X_{i,t}$ is the return of financial institution i at time t , M_{t-1} is a vector representing the lagged macrofinancial variables, and $\widehat{VaR}_{i,t,\tau}$ is the maximum loss of financial institution i at time t at quantile τ .

The CoVaR method determines the degree of interconnectedness in a univariate framework, measuring the interconnectedness of two institutions independently of the other institutions. It reflects the conditional dependence of institution j on changes in the tail of institution i . The CoVaR of a financial institution j at quantile level $\tau \in (0, 1)$

at time t is defined as follows:

$$P(X_{j,t} \leq \leq CoVaR_{j|i,t,\tau} | R_{i,t}) \stackrel{def}{=} \tau \quad (2.4)$$

Similarly, we estimate in a second step the $\leq CoVaR_{j|i,t,\tau}$ by performing the quantile regression of the return of institution j with the j with the $\leq VaR_{i,t,\tau}$ of the examined institution and the state variables.

$$X_{j,t} = \alpha_{j|i} + \gamma_{j|i} M_{t-1} + \beta_{j|i} X_{i,t} + \varepsilon_{j|i,t} \quad (2.5)$$

$$\widehat{CoVaR}_{j|i,t,\tau} = \widehat{\alpha}_{j|i} + \widehat{\gamma}_{j|i} M_{t-1} + \widehat{\beta}_{j|i} \widehat{VaR}_{i,t,\tau} \quad (2.6)$$

Here, $\widehat{CoVaR}_{j|i,t,\tau}$ is the value of the risk that financial institution j bears provided that institution i is distressed. We define the institution's distress event when $X_{i,t} = VaR_{i,t}$. The coefficient $\widehat{\beta}_{j|i}$ denotes the dependence of institution j 's returns on institution i 's tail effects. It reflects the interconnectedness between institution j and i .

2.3.2 The TENET

In contrast to the CoVaR approach of Tobias and Brunnermeier (2016), the TENET model of Härdle et al. (2016), estimates the interconnection of a financial institution in a multivariate framework. Indeed, instead of estimating the interconnection per peer, the TENET model takes into account the mutual interconnection possibilities of all financial institutions. Furthermore, the CoVaR approach is based on a parametric regression, which may not be appropriate in reality, if a linear functional form is imposed between the two financial institutions (Ouyang et al. (2020)). The TENET model proposes a single index semi-parametric model that takes into account the non-linearity of the dependence between the financial institutions. The TENET model is constructed in two steps. The first step consists of estimating the VaR of each financial institution from Eqs. (2.3) and (2.6). The second step is to use single-index quantile regression in a semipara-

metric framework to construct the structure of interconnectedness between institutions, incorporating institution-specific information. The TENET model is written :

$$X_{j,t} = g(\beta_{j|R_j}^T R_{j,t}) + \varepsilon_{j,t} \quad (2.7)$$

$$\widehat{CoVaR}_{j|R_j,t,\tau}^{TENET} \stackrel{def}{=} \widehat{g}(\widehat{\beta}_{j|R_j}^T \widehat{R}_{j,t}) \quad (2.8)$$

$$\widehat{D}_{j|R_j} \stackrel{def}{=} \left. \frac{\partial \widehat{g}(\widehat{\beta}_{j|R_j}^T R_{j,t})}{\partial R_{j,t}} \right|_{\widehat{R}_{j,t}} = \widehat{g}(\widehat{\beta}_{j|R_j}^T \widehat{R}_{j,t}) \quad (2.9)$$

With $R_{j,t} = \{X_{-j,t}, M_{t-1}, B_{j,t-1}\}$ is the set of information that includes the following variables: $X_{-j,t} \stackrel{def}{=} \{X_{1,t}, X_{2,t}, \dots, X_{k,t}\}$ are the explanatory variables comprising the returns of all financial institutions except one j , k represents the number of institutions. $B_{j,t-1}$ are the characteristics of the institutions calculated from their balance sheet information. M_{t-1} is the vector of macrofinancial variables.

$\widehat{R}_{j,t} = \{\widehat{VaR}_{-j,t,\tau}, M_{t-1}, B_{j,t-1}, \widehat{VaR}_{-j,t,\tau}\}$, with $\widehat{VaR}_{-j,t,\tau}$ is the VaR estimated by Eq. (2.3) for all financial institutions not including the j institution, while $\widehat{\beta}_{j|R_j} \stackrel{def}{=} \{\widehat{\beta}_{j|-j}, \widehat{\beta}_{j|M}, \widehat{\beta}_{j|B_j}\}^T \cdot g(\cdot)$ to account for non-linearity by the shape of the smooth linkage function $g(\cdot)$. The marginal effects of the explanatory variables are captured by the gradient measure $\widehat{D}_{j|R_j}$ which includes $\widehat{D}_{j|R_j} \stackrel{def}{=} \{\widehat{D}_{j|-j}, \widehat{D}_{j|M}, \widehat{D}_{j|B_j}\}^T$. The element $\widehat{D}_{j|-j}$ is used to construct a weighted adjacency matrix between institutions. We consider only the elements in $\widehat{D}_{j|-j}$ since we are measuring the contagion effect from the financial network to the j institution.

The weighted adjacency matrix between institutions $\widehat{D}_{j|-j}$, which reflects total connectivity and provides a measure of overflow is written :

$$A_s = \begin{pmatrix} 0 & |\widehat{D}_{1|2}^s| & |\widehat{D}_{1|3}^s| & \cdots & |\widehat{D}_{1|k}^s| \\ |\widehat{D}_{2|1}^s| & 0 & |\widehat{D}_{2|3}^s| & \cdots & |\widehat{D}_{2|k}^s| \\ |\widehat{D}_{3|1}^s| & |\widehat{D}_{3|2}^s| & 0 & \cdots & |\widehat{D}_{3|k}^s| \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ |\widehat{D}_{k|1}^s| & |\widehat{D}_{k|2}^s| & |\widehat{D}_{k|3}^s| & \vdots & 0 \end{pmatrix}$$

The matrix A_s is a matrix of order k . The element $|\widehat{D}_{j|i}^s|$ represents the tail spillover effect of the institution i on the institution j . In our case the financial institutions are the Islamic and conventional banks. They will be modeled as nodes, and the links between these nodes as edges. For example $|D_{j|i}^s|$ means a link directed from bank i to bank j and vice versa.

In the constructed network, the total connectivity is defined as the sum of all incoming (rows) and outgoing (columns) edges of the adjacency matrix. The total connectivity, the incoming edges (which reflect the incoming connectivity) and the outgoing edges (which reflect the outgoing connectivity) are defined, respectively:

$$TC = \sum_{i=j}^N \sum_{i=j}^N |\widehat{D}_{j|i}^s| \quad (2.10)$$

$$GC_{r,s}^{IN} = \sum_{i \in \varepsilon_g} \sum_{i=j}^N |\widehat{D}_{j|i}^s| \quad (2.11)$$

$$GC_{r,s}^{OUT} = \sum_{i \in \varepsilon_g} \sum_{i=j}^N |\widehat{D}_{i|j}^s| \quad (2.12)$$

Where $r = 1, 2$ correspond to the two sectors (Islamic and conventional).

2.3.3 Measuring the systemic relevance of each bank

In line with Härdle et al. (2016), we define two indices to identify systemically important banks: the Systemic Risk Receiver (SSR) index and the Systemic Risk Emitter (SRE) index:

1. The index Systemic Risk Receiver (SSR)

$$SSR_{j,s} \stackrel{def}{=} MC_{j,s} \cdot \left\{ \sum_{i \in k_s^{IN}} (|\widehat{D}_{j|i}^s| \cdot MC_{i,s}) \right\} \quad (2.13)$$

2. The index Systemic Risk Emitter (SRE)

$$SRE_{j,s} \stackrel{def}{=} MC_{j,s} \cdot \left\{ \sum_{i \in k_s^{OUT}} (|\widehat{D}_{i|j}^s| \cdot MC_{i,s}) \right\} \quad (2.14)$$

Where k_s^{IN} and k_s^{OUT} are the sets of banks linked to bank j by incoming and outgoing links and $MC_{i,s}$, is the market capitalization of bank i . $|\widehat{D}_{j|i}^s|$ and $|\widehat{D}_{i|j}^s|$ represent the directed connectivity of bank j in the row (inbound) and column (outbound) directions as in the matrix.

Following Kenett et al. (2010), we assess inter-sectoral spillover levels by defining the relative influence of each sector as the ratio between the difference and the sum of the degree of output and the degree of input. The relative influence is written as follows:

The relative influence is between $(-1, 1)$. A positive (negative) value means that the sector is emitting (receiving) systemic risk.

2.3.4 Data inputs

We apply the TENET model to 53 listed banks in 5 Gulf countries (Bahrain, Kuwait, Qatar, Saudi Arabia and the United Arab Emirates). We analyze the interconnection structure and systemic relevance of a panel of 20 Islamic and 33 conventional banks over a period from the 1 of January 2007 to the end of December 2017. In line with Härdle et al. (2016); Wang et al. (2018a) and Foglia and Angelini (2020b) we use the weekly closing prices of each bank following the following formula: $R_{it} = Ln(P_t) - Ln(P_{t-1})$, where P_{it} is the closing price of bank i in week t . All our data are extracted from the Datastream database.

Following the example of Härdle et al. (2016), we include both micro and macro-financial variables to reflect the specific characteristics of each bank, and the state of the

economy respectively. Regarding the micro financial variables, these include the leverage which is defined as the ratio of total assets to total equity; the market-to-book variable which is used to reflect the performance of the stock price; and the logarithm of the book value of equity, is used as a proxy for the size of the bank. With regard to macro-financial variables, the economies of the Gulf countries have great economic and environmental similarities. Indeed, these countries have a common religion, share the same culture and are characterized by a high dependence of their economies on oil (Abedifar et al. (2017)). The dependence on the energy sector makes stock markets in the GCC region sensitive to oil price volatility. Changes in oil prices have been shown to affect stock prices in the GCC region (See for example, Arouri and Rault (2010); Arouri and Rault (2012); Alhayki (2014) and Alqattan and Alhayky (2016)). Furthermore, in terms of spillover effects, there is a systemic dependence on oil price spillover effects in GCC stock markets (Maghyreh et al. (2017) and Abuzayed and Al-Fayoumi (2021)).

Given this specificity, we use the West Texas Intermediate (WTI) crude oil index to capture oil price changes and oil risk spillover effects on the GCC region equity market. We also used the Oil Volatility Index (OVX). This index captures the uncertainty of future oil price volatility (Haugom et al. (2014)). It has been suggested by Dutta et al. (2017) that Middle Eastern equity returns are likely to vary with the Oil Implied Volatility Index (OVX) and that expectations of future oil market uncertainty are a non-trivial determinant of Middle Eastern and African equity market returns and volatilities. Finally, financial markets in the GCC region are interdependent with the US financial market (Mensi et al. (2014) and McMillan et al. (2021)). In order to account for financial market uncertainty, we incorporate the VIX (Volatility Index) to capture the interdependencies of the US-GCC financial markets and to account for systemic risk from international financial markets (Caliskan et al. (2021)).

2.4 Empirical results and discussions

This section presents a discussion of the results obtained through the TENET approach. To apply the TENET model, we set the quantile level to $\tau = 0,05$, the size of the sliding window to $w = 48$, which is equivalent to one year of weekly frequency data, and the observation total to $T = 358$ over a period from 2007 to 2017. In a first step, we estimate the VaR and the CoVaR. Then, we analyse the characteristics of the network. Finally, we compare the set of systemic risk sending and receiving banks in order to identify the systemically important banks.

2.4.1 Analysis of total, incoming and outgoing connectivity

In Table 2.8, we present the descriptive statistics for a panel of 20 Islamic and 33 conventional banks from five Gulf countries (Bahrain, Saudi Arabia, the United Arab Emirates, Qatar and Kuwait) over a period from 2007 to 2017. We find that 35 out of 53 banks in our sample have a negative average return. This means that these banks represent declines in returns. Furthermore, most of the absolute minimum values exceed the maximum values, which corresponds to a strong extreme drop in the distributions of returns. This result suggests a strong presence of extreme left tail risk (Wang et al. (2018a)).

In Figure 2.1, we illustrate the evolution of total connectivity (red solid line), and the evolution of the Lambda coefficient that captures the average evolution of systemic risk (black dotted line) for the whole banking system. We observe that from 2008 onwards, the total connectivity of the banking system in the Gulf countries experienced a sharp increase that peaks in 2009. From 2010 onwards, this trend started to decrease and oscillated between small upward and downward trends until the end of 2014. From 2015 onwards, the system-wide connectivity increased significantly and reached its second highest level in 2016. This result suggests that the Gulf banking system was affected by the contagion effects of the 2008 financial crisis, the tensions related to geopolitical instability in the region, and the collapse of oil prices in 2014-2015. This result also confirms the finding of Mensi et al. (2019) who show that spillover effects were increased as a

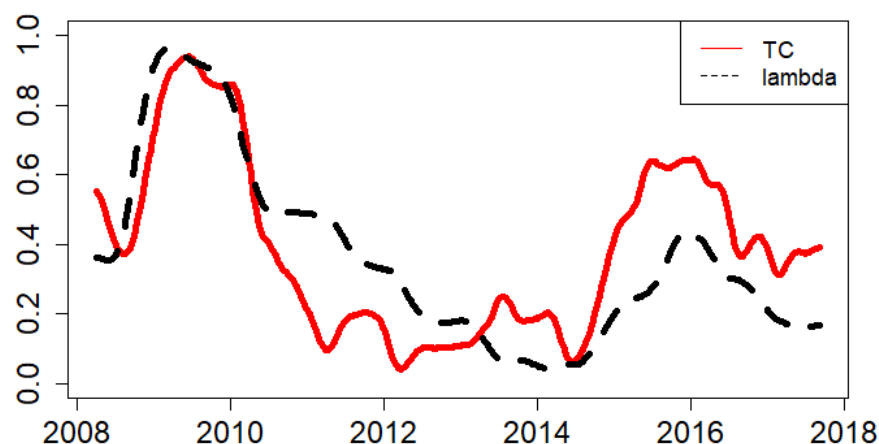


Figure 2.1: Total connectedness (solid red line) and average lambda (dashed black line) of 53 financial institutions from 2007-01-01 to 2017-12-31, $\tau = 0.05$, window size $n = 48$, $T = 358$.

result of the 2008 financial crisis and the 2014-2015 oil price decline for the Gulf countries. Indeed, the total connectivity increases following extreme events, causing uncertainties in financial markets, which increases the number of interconnectedness within financial systems (Billio et al. (2012); Wang et al. (2018a) and Foglia and Angelini (2020b)).

Given the specificity of the Gulf region, geopolitical instability (in this case, the Arab Spring, the wars in Yemen and Syria, the Arab military collision etc.) and oil dependency play a key role in changing the connectivity structure. Indeed, geopolitical risk increases the volatility of the stock market in the Gulf countries, which leads to the transmission of spillover effects (Charfeddine and Al Refai (2019) and Selmi and Bouoiyour (2020)). The dependence of the Gulf countries on the energy market (in this case the oil sector) has been a factor of financial instability. The spillover effects of oil price volatility create spillover effects on financial markets in the GCC region (Maghyreh et al. (2017) and Abuzayed and Al-Fayoumi (2021)). The common economic and geopolitical conditions could lead to strong interconnectedness and therefore to the propagation of systemic risk

in the event of a crisis.

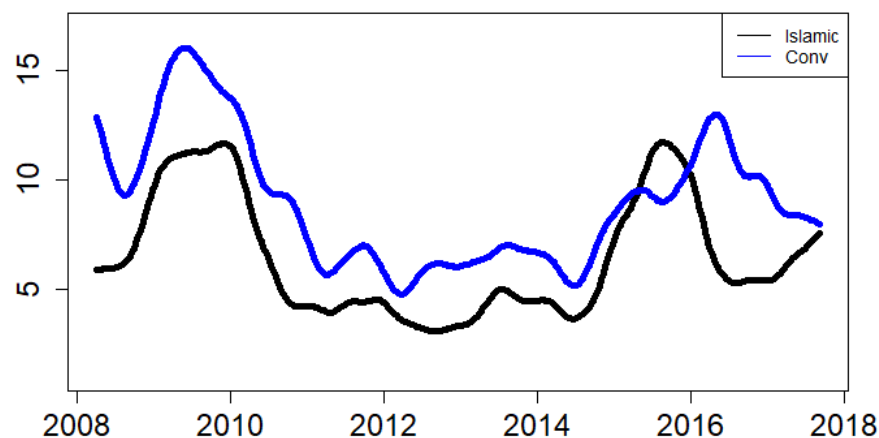


Figure 2.2: Incoming links for the two types of banks . Islamic Banks: solid black line, Conventional Banks dashed blue line. $\tau = 0.05$, window size $n = 48$, $T = 358$.

Regarding the average evolution of systemic risk, we observe that its increase is correlated with the evolution of total connectivity. In other words, the greater the connectivity of the Gulf banking system, the higher the risk of a systemic shock. It is important to note that total connectivity is the sum of outbound connectivity (outgoing links) and inbound connectivity (incoming links) within the banking system. By looking at outgoing and incoming links independently, we can determine the overall trend in total connectivity. In Figure 2.2, we illustrate the dynamics of inbound linkages for Islamic banks (black line) and conventional banks (blue line). We observe that the evolution of inbound links for conventional banks is higher than that for Islamic banks. Similarly, in Figure 2.3, we present the evolution of outgoing links for Islamic and conventional banks. We observe that the outbound connectivity movements of conventional banks exceed those of Islamic banks between 2008 and 2012. Beyond this period, outbound connectivity is now dominated by Islamic banks. Focusing specifically on the period of the 2008 financial crisis, we can observe that the dynamics of total connectivity is more influenced by

conventional banks. This result can be explained by the fact that the banking system in the Gulf countries is predominantly composed of conventional banks, which influences the total connectivity. Although Islamic banks influence only outbound connectivity, this suggests that despite the fact they are in the minority compared to conventional banks, they are able to influence the connectivity of the banking system.

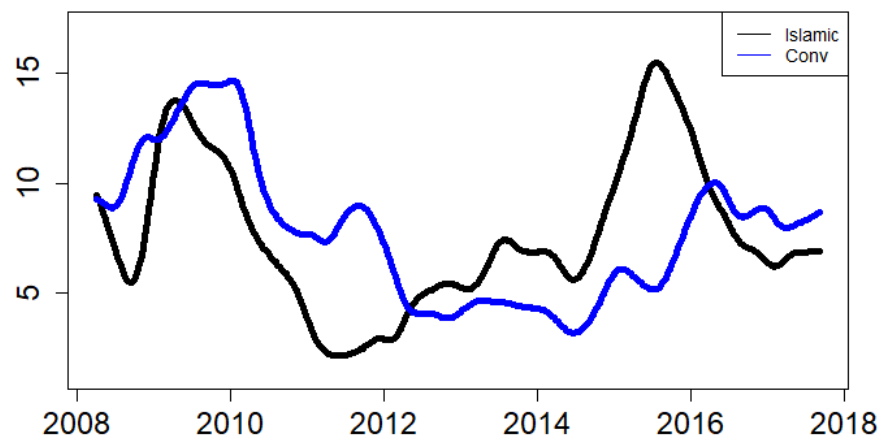


Figure 2.3: Outgoing links for the two types of banks . Islamic Banks: solid black line, Conventional Banks dashed blue line. $\tau = 0.05$, window size $n = 48$, $T = 358$.

2.4.1.1 Analysis of the dynamics of relative influence (RI)

By analyzing Figures 2.4 and 2.5, we highlight the dynamics of the relative influence (RI) between Islamic and conventional banks. It should be noted that the negative and positive values correspond to the emission and reception of systemic risk, respectively. Figure 2.4 illustrates the dynamics of the relative influence of the Islamic banking sector. The RI of this sector shows positive and negative values between 2008 and 2011. This movement suggests that the Islamic banking sector served as both a sender and receiver of systemic risk during this period. Between 2011 and 2012, the Islamic banking sector has the largest negative value: this means that, during this period, the Islamic banking

sector was a receiver of systemic risk spillovers. However, from 2012 onwards, this sector changed its relative influence to become a sender of systemic risk: this explains its dominance of outbound connectivity during this period (see Figure 2.3).

Similarly, Figure 2.5 illustrates the RI of the conventional banking sector. This sector acted as a transmitter and receiver of systemic risk between 2008 and 2011. Between 2011 and 2012, the conventional banking sector shows the largest positive value: this means that the conventional banking sector was acting as a sender of systemic risk. However, from 2012 onwards, this sector takes on negative values until 2017. This behavior implies that the conventional banking sector becomes a receiver of systemic risk and the Islamic sector intervenes as a sender of systemic risk.

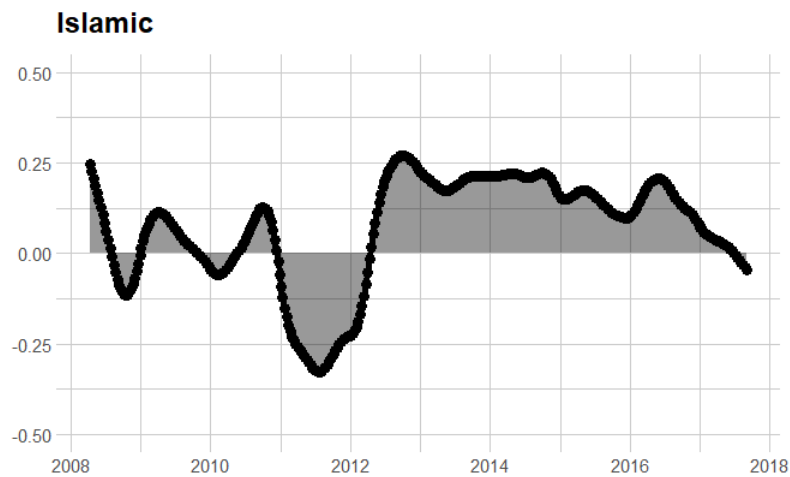


Figure 2.4: Dynamic relative influence of Islamic banks

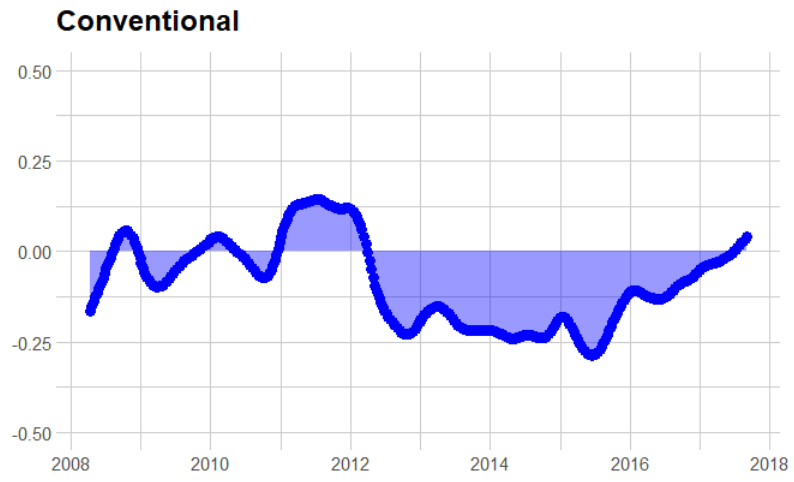


Figure 2.5: Dynamic relative influence of conventional banks

2.4.1.2 Analysis of the structural characteristics of the network

In Figures 2.6, 2.7 and 2.8, we present, respectively, the interconnection structure of Islamic and conventional banks. While Figure 2.6 shows the structure for the whole study period, Figures 2.7 and 2.8 specifically present the crisis and post-crisis sub-period. Note that the nodes represent the different banks, the links between the nodes signify the existence of an interconnection link, the thickness of the line reflects the magnitude of the link and each color groups the banks in the same sector in each country.

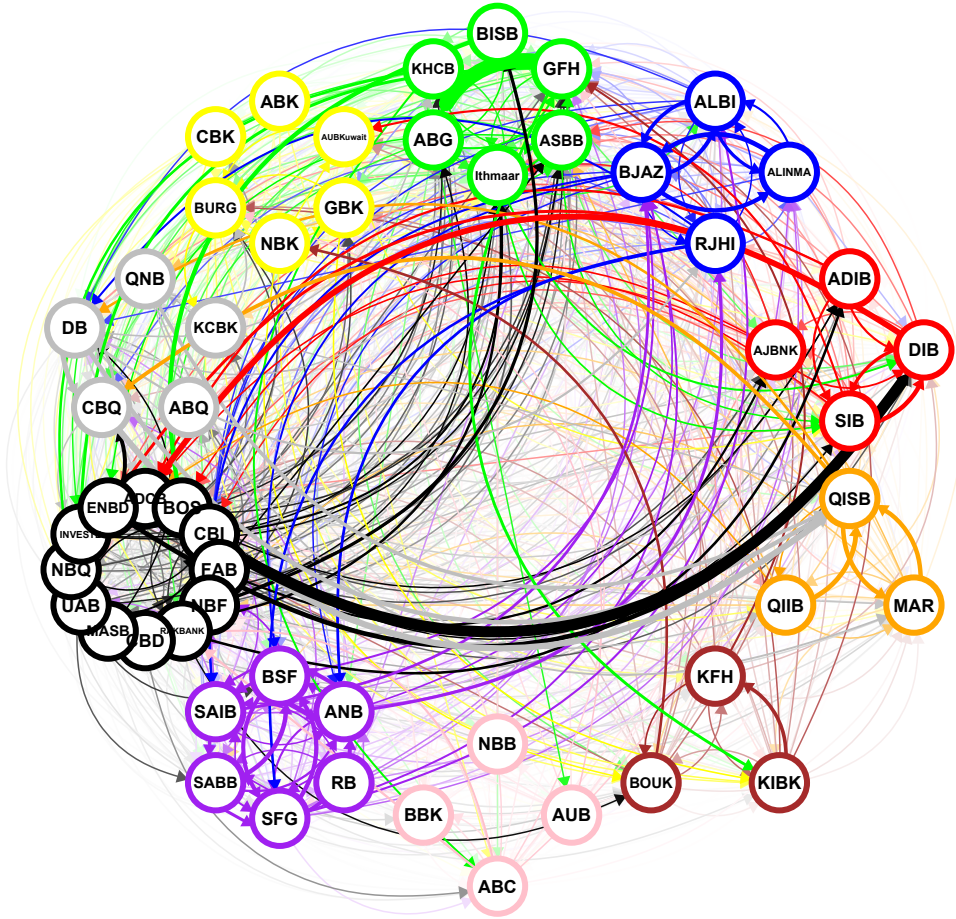
From Figure 2.6, which represents the topology of interconnectedness for the whole period, we see that the nature of interconnectedness between Islamic and conventional banks is structured according to three types of interconnectedness, which can be unidirectional or bidirectional: (i) Close links between banks in the same sector, which can be seen in the framework of intra-sectoral interconnectedness. For example, in the Islamic banking sector, we observe interconnectedness between banks (*ALBI*) and (*BJAZ*) and between banks (*ADIB*) and (*DIB*). Similarly, in the conventional sector, there are interconnectedness between banks (*BBK*) and (*ABC*) and banks (*DB*) and (*CBQ*). (ii) Close links between conventional and Islamic banks, in this case cross-sectoral interconnectedness. For example, the Islamic bank (*DIB*) is interconnected with the conventional bank (*ABDC*) in the United Arab Emirates and the Islamic bank (*QIBS*) is interconnected with the conventional bank (*CBQ*) in Qatar. (iii) Close links between countries, this refers to bilateral cross-border interconnectedness that can be both intra-sectoral and inter-sectoral. With regard to intra-sectoral linkages, we cite for example the linkage between Islamic banks, which is manifested between the Islamic bank (*BOUK*) of Kuwait and the Islamic Bank (*GFH*) of Bahrain, and between conventional banks, notably the conventional bank (*CBD*) of Emirates and the Conventional Bank (*ABC*) of Bahrain. In terms of cross-sectoral interconnectedness, we observe for example the interconnection between the Islamic bank (*ALBI*) of Saudi Arabia and the conventional bank (*DB*) of Qatar.

By analyzing independently the periods during and after the crisis, we can see that during the crisis the interconnectedness are visibly strengthened and intensified (see fig-

ures 2.7 and 2.8). Indeed, during the crisis there are interconnectedness that become stronger and disappear and become less intense after this specific period. We can illustrate this structural change of interconnectedness between the two sub-periods of crisis and post-crisis by some examples between several banks. During the crisis, on the one hand, we observe more pronounced unidirectional interconnectedness between the Islamic bank of Bahrain (*GFH*) and the Islamic bank of Kuwait (*KIBK*), as well as between the conventional bank of the United Arab Emirates (*ENBD*) and the conventional bank of Qatar (*CBQ*). On the other hand, there are more intense two-way interconnectedness between the conventional bank (*CBQ*) and the Islamic bank (*QISB*) of Qatar, or between the conventional bank (*ANB*) and the Islamic bank (*RJHI*) of Saudi Arabia. It is also worth noting that the outbound connectivity of conventional banks is larger and more intense, as indicated by the thickness of the edge line. After the crisis, most of the above-mentioned linkages have become weaker and less intense. Similarly, there are linkages that emerged during the crisis period and disappeared after the crisis, such as between the conventional bank (*ABC*) of the Emirates and the conventional bank (*ABC*) of Bahrain and the conventional bank (*SFG*) of Saudi Arabia and the conventional bank (*ABC*) of Bahrain.

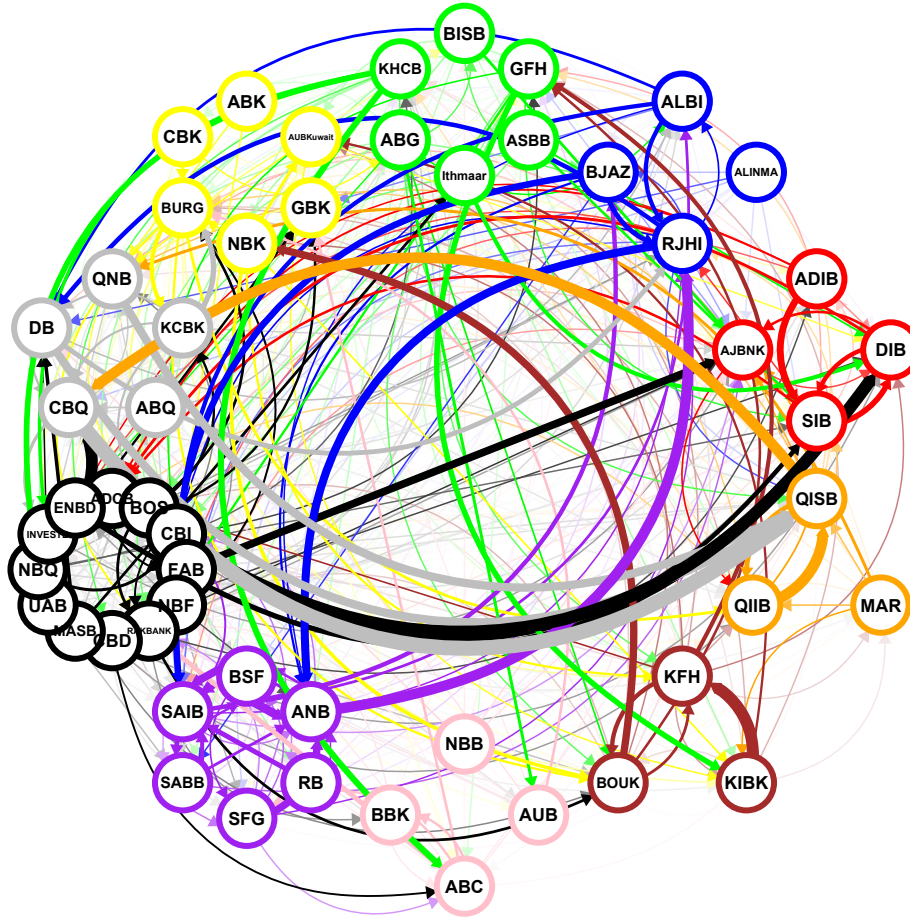
This analysis of the interconnectedness properties shows that the Gulf banking system is closely interconnected at both the national and regional levels with conventional banks dominating. Our results also highlight that the number of interconnectedness increases significantly during moments of instability, notably during the external shock of the 2008 financial crisis and during the regional shocks related to geopolitical tensions and the collapse of oil prices in 2014-2015. This high interconnectivity could be explained by the presence of geographical proximity and bilateral and multilateral economic and financial relations between these countries (Balli et al. (2019)). Indeed, the multiplicity of links between the banks of the Gulf countries influences the interconnectedness and accentuates spillover effects and spillovers.

Figure 2.6: The network representations of weighted adjacency matrices from 01-01-2007 to 31-12-2017 with $\tau = 0.05$ and window size $n = 48$.



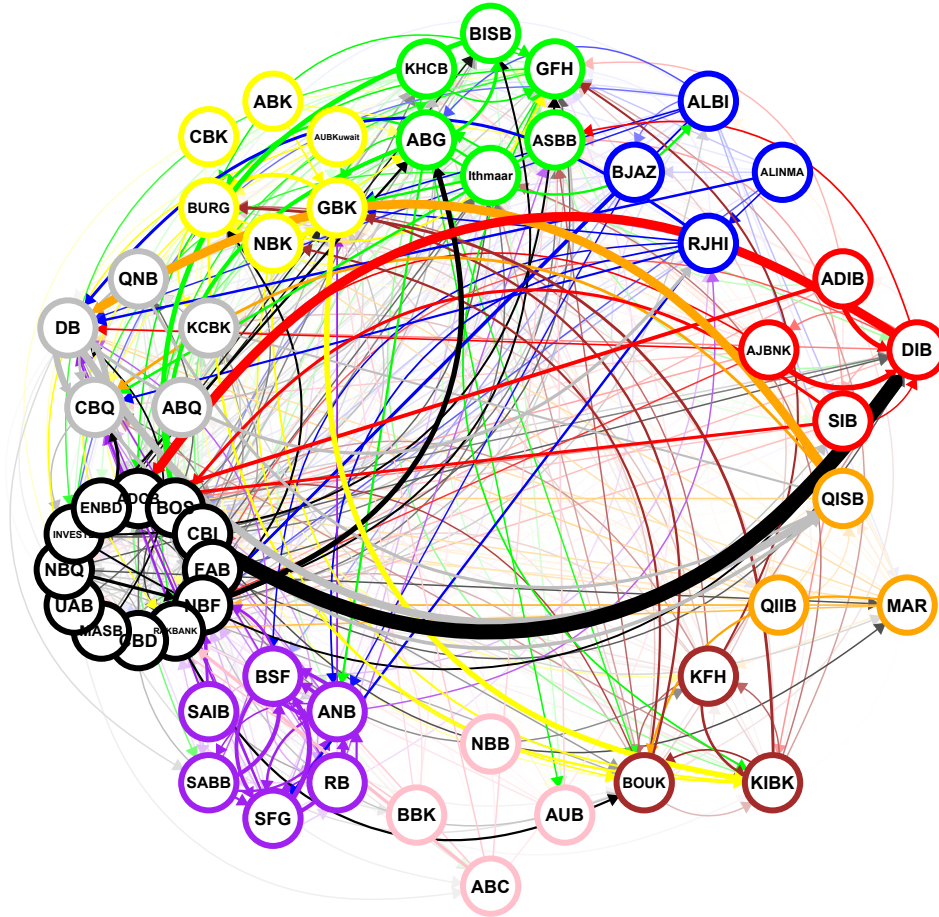
Note : color **green** Islamic banks of Bahrain, color **blue** Islamic banks of Saudi Arabia, color **red** Islamic banks of United Arab Emirates, color **orange** Islamic banks of Qatar, color **purple** Islamic banks of Kuwait, color **pink** conventional banks of Bahrain, color **violet** conventional banks of Saudi Arabia, color **black** conventional banks of United Arab Emirates, color **gray** conventional banks of Qatar, color **yellow** conventional banks of Kuwait.

Figure 2.7: The network representations of weighted adjacency matrices during the 2008 crisis with τ 0.05 and window size $n = 48$.



Note : color **green** Islamic banks of Bahrain, color **blue** Islamic banks of Saudi Arabia, color **red** Islamic banks of United Arab Emirates, color **orange** Islamic banks of Qatar, color **purple** Islamic banks of Kuwait, color **pink** conventional banks of Bahrain, color **violet** conventional banks of Saudi Arabia, color **black** conventional banks of United Arab Emirates, color **gray** conventional banks of Qatar, color **yellow** conventional banks of Kuwait.

Figure 2.8: The network representations of weighted adjacency matrices after 2008 crisis with $\tau = 0.05$ and window size $n = 48$.



Note : color **green** Islamic banks of Bahrain, color **blue** Islamic banks of Saudi Arabia, color **red** Islamic banks of United Arab Emirates, color **orange** Islamic banks of Qatar, color **purple** Islamic banks of Kuwait, color **pink** conventional banks of Bahrain, color **violet** conventional banks of Saudi Arabia, color **black** conventional banks of United Arab Emirates, color **gray** conventional banks of Qatar, color **yellow** conventional banks of Kuwait.

Table 2.1: Top 10 directional edges from i financial institution to j . Following Härdle et al. (2016)

Rank	Type of banks	From i	Type of banks	to j	sum
1	IB	ABG	IB	GFH	136,48
2	IB	DIB	CB	ADCB	100,30
3	IB	QISB	CB	CBQ	55,51
4	CB	ADCB	IB	DIB	52,25
5	CB	CBQ	CB	DB	45,59
6	CB	ANB	CB	BSF	44,61
7	IB	BJAZ	IB	ALINMA	41,43
8	IB	MAR	IB	QISB	40,18
9	CB	BSF	CB	SABB	39,34
10	CB	NBF	IB	BISB	38,44

2.4.1.3 Identification of the systemic relevance of banks according to the (SRR) and (SRE) index

Table 2.1 divides the top 10 banks according to their directional connectivity from bank i to bank j . According to Table 2.1, the strongest connectivities reside between the Islamic bank (*ABG*) and the Islamic bank (*GFH*) in Bahrain, and between the Islamic bank (*DIB*) and the conventional bank (*ADCB*) in the United Arab Emirates. This means that there is a strong spread of tail risk between these banks. In general, there are three strong directional links, respectively, between Islamic and conventional banks, and two strong directional links from different sectors.

This result suggests that there is heterogeneity in directional connectivity. This highlights, on one hand, the presence of reciprocal interconnectedness between banks in the same sector and those in different sectors. On the other hand, these different directional linkages that characterize the Gulf banking system are likely to transmit extreme risk spillovers between banks in the same sector and banks in different sectors.

Table 2.2 presents the top 10 IN-Links and OUT-Links and the classification of banks according to their market capitalisation for the period 2007 to 2017. Table 2.2 classifies the top 10 banks according to their connectivity (IN-links) and their outward connectivity (OUT-links) from 2007 to 2017. From Table 2.2, it can be seen that 4 Islamic banks and 6 conventional banks dominate inbound connectivity, and 7 Islamic banks versus 3

Table 2.2: Notes : The top 10 banks ranked by IN and OUT links, with a ranking by market capitalization (MC ranking) in 2017

Rank	Banks	Type of Banks	IN-Links	MC Rank	Banks	Type of Banks	OUT-Links	MC Rank
1	GFH	IB	257,57	38	DIB	IB	310,45	12
2	BSF	IB	177,46	11	QISB	IB	235,05	15
3	DB	CB	176,93	36	NBF	CB	222,25	28
4	SFG	CB	176,01	7	ADCB	CB	210,52	45
5	ADCB	CB	163,46	45	GFH	IB	207,53	38
6	BJAZ	IB	154,16	35	Ithmaar	IB	205,52	52
7	CBQ	CB	150,08	24	ABG	IB	191,67	49
8	DIB	IB	140,30	12	ASBB	IB	187,07	47
9	RJHI	IB	137,78	3	BJAZ	IB	182,61	35
10	ANB	CB	136,15	9	BSF	CB	180,83	11

Note: the classification of all banks is included in the appendix (see table 2.9 in the appendix).

conventional banks influence outbound connectivity. The majority of these banks are represented by small or modest market capitalization. This indicates that small banks are highly interconnected and are, therefore, likely to influence the total conductivity of the banking system. It is interesting to note that most of these banks are Saudi and UAE banks. This implies that the banks of these countries monopolise the banking system of the Gulf countries.

Table 2.3: Notes : Top 10 banks ranked by SRR and SRE indexes, with market capitalisation ranking (MC rank) in 2017

Rank	Banks	Type of banks	Systemic Risk receivers SRR	Rank MC	Banks	Type of banks	ranks the risk emitters SRE	Rank MC
1	RJHI	IB	7,45E+13	3	CBI	CB	4,75E+13	2
2	ANB	CB	4,49E+13	9	ENBD	CB	4,67E+13	1
3	ENBD	CB	3,61E+13	1	ANB	CB	4,67E+13	9
4	SFG	CB	3,29E+13	7	SFG	CB	4,40E+13	7
5	BSF	CB	2,86E+13	11	DIB	IB	4,13E+13	12
6	CBI	CB	2,53E+13	2	RJHI	IB	3,70E+13	3
7	DIB	IB	2,18E+13	12	BSF	CB	3,29E+13	11
8	RB	CB	1,92E+13	5	INVESTB	CB	1,96E+13	6
9	INVESTB	CB	1,88E+13	6	GBK	CB	1,55E+13	4
10	QISB	IB	1,07E+13	15	QISB	IB	1,37E+13	15

Note: the classification of all banks is included in the appendix (see table 2.10 in the appendix).

Table 2.4: Notes : Classification of banks by IN and OUT links, with a classification by market capitalization (MC classification): during the crisis

Rank	Firms	Type of Banks	IN-Links	MC Rank	Firms	Type of Banks	OUT-Links	MC Rank
1	CBQ	CB	57,15	24	QISB	IB	117,32	15
2	BSF	CB	55,56	11	DIB	IB	86,35	12
3	QISB	IB	49,91	15	ANB	CB	85,93	9
4	RJHI	IB	49,16	3	SAIB	CB	85,85	27
5	KHCB	IB	48,36	53	RJHI	IB	74,51	3
6	DB	CB	46,20	36	CBQ	CB	73,72	32
7	ANB	CB	45,58	9	AJBNK	IB	62,23	48
8	ADCB	CB	40,29	45	SIB	IB	59,18	42
9	BJAZ	IB	39,55	35	KFH	IB	49,35	8
10	KCBK	CB	39,04	53	BURG	CB	48,41	31

Note: the classification of all banks is included in the appendix (see 2.11 in the appendix).

To analyse the systemic relevance, we rank Islamic and conventional banks according to the SRR and SRE indices. According to Table 2.3, among the top ten SRR and SRE banks, there are seven conventional banks. The first bank receiving the most risk is the Saudi Islamic bank (*RJHI*), and the bank issuing the most risk is the UAE bank (*CBI*). This means that conventional banks are the main senders and receivers of systemic risk spillovers. Based on the market capitalisation ranking, we can observe that most of these banks are large banks, which means that they represent high levels of systemic importance. This suggests that these banks are capable of playing an active role in financial instability. From a systemic point of view, banks identified as systemically important should be considered as risky banks at national and regional level and should be subject to special supervision. Other banks, especially those with common links to these banks, should seek to limit their links and diversify with less risky banks. In order to analyse the influence of moments of instability on interconnectedness, we study the connectivity and systemic relevance of banks in two sub-periods: the 2008 crisis period and the post-crisis period. Comparing inbound and outbound connectivity according to Tables 2.4 and 2.5, we find that the number of links was significantly increased during the crisis period. On the other hand, conventional banks are still predominant in terms of transmitting and receiving connectivity. From the point of view of the SRR and SRE index, the systemic relevance of banks has been increased and conventional banks influence the transmission and reception of systemic risk. It is worth noting that the Saudi bank *RJHI* is still the most systemic risk recipient in all periods considered (see Tables 2.6 and 2.7).

Table 2.5: Notes : Classification of banks by IN and OUT links, with a classification by market capitalization (MC classification): post-crisis

Rank	Firms	Type of Banks	IN-Links	MC Rank	Firms	Type of Banks	OUT-Links	MC Rank
1	DB	CB	43,91	36	ADCB	CB	74,68	45
2	ADCB	CB	37,38	45	NBF	CB	70,10	28
3	ABG	IB	37,33	49	DIB	IB	69,72	12
4	BURG	CB	31,75	31	DB	CB	68,82	36
5	SFG	CB	31,16	7	CBQ	CB	55,35	24
6	DIB I	B	29,56	12	GBK	CB	50,52	4
7	CBQ	CB	27,66	24	BSF	CB	39,05	11
8	RJHI	IB	27,26	3	GFH	IB	37,90	38
9	QISB	IB	27,20	15	BURG	CB	37,62	31
10	ANB	CB	25,89	9	ANB	CB	36,99	9

Note: the classification of all banks is included in the appendix (see 2.12 in the appendix).

Table 2.6: Notes : The classification of banks by the SRR and SRE indices, with the market capitalization ranking (MC rank): during the crisis

Rank	Banks	Type of banks	Systemic Risk receivers SRR	Rank MC	Banks	Type of banks	ranks the risk emitters SRE	Rank MC
1	RJHI	IB	3,04E+13	3	RJHI	IB	3,06E+13	3
2	ANB	CB	2,48E+13	9	ANB	CB	2,93E+13	9
3	ENBD	CB	1,04E+13	1	CBI	CB	1,78E+13	2
4	SFG	CB	9,81E+12	7	DIB	IB	1,17E+13	12
5	CBI	CB	8,66E+12	2	INVESTB	CB	8,59E+12	6
6	BSF	CB	8,43E+12	11	QISB	IB	5,65E+12	15
7	INVESTB	CB	5,46E+12	6	ENBD	CB	5,18E+12	1
8	ALBI	IB	3,67E+12	18	GBK	CB	4,19E+12	4
9	KFH	IB	3,60E+12	8	CBQ	CB	3,83E+12	24
10	QISB	IB	2,76E+12	15	SAIB	CB	3,68E+12	27

Note: the classification of all banks is included in the appendix (see 2.13 in the appendix).

Table 2.7: Notes : The classification of banks by the SRR and SRE indices, with the market capitalization ranking (MC rank) : post-crisis

Rank	Banks	Type of banks	Systemic Risk receivers SRR	Rank MC	Banks	Type of banks	ranks the risk emitters SRE	Rank MC
1	RJHI	IB	1,68E+13	3	BSF	CB	1,01E+13	7
2	ANB	CB	8,66E+12	9	GBK	CB	9,86E+12	4
3	CBI	CB	6,91E+12	2	SFG	CB	9,33E+12	11
4	SFG	CB	6,81E+12	11	ANB	CB	9,31E+12	9
5	RB	CB	6,07E+12	5	CBI	CB	7,45E+12	2
6	BSF	CB	5,62E+12	7	RJHI	IB	4,75E+12	3
7	INVESTB	CB	2,47E+12	6	DIB	IB	3,44E+12	12
8	ALINMA	IB	2,23E+12	14	INVESTB	CB	3,10E+12	6
9	BBK	CB	1,81E+12	10	CBQ	CB	2,37E+12	24
10	SABB	CB	1,71E+12	23	ENBD	CB	2,30E+12	1

Note: the classification of all banks is included in the appendix (see 2.14 in the appendix).

The structure of interconnectedness between Islamic and conventional banks is not only characterized by a strong interconnection at the national level of the same country, but also by a tendency to connect to other banks in neighboring countries. Based on this structure, it can be seen that the banking systems in the Gulf countries are geographically interconnected and form cluster interconnectedness. This result hints that the transmission of systemic risk does not propagate exclusively at the national level, but also at the regional level. The high density of connectivity in the banking systems of the Gulf countries could be interpreted by several macro and micro economic factors. Indeed, the banks in these countries form a grouping that operates under the same economic and environmental conditions. The economies of these countries are very sensitive to oil price variations. This dependence has important implications for financial stability, particularly when economic conditions are subject to falling oil prices. Under these conditions, economic shocks are easily and intensively transmitted. In addition, the region is singularly independent of geopolitical insecurity, which has the effect of making financial markets in the Gulf countries less volatile and resilient to extreme risks (Mensi et al. (2019) and Balli et al. (2019))).

The banking system in the Gulf countries is a hybrid system, combining Islamic and conventional banks. The majority of conventional banks have started marketing Islamic products. This heterogeneous business strategy at the level of the conventional banks favors the formation of new interconnectedness with the Islamic banking sector. Both types of banks face two types of interconnectedness, inter-sectoral and intra-sectoral, which undoubtedly increases the number of connections. This structuring could lead to a potential risk of contagion for the whole financial system. This result is in line with that of Abedifar et al. (2017) who proved, using graphical network models, that conventional banks with Islamic windows are fragile to systemic shocks and are highly interconnected given their market synchronizations.

Moreover, conventional banks are heavily involved in the banking system of each country compared to Islamic banks, which are gradually growing while being smaller in terms of market capitalisation (Abedifar et al. (2017)). This suggests that a high

involvement in the banking system could increase the exposure to systemic risk in case of a systemic shock (Bostandzic and Weiss (2018)). As for Islamic banks, they differ from conventional banks in terms of structure, do not have the same risk management tools and are smaller in size. This imbalance in size and development is likely to lead to an inability to absorb a systemic shock for Islamic banks. Indeed, the size of Islamic banks is a key factor of their financial stability (Čihák and Hesse (2010) and Ibrahim and Rizvi (2017)). In order to grow, an Islamic bank would have to take on more risk, although this could undermine its financial stability if it takes on too much risk (DörIng et al. (2016)). Furthermore, as Islamic banking develops, the complexity of risk management increases due to its risk management shortcomings (Čihák and Hesse (2010) and Mensi et al. (2019)).

2.5 Conclusions

This study examines the interconnectedness structure and systemic risk contribution of Islamic and conventional banks in the Gulf countries. To analyze the interconnectedness properties and systemic relevance of each bank, we applied the TENET model of Härdle et al. (2016) for a panel of 20 Islamic banks and 33 conventional banks from 2007 to 2017. Our results allow us to draw several conclusions. Firstly, our analysis suggests evidence of strong interconnectivity in the hybrid banking system of the Gulf countries. Secondly, the structural characteristics of the interconnectedness of Islamic and conventional banks highlight a multiplicity of directional (uni-directional and bi-directional) interconnectivity links. These include inter- and intra-sectoral interconnectedness and bilateral interconnectedness between countries. Thirdly, the analysis of individual systemic relevance shows that small banks are highly interconnected and that conventional banks are the main senders and receivers of systemic risk spillovers.

Our estimates suggest that Islamic and conventional banks in the Gulf countries form a geographically interconnected financial network. This typology of Gulf countries can be attributed to geographical proximity, similar bilateral and multilateral economic interests

and geopolitical stakes in the region. Conventional banks show strong interconnectivity with the banking system due to their involvement and commercial heterogeneity. This high interconnectedness of conventional banks multiplies inter- and intra-sectoral linkages, influences the number of interconnectedness and promotes the risk of contagion at national and regional level. However, it should be noted that Islamic banks, due to their development, may influence connectivity and are likely to be exposed to a systemic shock. The findings of our study imply several economic and political implications. Given the geopolitical instability and the instability of oil prices that influencing the connectivity of financial systems in the Gulf countries, Islamic and conventional banks should diversify their investments and look for other investment sectors than oil. From a macro-prudential perspective, banks that have been identified as systemically important at the national and regional level should be subject to special scrutiny by regulators. Underestimating their systemic risk implications is likely to increase extreme risk in the financial system as a whole.

2.6 Appendixes

Table 2.8: Descriptive statistics

Banks	Names of Banks	Country	Type	Obs	Mean	Std. Dev.	Min	Max
BISB	BAHRAIN ISLAMIC BANK	BAHRAIN	IB	406	-.0019844	.0433204	-.2241283	.1881867
GFH	GFH FINANCIAL GROUP	Bahrain	IB	406	-.0060794	.0880046	-.8946292	.3993861
ASBB	AL SALAM BK BAHRAIN	Bahrain	IB	406	-.0003702	.0791464	-.853607	.7982082
Ithmaar	ITHMAAR BK	Bahrain	IB	406	-.0022163	.0701749	-.2295744	.4567584
ABG	AL BARAKA BANKING GROUP	Bahrain	IB	406	-.0029015	.0434619	-.2576611	.3004712
KHCB	KHALEEJI COMMERCIAL BK	Bahrain	IB	406	-.0033446	.1352282	-1.280212	1.280212
ALBI	BK ALBILAD	Saudi Arabia	IB	406	.0008371	.0475127	-.1870583	.2766979
ALINMA	ALINMA BK	Saudi Arabia	IB	406	-.0006142	.0326221	-.0992443	.1668373
RJHI	AL RAJHI BK	Saudi Arabia	IB	406	-.000393	.0396625	-.1976589	.1531076
BJAZ	BK ALJAZIRA	Saudi Arabia	IB	406	-.0018669	.0489947	-.221291	.1576029
ADIB	ABU DHABI ISLAMIC BK	United Arab Emirates	IB	406	-.0004105	.0399408	-.2806779	.1310598
DIB	DUBAI ISLAMIC BK	United Arab Emirates	IB	406	-.0003656	.0516958	-.2884486	.1859836
SIB	SHARJAH ISLAMIC BK	United Arab Emirates	IB	406	-.0006267	.0455466	-.3416252	.1849566
AJBK	AJMAN BK	United Arab Emirates	IB	406	-.0026596	.0474944	-.3691751	.1516662
QISB	QATAR ISLAMIC BK	Qatar	IB	406	.0004032	.0431912	-.1960703	.1296851
MAR	MASRAF AL RAYAN	Qatar	IB	406	.0016222	.0399886	-.2257602	.174717
QIIB	QATAR INTL ISLAMIC BK	Qatar	B	406	.0004587	.0398762	-.268264	.1599714
KFH	KUWAIT FINANCE HOUSE	Kuwait	IB	406	.0003383	.0380406	-.1975549	.2023975
KIBK	KUWAIT INTL BK	Kuwait	IB	406	-.0018126	.0386941	-.2027376	.1613981
BOUK	BOUBYAN BK	Kuwait	IB	406	.0010272	.041584	-.2354136	.2896642
NBB	NATIONAL BK OF BAHRAIN	Bahrain	CB	406	.0007253	.0232552	-.0817894	.1111333
AUB	AHLI UNITED BK	Bahrain	CB	406	.0005563	.0345981	-.1775483	.123614
ABC	ARAB BANKING CORPORATION	Bahrain	CB	406	-.0035971	.0456735	-.3205548	.2306342
BBK	BK OF BAHRAIN AND KUWAIT	Bahrain	CB	406	-.0000317	.0247005	-.1115911	.1463019
BSF	BANQUE SAUDI FRANSI	Saudi Arabia	CB	406	-.0009279	.041892	-.1882112	.1298569
ANB	ARAB NATIONAL BK	Saudi Arabia	CB	406	-.0011975	.0426005	-.2067415	.1628859
RB	RIYAD BK	Saudi Arabia	CB	406	-.000535	.0356986	-.1421098	.1667323
SFG	SAMBA FINANCIAL GROUP	Saudi Arabia	CB	406	-.0007674	.0450686	-.1584342	.1830702
SABB	THE SAUDI BRITISH BK	Saudi Arabia	CB	406	-.0001833	.0428701	-.2434589	.1524886
SAIB	THE SAUDI INVESTMENT BK	Saudi Arabia	CB	406	-.0013334	.0421878	-.2875681	.1511428
ADCB	ABU DHABI COML BK	United Arab Emirates	CB	406	-.0005629	.0539306	-.2979448	.186586
BOS	BK OF SHARJAH	United Arab Emirates	CB	406	-.0012662	.0480844	-.349051	.2845125
CBI	COMMERCIAL BK INTL	United Arab Emirates	CB	406	-.0004472	.0644053	-.247354	.3703012
FAB	FIRST ABU DHABI BK	United Arab Emirates	CB	406	.0004531	.0418201	-.22385	.1693746
NBF	NATIONAL BK OF FUJAIRAH	United Arab Emirates	CB	406	.0005052	.0634622	-.337629	.2870474
RAKBANK	NATIONAL BK OF RAS AL KHAIMAH	United Arab Emirates	CB	406	.0014548	.049765	-.2435402	.4991637
CBD	COMMERCIAL BK OF DUBAI	United Arab Emirates	CB	406	.0007777	.0402709	-.1792304	.1615954
MASB	MASHREQ BK	United Arab Emirates	CB	406	-.0010437	.0472159	-.2285763	.3900223
UAB	UNITED ARAB BK	United Arab Emirates	CB	406	-.0019215	.052374	-.3519529	.3291818
NBQ	NB OF UMM AL-QAIWAIN	United Arab Emirates	CB	406	.001223	.049996	-.1647552	.2248662
INVESTB	Emirates Investment Bank	United Arab Emirates	CB	406	.0015767	.0577054	-.428668	.2536362
ENBD	EMIRATES NBD	United Arab Emirates	CB	406	-.0003728	.0526386	-.2266876	.4492228
QNB	QATAR NATIONAL BK	Qatar	CB	406	-.0036162	.0462155	-.2885714	.1983022
KCBK	AL KHALIJ COML BK	Qatar	CB	406	.0023113	.0361886	-.2619362	.1588788
ABQ	AHLI BK	Qatar	CB	406	.0009777	.040848	-.1855216	.2076394
CBQ	COMMERCIAL BK OF QATAR	Qatar	CB	406	-.0009713	.0457546	-.2844034	.1416972
DB	DOHA BANK	Qatar	CB	406	-.0023717	.0442768	-.2621752	.1548542
ABK	AL AHLI BK OF KUWAIT	Kuwait	CB	406	-.0015492	.0289262	-.2020116	.119171
AUBKuwait	AHLI UNITED BK	Kuwait	CB	406	.0002738	.0353909	-.1768195	.2833342
GBK	GULF BK OF KUWAIT	Kuwait	CB	406	-.0028591	.0434993	-.4526788	.3649673
NBK	NATIONAL BK OF KUWAIT	Kuwait	CB	406	-.0002687	.0310964	-.1592397	.2050211
BURG	BURGAN BK	Kuwait	CB	406	.0000334	.0405863	-.2828628	.1743534
CBK	COMMERCIAL BK OF KUWAIT	Kuwait	CB	406	-.0018669	.031728	-.1228074	.1614875

Table 2.9: All banks ranked by IN and OUT links from 2007 to 2017

Rank	Banks	Type of Banks	IN-Links	MC Rank	Banks	Type of Banks	OUT-Links	MC Rank
1	GFH	IB	257,57	38	DIB	IB	310,45	12
2	BSF	IB	177,46	11	QISB	IB	235,05	15
3	DB	CB	176,93	36	NBF	CB	222,25	28
4	SFG	CB	176,01	7	ADCB	CB	210,52	45
5	ADCB	CB	163,46	45	GFH	IB	207,53	38
6	BJAZ	IB	154,16	35	Ithmaar	IB	205,52	52
7	CBQ	CB	150,08	24	ABG	IB	191,67	49
8	DIB	IB	140,30	12	ASBB	IB	187,07	47
9	RJHI	IB	137,78	3	BJAZ	IB	182,61	35
10	ANB	CB	136,15	9	BSF	CB	180,84	11
11	ALBI	IB	134,71	18	CBQ	CB	179,13	24
12	QISB	IB	131,84	15	ANB	CB	167,20	9
13	SAIB	CB	130,46	27	DB	CB	157,87	36
14	INVESTB	CB	125,27	6	SFG	CB	154,61	7
15	SIB	IB	125,15	42	SIB	IB	147,69	42
16	Ithmaar	IB	123,16	52	ALBI	IB	146,94	18
17	SABB	CB	120,21	23	CBI	CB	144,85	2
18	QIIB	IB	117,48	25	ENBD	CB	136,49	1
19	ABC	CB	107,30	40	INVESTB	CB	126,53	6
20	ABG	IB	106,45	49	KHCB	IB	112,99	53
21	CBI	CB	104,56	2	BURG	CB	112,50	31
22	BURG	CB	103,18	31	ALINMA	IB	104,09	14
23	KHCB	IB	102,71	53	SAIB	CB	102,99	27
24	QNB	CB	101,24	39	AJBNK	IB	99,53	48
25	KCBK	CB	100,17	30	MAR	IB	99,08	13
26	MAR	CB	97,65	13	SABB	CB	92,43	23
27	FAB	CB	97,56	34	NBQ	CB	92,42	41
28	ALINMA	IB	95,54	14	RAKBANK	CB	90,54	22
29	NBF	CB	95,29	28	RJHI	IB	89,42	3
30	RB	CB	94,30	5	GBK	CB	88,37	4
31	UAB	CB	89,95	37	UAB	CB	81,72	37
32	KIBK	IB	89,77	46	KIBK	IB	75,83	46
33	RAKBANK	CB	87,59	22	BOUK	IB	73,01	20
34	BOUK	IB	87,04	20	BISB	IB	69,04	51
35	NBQ	CB	86,08	41	ADIB	IB	64,24	19
36	BISB	IB	84,88	51	KFH	IB	61,77	8
37	AJBNK	IB	84,38	48	BOS	CB	60,52	50
38	KFH	IB	82,11	8	AUBKuwait	CB	60,34	26
39	ENBD	CB	81,66	1	QIIB	IB	59,22	25
40	ADIB	IB	79,37	19	CBD	CB	44,01	17
41	BOS	CB	77,74	50	MASB	CB	43,15	44
42	NBK	CB	76,12	29	ABC	CB	43,04	40
43	MASB	CB	75,81	44	KCBK	CB	35,42	30
44	AUBKuwait	CB	70,21	26	QNB	CB	32,76	39
45	ASBB	IB	69,95	47	NBK	CB	31,73	29
46	ABQ	CB	68,76	41	FAB	CB	30,63	34
47	AUB	CB	64,33	43	ABQ	CB	17,73	21
48	CBD	CB	56,42	17	RB	CB	13,92	5
49	GBK	CB	54,128	4	AUB	CB	12,58	43
50	CBK	CB	53,260	32	BBK	CB	10,32	10
51	ABK	CB	46,074	33	CBK	CB	10,32	30
52	BBK	CB	36,281	10	NBB	CB	6,34	16
53	NBB	CB	31,633	16	ABK	CB	0,82	33

Notes : All banks ranked by IN and OUT links, with market capitalization ranking (MC ranking) in 2017.

Table 2.10: All banks ranked by IN and OUT links during the 2008 crisis

Rank	Banks	Type of Banks	IN-Links	MC Rank	Banks	Type of Banks	OUT-Links	MC Rank
1	CBQ	CB	57,15	24	QISB	IB	117,31	15
2	BSF	CB	55,56	11	DIB	IB	86,34	12
3	QISB	IB	49,91	15	ANB	CB	85,93	9
4	RJHI	IB	49,16	3	SAIB	CB	85,84	27
5	KHCB	IB	48,36	53	RJHI	IB	74,50	3
6	DB	CB	46,20	36	CBQ	CB	73,71	24
7	ANB	CB	45,58	9	AJBK	IB	62,23	48
8	ADCB	CB	40,29	45	SIB	IB	59,18	42
9	BJAZ	IB	39,55	35	KFH	IB	49,34	8
10	KCBK	CB	39,04	30	BURG	CB	48,41	31
11	KIBK	IB	38,99	46	RAKBANK	CB	47,82	22
12	SAIB	CB	38,61	27	BOUK	IB	44,75	20
13	KFH	IB	38,53	8	DB	CB	43,09	36
14	BURG	CB	38,14	31	CBI	CB	42,00	2
15	BOUK	IB	38,13	20	INVESTB	CB	39,22	6
16	INVESTB	CB	37,69	6	QIIB	IB	34,29	25
17	ABC	CB	37,02	40	GFH	IB	31,30	38
18	QIIB	IB	36,85	25	KIBK	IB	30,46	46
19	BOS	CB	36,46	50	ABC	CB	25,90	40
20	ALBI	IB	35,89	18	GBK	CB	25,69	4
21	GFH	IB	35,16	38	BOS	CB	25,12	50
22	SFG	CB	33,32	7	QNB	CB	24,36	39
23	NBK	CB	31,36	29	KCBK	CB	23,11	30
24	ABG	IB	30,34	49	ADCB	CB	23,02	45
25	ADIB	IB	30,11	19	ALBI	IB	22,57	18
26	QNB	CB	28,48	39	NBK	CB	21,86	29
27	DIB	IB	28,26	12	SABB	CB	21,77	23
28	SIB	IB	27,87	42	BJAZ	IB	21,59	35
29	FAB	CB	27,32	34	AUBKuwait	CB	20,73	26
30	NBQ	CB	25,65	41	BSF	CB	20,20	11
31	RAKBANK	CB	25,00	22	FAB	CB	18,88	34
32	MASB	CB	24,63	44	NBQ	CB	18,79	41
33	SABB	CB	23,44	23	SFG	CB	15,43	7
34	Ithmaar	IB	20,28	52	ENBD	CB	14,78	1
35	MAR	CB	19,89	13	KHCB	CB	11,66	53
36	AUBKuwait	CB	18,29	26	AUB	CB	8,40	43
37	CBI	CB	17,81	2	CBD	CB	8,34	17
38	RB	CB	16,68	5	Ithmaar	IB	7,98	52
39	CBK	CB	15,06	32	BBK	CB	7,79	10
40	ASBB	CB	15,02	47	BISB	IB	5,58	51
41	ENBD	CB	14,75	1	ABG	IB	5,44	49
42	NBF	CB	14,53	28	ADIB	CB	5,12	19
43	ABQ	CB	14,33	21	NBF	CB	4,72	28
44	AUB	CB	13,91	43	RB	CB	4,18	5
45	BISB	IB	13,65	51	UAB	CB	2,89	37
46	CBD	CB	12,47	17	MAR	IB	2,53	13
47	AJBK	IB	10,73	48	ABQ	CB	1,11	21
48	NBB	CB	10,09	16	CBK	CB	0,64	30
49	UAB	CB	8,33	37	ASBB	CB	0,42	47
50	ABK	CB	7,07	33	ALINMA	IB	0,00	14
51	ALINMA	IB	6,67	14	NBB	CB	0,00	16
52	BBK	CB	5,23	10	MASB	CB	0,00	44
53	GBK	CB	3,61	4	ABK	CB	0,00	33

Notes : All banks ranked by IN and OUT links, with market capitalization ranking (MC ranking) in 2017.

Table 2.11: All banks ranked by IN and OUT links post 2008 crisis

Rank	Banks	Type of Banks	IN-Links	MC Rank	Banks	Type of Banks	OUT-Links	MC Rank
1	DB	CB	43,91	36	ADCB	CB	74,68	45
2	ADCB	CB	37,38	45	NBF	CB	70,10	28
3	ABG	IB	37,33	49	DIB	IB	69,72	12
4	BURG	CB	31,75	31	DB	CB	68,82	36
5	SFG	CB	31,16	7	CBQ	CB	55,35	24
6	DIB I	B	29,56	12	GBK	CB	50,52	4
7	CBQ	CB	27,66	24	BSF	CB	39,05	11
8	RJHI	IB	27,26	3	GFH	IB	37,90	38
9	QISB	IB	27,20	15	BURG	CB	37,62	31
10	ANB	CB	25,89	9	ANB	CB	36,99	9
11	BSF	CB	25,63	11	QISB	IB	35,86	15
12	RB	CB	24,19	5	KIBK	IB	32,52	46
13	NBF	CB	23,49	28	ABG	IB	31,67	49
14	AJBK	IB	22,51	48	RAKBANK	CB	27,89	22
15	GBK	CB	21,75	4	SFG	CB	25,98	7
16	SABB	CB	21,71	23	BOUK	IB	23,57	20
17	NBQ	CB	21,64	41	INVESTB	CB	19,79	6
18	Ithmaar	IB	21,38	52	ASBB	CB	18,59	47
19	ADIB	IB	21,31	19	BOS	CB	17,76	50
20	SIB	IB	20,21	42	CBI	CB	15,17	2
21	BISB	IB	20,21	51	Ithmaar	IB	15,01	52
22	BOUK	IB	19,65	13	BISB	IB	14,46	51
23	QNB	CB	18,99	39	KHCB	IB	13,51	53
24	KFH	IB	18,93	8	RJHI	IB	12,30	3
25	INVESTB	CB	18,70	6	FAB	CB	8,34	34
26	ALBI	IB	17,99	18	ENBD	CB	7,97	1
27	CBI	CB	17,69	2	SABB	CB	7,17	23
28	KIBK	IB	17,32	46	UAB	CB	7,15	37
29	GFH	IB	17,27	38	KCBK	CB	6,83	30
30	FAB	CB	16,25	34	QNB	CB	6,24	39
31	BOS	CB	16,01	50	MAR	IB	6,07	13
32	RAKBANK	CB	15,69	22	NBQ	CB	6,03	41
33	ABC	CB	14,77	40	ALBI	IB	5,92	18
34	MAR	CB	14,62	13	KFH	IB	5,43	8
35	SAIB	CB	14,47	27	NBK	CB	4,77	29
36	NBK	CB	13,41	28	AUB	CB	3,72	43
37	ALINMA	IB	11,55	14	MASB	CB	3,64	44
38	KCBK	CB	11,36	30	RB	CB	3,48	5
39	BJAZ	IB	11,12	35	SIB	IB	3,20	42
40	ENBD	CB	11,06	1	AJBK	IB	2,70	48
41	MASB	CB	9,36	44	BJAZ	IB	2,28	35
42	ABK	CB	8,81	33	CBD	CB	1,72	17
43	QIIB	IB	8,63	25	ADIB	IB	1,14	19
44	ABQ	CB	8,08	21	QIIB	IB	0,91	25
45	BBK	CB	8,02	10	ABC	CB	0,88	40
46	ASBB	CB	7,43	47	AUBKuwait	CB	0,77	26
47	CBD	CB	7,10	17	ABQ	CB	0,71	21
48	KHCB	IB	7,10	53	BBK	CB	0,25	10
49	AUBKuwait	CB	7,05	26	CBK	CB	0,14	30
50	AUB	CB	5,65	43	SAIB	CB	0,08	27
51	UAB	CB	2,39	37	ABK	CB	0,07	33
52	NBB	CB	1,55	16	ALINMA	IB	0,00	14
53	CBK	CB	1,29	32	NBB	CB	0,00	16

Notes : All banks ranked by IN and OUT links, with market capitalization ranking (MC ranking) in 2017.

Table 2.12: The classification of banks by the SRR and SRE indices, with the market capitalization ranking (MC rank) from 2007 à 2017

Rank	Banks	Type of banks	Systemic Risk receivers SRR	Rank MC	Banks	Type of banks	ranks the risk emitters SRE	Rank MC
1	RJHI	IB	7.45E+13	3	CBI	CB	4.74E+13	2
2	ANB	CB	4.49E+13	9	ENBD	CB	4.67E+13	1
3	ENBD	CB	3.60E+13	1	ANB	CB	4.66E+13	9
4	SFG	CB	3.29E+13	7	SFG	CB	4.39E+13	7
5	BSF	CB	2.86E+13	11	DIB	IB	4.12E+13	12
6	CBI	CB	2.53E+13	2	RJHI	IB	3.70E+13	3
7	DIB	IB	2.17E+13	12	BSF	CB	3.28E+13	11
8	RB	CB	1.92E+13	5	INVESTB	CB	1.95E+13	6
9	INVESTB	CB	1.88E+13	6	GBK	CB	1.55E+13	4
10	QISB	CB	1,061E+13	15	QISB	IB	1,36E+13	15
11	KFH	IB	9,97E+12	8	ALINMA	IB	1,28E+13	14
12	MAR	IB	9,83E+12	13	MAR	IB	1,01E+13	13
13	GBK	CB	8,63E+12	4	ALBI	IB	8,76E+12	18
14	SABB	CB	8,21E+12	23	CBQ	CB	7,66E+12	2
15	ALINMA	IB	8,12E+12	14	BJAZ	IB	5,991E+12	35
16	ALBI	IB	7,95E+12	18	SABB	CB	5,91E+12	23
17	SAIB	CB	6,27E+12	27	DB	CB	4,90E+12	36
18	BJAZ	IB	5,60E+12	35	NBF	CB	4,53E+12	28
19	BOUK	IB	5,28E+12	20	SAIB	CB	4,50E+12	27
20	CBQ	CB	5,19E+12	24	RAKBANK	CB	4,16E+12	22
21	DB	CB	4,48E+12	36	GFH	IB	4,11E+12	38
22	ADIB	IB	4,32E+12	19	ADIB	IB	3,67E+12	19
23	ABQ	CB	4,22E+12	21	KFH	IB	3,64E+12	8
24	BBK	CB	4,08E+12	10	RB	CB	3,23E+12	5
25	RAKBANK	CB	3,58E+12	22	BOUK	IB	3,02E+12	20
26	QHIB	IB	3,55E+12	25	NBQ	CB	2,85E+12	41
27	GFH	IB	3,50E+12	38	BURG	CB	2,42E+12	31
28	CBD	CB	3,42E+12	17	UAB	CB	2,39E+12	37
29	KCBK	CB	3,32E+12	30	ADCB	CB	2,36E+12	45
30	BURG	CB	3,28E+12	31	ASBB	IB	2,20E+12	47
31	ADCB	CB	3,08E+12	45	SIB	IB	1,88E+12	42
32	UAB	CB	3,00E+12	37	QHIB	IB	1,52E+12	25
33	FAB	CB	2,59E+12	34	AUBKuwait	CB	1,32E+12	26
34	SIB	IB	2,36E+12	42	Ithmaar	IB	1,196E+12	52
35	NBQ	CB	2,35E+12	41	FAB	CB	9,62E+11	34
36	QNB	CB	2,32E+12	39	KIBK	IB	7,67E+11	46
37	ABC	CB	2,32E+12	40	ABG	IB	7,42E+11	49
38	AUBKuwait	CB	1,94E+12	26	QNB	CB	7,14E+11	39
39	CBK	CB	1,52E+12	32	CBD	CB	6,97E+11	17
40	ABK	CB	1,43E+12	33	NBK	CB	6,75E+11	29
41	NBF	CB	1,41E+12	28	ABQ	CB	6,27E+11	21
42	NBK	CB	1,37E+12	29	BBK	CB	6,06E+11	10
43	ASBB	IB	1,08E+12	47	KCBK	CB	5,76E+11	30
44	NBB	CB	1,02E+12	16	AJBK	IB	5,60E+11	48
45	KIBK	IB	1,01E+12	46	KHCB	IB	3,59E+11	53
46	AJBK	IB	7,90E+11	48	ABC	CB	2,99E+11	40
47	AUB	CB	7,80E+11	43	MASB	CB	2,88E+11	44
48	MASB	CB	5,66E+11	44	BOS	CB	2,24E+11	50
49	ABG	IB	4,84E+11	49	BISB	IB	1,98E+11	51
50	Ithmaar	IB	4,63E+11	52	CBK	CB	1,71E+11	32
51	BISB	IB	3,24E+11	51	NBB	CB	8,68E+10	16
52	KHCB	IB	3,00E+11	53	AUB	CB	3,04E+10	43
53	BOS	CB	3,00E+11	50	ABK	CB	7,84E+09	33

Notes : The classification of banks by the SRR and SRE indices, with the market capitalization ranking (MC rank).

Table 2.13: The classification of banks by the SRR and SRE indices, with the market capitalization ranking (MC rank) during the 2008 crisis

Rank	Banks	Type of banks	Systemic Risk receivers SRR	Rank MC	Banks	Type of banks	ranks the risk emitters SRE	Rank MC
1	RJHI	IB	3,03E+13	3	RJHI	IB	3,05E+13	3
2	ANB	CB	2,48E+13	9	ANB	CB	2,92E+13	9
3	ENBD	CB	1,03E+13	1	CBI	CB	1,77E+13	2
4	SFG	CB	9,81E+12	7	DIB	CB	1,17E+13	12
5	CBI	CB	8,65E+12	2	INVESTB	CB	8,59E+12	6
6	BSF	CB	8,43E+12	11	QISB	IB	5,64E+12	15
7	INVESTB	CB	5,45E+12	6	ENBD	CB	5,17E+12	1
8	ALBI	IB	3,67E+12	18	GBK	CB	4,18E+12	4
9	KFH	IB	3,60E+12	8	CBQ	CB	3,82E+12	24
10	QISB	IB	2,75E+12	15	SAIB	CB	3,68E+12	27
11	DIB	IB	2,64E+12	12	BSF	CB	3,16E+12	7
12	CBQ	CB	2,54E+12	24	SFG	CB	2,42E+12	11
13	RB	CB	2,35E+12	5	KFH	IB	2,14E+12	8
14	SAIB	CB	2,31E+12	27	RAKBANK	CB	2,13E+12	22
15	DB	CB	2,21E+12	36	BOUK	IB	1,84E+12	20
16	BJAZ	IB	2,169E+12	35	DB	CB	1,67E+12	36
17	ADIB	IB	1,50E+12	19	ALBI	IB	1,38E+12	18
18	RAKBANK	CB	1,46E+12	22	SABB	CB	1,20E+12	23
19	BOUK	IB	1,29E+12	20	GFH	IB	1,05E+12	38
20	NBQ	CB	1,20E+12	41	QIIB	IB	9,14E+11	25
21	SABB	CB	1,13E+12	23	RB	CB	8,60E+11	5
22	QIIB	IB	1,13E+12	25	BJAZ	IB	6,43E+11	35
23	GBK	CB	1,11E+12	4	FAB	CB	6,40E+11	31
24	MAR	IB	1,05E+12	13	QNB	CB	6,01E+11	39
25	ABC	CB	9,97E+11	40	SIB	IB	5,98E+11	42
26	QNB	CB	9,06E+11	39	NBK	CB	5,26E+11	29
27	GFH	IB	8,66E+11	38	AUBKuwait	CB	3,69E+11	26
28	BURG	CB	7,53E+11	31	AJBK	IB	3,51E+11	48
29	NBK	CB	7,46E+11	29	BBK	CB	3,30E+11	10
30	ABQ	CB	7,36E+11	21	FAB	CB	2,90E+11	34
31	AUBKuwait	CB	7,04E+11	26	KCBK	CB	2,43E+11	30
32	SIB	IB	6,68E+11	42	MAR	IB	2,42E+11	13
33	FAB	CB	6,52E+11	34	ABC	CB	1,98E+11	40
34	KIBK	IB	6,51E+11	46	ADCB	CB	1,8465E+11	45
35	ALINMA	IB	6,42E+11	14	KIBK	IB	1,76E+11	46
36	KCBK	CB	5,97E+11	30	BOS	CB	1,39E+11	50
37	NBF	CB	5,85E+11	28	ADIB	CB	1,12477E+11	19
38	ADCB	CB	5,576E+11	45	NBF	CB	9,89E+10	28
39	ABK	CB	5,57E+11	33	NBQ	CB	9,016E+10	41
40	NBB	CB	5,05E+11	16	CBD	CB	6,35E+10	17
41	BBK	CB	4,13E+11	10	KHCB	CB	3,03E+10	53
42	CBD	CB	2,54E+11	17	ABQ	CB	2,61E+10	21
43	ASBB	IB	1,89E+11	47	ABG	IB	1,55E+10	49
44	KHCB	CB	1,86E+11	53	BISB	IB	1,24 E+10	51
45	BOS	CB	1,64E+11	50	UAB	CB	1,22 E+10	37
46	ABG	IB	1,59E+11	49	AUB	CB	1,192 E+10	43
47	CBK	CB	1,56E+11	32	Ithmaar	IB	8,92E+09	52
48	AUB	CB	1,41E+11	43	ASBB	IB	4,74E+09	47
49	MASB	CB	1,32E+11	44	CBK	CB	2,03E+09	32
50	Ithmaar	IB	1,29E+11	52	ALINMA	CB	0,00E+00	14
51	UAB	CB	8,21E+10	37	NBB	CB	0,00E+00	16
52	AJBK	IB	5,89E+110	48	MASB	CB	0,00E+00	44
53	BISB	IB	3,59 E+10	51	ABK	CB	0,00E+00	33

Notes : The classification of banks by the SRR and SRE indices, with the market capitalization ranking (MC rank).

Table 2.14: The classification of banks by the SRR and SRE indices, with the market capitalization ranking (MC rank) post 2008 crisis

Rank	Banks	Type of banks	Systemic Risk receivers SRR	Rank MC	Banks	Type of banks	ranks the risk emitters SRE	Rank MC
1	RJHI	IB	1,68E+13	3	BSF	CB	1,01E+13	7
2	ANB	CB	8,66E+12	9	GBK	CB	9,86E+12	4
3	CBI	CB	6,91E+12	2	SFG	CB	9,33E+12	11
4	SFG	CB	6,81E+12	11	ANB	CB	9,31E+12	9
5	RB	CB	6,07E+12	5	CBI	CB	7,45E+12	2
6	BSF	CB	5,62E+12	7	RJHI	IB	4,75E+12	3
7	INVESTB	CB	2,47E+12	6	DIB	IB	3,44E+12	12
8	ALINMA	IB	2,23E+12	14	INVESTB	CB	3,10E+12	6
9	BBK	CB	1,81E+12	10	CBQ	CB	2,37E+12	24
10	SABB	CB	1,71E+12	23	ENBD	CB	2,30E+12	1
11	DB	CB	1,44E+12	36	DB	CB	2,07E+12	36
12	KFH	IB	1,43E+12	8	RB	CB	1,82E+12	5
13	MAR	IB	1,35E+12	13	MAR	IB	1,39E+12	13
14	BURG	CB	1,16E+12	31	NBF	CB	1,37E+12	28
15	GBK	CB	1,09E+12	4	RAKBANK	CB	1,36E+12	22
16	BOUK	IB	1,06E+12	20	QISB	CB	1,19E+12	15
17	QISB	IB	9,50E+11	15	BURG	CB	1,11E+12	31
18	ADIB	IB	9,11E+11	19	BOUK	IB	1,10E+12	20
19	ENBD	CB	9,08E+11	1	ADCB	CB	8,65E+11	45
20	SAIB	CB	8,84E+11	27	GFH	IB	7,38E+11	38
21	CBQ	CB	8,24E+11	24	FAB	CB	6,30E+11	34
22	ALBI	IB	7,52E+11	18	KIBK	IB	4,82E+11	46
23	ADCB	CB	7,51E+11	45	SABB	CB	3,86E+11	23
24	DIB	IB	5,85E+11	12	KFH	IB	2,78E+11	8
25	RAKBANK	CB	4,42E+11	22	ABG	IB	2,73E+11	49
26	GFH	IB	4,14E+11	38	ASBB	IB	2,23E+11	47
27	BJAZ	IB	3,45E+11	35	BBK	CB	2,01E+11	10
28	NBF	CB	3,41E+11	28	KCBK	CB	1,32E+11	30
29	NBQ	CB	3,40E+11	41	NBQ	CB	1,15E+11	41
30	QHIB	IB	3,14E+11	25	KHCB	CB	8,70E+10	53
31	KCBK	CB	3,09E+11	30	NBK	CB	8,68E+10	29
32	ABK	CB	2,77E+11	33	QNB	CB	8,51E+10	39
33	QNB	CB	2,62E+11	39	MASB	CB	7,30E+10	44
34	SIB	IB	2,54E+11	42	Ithmaar	IB	7,20E+10	52
35	ABC	CB	2,44E+11	40	BJAZ	IB	6,36E+10	35
36	NBB	CB	2,08E+11	16	BOS	CB	5,89E+10	50
37	ABG	CB	1,78E+11	49	UAB	CB	4,78E+10	37
38	ABQ	CB	1,78E+11	21	ALBI	IB	4,47E+10	18
39	AJBK	IB	1,60E+11	48	SIB	IB	3,60E+10	42
40	FAB	CB	1,54E+11	34	AUBKuwait	CB	2,80E+10	26
41	CBD	CB	1,35E+11	17	ADIB	IB	2,77E+10	19
42	NBK	CB	1,34E+11	29	QHIB	IB	2,65E+10	25
43	Ithmaar	IB	1,30E+11	52	ABQ	CB	2,25E+10	21
44	KIBK	IB	1,08E+11	46	AJBK	IB	2,14E+10	48
45	AUBKuwait	CB	1,04E+11	26	BISB	IB	1,90E+10	51
46	BOS	CB	8,06E+10	50	ABC	CB	1,90E+10	40
47	ASBB	IB	6,96E+10	47	CBD	CB	1,60E+10	17
48	BISB	IB	5,28E+10	51	AUB	CB	7,15E+09	43
49	AUB	CB	4,09E+10	43	SAIB	CB	1,64E+09	27
50	MASB	CB	3,75E+10	44	ABK	CB	5,57E+08	33
51	KHCB	CB	3,37E+10	53	CBK	CB	3,29E+08	32
52	UAB	CB	3,10E+10	37	ALINMA	IB	0,00E+00	14
53	CBK	CB	9,21E+09	32	NBB	CB	0,00E+00	16

Notes : The classification of banks by the SRR and SRE indices, with the market capitalization ranking (MC rank).

Bearish Vs Bullish risk network: a Eurozone financial system analysis

Abstract

This paper¹ studies the extreme risk spillover between 183 Eurozone financial institutions (such as banks, insurances, diversified financial, real estate firms) over the period 2005–2020. Employing the Granger causality test across quantiles, we are able to investigate the tail risk interdependence between financial firms under extreme (downside and upside) conditions. Thanks to this framework, we can understand and estimate the risk spillover effect, in different propagation mechanisms, during bad and good conditions. Our findings show a heterogeneous effect between risk spillovers depending on the level of risk considered, highlighting how bearish conditions play an important role in the sectoral propagation of risk spillover. We document the presence of "shift-contagion" effect. Finally, we investigate the risk-monetary policy nexus. Our findings provide new insights into the impact of the monetary stance on financial stability, documenting the double strategy played by the European Central Bank, namely the "leaning against the wind" and the "modified Jackson Hole consensus" approach.

Keywords: Extreme risk spillover; Eurozone financial firms; Financial connectedness; Systemic risk; Monetary policy

JEL Classification: C32; G10; G20; E52

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3.1 Introduction

Mapping the interdependencies of financial actors has become a widely studied field of research in recent years. The financial crises (US and Eurozone), the various political events (such as the Brexit), and the COVID-19 pandemic, have shown how the connection between financial institutions plays a fundamental role in shock transmission. In fact, high connectivity among firms contributes to the rapid spread of risks within the system, resulting in financial instability (Battiston et al., 2016; Abad et al., 2017; Daly et al., 2019). High uncertainty in financial markets has highlighted the need to implement measures to accurately assess the systemic importance of institutions, the stability of the financial system and to develop effective macroprudential policies to limit the extent of contagion and systemic risk (Rizwan, 2021). Recently several measurements have been developed to quantify the contagion risk of financial institutions. For example, Tobias and Brunnermeier (2016) proposed the conditional value-at-risk (CoVaR), while Acharya et al. (2012) developed the marginal expected shortfall (MES), also, Brownlees and Engle (2017) designed the conditional capital shortfall index (SRISK)².

Nevertheless, a purely quantitative analysis often does not reflect the real complexity of the contagion risk, leading to a partial estimate of the probability of default. A different approach, explicitly oriented towards estimating the interrelationships between all institutions, is based on network models (Nier et al., 2007). A network approach for financial systems is a powerful tool for understanding financial markets (interconnectedness) to assess risks and stability measures. More generally, it is known that market prices are formed by complex mechanisms of interactions that often reflect speculative behaviour rather than by the fundamentals of the companies to which they refer. Models based only on market data may reflect “partial” components that could lead to a biased estimation of systemic risk (Giudici and Parisi, 2018; Brogi et al., 2021). This weakness suggests that models should also be enriched by considering the structure of the financial system as a whole. For this purpose, recent studies have proposed network connected-

²See Bongini and Nieri (2014) and Silva et al. (2017) for a review of systemic risk (contagion) measures.

ness frameworks, e.g., the Granger connectedness causality network model of Billio et al. (2012), the connectedness spillover network framework proposed by Diebold and Yilmaz (2012, 2014a), the time-varying systemic risk contributions of Betz et al. (2016), and the tail-event driven network (TENET) model of Härdle et al. (2016). More recently, Wang et al. (2017) built, using the Granger causality risk model (Hong et al., 2009), extreme dynamic tail risk networks to investigate the interconnectedness and systemic risk of financial institutions. Chen et al. (2019) extended the TENET to tail event-driven network quantile regression (TENQR) model, which addresses the interdependence, risk propagation and systemic importance of financial institutions. Further, Wang et al. (2021a) developed the multilayer information spillover networks, which include return, volatility and extreme risk spillover layers in the variance decomposition model.

However, these models allow to understand and estimate the risk spillover effect, but not to deal with the measurement of different propagation mechanisms, during bad and good conditions. Here, different from these works, we investigate the tail risk interdependence between financial firms under extreme (downside and upside) conditions. In this paper, we follow Li et al. (2020) and apply a novel framework to study the (downside and upside) risk spillovers between Eurozone financial firms based on the Granger causality risk model of Candelon and Tokpavi (2016). We aim to measure the risk spillovers between financial institutions in bearish and bullish market conditions, to have a more deeply picture of the potential contagion within the financial actors. Thanks to this model, we can understand and estimate the risk spillover effect, in different propagation mechanisms, during different market conditions.

The contribution of our research is fourfold. First, we develop an approach that constructs different types of spillover networks to estimate the risk spillovers in specific cases. Many studies analyzed the risk spillover between financial institutions (Billio et al., 2012; Diebold and Yilmaz, 2012, 2014a; Hautsch et al., 2015; Härdle et al., 2016; Kleinow and Moreira, 2016; Wang et al., 2018a; Bongini et al., 2018; Demirer et al., 2018; Barigozzi and Brownlees, 2019; Fang et al., 2019; Foglia and Angelini, 2020b), however, a not “market-specific condition” analysis can mask the heterogeneity that can

be observed when considering distinct cases. Indeed, we consider two cases, i.e., the left tail (a downturn or crisis period), and the right tail (an upswing period) of the distributions of the institutions' stock returns. This allows us to better understand the dynamics within financial firms depending on the type of market conditions, i.e. bearish or bullish. Second, our dataset is composed of 183 listed financial institutions, located in 10 countries: Austria, Belgium, France, Germany, Greece, Ireland, Italy, the Netherlands, Portugal, and Spain. To the best of our knowledge, it is the first research using such a large sample of financial firms in the Eurozone context. Hence, we are able to investigate the risk contagion of a large part of the financial system. Third, we contribute to the small but growing literature on the study of risk spillovers (contagion) among the different operators of the European financial system (Billio et al., 2013; Abad et al., 2017; Foglia and Angelini, 2020b; Fong et al., 2021). We contribute to the relevant literature by profoundly examining the risk spillovers between different type of Eurozone financial institutions (such as banks, insurances, diversified financial and real estate firms). This allows us to build a complete picture of risk spillovers in the financial industry. Fourth, we contribute to the literature that investigates the risk-monetary policy nexus (Roache and Rousset, 2013; Altunbasa et al., 2014; Colletaz et al., 2018; Faia and Karau, 2019; Foglia and Angelini, 2019; Kabundi and De Simone, 2020; Jin and De Simone, 2020; Rizwan, 2021). Our findings provide new insights into the impact of the monetary stance on financial stability, documenting the double strategy played by the European Central Bank (ECB), i.e., the "leaning against the wind" and the "modified Jackson Hole consensus" approach.

3.2 Literature review

The structures of financial networks are a determining factor in the propagation of systemic events. The literature aims to provide answers that make it possible to understand and prevent the various origins of systemic risk. The existing literature can be classified into two broad approaches in measuring systemic risk. The first approach mea-

asures the contribution to systemic risk by conditional tail dependence in a uni-variate framework (Acharya et al., 2017; Tobias and Brunnermeier, 2016; Brownlees and Engle, 2017). Hence, these models are unable to consider the network dimension structuring the interconnections between financial institutions (Giudici and Parisi, 2018; Chabot and Bertrand, 2019; Brogi et al., 2021).

To this end, a second stream of literature has focused on interconnections as a potential source of systemic risk and contagion (Billio et al., 2012; Diebold and Yılmaz, 2014a; Härdle et al., 2016; Wang et al., 2017; Brunetti et al., 2019; Hué et al., 2019; Torri et al., 2021; Wang et al., 2021a). For this purpose, several econometric models have been suggested. For example, Diebold and Yılmaz (2014a), Demirer et al. (2018) and Su (2020) proposed the volatility propagation index. These frameworks make it possible to statically and dynamically capture the changes in connectivity reflected by the sensitivity of stock prices to shocks (exogenous or endogenous). Other works, use Granger's causality method. By Granger linear causality tests, Billio et al. (2012) constructed a causal network, which traces the directions of causal relationships between different actors in the financial system.

In particular, some of the literature has focused on tail risk as a measure of systemic risk. The models that have been developed on this topic have focused on extreme movements in the tail distribution. Indeed, these approaches seek to capture systemic interconnections through the simultaneous presence of a tail event (Hong et al., 2009; Hautsch et al., 2015; Härdle et al., 2016; Kleinow and Moreira, 2016; Wang et al., 2017; Nguyen and Lambe, 2021). For example, Hong et al. (2009) suggested a tail Granger causality test. This one focused on tail behavior to detect the effects of the tail. Candelon and Tokpavi (2016) extended the model Hong et al. (2009), proposing a multivariate Granger risk framework. This design allows checking the Granger causality based on the tail events on full distribution (left, center and right). Moreover, in order to maximize the information content resulting from the network structure, many authors have sought to extend or combine the several econometric methods (Härdle et al., 2016; Candelon and Tokpavi, 2016; Brunetti et al., 2019; Su, 2020; Torri et al., 2021; Wang et al., 2021a). By

considering the network dimension, Härdle et al. (2016) extend the CoVaR^{*ij*} model of Tobias and Brunnermeier (2016). The merit of this model is that it can take into account all the interconnections, which arise as a result of the tail changes of one firm conditioned by the tail changes of the other firms belonging to the same network. Wang et al. (2017) used the Granger causality in risk (Hong et al., 2009) to study the directional risk connectivity of different financial actors and showed that spillover was transmitted from the real estate and banking sector to the insurance and financial services sector. Hué et al. (2019) proposed an approach that combines the pairwise Granger causality approach with the leave-one-out concept to measure systemic risk. In addition, and to measure volatility spillover effects, Su (2020) extended the volatility spillover index suggested by Diebold and Yilmaz (2009) by a quantile decomposition of the variance. By quantile regression of the least absolute selection and shrinkage operator (LASSO), Nguyen and Lambe (2021) constructed a comprehensive network that describes directional tail risk spillovers. Finally, by a multi-layer spillover network, Wang et al. (2021a) have highlighted the usefulness of multi-layer networks to study the different spillover channels at the system and individual firms-level.

The literature on the European financial network is increasingly developing. Among the first attempts to study risk spillover effects are Foglia and Angelini (2020b), which have shown that risk spillover dynamics become strong during crisis periods in the euro area. Similarly, Torri et al. (2021) have found strong interconnectivity in the structures of the European banking sector’s conditional tail risk networks. Brunetti et al. (2019) studied two network structures of European interbank markets. By constructing physical networks based on interbank transactions and correlation networks based on stock returns, they found that the former can only predict liquidity problems. At the same time, the latter can predict systemic risk. Dreassi et al. (2018) analysed the credit risk spillover between the banking and insurance sectors. Their results suggest that the asset-holding and the guarantee are the main risk transmission for the insurance sector, while the additional collateral for the banking sector. Furthermore, Paltalidis et al. (2015) have suggested that the European banking structure is highly interconnected, facilitat-

ing financial contagion. Recently, Borri and Di Giorgio (2021) analyzed the systemic risk contribution for large listed European banks. They found that the larger banks contribute more to financial contagion. Moreover, their results showed that during the COVID-19 shock, sovereign default risks influenced the systemic risk of all European banks.

However, these works on financial actors in the euro area did not take into account market conditions separately. Indeed, a global analysis of the propagation of extreme risk without distinguishing the tail level does not allow us to know who influences the directionality of the extreme event more. Stock market returns are jointly influenced by extreme events, suggesting the importance of distinguishing tail levels (Hong et al., 2009). In addition, market conditions can be related to either the left end of the return distribution, which occurs during downturns (left tail) or the right end during economic recoveries (right tail). Including both tail ends in the analysis makes it possible to detect the unobserved heterogeneity that determines the spillovers of extreme risk. In this sense, by distinguishing between the left and right tails of stock return distributions, one could test whether spillover effects are captured primarily by bearish or bullish market conditions. Therefore, our work, catching the tail risk spillover of full distribution, can help predict financial crises as suggested by Brunetti et al. (2019), i.e. stock networks predict systemic risk.

3.3 Methodology

Our method aims to estimate the risk spillover between Eurozone financial firms in bearish (downside), and bullish (upside) market conditions. For this purpose, we follow the approach of Li et al. (2020). First, we estimate the risk spillover between two institutions by Granger’s causality test in risk (Candelon and Tokpavi, 2016). Second, we build the three types of spillover networks and compute the network-based spillover indicators.

3.3.1 Granger causality in risk

Hong et al. (2009) introduce the concept of Granger causality in risk, i.e., the co-movement between the left quantiles of two distributions. This model is an extension of general Granger causality test (Granger, 1980). More precisely, Hong et al. (2009) use a kernel-based test to verify whether a significant downside risk in one market will cause a significant downside risk in another market. In other words, the ability to predict the future risk of a variable is improved by adding information about the past risk of the other variables. They define downside risk, a situation where asset returns are below value-at-risk (VaR) at a predefined level α . However, considering Granger causality in the downside risk between two markets only at a particular level of risk seems a restrictive hypothesis. For this reason, Candelson and Tokpavi (2016) extend this method to a multivariate framework, which thus permits the identification of Granger Causality in the full distribution between two time series.

Following Peng et al. (2018), we consider a set $T^{\text{up}} = \{\theta_1^{\text{up}}, \dots, \theta_{m+1}^{\text{up}}\}$ of $m+1$ quantiles that covers the right-tail regions on the distribution support with $0 \leq \theta_1^{\text{up}} < \dots < \theta_{m+1}^{\text{up}} \leq 1$. Now, we divide the distribution support of return series r_{it} into m disjoint regions and we specify the upside VaR such as $Q_{it}(\theta_1^{\text{up}}|F_{i,t-1}) < \dots < Q_{it}(\theta_{m+1}^{\text{up}}|F_{i,t-1})$. Now let $H_{it}^{\text{up}} = (Z_{it,1}^{\text{up}}, \dots, Z_{it,m}^{\text{up}})'$ be the vector, where

$$Z_{it,k}^{\text{up}} = \begin{cases} 1 & \text{if } Q_{it}(\theta_k^{\text{up}}) \leq r_{it} < Q_{it}(\theta_{k+1}^{\text{up}}) \\ 0 & \text{else} \end{cases} \quad (3.1)$$

For $k = 1, \dots, m$, H_{it}^{up} has the information of upside risk. The same steps regard the downside risk. Therefore, we have $H_{it}^{\text{down}} = (Z_{it,1}^{\text{down}}, \dots, Z_{it,m}^{\text{down}})'$. In order to study the upside and the downside relationship between financial institutions, the null hypothesis of Granger causality in distribution is given by:

$$H_0 : E(H_{i,t}^{\text{up(down)}} | F_{i,t-1}^{\text{up(down)}}, F_{j,t-1}^{\text{up(down)}}) = E(H_{i,t}^{\text{up(down)}} | F_{i,t-1}^{\text{up(down)}}) \quad (3.2)$$

where $F_{j,t-1}^{\text{up(down)}}$ and $F_{i,t-1}^{\text{up(down)}}$ are the information set available of upside (downside) risk at time $t - 1$, for firms i and j . If H_0 is rejected, it means that the upside (downside) risk spillover exists, i.e., the upside (downside) risk of firm j can be used to forecast the upside (downside) risk of firm i . In this paper, we examine two types of causality: i) the down-to-down ($T^{\text{down}} = \{0, 1\%, 5\%, 10\%\}$), and ii) the upside-to-upside ($T^{\text{up}} = \{90\%, 95\%, 99\%, 100\%\}$).

According to Hong et al. (2009), it is particularly important to monitor extreme (downside or upside) risk spillovers between financial institutions when markets are positively correlated and suffer from the same global shock (e.g., the COVID-19 outbreak). Using the Granger causality test in risk, defined as the predictive capacity of one market to forecast other ones, we are able to predict the effects of risk, and we can provide information for capital allocation decisions, investments, and thus regulation, particularly crucial in this sector.

3.3.2 Bearish-Bullish risk spillover network

Let $G(V, E)$ be a network of extreme risk spillovers (downside-to-downside; upside-to-upside), where $V = \{1, 2, \dots, N\}$ is the set of nodes and E is the set of edges. Following Wang et al. (2017), we define a node as a financial institution, and the edge is Granger causality connectivity in risk from one financial institution to another. For example, in the bearish spillover network, a directional edge between two institutions is formed when there is a Granger causality between the downside risk from one institution to the other one. Formally,

$$E_{i \rightarrow j} = \begin{cases} 1, & \text{if } i \text{ Granger causes risk to } j \\ 0, & \text{otherwise} \end{cases} \quad (3.3)$$

By using rolling windows procedure, we build networks that vary over time to in-

investigate the dynamic interconnection between financial institutions. According to Yan et al. (2015) and Wang et al. (2017), we set the time period width L and step size σ to 250 and 20 trading days, respectively.

Following Billio et al. (2012), we build connectivity measures to identify the degree of risk and connectivity between banks. We calculate the total connection spillover (TCS) index as follows:

$$\text{TCS} = \frac{1}{N(N-1)} \sum_{i=1}^N \sum_{j \neq i} E_{i \rightarrow j} \quad (3.4)$$

The TCS index indicates the degree level of interconnection of the financial system. Therefore, a higher TCS value suggests that the financial system is highly interconnected.

Moreover, following Wang et al. (2017), we calculate the strength of the cross-sector (SCS) index. This measure is able to capture the cross-sector risk spillover, which is defined as follows:

$$\text{SCS}_{m \rightarrow n} = \frac{1}{N_m N_n} \sum_{i=1}^{N_m} \sum_{j=1}^{N_n} E_{i \rightarrow j} \quad (3.5)$$

where N_m and N_n is the number of financial institutions belonging to m and n financial sectors. When $m = n$, this implies $N_n = N_m - 1$.

Following Kenett et al. (2010), we compute the relative influence (RI) of sector m as the ratio between the difference and the sum of out-degree ($k_{\text{out}}(m)$) and in-degree ($k_{\text{in}}(m)$):³

$$\text{RI}_{\text{sector}}(m) = \frac{k_{\text{out}}(m) - k_{\text{in}}(m)}{k_{\text{out}}(m) + k_{\text{in}}(m)} \quad (3.6)$$

³The out-degree of financial institution sector m is the number of outgoing edges from sector m to other sectors. The in-degree of financial institution sector m is the number of incoming edges from other sectors to sector m .

where $RI_{\text{sector}} \in [-1 : 1]$. The index measures the degree of risk spillover from one sector to the other one. A negative value indicates that the sector in question receives more extreme risk than it emits.

3.4 Data

Our empirical study focuses on Eurozone financial system. Following Wang et al. (2017) and Foglia and Angelini (2020b), we divide the financial institutions into three groups according to global industry classification standard (GICS): 40 - Financial. In particular, we select three types of financial institutions, (1) banks, (2) insurance firms, and (3) others financial institutions (which include diversified financial and real estate companies). The sample is composed of 183 financial institutions, grouped as follows: 58 Banks, 19 Insurers and 106 Others, located in 10 countries: Austria, Belgium, France, Germany, Greece, Ireland, Italy, the Netherlands, Portugal, and Spain. To our knowledge, this is the first research using such a large sample of financial institutions in the Eurozone context. Table 3.1 shows the list of financial institutions included. We collect the daily stock prices of our sample from Datastream. The period spans from 1 August 2005 to 31 December 2020 (including 4024 observations). Finally, we compute the daily stock returns of each financial firm as $r_{i,t} = \ln P_{i,t} - \ln P_{i,t-1}$, where $P_{i,t}$ is the closing price of firm i at daily t .

3.5 Empirical results

In this section, we present the results of our empirical analysis. We estimate tail risk spillovers in relation to market conditions. Specifically, we differentiate the tail event across two distinct periods. These are a quiet period (bullish cases) and a crisis period (bearish cases) in the tail distribution of returns. We apply the model of Candelon and Tokpavi (2016), which relies on Granger causality tests between quantiles in the distribution.

The model of Candelon and Tokpavi (2016), estimates causality in the distribution

Table 3.1: List of sample firms

Number	Firms	Country	Number	Firms	Country
	Banks			Others	
1	RAIFFEISEN	Austria	92	COURBET	France
2	OBERBANK	Austria	93	BOURSE DIRECT	France
3	BANK FUR TIROL UND VBG.	Austria	94	EUROLAND CORPORATE	France
4	BKS BANK	Austria	95	COFIN.DE L AFR.DE L OUEST AFCN.	France
5	VOLKSBANK VBG.PARTN. (~US)	Austria	96	SC.FONFNC.ET DE PARTS.	France
6	ERSTE GROUP BANK	Austria	97	VERNEUIL FINANCE	France
7	KBC GROUP	Belgium	98	ADVENIS	France
8	BANQUE NATIONALE DE BELGIQUE	Belgium	99	ABC ARBITRAGE	France
9	CRCAM DE NORMANDIE SEINE CCI PAR	France	100	UNION FINC.FRANC.	France
10	CREDIT AGRICOLE	France	101	IDSUD	France
11	CRCAM ATLANTIQUE VENDEE	France	102	VIEL ET CIE	France
12	CARDE.CRAG.LRE. HAUTE- LOIRE PAR	France	103	ALTAMIR	France
13	CAISSE REGIONALE CREDIT AGRICOLE MUTUEL	France	104	FORESTIERE EQUATORIALE	France
14	CAISSE REG CRED AGRIC MUT TOURAIN POITOU	France	105	FIPP	France
15	BNP PARIBAS	France	106	EURAZEO	France
16	CR.AGRICOLE MORBIHAN	France	107	WENDEL	France
17	CRCAM NORD CCI	France	108	CAMBODGE (CIE DU)	France
18	CREDIT AGR.TOULOE	France	109	GROUPE IRD	France
19	CARDE.CAMU.APR.PAR	France	110	FAUVET-GIREL	France
20	SOCIETE GENERALE	France	111	LEBON	France
21	CREDIT AGR.ILE DE FRANCE	France	112	ARTOIS INDFIN.DE L'ARTO	France
22	CARDE.CAMU.SRA.	France	113	ROTHSCHILD & CO	France
23	CREDIT FONCIER DE MONACO	France	114	MONCEY FINANCIERE	France
24	NATIXIS	France	115	KONSORTIUM	Germany
25	LOCINDUS SA	France	116	DEUTSCHE BOERSE	Germany
26	UMWELTBANK	Germany	117	BAADER BANK	Germany
27	HOEVELRAT H. AG	Germany	118	MAIER & PARTNER	Germany
28	AAREAL BANK	Germany	119	SHAREHOLDERS VALUE BET.	Germany
29	MERKUR PRIVATBANK	Germany	120	DLB-ANLAGESERVICE	Germany
30	COMMERZBANK	Germany	121	MPC MUENCHMEYER CAP.K	Germany
31	DEUTSCHE BANK	Germany	122	HOR	Germany
32	ATTICA BANK	Greece	123	DNI BETEILIGUNGEN	Germany
33	EUROBANK HOLDINGS	Greece	124	SCHNIGGE CAPITAL MARKETS	Germany
34	PIRAE FINANCIAL HOLDINGS	Greece	125	CLERE N	Germany
35	ALPHA BANK	Greece	126	OEKOWORLD N PREFERENCE	Germany
36	BANK OF GREECE	Greece	127	INSTANT GROUP	Germany
37	NATIONAL BK.OF GREECE	Greece	128	FALKENSTEIN NEBENWERTE	Germany
38	PERMANENT TSB GHG.	Ireland	129	GBK BETEILIGUNGEN	Germany
39	AIB GROUP	Ireland	130	SYRAK HOLDING	Germany
40	BANK OF IRELAND GROUP	Ireland	131	SCHERZER & CO.	Germany
41	BANCA PPO.DI SONDRIO	Italy	132	GRENKE N	Germany
42	BNC.DI DESIO E DELB.	Italy	133	EUWAX	Germany
43	BCA.PICCOLO CDT.VALTCELL	Italy	134	SINO	Germany
44	BPER BANCA	Italy	135	HELIAD EQ.PARTNERS	Germany
45	BANCA MONTE DEI PASCHI	Italy	136	TRADE & VALUE	Germany
46	BANCA PROFILO	Italy	137	RM RHEINER MANAGEMENT	Germany
47	BANCO BPM	Italy	138	NAVIGATOR EQUITY	Germany
48	UNICREDIT	Italy	139	DEUTSCHE BETEILIGUNGS	Germany
49	INTESA SANPAOLO	Italy	140	MLP	Germany
50	BANCA FINNAT EURAMERICA	Italy	141	RED ROCK CAPITAL	Germany
51	CREDITO EMILIANO	Italy	142	EFFECTEN-SPIEGEL	Germany
52	ING GROEP	the Netherlands	143	VALUE-HOLDINGS	Germany
53	VAN LANSCHOT KEMPEN	the Netherlands	144	KST BETEILIGUNGS	Germany
54	BANCO COMR.PORTUGUES 'R'	Portugal	145	SPARTA	Germany
55	BANCO DE SABADELL	Spain	146	BET.IM BALTIKUM	Germany
56	BANCO SANTANDER	Spain	147	FORIS	Germany
57	BANKINTER 'R'	Spain	148	VALUE MANAGEMENT & RESEARCH	Germany
58	BBV.ARGENTARIA	Spain	149	FRITZ NOLS GLB.EQ.SVS.	Germany
	Insurances		150	PEH WERTPAPIER	Germany
59	VIENNA INSURANCE GROUP A	Austria	151	SM WIRTSCHAFTSBERATUNGS	Germany
60	UNIQA INSU GR AG	Austria	152	UCA	Germany
61	AGEAS (EX-FORTIS)	Belgium	153	MWB FAIRTRADE WPHDLSBANK	Germany
62	CNP ASSURANCES	France	154	SINO GERMAN UNITED K	Germany
63	SCOR SE	France	155	SLEEPZ	Germany
64	AXA	France	156	ALLERTHAL-WERKE	Germany
65	CASH LIFE	Germany	157	ADCAPITAL	Germany
66	HANNOVER RUECK	Germany	158	HEIDELBERGER BETEILIGUNGSHOLDING	Germany
67	RHEINLAND HOLDING	Germany	159	POMM.PRIV.ZUCKSIE.	Germany
68	NUERNBERGER BETS.	Germany	160	GOLD-ZACK	Germany
69	ALLIANZ	Germany	161	DEUTSCHE BALATON K	Germany
70	MUENCHENER RUCK	Germany	162	BERLINER EFFTG.	Germany
71	CATTOLICA ASSICURAZIONI	Italy	163	VALORA EFFKTEN HANDEL	Germany
72	UNIPOL GRUPPO FINANZIARI	Italy	164	WUESTENROT & WUERTT.	Germany
73	ASSICURAZIONI GENERALI	Italy	165	DT.EFF.UD.WCH.- BTGU.	Germany
74	UNIPOLSAI	Italy	166	HELLENIC EXCHANGES HDG.	Greece
75	AEGON	Spain	167	MARFIN INV.GP.HDG.	Greece
76	GRUPO CATALANA OCCIDENTE	Spain	168	DEA CAPITAL	Italy
77	MAPFRE	Spain	169	AZIMUT HOLDING	Italy
	Others		170	BANCA IFIS	Italy
78	FRAUENTHAL HOLDING	Austria	171	BANCA INTERMOBILIARE	Italy
79	UNTERNEHMENS INVEST	Austria	172	GEQUITY	Italy
80	WIENER PRIVBK.IM.INVT.	Austria	173	IVENTURE GROUP	Italy
81	AB EFFECTENBETEILIGUNGEN	Austria	174	BANCA MEDIOLANUM	Italy
82	ACKERMANS & VAN HAAREN	Belgium	175	MITTEL	Italy
83	GIMV	Belgium	176	TITANMET	Italy
84	SOFINA	Belgium	177	ITALMOBILIARE	Italy
85	GBL NEW	Belgium	178	MEDIOBANCA BC.FIN	Italy
86	COMPAGNIE DU BOIS SAUVAGE	Belgium	179	VALUES	the Netherlands
87	BELUGA	Belgium	180	HAL TRIT	the Netherlands
88	PALMBOOMEN CULT. MIJ. MOPOLI PALMERAIES DE	Belgium	181	ALANTRA PARTNERS	Spain
89	BREDERODE	Belgium	182	MOBILIARIA MONESA	Spain
90	FINANCIERE HOCHE BAINS LIMITED DATA	France	183	CORPORACION FINCA.ALBA	Spain
91	PRTE.INDTR.MRE. LIMITED	France			

of the tails, which allows us to map the dynamics of contagion in the financial network according to the tail state of the returns. We examine two types of causality: i) the down-to-down, namely $\text{VaR}^{\text{down}} = \{0, 1\%, 5\%, 10\%\}$, and the upside-to-upside, i.e., $\text{VaR}^{\text{up}} = \{90\%, 95\%, 99\%, 100\%\}$. These types of VaRs indicate the risk spillovers in the bearish and bullish conditions.

First, we present the static results of our estimates to highlight the network structure of risk spillover. Then, we illustrate the dynamic evolution of the total connectivity and directional connectivity of risk spillover between the different sectors. Finally, we present the relative risk spillover dynamics. The analysis takes into account the favorable (bullish) market conditions, i.e., the extreme tail high during the recovery period, on the one hand. On the other hand, the analysis also highlights unfavorable (bearish) market conditions, i.e., the extreme bottom of the tail during the recession period.

Our sample includes banks, insurers, and other financial institutions in the euro area. Our results shed light on the topological structure of the risk spillover over a representative time period, which includes both quiet periods and periods of instability including, the 2008 financial crisis, the 2010 Eurozone sovereign-debt crisis and the COVID-19 health crisis.

3.5.1 Static analysis

Figure 4.1 shows the static risk spillover results for our entire sample of banks, insurances and other financial institutions. The left-side network reflects the extreme downside-downside case while the right-side network reflects the extreme upside-upside case. The following colors: red, purple and yellow refer to banks, insurance companies and other financial institutions, respectively. The network is constructed using Granger causality tests for the tail event in a multivariate framework. Each line in the network confirms a causal relationship between two institutions at 1% significance level. Each line's color reflects the direction of causality for a financial actor in a sector.

Comparing the two networks on the left-side and the right-side, which represent respectively bearish and bullish market conditions, we can see that banks, insurances

and other financial institutions are strongly linked in the case where the tails of the return distribution are on the left (bearish). More concretely, the total spillover index in the bearish case amounts to 0.49. In contrast, in the bullish case, this index only reaches 0.12. This suggests that the bearish cases enhance connectivity, and therefore, risk spillovers. This result clarified the reactive behavior of institutions under different market conditions. When the market is under crisis, the risk spillovers between players in different sectors increase, which could threaten the resilience of the entire financial system.

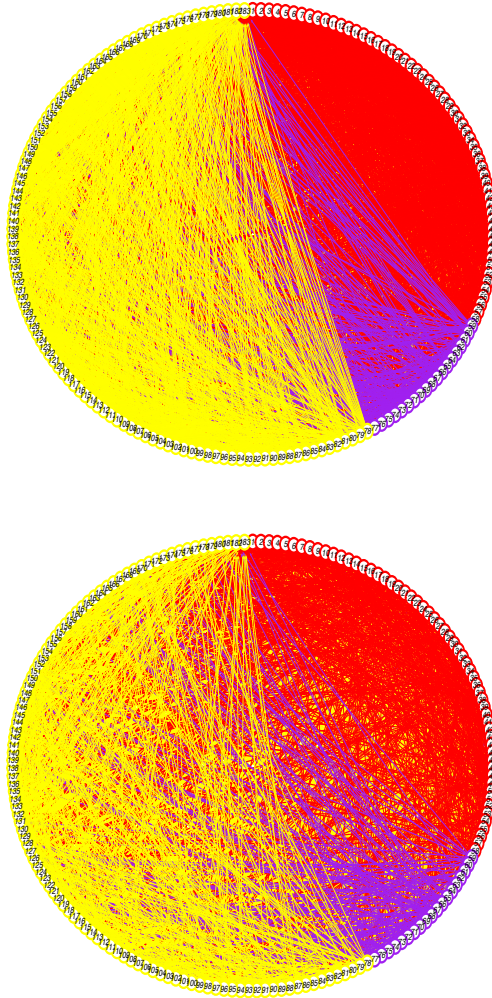


Figure 3.1: Snapshot of extreme risk spillover networks

Notes: On the left-side is the extreme downside-downside network (Total spillover index = 0.49), and on the right-side is extreme upside-upside network (Total spillover index = 0.12). The color of the node indicates the Bank (red), Insurance (violet) and Others (yellow).

After analyzing the risk spillovers in general, we focus on the directionality of risk spillovers between the three sectors: banking, insurance and other financial institutions. Table 3.2 specifies the risk spillovers between these three sectors and plots the matrix of total risk spillover directionality indices between sectors (non-diagonal elements) and for the sectors themselves (diagonal elements). We find that the spillover indices in the

bearish case, greatly exceed those in the bullish cases. This result shows that bearish conditions play an important role in the sectoral propagation of risk spillover. The different sectors tend to influence each other in a significant and reciprocal way in bearish market conditions than in bullish market conditions. We document evidence to support the asymmetry between negative and positive risk spillovers. In particular, the former is more severe than the case of positive risk spillovers.

Table 3.2: Risk spillovers across sectors

	TO		
FROM	Banks	Insurances	Others
Bearish case			
Banks	0.587	0.621	0.401
Insurances	0.639	0.667	0.409
Others	0.536	0.627	0.436
Bullish case			
Banks	0.146	0.102	0.088
Insurances	0.098	0.093	0.088
Others	0.125	0.131	0.126

3.5.2 Dynamic Analysis

Here we analyze the dynamic evolution of total connectivity and directional risk spillover connectivity across sectors. Following Wang et al. (2017), we estimate the directional spillovers using 250-day rolling windows, when $M = 20$ (one trading month). Figure 4.2 represents the dynamic evolution of the total connectivity spillover (TCS) index under bearish (left-side) and bullish (right-side) market conditions. We observe that the dynamic risk spillover is significantly volatile and peaks during crisis periods in bearish market conditions. We notice peaks of 0.45, 0.30 and 0.50 during the financial crisis (2008), sovereign debt crisis (2010-13) and COVID-19 era (2020-to date), respectively.

The behaviour is coherent with the analysis of Claeys and Vasicek (2015), Foglia and Angelini (2020b) and Borri and Di Giorgio (2021), which found similar dynamics of risk spillovers. Turning our attention to upside-upside risk spillovers, we see that the connections are fairly stable, with the highest peak in the COVID-19 period. This means that positive risk spillover is less severe than negative risk spillovers.

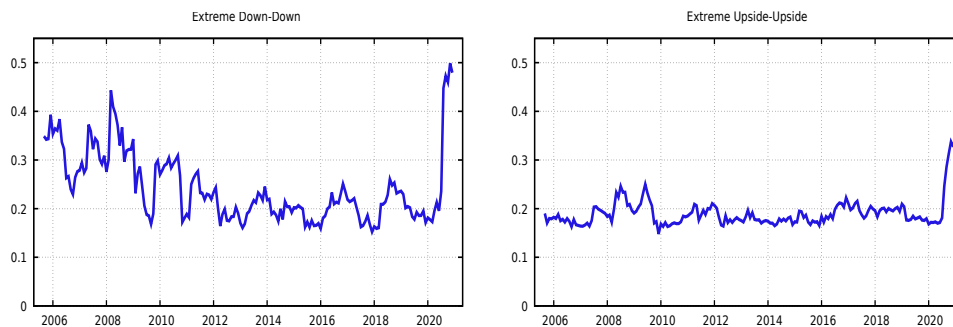


Figure 3.2: Total connectivity spillover (TCS) index

Notes: On the left-side is the TCS index of the extreme downside-downside network, and on the right-side is that of the extreme upside-upside network.

The findings document that the financial system becomes highly interconnected in bearish conditions and especially during periods of instability. In other words, the results imply that the co-movement effect is more likely to occur under negative extreme risk conditions. This result is fully consistent with the “shift-contagion” theory of Caporin et al. (2018). The authors argue that we can note the “shift-contagion” when the intensity of relationship (between financial firms) changes across different quantiles. Their findings suggest that the degree is higher for lower quantiles, as well as in our case.

Now, we examine the dynamic sector spillover, from one sector to another and to itself. Figure 4.3 exhibits the risk spillover connectivity across sectors, at downside-downside (left-side) and upside-upside (right-side) risk levels, respectively. At first look, we can note, also in this case, the asymmetric pattern between the two types of risk. The dynamics of the bearish condition are more volatile and reaches peaks of high values. On the other hand, the bullish dynamics are more stable with low peaks value. Focusing on sector spillovers, the findings document the key role played by the bank sector and the insurance sector in the transmission of risk. As we can note, these sectors spread major

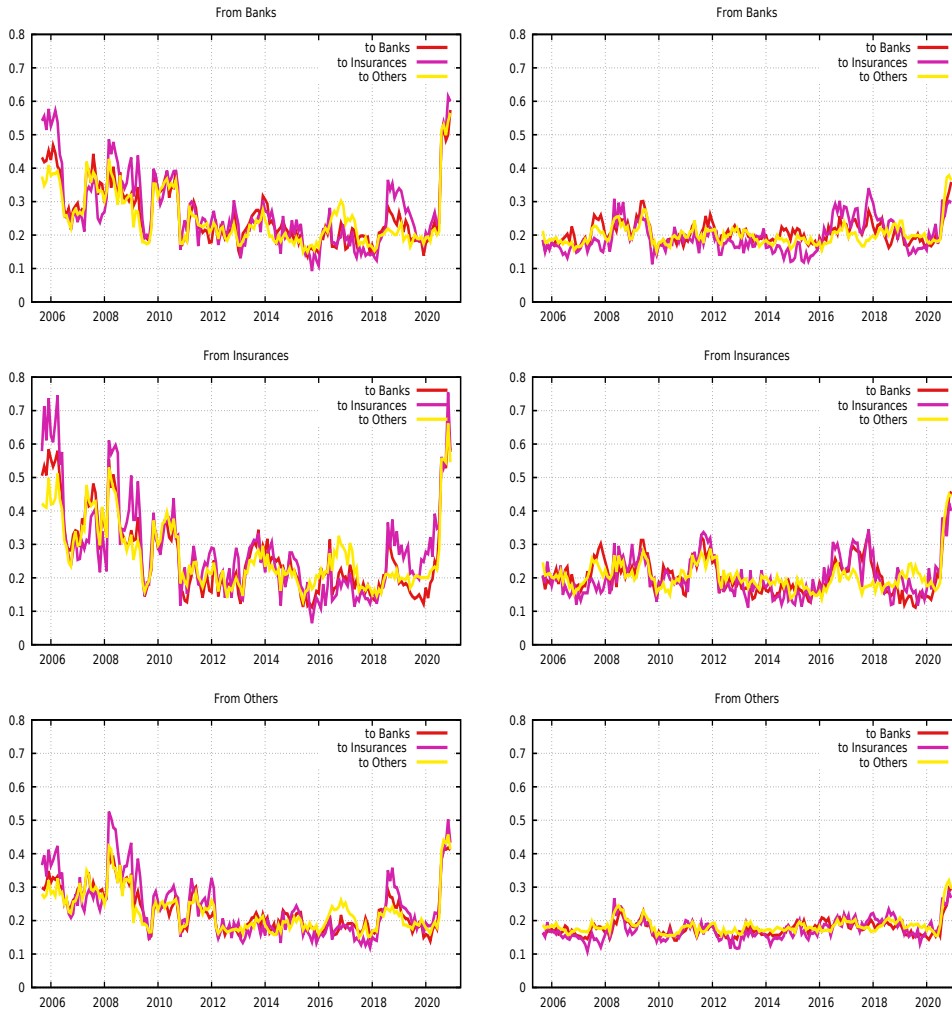


Figure 3.3: Dynamic risk spillovers across sectors

Notes: Here shows dynamic risk spillovers from one sector to another or itself. On the left-side is the extreme downside-downside network, and on the right-side is extreme upside-upside network.

risk in the Eurozone financial system. In the contrast to the “others” sector, which emits less risk spillovers.

To further investigate directional information, in Figure 4.4, we plot the relative influence (RI) index of each sector. Analyzing the RI index, we can see whether a sector is a net transmitter or a net receiver of extreme risk spillovers. On the basis of the value of the index, we can distinguish sectors that emit on extreme risk (positive value), and

sectors that receive tail risk (negative value). The banking sector, on average, acts as a net-sender of risk spillovers under bearish market conditions. This dynamic is consistent with the events that have most affected the Eurozone financial system. In fact, we can see that the banking system is the net sender of extreme risk particularly during the sovereign debt crisis, the Brexit, the Non-Performing-Loans issues, and finally the COVID-19 pandemic. One possible explanation is that the European financial system is bank-centred (ECB, 2017; Borri and Di Giorgio, 2021). For the upside-upside risk, the dynamics are quite interspersed. However, the impact of the COVID-19 outbreak is clear. In this period the banking sector played a significant role on spread tail risk on the financial system (Akhtaruzzaman et al., 2020; Rizwan et al., 2020). The RI index of the insurance sector, on bearish market conditions, changes over time. We can note positive and negative values. On the other hand, on bullish market conditions, the insurance sector, on average, assumes the role of net-sender. Finally, we can see how the "others" sector is a net-receiver of tail risk, especially on upside-upside condition. Our investigation of risk spillover reveals that there is heterogeneity in tail risk transmission. This result is informative enough for the policymaker to take specific policy measures depending on the role assumed by a given sector in a given time period.

3.5.3 Extreme connectedness and monetary policy

In this section, we evaluate the monetary policy impact on contagion in the Eurozone financial system. The aim is to analyze the ability of the European Central Bank (ECB) to intervene in the reduction of risk spillover.

We investigate the causality relationship between monetary stance and our two measures of connectedness: bearish and bullish risk networks. Therefore, we examine if this relationship is homogeneous between the two connectedness measures, i.e., whether there are asymmetrical effects. In particular, we attempt to answer two questions: does the monetary policy affect risk, i.e., does the connection imply monetary policy intervention? Are the asymmetric effects impacting upside and downside risks? Answering these questions, in our view, provides an important and innovative contribution to this recent

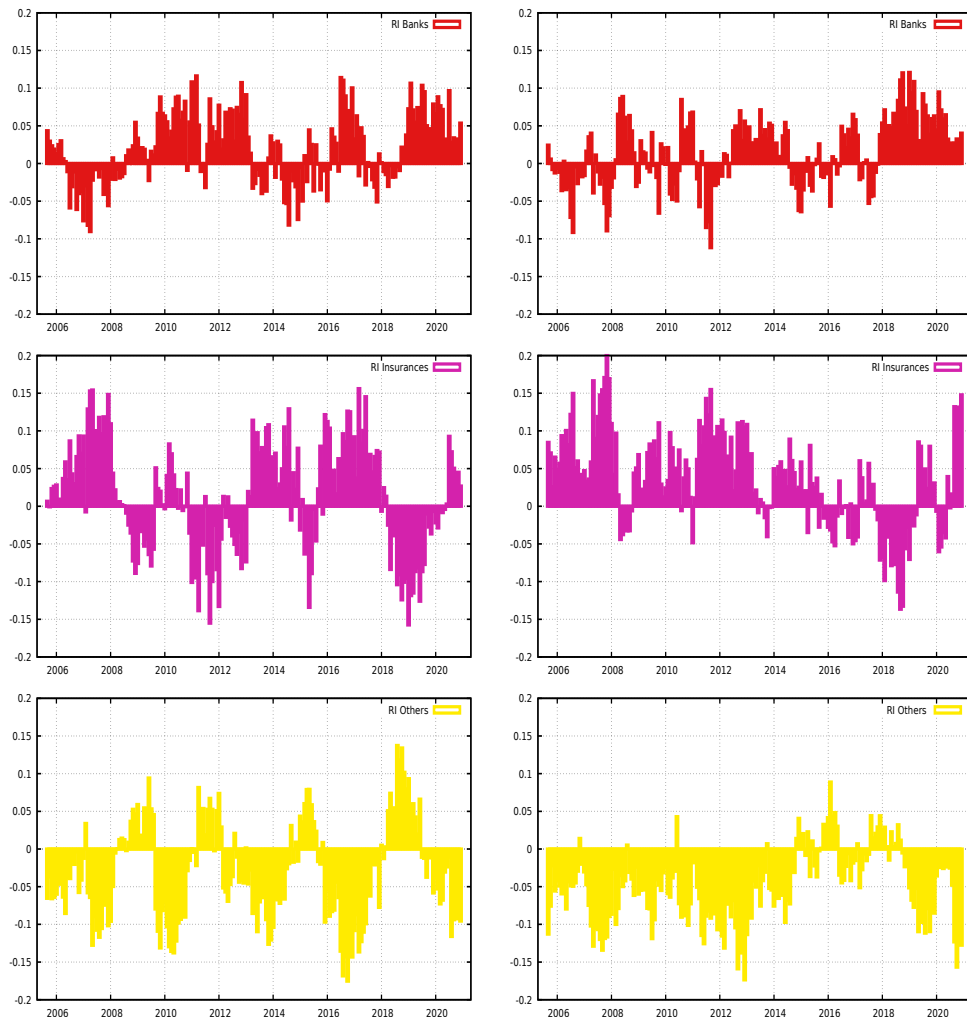


Figure 3.4: Dynamic relative influence index of each sector
Notes: On the left-side is the extreme downside-downside network, and on the right-side is extreme upside-upside network.

literature.

For this purpose, we use the Shi et al. (2020) model. This framework is a useful method to investigate the time-varying causality. In particular, the model computes three time-varying causality algorithms: the forward-recursive causality, rolling causality, and recursive evolving causality.⁴

To capture the monetary policy stance, we use a unique index of monetary policy,

⁴Please see Shi et al. (2020) for the methodological aspect of the model.

namely the “shadow rate” (Wu and Xia, 2016; Pattipeilohy et al., 2017; Lombardi and Zhu, 2018). We use a factor analysis to compute the “shadow rate” index from the yield curve provided by ECB, following the approach of Pattipeilohy et al. (2017).⁵

Figures 4.5–4.6 plot the causality results between the total connection spillover TCS (for bearish and bullish networks, respectively) and monetary policy. We plot the three causality tests: (i) the forward-recursive causality, (ii) the rolling causality, and (iii) the recursive evolving causality. The red line represents Wald’s statistical sequence. If it exceeds its corresponding critical value (blue dashed line), then the causality is significant. The left side of Figure 4.5, shows the causal relationship of risk \rightarrow shadow rate (monetary stance), while the right side shows the shadow rate \rightarrow risk causality. Looking at the left side, we can see that the bearish connectedness does not exert any causal effect on monetary policy over the entire period. The non-relation between risk and policy can be attributed to the fact that financial stability is not an objective of the ECB. Indeed, financial stability is not among the ECB’s objectives as set out in the first paragraph of Article 127 (Mersch, 2018). Focusing on the right-hand side, we can instead identify periods where instead monetary policy Granger causes risk. That is, ECB monetary policies in response to the U.S. financial crisis, such as the cut of the main refinancing rate, the LTROs, and the covered bond purchase programme during 2009, the creation of Single Supervisory Mechanism (SSM, November 2014), the announced (January 2015) and application (March 2015) of the ABS purchase programme (QE), have had an effect on risk. These results confirm the analyses of Colletaz et al. (2018) and Foglia and Angelini (2019) who document the same results. They, find, on the one hand, a significant casual relationship from policy to risk, on the other hand an insignificant causality from risk to policy.

Turning our attention on Figure 4.6, we can observe a different picture of the relationship. In this case, we find, on one hand, that the risk causes the monetary stance. On the other hand, we find that the monetary stance causes the risk. This means that

⁵For the sake of brevity, we do not report the methodological aspects of shadow-rate estimation. However, they are available on request. The ECB yield curve is extracted from ECB Statistical Data Warehouse.

the contagion risk induces an intervention of the ECB, and the policy of the ECB also has an effect on the risk. The results document the existence of bi-directional causality. We observe that positive risk spillover causes monetary policy stance during 2009 and 2012, i.e., during the most acute phases of the two crises that affected the Eurozone financial system. Indeed, these feedback effects coincide with periods of high volatility in European financial markets (Samarakoon, 2017; MacDonald et al., 2018; Bratis et al., 2020). Focusing on the right side of the figure, we note, again, how monetary policies had an effect on positive risk spillover. The forward and recursive rolling estimates show how from 2014 onwards, the relationship is significant until 2020 (pre-COVID-19 period).

These results add new information to the evidence of time-varying dependence between risk and ECB monetary policy reported by Colletaz et al. (2018) and Foglia and Angelini (2019). In fact, for the first time, we find that positive risk Granger causes monetary policy, i.e., there are asymmetric effects between the two types of risk. This result sheds new light on the nature of the relationship between monetary policy and financial stability. For example, if we focus on the left-side of Figure 4.6, we can observe a significant causality relationship from monetary to risk during 2009. In this period, the ECB intervened on upside risk by cutting interest rates. This effect was also spread on downside risk (see the right-side of Figure 4.5). As can be seen from the graphs, first, there is the intervention (effect) on upside risk and then at downside level. Hence, the paper provides new evidence on the debate between monetary policy intervention and non-intervention. In fact, our results show that the ECB follows both the “leaning against the wind” approach, i.e., central banks should also use monetary guidance to manage financial imbalances (in the case of upside risk) and the “modified Jackson Hole consensus” approach, i.e., central banks should only focus on price stability (in the case of downside risk).

3.5.4 Discussion of results

We developed this research with the following objectives: (i) to develop an approach to identify the downside and upside tail extreme risk between financial institutions, (ii) to

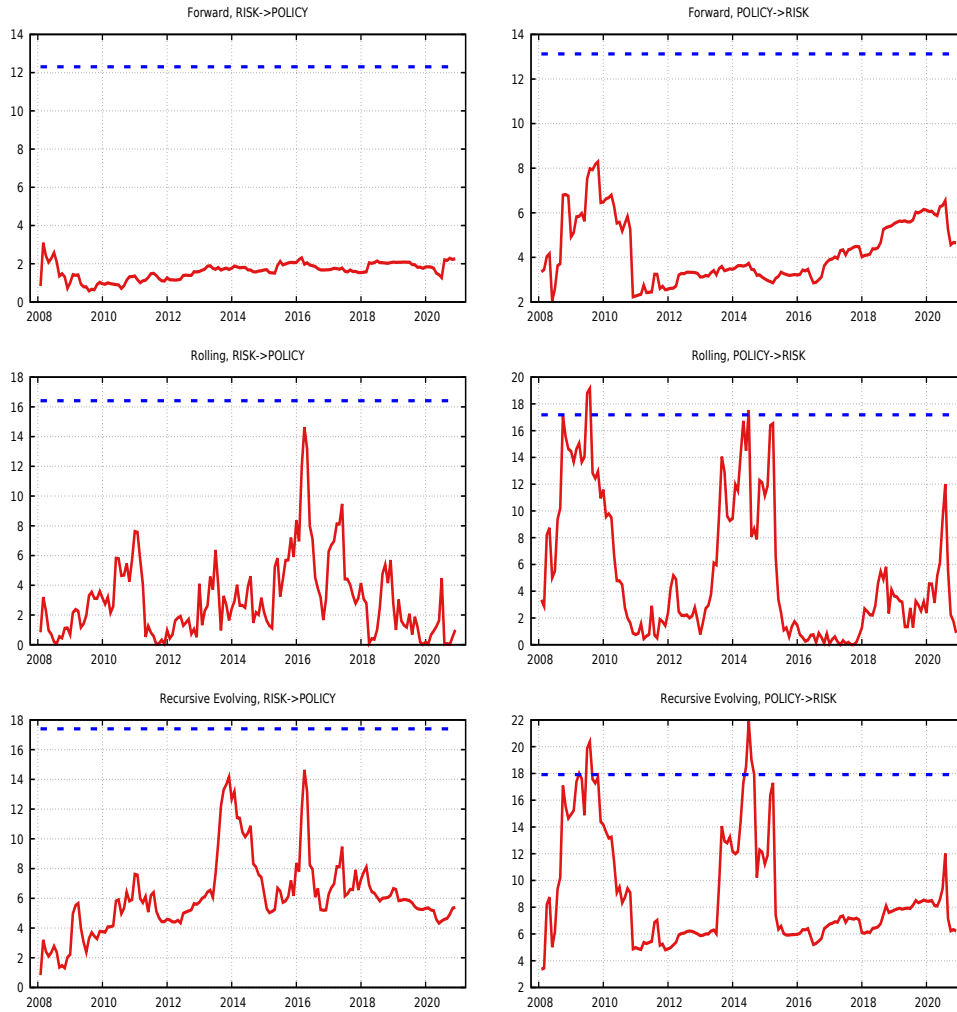


Figure 3.5: Time-varying causality between downside-downside extreme connectedness and shadow rate.

Notes: The left-side shows risk \rightarrow shadow rate causality, while the right-side shows the shadow rate \rightarrow risk causality. The blue dashed line is the 5% critical value, while the red solid line is the Granger test sequence.

analyze the dynamics of contagion, highlighting the co-movement within financial sectors in bearish and bullish market conditions, and (iii) to study the ability of ECB monetary policy to manage the contagion risk.

In terms of implications, our study focused on several key points to better conceptualizing the extreme risk spillover effect and understanding regulatory policies to maintain financial stability. Distinguishing the influence of extreme level events, whether positive

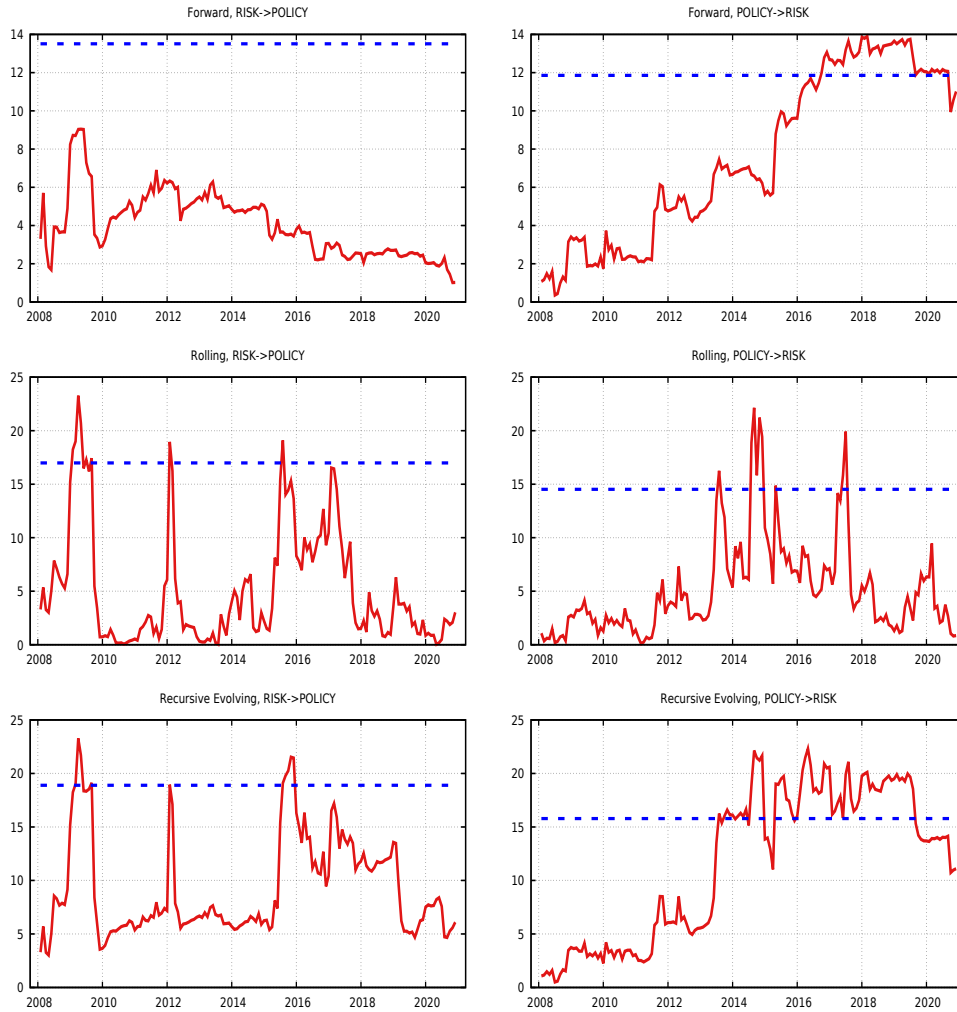


Figure 3.6: Time-varying causality between upside-upside extreme connectedness and shadow rate.

Notes: The left-side shows risk \rightarrow shadow rate causality, while the right-side shows the shadow rate \rightarrow risk causality. The blue dashed line is the 5% critical value, while the red solid line is the Granger test sequence.

or negative, on interconnections allowed us to visibly capture the hidden heterogeneity in interconnection changes. Indeed, an analysis without differentiating the level of the tail risk (left or right) could lead to biased research, and consequently, to an inadequacy of the regulators' interventions. Furthermore, looking at the entire financial system allows for a better understanding of the dynamics between different sectors, which is crucial for effective financial stability policies. The framework that we have suggested enable us to

visualize changes in the structure of interconnections in response to externalities to know which sector influences more the extreme behaviors of contagion.

Our results suggest that negative externalities intensify interconnections more than positive ones, i.e., asymmetric effect. In times of crisis, extreme connections between institutions increased dramatically, both within the same sector and between different sectors. This has made it possible to identify sectors that contribute most to the spread of systemic risk. It is also worth noting the role assumed by alternative financial intermediation ("others"). In recent years, investors have shifted their focus to these activities for higher returns encouraged to exploit regulatory gaps in the industry. However, although the growth of non-bank financial intermediaries could bring benefits in terms of financial development, it also requires special prudential attention (ECB, 2020a). In fact, in the pre-COVID-19 period (2018–19), our analysis suggests that this sector issued the most risk.

Second, the non-causal relationship between downside risk and monetary policy suggests that the changes in interconnections could be due to idiosyncratic risks, which could systematically affect systemic risk and therefore lead to cascading bankruptcies (Fiordelisi and Marques-Ibanez, 2013). Indeed, the individual default risk can directly impact the behavior of systemic risk, which leads to the reinforcement of conditional dependence due to interconnections. This is what happened during the COVID-19 outbreak. The coronavirus dramatically increased the connections between financial institutions (highest peak), showing how the COVID-19 pandemic is both an economic and financial crisis. Given its twin-crisis nature, the coronavirus crisis could lead to a re-emergence of asymmetries within the Eurozone financial system, both at the country and sector levels. Hence, policies aimed at strengthening financial stability and financial market integration would be welcome. The objective of financial stability should be incorporated into a framework of main policies to avoid self-fulfilling crisis, i.e., to overcome the domino effect of contagion, which is not essentially the cause of the structural conditions of the banks (such as the COVID-19 pandemic). A key message of this study is that the ECB response of contagion risk is not symmetric. An ideal policy would be to follow the

“leaning against the wind” approach even under bearish market conditions.

Overall, our findings can be helpful, both in portfolio investment strategies (taking into account systemic risk) and in designing regulatory policies. Analyzing the risk contribution for each sector, we help investors in their investment strategies to include sectors depending on their level of tail risk in that particular period and allow managers to mitigate the risks arising from all financial system. Furthermore, the information can enable policymakers to clearly comprehend the relationship between the Eurozone financial sector depending on market conditions.

3.6 Conclusion

In this study, we analyze the risk spillover effects among a sample of 183 financial institutions (such as banks, insurances, diversified financials, and real estate firms) in the Eurozone financial system. Following Li et al. (2020)’s approach, we are able to provide an in-depth picture of interactions in the financial system. In fact, thanks to Candelon and Tokpavi (2016)’s model, we have analyzed the Eurozone financial system both from a downside risk perspective and an upside risk perspective. This allowed us to better understand the dynamics within sectors depending on the type of market conditions. The results reveal a heterogeneous effect depending on the level of risk considered, highlighting how bearish conditions play an important role in the sectoral propagation of risk spillover. Different sectors tend to influence each other significantly and reciprocally in bearish conditions than in bullish market conditions. This result documents the presence of “shift-contagion” effect (Caporin et al., 2018). Moreover, as the relative index suggests, we find that banks play a key role in transmitting contagion risk. Finally, we studied, by time-varying Granger causality (Shi et al., 2020), the nexus between monetary policy and risk. Our results show heterogeneity in the relationship depending on the risk considered. We find fresh evidence of ECB monetary policy-risk nexus. In particular, our findings document that the ECB follows the “leaning against the wind” monetary stance in case of upside risk, and the “modified Jackson Hole consensus” approach in case of downside

risk.

Future research directions could include further development of the quantile Granger causality in risk models by including firms balance sheet variables in the computation. This new multivariate approach would be able to assess the causal connection by taking into account the fundamental variables of financial firms and the inherent tail risk of the financial market. Thus, mixing two types of risk: "too-big-to-fail" and "too-interconnected-to-fail", respectively. Besides, in this research, we focused on Eurozone financial firms. Future study may involve other geographical areas and other economic sectors.

The Eurozone banking sector in the time of COVID-19: measuring volatility connectedness

Abstract

This article¹ investigates the volatility connectedness of the Eurozone banking system over the last 15 years (from 2005 to 2020). Applying the Diebold-Yilmaz Connectedness Index model to the daily stock return volatilities of 30 major Eurozone banks, we are able to measure the risk spillover effects and to capture the COVID-19 outbreak's impact on banking stability. The empirical findings show that the 30 banks are highly interconnected. Furthermore, we show the strong impact of the COVID-19 pandemic on the volatility dynamics, i.e., on the structure of the Eurozone banking system. Dynamically, we find that volatility connectedness increases during crises, reaching its maximum peak at the time of COVID-19. The analysis points out the critical role of volatility transmission played by large banks, highlighting the “too-big-to-fail” characteristic of this banking system. However, we find that small-medium banks are important actors of contagion, supporting the thesis that the Eurozone banking system is also “too-interconnected to fail.” Finally, we document the heterogeneity effect of the COVID-19 pandemic between Eurozone banking systems. This heterogeneity impact could be a future source of financial instability within the Eurozone.

Keywords: volatility spillovers; Eurozone banking system; financial connectedness; COVID-19; financials asymmetries

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JEL Classification: G21, G01, C32

4.1 Introduction

This research investigates the structure and dynamics of interconnections between 30 banks in the Eurozone before and during the COVID-19 pandemic. Over the last 15 years, several important events have shaken the global financial markets (the U.S. crisis, the European crisis, the Chinese crisis, and lastly, the COVID-19 pandemic), endangering financial and banking stability (ECB, 2020b; Aldasoro et al., 2020a). These events highlight how the interconnections between financial actors can play a fundamental role in risk spillovers (Brogi et al., 2021). Therefore, this research aims to investigate the volatility connectedness between banks to create a detailed picture of contagion dynamics within the Eurozone banking system. The decision to focus on this banking sector is motivated by the fact that banks are the primary source of financing for businesses and households in Europe (ECB, 2017), so they are highly exposed to the negative effect of the pandemic. Indeed, COVID-19 could substantially increase the credit risk of intermediaries, i.e., the ability of firms and households to repay their debts. The relationship between credit risks, non-performing loans (NPLs), and banking stability is well established in the literature (Imbierowicz and Rauch, 2014; Vazquez and Federico, 2015). Therefore, the i) falling business revenues, ii) substantial job destruction, and iii) increase in households' financial liabilities due to the COVID-19 outbreak could have severe consequences for Eurozone banking stability, and hence for systemic risk (Rizwan et al., 2020; Goodell, 2020).

In this context, our research aims i) to show which are the actors that transmit the most risks, and therefore which are the banks that receive the most volatility, and ii) to quantify the impact of the COVID-19 pandemic on the banking stability. We would like to understand how major Eurozone banks contribute to the evolution of financial contagion (systemic) risk. For this purpose, we measure the volatility connectedness of 30 Eurozone bank stocks from June 2005 to August 2020 by using the Diebold and Yilmaz

(2012, 2014a) framework. This methodology allows us to study how an idiosyncratic shock (e.g., the COVID-19 outbreak) can spread to the banking system over time.

Our most relevant results are the following. First, we find that all banks contribute significantly to contagion; however, larger banks (such as G-SIBs) contribute more. Second, the findings show the strong impact of the COVID-19 outbreak on volatility connectedness (an increase of 20%). The coronavirus has led to a change in the structure of the banking system, from a network dominated by the banks receiving volatility shocks to a connectivity structure dominated by banks emitting volatility risks. In addition, by amplifying their interconnections, COVID-19 has increased the potential value of shocks, which can be small (7.96%) or strong (137.74%), but are distributed relatively evenly among the other banks. Third, the dynamic results show how the connectedness increases during crises, with strong peaks during the financial crisis, the European sovereign debt crisis, the NPLs problem, and the COVID-19 era (higher peak). Moreover, the findings highlight the important role played by G-SIBs in volatility transmission, supporting the thesis that the Eurozone banking system is “too big to fail.” Furthermore, we find that small-medium banks (such as the National Bank of Greece, MedioBanca, and Nordea Bank) are important sources of volatility spillover. This shows how the Eurozone banking sector is also “too interconnected to fail.” Our bank ranking can provide possible help to policymakers in identifying the riskiest banks. Finally, we document the heterogeneity effect of the COVID-19 pandemic between Eurozone banking systems. This heterogeneity impact could be a future source of financial instability within the Eurozone.

The study contributes to the literature in several ways. First, we provide fresh evidence of volatility connectedness between Eurozone banks and the impact of the COVID-19 outbreak on the banking sector. Although many papers have investigated the interconnectedness of the Eurozone financial structure (Billio et al., 2012; Glasserman and Young, 2015; Betz et al., 2016; Dreassi et al., 2018; Brunetti et al., 2019; Foglia and Angelini, 2020b), none have focused specifically on this banking system using Diebold and Yilmaz (2012, 2014a) volatility connectedness model. This approach provides us with a powerful tool to analyze the volatility risk spillover, taking into account idiosyncratic

and common shocks within the network system. For example, Demirer et al. (2018), study the global bank connections by extending the Diebold and Yilmaz (2012, 2014a) methodology. However, studying volatility spillover at the global level, while useful in investigating the riskiest and, therefore, most interconnected global financial systems, cannot provide relevant information about a specific banking system. Given the high uncertainty that characterizes the modern world, it is essential to have a picture of the specific risk of a “confined” banking sector in order to offer targeted banking regulations (e.g., macro-prudential policy, Basel, ECB). Second, we contribute to the recent literature that studies the impact of COVID-19 on financial markets (Lyócsa and Molnár, 2020; Rizwan et al., 2020; Corbet et al., 2020; Nițoi and Pochea, 2020; Ortmann et al., 2020; Broadstock et al., 2020; Le et al., 2020; Seven and Yilmaz, 2020; Albulescu, 2020; Conlon et al., 2020; Ashraf, 2020; Corbet et al., 2021a; Hung and Vo, 2021; Hasan et al., 2021; Salisu and Ogbonna, 2021). We study the contagion effect due to the coronavirus on Eurozone banking system. Third, the work contributes to the literature which argues that a financial institution can not only be “too big” but also “too interconnected” to fail (Acharya and Yorulmazer, 2007; Zhou, 2009; Beccalli et al., 2015; Gofman, 2017; Quaglia and Spendzharova, 2017; Foglia and Angelini, 2020b,c). In fact, we show how large banks play an important role in volatility spillover, but also how the Eurozone banking system is highly interconnected.

4.2 Literature review

The COVID-19 health crisis has taken on a universal character, contrary to other crises that have affected only certain countries, regions, markets, or sectors. The universality of COVID-19 has plunged the financial markets of the whole world into absolute uncertainty, with a consistent drop in stock prices (Corbet et al., 2021b), a significant rise in systemic risk (Rizwan et al., 2020), and a substantial impact on financial stability (Aldasoro et al., 2020b). The literature has highlighted how the financial system instability is linked to the degree of interconnectedness of financial institutions. Indeed, in periods of disruption,

uncertainty, and extreme events, the connectivity of the financial system increases, which consequently facilitates the transmission of shocks and spillover effects (Billio et al., 2012; Diebold and Yilmaz, 2012, 2014a; Wang et al., 2017, 2018a; Gong et al., 2019; Foglia and Angelini, 2020b).

Several econometric models have been developed in order to study the financial network. Billio et al. (2012) have proposed the Granger causal network approach to investigate the interconnections of the financial system. In the same line, Diebold and Yilmaz (2012, 2014a) have developed the connectedness index model to study the risk spillover effects. This framework is based on variance decomposition to detect directional contagion (incoming and outgoing). The model has been successfully applied in different financial contexts (see Maghyreh et al., 2016; Gamba-Santamaria et al., 2017; Demirer et al., 2018; Wang et al., 2018b; Kang et al., 2019; Kang and Lee, 2019; Hassan et al., 2020; Geng et al., 2020). Using the least-absolute shrinkage and selection operator (LASSO) method, Hautsch et al. (2015) have developed an extreme risk network model. This approach allows researchers to identify the degree of interdependence of a company and the potential channels of contagion in the financial system through the beta-systemic-risk. Recently, in order to analyze the interconnection structure of systemically important institutions, Härdle et al. (2016) have proposed the TENET technique (Tail Event driven NETWORK), which combines the dynamics of tail and network events in a single framework. The model classifies the financial actors according to their reception and/or emission of systemic risk. The TENET method has been extended to various contexts, notably Europe (Foglia and Angelini, 2020b), China (Wang et al., 2018a), the emerging American countries (Hernandez et al., 2020), and the Indian financial system (Verma et al., 2019). More recently, Chen et al. (2019) have proposed a Tail Event-driven Network Quantile Regression (TENQR) design.

Overall, the literature has highlighted the positive implications of these network models. Indeed, these methods have the advantage of taking into account the global connectivity of all actors in the financial system, unlike the models developed by Tobias and Brunnermeier (2016), Brownlees and Engle (2017) and Acharya et al. (2017), which

only consider the individual connectivity between a financial institution and the financial system, independent of other financial institutions.

The empirical analysis of the global interconnectedness of the banking sector has generated a great deal of interest among researchers. The causal approach has been applied to study the connectivity of four sectors: hedge funds, banks, merchants, and insurance companies. Billio et al. (2012) found that there is an asymmetry in the degree of connectivity of these financial actors, and that banks are much more involved in the transmission of shocks. Gong et al. (2019) built a causal network of Chinese financial actors, and demonstrated that periods of turbulence are associated with an increase in the connectivity of the Chinese financial system. Their results corroborate the analysis of Wang et al. (2018a), who highlighted how risk connectivity increases during periods of financial turmoil. Diebold and Yilmaz (2014a) showed that in times of crisis, the volatility of U.S. financial institutions becomes relatively high compared to the normal periods. Based on the volatility propagation index, Diebold and Yilmaz (2015) examined the directional connectivity between large U.S. and European financial institutions. These authors proved that this connectivity is bidirectional, but becomes unidirectional in times of crisis. Using Diebold and Yilmaz (2014a) volatility diffusion network, Wang et al. (2018b) studied the volatility connectivity of Chinese banks. Their results suggest that 14 Chinese commercial banks are highly interconnected, both statically and dynamically. Also, they found that bank size is a determinant of from-connectedness.

The European banking sector has been the subject of particular attention because of its specificities. A large number of studies have been carried out on sovereign risk and its impact on default risk, including studies by De Bruyckere et al. (2013), Cantero-Saiz et al. (2014), and Keddad and Schalck (2020). Other research has focused on the analysis of the interconnection structure. For example, Paltalidis et al. (2015) have shown that the European banking sector has inherent characteristics that favor financial contagion depending on the degree of interconnection, the weight of the banking sector, and the area of the shock. Dreassi et al. (2018) have analyzed the cross-sector contagion risk spillover between European banks and insurances over the years 2006–2014. To measure

the financial risk, these authors used the CDS spread. The results highlighted that capital adequacy, funding, income diversification, and leverage played key roles in risk transmission for the banking sector, while size, investment, and leverage did the same for the insurance sector. Using the cross-quantile approach (Han et al., 2016), Shahzad et al. (2019) have shown that the network structure is bidirectional and asymmetric in Europe. Indeed, spillover effects are reversed between large banks and the finance sector depending on the state of the market. Using the TENET framework, Foglia and Angelini (2020b) have analyzed the interconnectedness between financial firms in the Eurozone context. Their findings suggest a strong interconnection between Eurozone financial actors (banks, insurance, and others). Further, they have found that the banking sector plays a key role in systemic risk spillover.

4.3 Volatility connectedness

We use the connectedness volatility network method proposed by Diebold and Yilmaz (2012, 2014a), in order to measure the risk spillover among Eurozone banks and to build the connectedness network. The covariance stationary $VAR(p)$ model is given as $Y_t = \sum_{i=1}^p \Theta_i Y_{t-i} + \varepsilon_t$, where Y_t is a $N \times 1$ vector of endogenous variables at time t , Θ_i are $N \times N$ coefficient matrices, p is the VAR lag order, and $\varepsilon_t \sim (0, \Sigma)$ is an N white noise vector. The stationary $VAR(p)$ model can be written as the moving average process $Y_t = \sum_{j=0}^{\infty} \Psi_j \varepsilon_{t-j}$, where Ψ_j stands for a $N \times N$ coefficient matrix defined as $\Psi_j = \Theta_1 \Psi_{j-1} + \Theta_2 \Psi_{j-2} + \dots + \Theta_k \Psi_{j-k}$ with Ψ_0 an $N \times N$ identity matrix and $\Psi_j = 0$ for $j < 0$.

The model is based on the variance decomposition coefficient that is computed following the generalized variance decomposition (GVD) framework of Koop et al. (1996), and Pesaran and Shin (1998), which is invariant to the variable ordering. Hence, the H -step-ahead generalized forecast error variance is given by:

$$\theta_{ij}^g(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} (e_i' B_h \Sigma e_j)^2}{\sum_{h=0}^{H-1} (e_i' B_h \Sigma B_h' e_i)} \quad (4.1)$$

where the $N \times N$ covariance matrix of the error vector ε is represented by Σ , σ_{jj} is the standard deviation of error term, and e_i is a $N \times 1$ selection vector, i.e., equal to 1 for element i and 0 otherwise. Therefore, we achieve a $N \times N$ generalized variance decomposition matrix $[\theta_{ij}(H)]_{N \times N}$. Since the sum of elements in each row of the variance decomposition matrix is not equal to 1, each element of H -step-ahead matrix is normalized by dividing by the row sum as:

$$\tilde{\theta}_{ij}(H) = \frac{\theta_{ij}(H)}{\sum_{j=1}^N \theta_{ij}(H)} \quad (4.2)$$

Finally, using the normalized variance contribution, we can compute several connectedness measures. Following Diebold and Yilmaz (2012) we define the total volatility connectedness index (TVC) as:

$$TVC(H) = \frac{\sum_{ij=1, i \neq j}^N \tilde{\theta}_{ij}(H)}{\sum_{ij=1}^N \tilde{\theta}_{ij}(H)} \times 100 = \frac{\sum_{ij=1, i \neq j}^N \tilde{\theta}_{ij}(H)}{N} \times 100 \quad (4.3)$$

The total volatility connectedness index measures the average contribution of spillover from shocks across all variables to the total forecast error variance.

Now, we introduce three directional connectedness indexes: i) *from-connectedness*, ii) *to-connectedness* and the iii) *net-connectedness*. The *from-connectedness* is defined as:

$$DS_{i \leftarrow j}(H) = \frac{\sum_{j=1, j \neq i}^N \tilde{\theta}_{ij}(H)}{\sum_{ij=1}^N \tilde{\theta}_{ij}(H)} \times 100 = \frac{\sum_{j=1, j \neq i}^N \tilde{\theta}_{ij}(H)}{N} \times 100 \quad (4.4)$$

The *to-connectedness* is given by:

$$DS_{i \rightarrow j}(H) = \frac{\sum_{j=1, j \neq i}^N \tilde{\theta}_{ji}(H)}{\sum_{ij=1}^N \tilde{\theta}_{ji}(H)} \times 100 = \frac{\sum_{j=1, j \neq i}^N \tilde{\theta}_{ji}(H)}{N} \times 100 \quad (4.5)$$

The *net-connectedness* volatility spillovers is the the difference between *to-connectedness* and *from-connectedness*, hence:

$$NS_i(H) = DS_{i \rightarrow j}(H) - DS_{i \leftarrow j}(H) \quad (4.6)$$

The net spillovers is useful to identify if a variable (bank, in our case) is a the net-recipient of or a net-contributor to volatility spillovers.

Finally, to analyze the bidirectional relationship between banks, we calculate the *net pairwise directional connectedness*, *i.e.*:

$$NPS_{ij}(H) = \frac{\tilde{\theta}_{ji,t}^g(H) - \tilde{\theta}_{ij,t}^g(H)}{N} \times 100 \quad (4.7)$$

4.4 Data and banking sample

We compute the Diebold and Yilmaz (2012, 2014a) volatility model on the Eurozone banking system to study its volatility connectedness and the impact of the COVID-19 outbreak. We select the banks in our sample to comply with two constraints: i) the bank must be listed before 2005 in order to study the impact of the global financial crisis, and ii) it must not have a long suspension period². Hence, we select the top 30 Eurozone banks in terms of the total assets (see Table 4.1), according to Bankscope Country rank. Our data consisted of daily closing stock prices, and the sample periods cover from June 2005 to August 2020 (3836 daily observations). All bank stock prices are collected from Datastream.

Following Forsberg and Ghysels (2007), Antonakakis and Kizys (2015), Antonakakis et al. (2018), and Gong et al. (2021), we compute the price volatility as follows: $V = |\ln p_{i,t} - \ln p_{i,t-1}|$, where $p_{i,t}$ is the closing price of firm i at daily t ³.

Figure 4.1 exhibits the price volatility. We can see common patterns of volatility. In all banks, we can observe the significant impact of the global crisis of 2007–2009. In addition, we can see another peak of volatility during the sovereign debt crisis and during

²For example, we have not included Caixa Bank because it has been listed since 2007, or Banca Monte Paschi di Siena because it has had a long suspension period.

³To test the robustness, we also consider a GACRH (1,1) estimation process of volatility (please see Section 4.5.4). For the sake of brevity, the estimation results of the GARCH model are omitted, but they are available from the authors upon request.

Table 4.1: Bank Sample

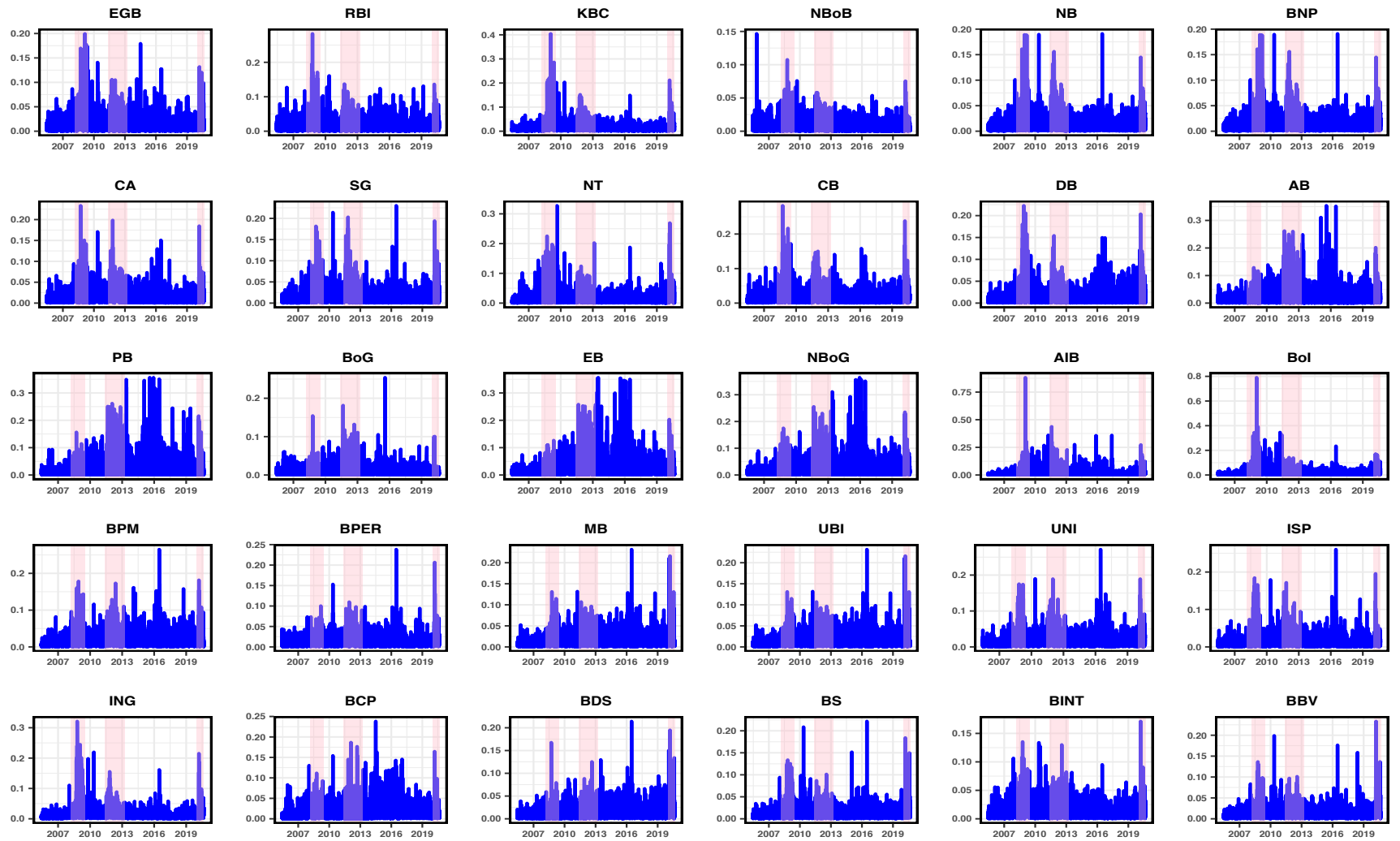
Country	Name	Abbr.	Tot. Asset	Market Cap.
Austria	Erste Group Bank AG	EGB	245,692,847	14,424.09
Austria	Raiffeisen Bank International AG	RBI	152,199,504	7,364.96
Belgium	KBC Groep NV	KBC	290,735,000	27,907.40
Belgium	National Bank of Belgium	NBoB	181,789,087	972.00
Finland	Nordea Bank	NB	554,848,000	29,321.65
France	BNP Paribas SA	BNP	2,164,713,000	66,026.86
France	Credit Agricole	CA	1,767,643,000	37,284.60
France	Societe Generale SA	SG	1,356,303,000	26,467.32
France	Natixis SA	NT	513,170,000	12,479.88
Germany	Commerzbank	CB	463,636,000	6,916.77
Germany	Deutsche Bank	DB	1,297,674,000	14,308.27
Greece	Alpha bank	AB	63,457,621	2,968.53
Greece	Piraeus Bank	PB	61,231,000	1,305.61
Greece	Bank of Greece	BoG	109,154,917	294.79
Greece	Eurobank	EB	64,761,000	3,412.43
Greece	National Bank of Greece	NBoG	64,248,000	2,762.44
Ireland	AIB Group	AIB	98,562,000	8,430.87
Ireland	Bank of Ireland Group	BoI	131,883,000	5,266.81
Italy	Banco BPM	BPM	167,038,201	3,072.79
Italy	BPER	BPER	79,033,498	2,333.97
Italy	MedioBanca	MB	78,244,729	8,043.50
Italy	UBI	UBI	126,525,297	3,332.16
Italy	Unicredit	UNI	855,647,000	29,078.57
Italy	Intesa SanPaolo	ISP	816,102,000	41,121.60
Netherlands	ING	ING	891,744,000	41,647.25
Portugal	Banco Comr. Portugues R	BCP	81,643,408	3,065.12
Spain	Banco de Sabadell	BDS	223,753,641	5,852.04
Spain	Banco Santander	BS	1,522,695,000	61,985.57
Spain	Bankinter R	BINT	83,732,345	5,871.39
Spain	BBV. Argentaria	BBV	698,690,000	33,226.08

Notes: Eurozone listed banks with country of affiliation, name, abbreviation, total asset and market capitalization. Total assets and market capitalization are in millions of Euro as of December 2019.

the years 2016–2017 (consequences of crisis and Brexit effect). Finally, the last peak in volatility is due to the COVID-19 pandemic⁴.

⁴The shaded areas of the figure outline the intervals of economic and financial crises that affected the euro area economy. The OECD identifies different crisis periods. We are only interested in those that occurred during the period of analysis under consideration. The crisis periods are: i) from March 2008 to June 2009 (US financial crisis impact), and ii) from June 2011 to March 2013 (Eurozone sovereign debt crisis). Moreover, we added a shaded area to identify the COVID-19 era (from January 2020 to now).

Figure 4.1: Price Volatility



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Notes: Time series plot of Absolute returns. The shaded area denotes the period of Eurozone crisis based on OECD recession indicators and COVID-19 outbreak (January 2020 to now).

In Table 4.2, we report the descriptive statistics of the daily price volatility (absolute returns) of our sample. As we can note, Greek (Eurobank [EB], Piraeus Bank [PB], the National Bank of Greece [NBoG], Alpha bank [AB]), Irish (AIB, the Bank of Ireland [BoI]) and Italian (Banco BPM [BPM], Unicredit [UNI]) banks have the highest average and median value, which indicates how financial turbulence has a more significant impact on these financial companies. The values of skewness and kurtosis show that all volatility series are non-Gaussian distributions, as tested by Jarque-Bera statistics. The augmented Dickey-Fuller (ADF) test shows that there is no evidence of a unit root. Hence, the stationarity requirement of VAR modeling is satisfied.

4.5 Empirical findings

In this section, we offer the results of our empirical analysis. First, we present the static connectivity findings during the two sub-periods (before and during the COVID-19 era). Second, we consider the dynamic nature of the connectivity using the rolling window estimation. In particular, dynamic connection measures are estimated using a rolling window size of 200 days and a forecast horizon of $H = 10$ days (as in Diebold and Yilmaz, 2012; Wang et al., 2018b; Ferrer et al., 2018)⁵. The optimal delay length of the VAR system is chosen based on Schwarz’s information criterion ($p = 1$).

4.5.1 Static connectedness

Table 4.3 and Table 4.4 report the static results of the average connection for the pre-COVID-19 and the COVID-19 era, respectively. The tables show several interesting findings. First, we can observe that the total volatility connectedness index of the system was 75.8% during the pre-COVID-19 period, while it is now 90.7%. This means how the 30 Eurozone banks are highly interconnected in terms of volatility spillover and how the COVID-19 pandemic accentuated these interconnections ($\simeq 20\%$ growth). This implies that the system is well integrated, with only a 9.3% change in the system, which is the

⁵To test the robustness, we also estimate the model based on alternative rolling windows (100, 250, 250, 300 days) and alternative forecast horizons (5, 10, 15). Please see Section 4.5.4.

result of idiosyncratic shocks in other markets, and which confirms the goodness of our sample. Therefore, these banks being highly interconnected, none of them can be isolated from volatility shocks. In the pre-COVID-19 period (Table 4.3), the banks' contribution to the volatility system (*to-connectedness*) varies from 14.3% to 121.93%, while their *from-connectedness* varies from 47.89% to 86.55%. This effect means that the volatility shocks issued by one bank can be small (14.3%) or strong (121.93%) but are distributed relatively evenly across the other banks. This result is even more pronounced if we consider the COVID-19 era. The *to-connectedness* ranges from a minimum of 7.96% to a maximum of 137.74%, while the *from-connectedness* is relatively uniform (from 84.06% to 97.58%). In this case, in addition to the increase in the size of the shock, we see greater distribution of the shock to the 30 banks in the system, i.e., more volatility risk spillover.

Table 4.2: Summary statistics of daily volatility (absolute returns)

	Mean	Median	Max	Min	Std.Dev	Skewness	Kurtosis	Jarque-Bera	ADF
EGB	0.019	0.013	0.200	0.000	0.021	2.913	15.531	30520***	-6.579***
RBI	0.020	0.014	0.283	0.000	0.022	2.867	17.518	38945***	-8.103***
KBC	0.020	0.012	0.405	0.000	0.026	4.413	36.484	191644***	-7.834***
NBoB	0.009	0.006	0.147	0.000	0.010	3.292	25.103	85015***	-10.141***
NB	0.015	0.010	0.201	0.000	0.017	3.177	19.254	48679***	-6.783***
BNP	0.017	0.011	0.191	0.000	0.019	3.320	21.424	61303***	-7.602***
CA	0.018	0.012	0.234	0.000	0.020	2.941	17.891	40970***	-7.438***
SG	0.019	0.013	0.230	0.000	0.021	3.124	19.062	47476***	-7.721***
NT	0.020	0.013	0.328	0.000	0.024	3.879	27.594	106292***	-8.234***
CB	0.020	0.014	0.282	0.000	0.022	3.133	20.522	55344***	-8.214***
DB	0.018	0.012	0.223	0.000	0.020	3.197	20.091	53221***	-6.851***
AB	0.030	0.019	0.354	0.000	0.036	3.020	17.516	39509***	-8.181***
PB	0.034	0.021	0.357	0.000	0.043	3.174	17.671	40843***	-8.621***
BoG	0.013	0.008	0.254	0.000	0.015	3.897	34.008	163390***	-9.865***
EB	0.034	0.021	0.357	0.000	0.043	3.098	16.793	36544***	-8.366***
NBoG	0.031	0.020	0.365	0.000	0.039	3.291	20.072	53510***	-8.904***
AIB	0.031	0.019	0.882	0.000	0.041	4.931	61.723	566706***	-9.201***
BoI	0.027	0.016	0.791	0.000	0.037	5.515	66.695	667905***	-7.367***
BPM	0.022	0.015	0.265	0.000	0.022	2.466	13.726	22277***	-9.372***
BPER	0.020	0.013	0.303	0.000	0.021	2.862	20.146	52225***	-8.707***
MB	0.016	0.011	0.238	0.000	0.016	3.167	25.548	87671***	-9.469***
UBI	0.019	0.013	0.232	0.000	0.019	2.585	16.494	33375***	-8.999***
UNI	0.020	0.014	0.272	0.000	0.022	2.855	17.020	36630***	-7.683***
ISP	0.017	0.012	0.261	0.000	0.019	3.272	22.616	68348***	-7.616***
ING	0.018	0.012	0.321	0.000	0.023	4.151	31.237	138458***	-7.061***
BCP	0.020	0.013	0.238	0.000	0.021	2.532	13.800	22744***	-9.922***
BDS	0.015	0.010	0.214	0.000	0.017	3.296	23.138	71764***	-10.634***
BS	0.015	0.011	0.222	0.000	0.017	3.448	26.009	92220***	-8.217***
BINT	0.016	0.011	0.171	0.000	0.016	2.379	13.201	20252***	-8.764***
BBV	0.015	0.011	0.233	0.000	0.017	3.354	25.233	86201***	-8.323***

Notes: Descriptive statistics for daily volatility of 30 Eurozone banks during the entire period from 2 June 2005 to 31 August 2020. The augmented Dickey-Fuller (ADF) statistic tests the null hypothesis of unit root. Each ADF statistic is negative and less than the test critical value at the 1% significant level, i.e., rejecting the null hypothesis of a unit root in each volatility series. All Jarque-Bera statistics are significant at the 1% level, which reject the null hypothesis of Gaussian distribution for the volatility.

Table 4.3: Static, pre COVID-19

	EGB	RBI	KBC	NBoB	NB	BNP	CA	SG	NT	CB	DB	AB	PB	BoG	EB	NBoG	AIB	BoI	BPM	BPER	MB	UBI	UNI	ISP	ING	BCP	BDS	BS	BINT	BBV	FROM
EGB	20.11	5.79	4.45	0.89	3.45	4.57	4.65	4.62	3.06	3.9	4.05	0.53	0.35	0.52	0.39	0.69	1.94	2.34	2.04	1.17	1.82	1.99	4.14	3.86	5.8	0.7	1.52	4.1	2.28	4.29	79.89
RBI	7.26	24.45	3.57	0.92	3.3	3.93	4.54	3.99	2.92	3.73	4.52	0.67	0.46	0.78	0.36	0.85	1.3	1.42	1.83	1.14	1.47	1.83	3.65	3.13	5.5	0.61	1.45	4.07	2.12	4.21	75.55
KBC	4.44	2.96	19.59	0.87	3.52	4.86	5.17	5.38	3.37	3.59	3.69	0.52	0.27	0.49	0.3	0.55	2.86	3.54	2.29	1.55	2.14	2.05	3.78	3.84	5.85	0.84	1.42	4.22	2.23	3.85	80.41
NBoB	2.98	2.87	2.72	52.11	2	3.07	3.84	2.62	1.35	2.19	2.79	0.33	0.14	0.5	0.13	0.22	0.89	1.32	0.6	0.45	0.62	0.69	1.88	1.8	4.25	0.36	0.31	2.52	1.86	2.61	47.89
NB	3.88	2.96	4.51	0.73	20.95	5.86	5.04	5.23	3.2	3.11	4.3	0.37	0.16	0.41	0.29	0.57	1.77	2.28	1.77	1.1	1.73	1.49	3.52	4.01	7.06	0.55	1.36	4.84	2.35	4.59	79.05
BNP	3.13	2.22	3.64	0.7	3.52	13.7	6.86	7.68	3.37	3.19	4.61	0.51	0.23	0.23	0.31	0.5	1.19	1.66	2.09	1.79	2.7	2.89	4.92	5.22	5.87	0.92	2.04	5.88	2.77	5.65	86.3
CA	3.21	2.63	3.58	0.75	3.34	7.08	14	7.57	3.96	3.58	4.1	0.61	0.38	0.53	0.44	0.58	1.22	1.7	2.07	1.86	2.71	2.77	4.33	4.79	5.58	0.99	2.32	5.13	3.14	5.03	86
SG	3.15	2.34	4.05	0.62	3.2	7.53	7.28	13.72	3.54	3.39	4.54	0.68	0.34	0.45	0.39	0.61	1.28	1.68	2.26	2.01	2.76	2.94	4.73	5.11	5.34	0.97	2.12	5.12	2.6	5.25	86.28
NT	3.46	2.51	3.92	0.64	3.2	5.41	6.13	5.61	21.85	3.69	3.65	0.34	0.22	0.29	0.16	0.54	1.33	1.53	2.21	1.75	2.52	2.43	3.85	4.01	4.89	0.97	2.11	4.19	2.6	3.97	78.15
CB	3.76	2.92	3.46	0.61	2.87	4.55	5.13	4.93	3.43	19.74	7.1	0.47	0.28	0.55	0.41	0.61	1.14	1.38	2.94	1.55	2.14	2.89	4.49	4.27	5.63	0.82	2.19	3.91	2.13	3.7	80.26
DB	3.19	2.92	3.29	0.66	3.27	5.57	4.9	5.59	2.77	6.14	17.02	0.48	0.29	0.41	0.24	0.62	1.07	1.63	2.51	1.66	2.26	3.06	4.75	4.34	5.75	0.83	2.03	5.56	2	5.19	82.98
AB	0.79	0.62	0.77	0.23	0.52	1.13	1.24	1.45	0.43	0.79	0.91	31.2	14.7	5.8	14.33	12.43	0.29	0.31	0.78	1.14	1.1	0.96	1.38	1.38	1.3	0.62	0.51	1.2	0.52	1.15	68.8
PB	0.55	0.45	0.38	0.09	0.25	0.53	0.79	0.81	0.29	0.54	0.55	15.12	34.73	5.13	15.13	14.69	0.45	0.17	0.72	1.1	0.72	0.93	0.96	0.81	0.64	0.87	0.69	0.85	0.26	0.79	65.27
BoG	1.21	1.04	1.52	0.57	0.88	1.03	1.71	1.51	0.55	1.24	1.05	7.55	6.4	47.54	6.63	7.3	0.35	0.47	0.58	0.65	0.57	0.81	1.32	1.48	1.64	0.57	0.18	1.35	0.84	1.44	52.46
EB	0.63	0.44	0.48	0.15	0.45	0.76	0.94	0.95	0.22	0.68	0.49	15.18	15.79	5.28	33.94	12.13	0.4	0.2	0.62	1.39	0.87	0.96	0.92	1.13	0.86	1.03	0.49	1.06	0.5	1.02	66.06
NBoG	1	0.85	0.91	0.15	0.78	1.13	1.35	1.35	0.67	0.96	1.11	12.11	14.78	5.38	12.47	30.59	0.48	0.31	0.74	1.19	0.8	1	1.39	1.39	1.49	0.89	0.75	1.85	0.66	1.5	69.41
AIB	3.11	1.41	4.62	0.32	2.15	2.8	3.43	2.91	1.63	2.56	2.3	0.45	0.37	0.38	0.34	0.53	41.98	10.18	1.27	0.57	0.59	1.1	1.96	1.88	4.01	0.48	0.74	2.37	1.5	2.06	58.02
BoI	3.81	1.99	5.84	0.4	2.89	3.69	4.07	3.7	2.44	3.1	3.33	0.36	0.17	0.34	0.2	0.37	7.85	30.6	1.89	0.88	1.29	1.25	2.69	2.17	5.21	0.32	1.23	3.23	1.97	2.72	69.4
BPM	1.94	1.41	2.09	0.24	1.44	3.28	3.15	3.46	1.95	3.1	3.01	0.61	0.47	0.22	0.45	0.53	0.84	1.12	20.58	6.46	5.65	8.06	6.67	5.89	2.81	1.66	2.58	4.32	1.98	4.02	79.42
BPER	1.2	1	1.78	0.19	1.14	2.96	3.04	3.21	1.87	1.82	2.34	0.83	0.65	0.32	0.82	0.78	0.56	0.54	7.02	22.25	6.51	8.43	5.96	6.36	2.49	1.91	3.11	4.38	2.49	4.04	77.75
MB	1.7	1.17	2.23	0.23	1.44	3.98	3.93	4.14	2.34	2.17	2.64	0.79	0.49	0.15	0.68	0.59	0.5	0.81	5.62	6.01	19.95	5.93	6.38	6.63	3.01	1.37	3.19	4.56	2.97	4.42	80.05
UBI	1.74	1.27	1.89	0.21	1.2	3.86	3.6	3.85	2	2.65	3.24	0.64	0.49	0.28	0.55	0.56	0.56	0.7	7.16	6.71	5.28	18.33	6.99	6.77	2.67	1.81	3.29	4.75	2.45	4.47	81.67
UNI	2.65	2.08	2.71	0.41	2.17	5.04	4.49	4.95	2.5	3.33	4.04	0.66	0.41	0.36	0.43	0.67	0.84	1.19	4.47	3.65	4.33	5.35	14.47	7.4	4.55	1.55	2.46	5.11	2.56	5.15	85.53
ISP	2.44	1.7	2.88	0.45	2.41	5.39	4.77	5.26	2.54	2.98	3.57	0.71	0.34	0.44	0.53	0.65	0.72	0.92	3.97	3.88	4.53	5.12	7.28	14	4.79	1.14	2.51	5.62	2.86	5.6	86
ING	4.09	3.12	4.51	1.07	4.54	6.02	5.58	5.54	3.01	3.73	4.88	0.66	0.33	0.6	0.39	0.78	1.56	2.24	1.89	1.47	2.02	2.1	4.56	4.84	15.65	0.71	1.51	5.26	2.37	4.97	84.35
BCP	1.14	0.97	1.65	0.24	0.97	2.68	2.81	2.96	1.71	1.52	1.85	1.35	1.31	0.56	1.38	1.31	0.62	0.46	3.38	3.43	2.95	4.02	4.31	3.13	2.08	39.98	2.83	3.57	1.95	2.86	60.02
BDS	1.82	1.42	1.9	0.12	1.52	3.61	4.01	3.84	2.33	2.76	2.98	0.46	0.52	0.1	0.32	0.59	0.7	0.97	3.03	3.33	3.82	4.41	4.27	4.41	2.66	1.74	23.52	6.84	5.66	6.36	76.48
BS	2.56	2.1	2.99	0.56	2.92	5.82	5.01	5.08	2.46	2.58	4.34	0.56	0.33	0.32	0.41	0.76	0.96	1.4	2.79	2.54	3.05	3.56	4.96	5.39	4.97	1.2	3.8	13.45	4.1	9.03	86.55
BINT	2.31	1.9	2.39	0.72	2.24	4.32	4.79	4.17	2.58	2.48	2.65	0.34	0.17	0.34	0.31	0.41	0.99	1.41	2.25	2.46	3.29	3.1	4.03	4.54	3.62	1.02	5.2	6.76	22.48	6.71	77.52
BBV	2.86	2.29	2.72	0.57	2.95	5.77	5	5.32	2.35	2.51	4.22	0.51	0.34	0.38	0.39	0.63	0.84	1.14	2.66	2.43	3.02	3.47	5.09	5.57	4.98	0.99	3.62	9.31	4.23	13.85	86.15
TO	76	57.34	81.47	14.3	64.53	116.23	117.24	117.67	64.85	77.99	92.87	64.43	61.2	31.55	59.17	62.05	35.5	45.01	73.43	65.33	73.26	85.6	115.19	115.55	115.3	28.46	57.58	121.93	65.94	116.67	2273.65
ALL	96.12	81.79	101.06	66.41	85.49	129.93	131.24	131.39	86.71	97.73	109.89	95.63	95.93	79.08	93.11	92.64	77.47	75.62	94.01	87.58	93.22	103.94	129.66	129.55	130.95	68.45	81.09	135.38	88.42	130.52	TVC
NET	-3.88	-18.21	1.06	-33.59	-14.51	29.93	31.24	31.39	-13.29	-2.27	9.89	-4.37	-4.07	-20.92	-6.89	-7.36	-22.53	-24.38	-5.99	-12.42	-6.78	3.94	29.66	29.55	30.95	-31.55	-18.91	35.38	-11.58	30.52	75.79

Notes: Volatility connectedness for 30 Eurozone banks for the pre-COVID-19 outbreak from 6 June January 2005 to 31 December 2019. Variance decompositions are based on 10-days-ahead forecasts. A VAR lag length of order 1 was selected by the Schwarz Bayesian information criterion and Akaike information criterion. “FROM” shows the total spillovers received by a firm i from all other series. “TO” shows the total spillovers transmitted by a company i to all other firms. The row “ALL” shows the total spillovers transmitted by variable i to all series, including itself. “NET” shows the net spillovers from firm i to all other firms j . TVC is the total spillover index.

Table 4.4: Static, COVID-19 era

	EGB	RBI	KBC	NBoB	NB	BNP	CA	SG	NT	CB	DB	AB	PB	BoG	EB	NBoG	AIB	BoI	BPM	BPER	MB	UBI	UNI	ISP	ING	BCP	BDS	BS	BINT	BBV	FROM
EGB	2.42	4.16	4.88	1.19	4.03	5.64	5.25	5.44	2.8	3.56	3.25	2.91	2.51	0.65	2.66	3.12	2.08	2.29	2.24	2.48	3.66	1.19	3.74	3.54	4.76	3.73	3.25	4.93	3.28	4.38	97.58
RBI	0.41	10.19	3.97	1.49	3.41	4.87	5.12	4.57	3.72	2.99	2.8	3.01	2.82	1.18	3.15	3.35	1.76	1.03	2.19	2.6	3.61	1.23	4.07	3.8	5.11	2.8	3.49	4.56	3.54	3.16	89.81
KBC	0.34	3.14	9.02	1.92	5.04	5.29	4.8	4.47	3.78	3.42	3.18	2.28	2.21	0.53	2.39	3.45	1.72	2.56	1.72	2.44	3.92	1.34	3.94	4.26	4.98	3.46	2.55	3.89	4.49	3.47	90.98
NBoB	0.53	3.68	4.73	10.41	3.8	4.77	3.82	4.68	5.11	2.64	2.26	3.11	3.07	1.18	2.71	3.63	1.41	1.13	2.59	2.83	3.4	2.09	3.87	4.65	3.48	2.5	2.49	2.74	3.67	3.03	89.59
NB	0.17	2.74	5.02	1.1	8.39	5.28	4.91	3.95	3.28	4.24	4.38	2.18	2.32	1.04	2.73	3.47	1.77	2.76	1.99	2.62	4.32	1.67	3.85	3.69	4.17	4.05	2.51	3.44	4.21	3.73	91.61
BNP	0.24	3.15	4.21	0.93	4.19	6.86	5.58	5.7	3.27	3.43	3.21	3.14	2.51	1.05	2.95	3.38	1.62	2.41	2.45	2.72	4.18	1.54	3.91	4.26	4.48	3.36	3.01	4.47	3.62	4.2	93.14
CA	0.21	3.22	3.86	0.92	3.87	5.39	6.67	5.41	3.38	3.72	3.62	2.94	2.62	1.27	3.03	3.41	1.23	2.32	2.97	2.92	4.02	1.82	4.18	4.47	4.3	3.27	2.94	4.51	3.53	3.96	93.33
SG	0.36	3.17	3.6	0.84	3.37	5.85	5.49	6.76	3.64	3.58	3.25	3.62	2.71	1.01	3.22	3.42	1.11	1.82	2.91	2.72	3.97	1.7	4.06	4.7	4.26	3.08	3.32	4.86	3.24	4.35	93.24
NT	0.84	4.11	4.27	1.72	3.88	5.29	4.58	4.97	10.06	2.85	2.65	3.67	3.44	1.67	3.5	3.84	1.58	1.14	2	1.84	3.28	1.52	3.44	4.42	3.95	2.89	2.67	3.41	3.16	3.36	89.94
CB	0.24	2.59	3.61	0.34	4.41	4.59	4.87	4.62	2.98	8.42	4.82	3.13	2.62	0.92	3.73	3.27	0.68	1.78	3.37	2.7	4.15	1.86	4.05	4.71	4.77	3.02	2.4	4.57	3.27	3.53	91.58
DB	0.3	2.41	3.66	0.65	5.02	4.36	5.06	4.44	2.81	5.14	9.13	2.91	2.89	1.47	3.6	3.22	0.86	1.9	3.15	1.93	4.29	2.16	4.45	4.38	4.29	3.17	2.14	3.79	2.74	3.67	90.87
AB	0.15	3.45	2.72	0.8	2.37	4.12	4.2	4.81	3.57	3.52	3.08	9.03	5.97	2.66	6.96	6.68	0.58	0.84	2.95	2.57	3.06	1.93	3.65	4.09	2.98	2.63	2.3	3.3	2.33	2.7	90.97
PB	0.06	3.09	2.73	1.41	2.71	3.51	3.98	3.88	3.19	3.24	3.44	6.89	10.53	3.53	6.65	7.42	0.48	1.1	3.08	1.68	3.21	1.61	4.07	4.39	2.98	2.43	1.5	2.96	1.92	2.34	89.47
BoG	0.31	3.04	1.34	1.25	2.5	3.09	3.49	3.09	3.7	2.61	3.16	6.1	7.47	15.54	6.8	6.25	1.07	0.86	2.89	2.23	3.19	2.79	2.77	3.97	2.4	1.57	0.86	2.17	1.42	2.05	84.46
EB	0.15	3.22	2.7	1.03	2.94	3.87	4.15	4.33	3.56	3.99	3.86	7.5	5.98	3.36	9.44	7.31	0.66	1.41	2.27	1.92	2.88	1.59	3.39	3.87	2.84	2.44	1.9	2.88	2.24	2.31	90.56
NBoG	0.14	3.12	3.37	1.42	3.29	4.18	4.3	4.38	3.52	3.29	2.92	6.61	5.92	2.64	6.4	8.39	0.86	1.58	2.53	2.27	3.2	1.78	3.61	3.93	3.03	2.63	2.06	3.22	2.8	2.59	91.61
AIB	0.89	4.06	4.34	0.92	4.04	5.59	4.22	3.94	2.24	1.65	1.82	2.21	1.18	1.21	1.63	2.33	15.94	5.86	1.46	2.18	2.85	0.75	2.84	2.4	4.81	2.85	3.64	3.73	4.32	4.08	84.06
BoI	0.39	1.79	4.27	0.5	4.53	5.43	5.1	4.26	2.15	2.82	2.6	1.98	1.64	0.9	2.34	2.86	4.81	12.48	2.1	2.87	3.57	1.14	3.31	2.84	4.25	2.97	3.68	4.23	4.4	3.81	87.52
BPM	0.16	2.16	1.82	0.34	2.67	3.29	4.46	4.15	2.39	4.31	3.62	2.84	3.3	1.75	2.99	3.45	0.54	1.33	9.62	5.09	4.76	4.39	5.81	5.44	3.48	1.66	3.61	4.58	2.39	3.61	90.38
BPER	0.13	3.26	3.27	0.48	3.64	3.87	4.7	3.91	2.85	3.91	2.3	2.29	1.97	1.05	2.54	3.42	0.75	1.98	5.75	9.58	4.1	4.45	4.98	4.56	3.41	1.6	3.28	4.26	4.81	2.88	90.42
MB	0.07	2.65	3.37	0.62	4.13	4.95	4.87	4.67	3.05	3.96	3.67	2.99	2.8	1.3	2.74	3.37	1	1.83	3.67	3.2	7.6	2.08	4.6	5.19	4.59	3.17	3.28	4.26	2.76	3.53	92.4
UBI	0.1	1.82	2.06	0.42	3.02	3.17	4.16	3.61	2.93	3.93	3.69	2.41	2.32	2	2.52	3	0.63	1.15	6.95	6.17	4.26	15.3	4.02	5.92	3.34	1.78	2.21	2.78	2.4	1.96	84.7
UNI	0.21	3.21	3.77	0.86	3.57	4.24	4.81	4.63	3.16	3.75	3.7	2.57	2.96	1.19	2.83	3.29	0.91	1.71	4.44	3.34	4.53	2.06	7.43	5.77	4.42	2.24	3.02	4.33	3.46	3.6	92.57
ISP	0.24	2.68	3.68	0.99	3.19	4.55	4.86	4.99	3.9	4.07	3.48	2.82	3.1	1.38	3.02	3.27	0.73	1.36	3.91	2.72	4.91	2.76	5.31	7.66	4.55	2.56	2.59	4.29	3.02	3.38	92.34
ING	0.35	3.84	4.53	0.83	3.79	5.32	5.16	4.85	3.07	4.06	3.55	2.1	2.11	0.81	2.18	2.57	1.97	2.23	2.71	2.43	4.62	1.72	4.41	4.74	7.72	2.69	3.71	5.24	3.34	3.33	92.28
BCP	0.25	2.57	4.2	0.72	5.23	5.26	5.39	4.71	2.92	3.7	3.8	3.32	3.13	0.85	3.23	3.61	1.36	2.17	1.88	1.82	4.29	1.08	3.19	3.46	3.58	10.96	2.95	3.46	2.91	4.02	89.04
BDS	0.06	2.99	2.73	0.54	3.31	4.66	4.7	5.46	2.53	3.32	2.62	3.13	1.8	0.49	2.61	2.93	1.6	2.45	4.33	3.78	4.75	1.9	4.33	3.91	4.47	2.83	8.75	5.85	3.14	4.02	91.25
BS	0.14	3.18	3.29	0.58	3.16	5.13	5.45	5.72	2.45	4.06	3.21	2.59	2.2	0.88	2.29	2.79	1.23	2.12	3.74	3.26	4.26	1.51	4.49	4.55	5.2	2.52	4.55	7.54	3.05	4.89	92.46
BINT	0.45	3.34	4.88	1.12	4.64	5.26	5.02	4.68	2.73	3.71	2.88	2.11	1.71	0.7	2.26	2.92	1.87	2.96	2.49	3.58	3.7	1.66	4.03	4.16	4.14	3.04	3.2	4.16	8.8	3.8	91.2
BBV	0.08	2.45	3.57	0.54	3.96	5.21	5.25	5.6	3.15	3.67	3.55	2.73	2.43	1.17	2.67	3.02	1.29	1.99	3.69	2.94	4.31	1.79	4.57	4.67	3.73	3.21	3.06	5.04	3.1	7.58	92.42
TO	7.96	88.3	104.46	26.47	107.7	136.02	137.74	133.93	91.85	103.14	94.38	96.08	87.7	39.83	96.33	108.05	38.16	56.06	88.4	81.85	113.24	55.15	116.92	124.72	116.77	80.16	82.19	115.93	92.57	99.73	2721.78
ALL	10.39	98.49	113.48	36.88	116.09	142.87	144.41	140.69	101.91	111.56	103.52	105.1	98.23	55.37	105.76	116.43	54.1	68.53	98.02	91.43	120.84	70.44	124.35	132.38	124.49	91.12	90.94	123.47	101.37	107.31	TVC
NET	-89.61	-1.51	13.48	-63.12	16.09	42.87	44.41	40.69	1.91	11.56	3.52	5.1	-1.77	-44.63	5.76	16.43	-45.9	-31.47	-1.98	-8.57	20.84	-29.56	24.35	32.38	24.49	-8.88	-9.06	23.47	1.37	7.31	90.73

Notes: Volatility connectedness for 30 Eurozone banks for during COVID-19 outbreak from 01 January 2020 to 31 August 2020. Variance decompositions are based on 10-days-ahead forecasts. A VAR lag length of order 1 was selected by the Schwarz Bayesian information criterion and Akaike information criterion. “FROM” shows the total spillovers received by a firm i from all other series. “TO” shows the total spillovers transmitted by a company i to all other firms. The row “ALL” shows the total spillovers transmitted by variable i to all series, including itself. “NET” shows the net spillovers from firm i to all other firms j . TVC is the total spillover index.

Table 4.3 and 4.4 also show the values of the net contentedness indices. If the net value is positive, it indicates that the bank in question is a volatility emitter (emits more volatility than it receives). If the value is negative, the bank in question receives volatility spillovers from other banks. We can see how the pandemic has played a decisive role in the transmission of volatility within the banking system. For example, the value of Erste Group Bank (EGB) went from -3.88% to -89.61% . Therefore, it receives much more risk from the system (an increase of 90%), as do the National Bank of Belgium (NBoB) (from -33.59% to -63.12%) and AIB (from -22.5% to -45.9%). In addition, several banks have changed from being net-receivers to net-emitters (such as Nordea Bank [NB], Natixis [NT], Commerzbank [CB], Alpha bank [AB], Eurobank [EB], the National Bank of Greece [NBoG], MedioBanca [MB], and Bankinter [BINT]), while only one bank has changed from a net-emitter to a net-receiver (UBI). Finally, the tables document how the composition of the banking sector has changed. In the pre-COVID-19 period, there were 19 banks receiving risk and 11 issuing, while now the composition is reversed, with 12 banks receiving volatility and 18 transmitting.

To capture the changes in connectivity in the Eurozone banking network before and during the COVID-19 outbreak, we ranked banks according to their directional spillovers (see Tables 4.5 and 4.6), following Wang et al. (2018b). Comparing the ranking before and during the coronavirus pandemic, we can clearly observe that the directional connectivity of the banks has changed. Looking at the *to-connectedness*, we can first notice that the banks with the highest *to-connectedness* are mainly systemically important banks (such as Crédit Agricole [CA], BNP Paribas SA [BNP] and Société Générale [SG]). This result validates the important role of large banks in the propagation of volatility shocks due to their strong interdependencies during extreme events (Pais and Stork, 2013; Varotto and Zhao, 2018; Bostandzic and Weiss, 2018). Furthermore, we find an interesting result that highlights the presence of three new banks (the National Bank of Greece [BNG], Nordea Bank [NB], and MedioBanca [MB]), and the exit of three banks from the ranking (Deutsche Bank [DB], BBV Argentario [BBV], and UBI) during the COVID-19 era. The banks that entered the ranking are small compared to those that exited from the ranking.

Table 4.5: Top 10 banks, pre COVID-19

Rank	Bank	TO	Bank	FROM	Bank	NET
1	BS	121.93	BS	86.55	BS	35.38
2	SG	117.67	BNP	86.30	SG	31.39
3	CA	117.24	SG	86.28	CA	31.24
4	BBV	116.67	BBV	86.15	ING	30.95
5	BNP	116.23	CA	86.00	BBV	30.52
6	ISP	115.55	ISP	86.00	BNP	29.93
7	ING	115.30	UNI	85.53	UNI	29.66
8	UNI	115.19	ING	84.35	ISP	29.55
9	DB	92.87	DB	82.98	DB	9.89
10	UBI	85.60	UBI	81.67	UBI	3.94

Notes: Top 10 banks ranked by *to-connectedness*, *from-connectedness* and *net-connectedness* during the pre-COVID-19 period from 6 June January 2005 to 31 December 2019.

This finding suggests that small banks are also likely to influence the transmission of volatility during periods of high fluctuations (Wang et al., 2018b; Foglia and Angelini, 2020c). It is worth noting that bank size is an important determinant of the potential transmission of volatility spillovers. In fact, a bank may be considered a small bank at the Eurozone level but a large bank at the national level, which could favor the transmission of shocks first at the national and then at the euro area level. Similarly, when analyzing the origin of the connections, we find that two large banks are excluded from the ranking (Deutsche Bank [DB] and UBI), and two other small banks are included in the ranking during the COVID-19 period (Erste Group Bank AG [EGB] and MedioBanca [MB]).

To sum up, we can see how: i) the *to-connectedness* and *net-connectedness* rankings are almost identical; ii) the change in *net-connectedness* is mainly determined by *to-connectedness* because *from-connectedness* is much less variable among banks; and iii) the Global Systemically Important Banks (BNP Paribas, Crédit Agricole, Société Générale, Deutsche Bank, Unicredit, ING, and Banco Santander)⁶ are the most interconnected and behave mainly as issuers of volatility shocks for other banks.

Moreover, in Figure 4.2, we plot the network diagram of net pairwise directional

⁶The list is available here: <https://www.fsb.org/wp-content/uploads/P221119-1.pdf>

Table 4.6: Top 10 banks, COVID-19 era

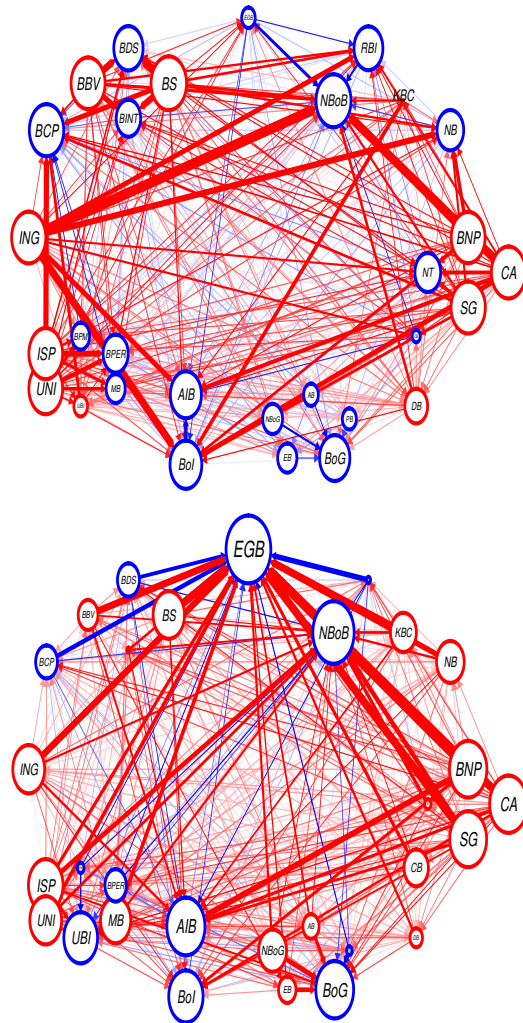
Rank	Bank	TO	Bank	FROM	Bank	NET
1	CA	137.74	EGB	97.58	CA	44.41
2	BNP	136.02	CA	93.33	BNP	42.87
3	SG	133.93	SG	93.24	SG	40.69
4	ISP	124.72	BNP	93.14	ISP	32.38
5	UNI	116.92	UNI	92.57	ING	24.49
6	ING	116.77	BS	92.46	UNI	24.35
7	BS	115.93	BBV	92.42	BS	23.47
8	MB	113.24	MB	92.40	MB	20.84
9	NBoG	108.05	ISP	92.34	NBoG	16.43
10	NB	107.70	ING	92.28	NB	16.09

Notes: Top 10 banks ranked by *to-connectedness*, *from-connectedness* and *net-connectedness* during the COVID-19 outbreak from 01 January 2020 to 31 August 2020.

spillovers for two sub-periods. The degree intensity of significant net pairwise volatility spillovers has increased markedly since the COVID-19 outbreak, i.e., there are more connectedness links. In addition, the graph shows the degree to which the net volatility between banks in the Eurozone has been affected. For example, the arrows of ING, BNP, CA, SG, BS, ISP are relatively thick. This means that the net volatility spillovers issued by these banks are strong (high level of risk transmission). The main static results can be summarized as follows. Before the COVID-19 outbreak, G-SIBs contributed more to the volatility contentedness (there are 19 banks out of 30 banks that behave as receivers of volatility shock). During the COVID-19 pandemic, the volatility connectedness increased by 20%. The pandemic crisis has led to a change in the structure of the network, from a connectivity structure dominated by the banks receiving the volatility shock to a connectivity structure dominated by the banks emitting the volatility shock (there are 18 banks out of 30 banks which are senders of the volatility shock). This change in structure could be explained by the decline in economic activity due to the coronavirus pandemic. Indeed, to manage the impact of the coronavirus, several companies were obliged to reduce their workforces. This has had socio-economic consequences, and, as a result, most households are in default, which increases the liquidity bank risk. Faced with

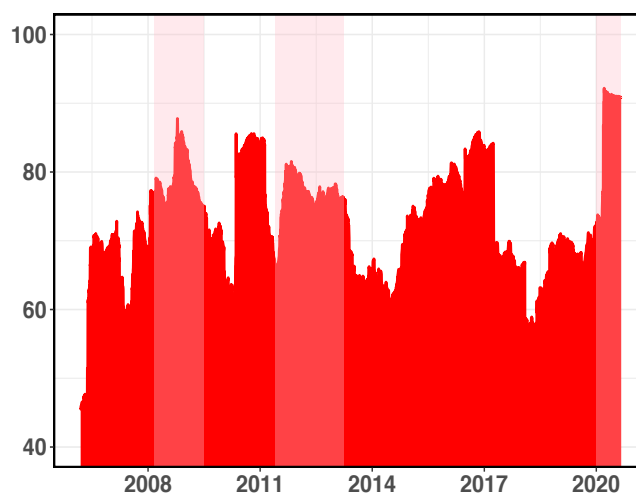
this situation, banks find themselves in panic situations, which explains the transmission of volatility shock.

Figure 4.2: Snapshot of net pairwise volatility spillover



Notes: Directional net pairwise volatility connectedness network. On left-side the volatility network for the pre-COVID-19 period; on the right-side the volatility network for COVID-19 era. The size of the node shows the magnitude of the net-pairwise directional connectedness. The colour of the node indicates whether a variable is a net transmitter (red) or net receivers (blue). The edge arrow thickness also indicates the strength of the net-pairwise directional connectedness.

Figure 4.3: Total volatility connectedness



Notes: Time series plot of total volatility connectedness. It is calculated with a rolling window of 200 day and predictive horizon for the underlying variance decomposition with 10-step-ahead forecasts. The shaded area denotes the period of Eurozone crisis based on OECD recession indicators and COVID-19 outbreak (January 2020 to now).

4.5.2 Rolling windows connectedness

A static spillover analysis (see Table 4.3 and Table 4.4) is not able to capture the volatility jumps that are caused by economic and financial events such as the financial crisis of 2009–2011, the sovereign debt crisis of 2010–2013, the Brexit effect, and the more recent COVID-19 outbreak. Hence, to better investigate the spillover dynamics, we plot the total volatility connectedness index, estimated with a rolling window size of 200 days and a forecast horizon of $H = 10$ days, in Figure 4.3. From Figure 4.3, it is possible to clearly distinguish different periods that highlight different spillover behavior.

The total volatility connectedness index has varied over time, ranging between 45% at the start of 2006 and 91% in 2020. We can distinguish four periods. The first period was during the sub-prime crisis and the collapse of Lehman, in which the index rose over 80%. The second peak was during the sovereign debt crisis of 2010–2013. Several events may exert influence on banks and stimulate their connectedness. For example, in this phase,

Eurozone banks were strongly exposed to sovereign risk and, therefore, given the strong interdependence between banks and governments, default risks materialized (BenSaïda, 2018; Bratis et al., 2018; Foglia and Angelini, 2020a; Keddad and Schalck, 2020; Malliaris and Malliaris, 2020). However, the conventional and non-conventional monetary policy of the European Central Bank (such as the “Whatever it takes” OMT announcement, July 2012; the establishment of the European Stability Mechanism, October 2012; the Single Supervisory Mechanism, November 2014; and the quantitative easing, March 2015) and the efforts of European governments have gradually reduced the risks. In the third period (2013–2017), the total volatility connectedness index shows the classic W-shaped recession (also known as a double-dip recession). The index, which had fallen at the end of 2011, began to rise in 2012, and then fell at the end of 2013 and rose again from 2014, reaching another peak at the beginning of 2017 (84.17%), which was also due to the Brexit effect (Clemente et al., 2020; Foglia and Angelini, 2020c). This trend was the result of a combination of government austerity, declining business investment, rising interest rates, global economic weakness, and weak consumption. This led to a substantial increase in contagion within the Eurozone banking system, giving rise to the problem of non-performing loans (Cincinelli and Piatti, 2017; Foglia and Angelini, 2020b). In the last period, the connection reached its peak (91%), testifying to the considerable impact of COVID-19 outbreak on banking stability (Akhtaruzzaman et al., 2020; Rizwan et al., 2020). In fact, it is well documented that during periods of financial distress, stock markets’ connectedness increases (Billio et al., 2012; Diebold and Yilmaz, 2014a; Glasserman and Young, 2015; Betz et al., 2016; Wang et al., 2017; Demirer et al., 2018; Dissem and Lobe, 2020; Foglia and Angelini, 2020b; Rizwan et al., 2020).

In Figure .1.1 (Annex), we plot the total volatility connectedness index with important financial events that affected the Eurozone economy during the past years. As we can observe, each event had a strong impact on the dynamics of the volatility spillover. For instance, we can see a substantial increase during the Greek and Irish bailouts (May 2010 and December 2010, respectively) and subsequently with the outbreak of the sovereign debt crisis. We notice a slight reduction in connections on the day of the “Whatever it

takes” announcement (July 2012). Focusing on the effect of the Brexit, we can see that it considerably increased the volatility spillover between banks (June 23, 2016), as did the Italian elections and the publication of the Brexit agreement (November 2018). Finally, the COVID-19 pandemic has delivered a strong hit to European economies (March 2020). In this period, the value of total volatility has been higher than that during the global financial crisis and the sovereign debt crisis. This counterintuitive result could be explained by the fact that, despite being a health crisis, the COVID-19 pandemic is playing a double economic and financial role. It has limited (interrupted) many economic activities (from manufacturing and tourism to the tertiary sector⁷), with the relative consequence of a reduction in individual consumption, and hence a reduction in business profit, and therefore in bank liquidity. At the same time, the increase in uncertainty generated by the pandemic has led to a feeling of negative confidence among investors, who have rebalanced their portfolios and exposures, in the so-called “dash for cash”⁸. This causes (and caused) a radical change in equity prices, therefore volatility, then sentiment, and again in equity prices (Nițoi and Pochea, 2020; Ortman et al., 2020; Goodell, 2020; Ashraf, 2020; David et al., 2020). Banks, by their nature, are more exposed in times of economic recession (due to the NPLs impact), given their important role in financing the real economy. As a result, the risks to euro area banking stability have increased substantially.

4.5.3 Net directional connectedness

To further analyze the dynamic of volatility connectedness between the 30 Eurozone banks, we focus our attention on their directional connectedness. Figure 4.4 exhibits the evolution of *net-connectedness*⁹. From an initial inspection, we can divide our sample into three categories: banks for which the value is almost always positive most of the time

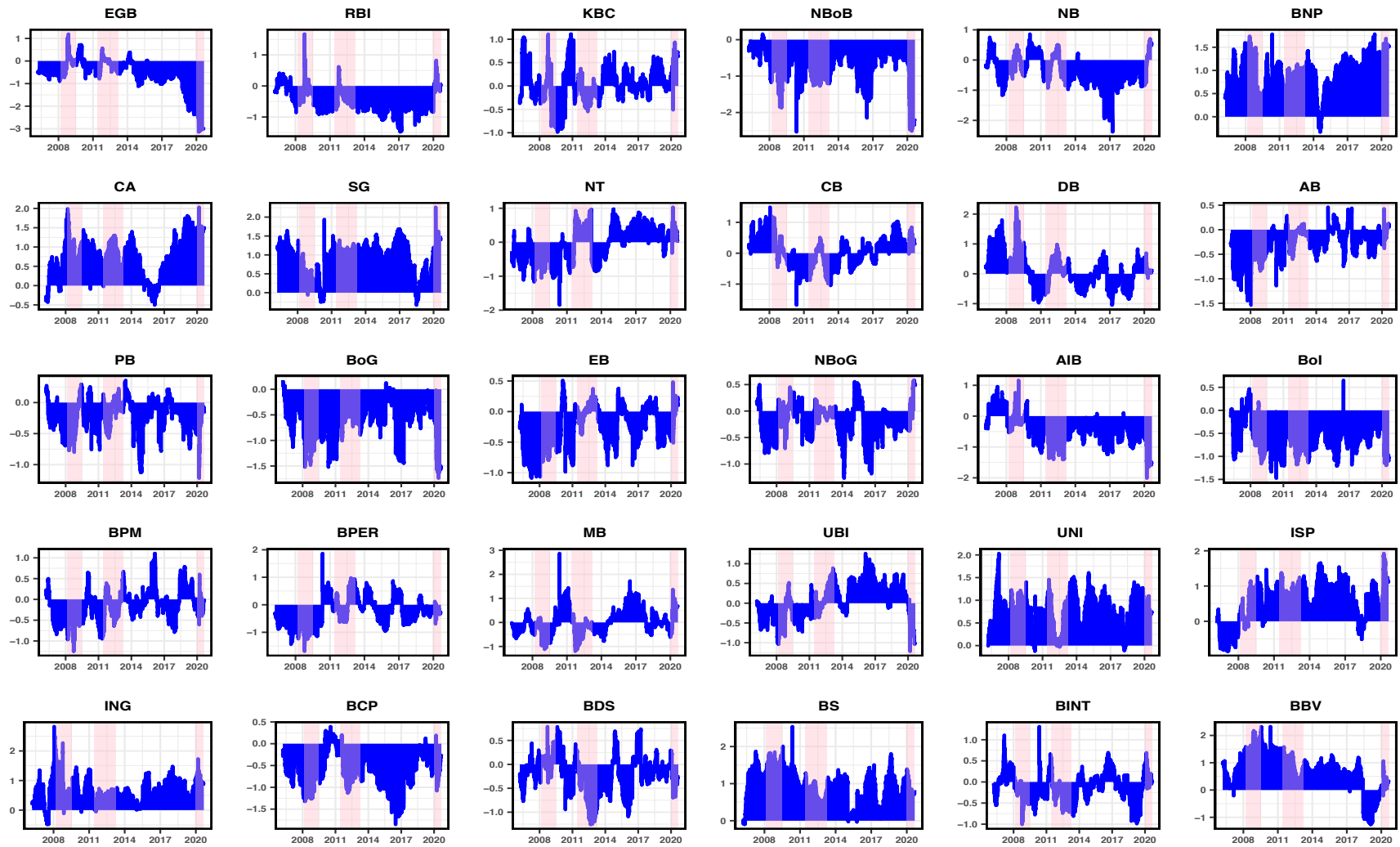
⁷For example, the OECD (2020) estimates that pandemic concerns could reduce the global tourism economy by 45-70% in 2020.

⁸See “Financial System Resilience: Lessons from a Real Stress”, speech, available at <https://www.bankofengland.co.uk/speech/2020/jon-cunliffe-speech-at-investment-association>

⁹The *from-connectedness* and the *to-connectedness* plots, can be found in Annex (see Figure .1.2 and Figure .1.3).

(volatility emitters); ii) banks for which the value is almost always negative (volatility receivers); and iii) banks that alternate their role, from being issuers to receivers and *vice versa*. The banks belonging to the first category are BNP Paribas (BNP), Crédit Agricole (CA), Société Générale (SG), Unicredit (UNI), ING, and Banco Santander (BS), or all banks classified as systemically important. This result, therefore, is perfectly in line with the Financial Stability Board classification, which testifies to how this methodology manages to identify the riskiest banks. In the second category, we find Erste Group Bank (EGB), Raiffeisen Bank International (RBI), the National Bank of Belgium (NBoB), Nordea Bank (NB), Alpha Bank (AB), the Bank of Greece (BoG), AIB, the Bank of Ireland (BoI), and Banco Comr. Portugues (BCP). These banks are those that receive the most risk from the system. From Figure 4.4, we can see the strong impact of the COVID-19 pandemic. In fact, several banks (Raiffeisen Bank International [RBI], KBC, Nordea Bank [NB], Eurobank [EB], the National Bank of Greece [NBoG], MedioBanca [MB], Bankinter [BINT], and BBV. Argentaria [BBV]) have changed their previous dynamics, becoming net emitters of volatility.

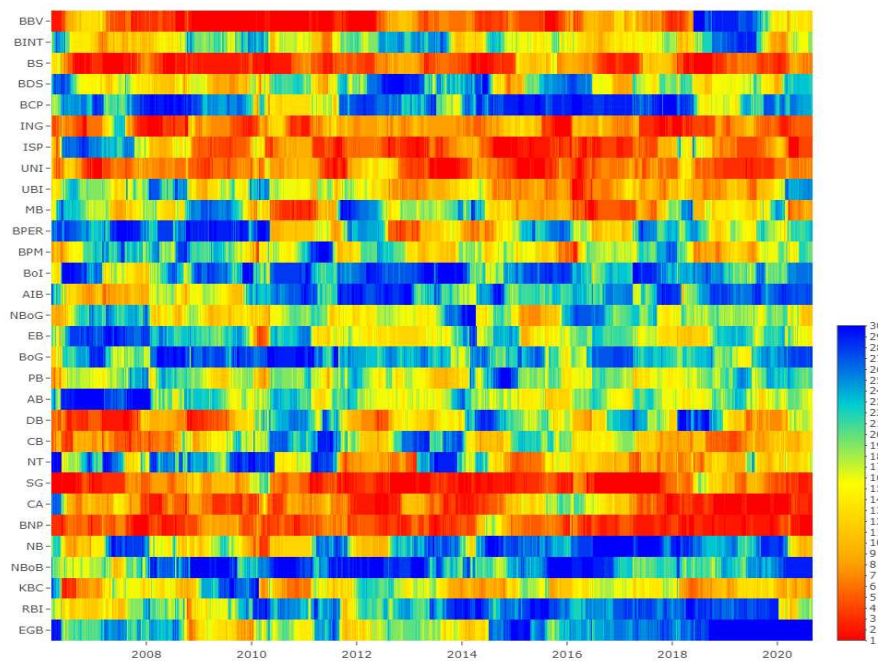
Figure 4.4: Net volatility connectedness



Notes: Time series plot of net volatility connectedness. The shaded area denotes the period of Eurozone crisis based on OECD recession indicators and COVID-19 outbreak (January 2020 to now).

Following Yi et al. (2018) and Wang et al. (2018b), we rank the 30 Eurozone banks based on net-connectedness (see Figure 4.5). The colors range from blue to red, indicating the ranking from the last (position 30 = largest volatility receiver) to the first (position 1 = largest volatility issuer). The ranking shows that G-SIBs are almost always in the top positions, unlike, for example, Austrian, Belgian, Irish and Portuguese banks, which play a marginal role in risk spillovers. This finding reveals that G-SIBs play a key part in the transmission of volatility within the Eurozone banking system, i.e., they serve as clear evidence of the “too big-to fail” issue (Beccalli et al., 2015). Our findings are fully consistent with the study by Rizwan et al. (2020), who show how the Systemically Important Financial Institutions (SIFIs) play a crucial role in risk spillover during the COVID-19 era. The small-medium banks (NBoG, MB, NB) are also important actors in volatility spillover, contributing to the high level of connectedness. This shows how the Eurozone banking sector is “too interconnected to fail.”

Figure 4.5: Rank net-connectedness

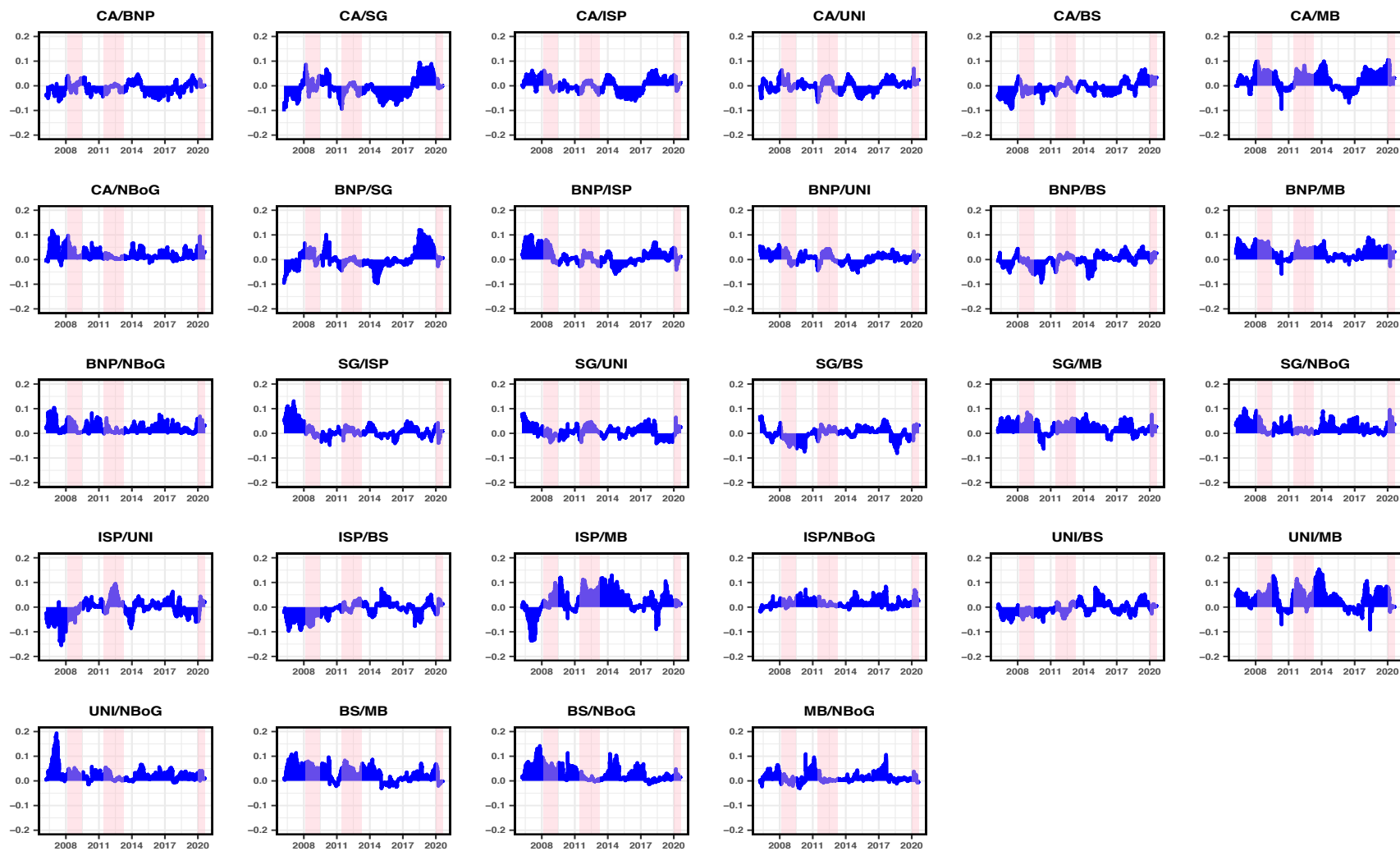


Notes: Dynamic of ranking *net-connectedness*. The colour indicates the ranking with a from range to 1 (first, therefore greater volatility emitter) to 30 (last, therefore higher volatility receiver).

Finally, in Figure 4.6, we plot the time-varying net pairwise connectedness for top-ranked banks (see Tables 4.5 and 4.6). The figure helps us to understand which banks mainly transmit or receive volatility spillover. Focusing on the COVID-19 era, we can observe that Crédit Agricole (CA) plays a key role as a sender of volatility shocks during the COVID-19 period. Crédit Agricole (CA) spread the stronger transmission of volatility shocks to European banks than the domestic banks, such as BNP Paribas (BNP) and Société Générale (SG). In general, we find that banks simultaneously play the role of the sender (positive values) and receiver (negative values) of volatility shocks, except the National Bank of Greece (NBoG) and MedioBanca (MB), which are (on average) receivers of volatility shocks.

These findings, on the one hand, underline the sensitivity of banks to volatility shocks resulting from extreme events. On the other hand, they show how the banks' vulnerability is transmitted to the banking system. Therefore, these banks should be subject to special monitoring to avoid possible transmission of risk to the financial system and their national counterparts.

Figure 4.6: Net pairwise connectedness

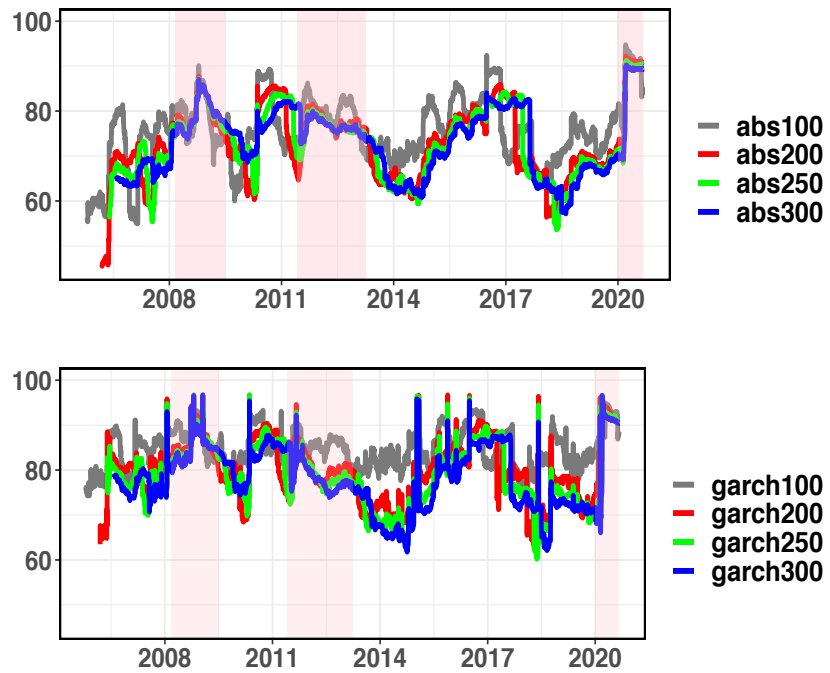


Notes: Time series plot the net pairwise connectedness. The shaded area denotes the period of Eurozone crisis based on OECD recession indicators and COVID-19 outbreak (January 2020 to now).

4.5.4 Robustness analysis

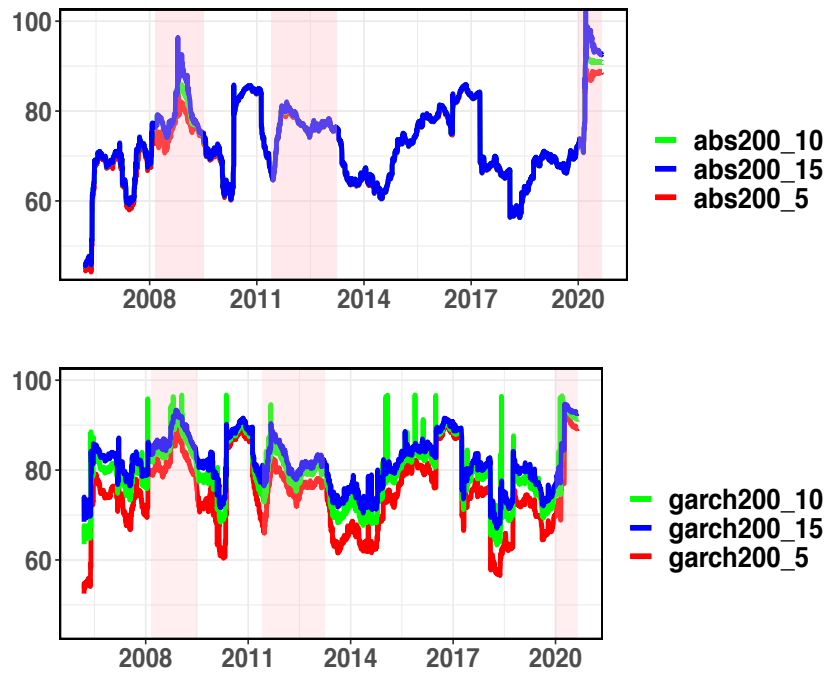
Now, we perform two robustness checks to ensure the reliability of the empirical findings. The robustness checks are based on the dynamic of total volatility connectedness. First, we analyze the sensitivity of the volatility spillover index to the size of the rolling window estimation, i.e., we set $W = 100, 200, 250, 300$ with forecast horizon $H = 10$. Figure 4.7 (up) displays the results, showing similar qualitative dynamics. Our results are robust to different rolling windows. In the second step, we check whether our findings are sensitive to the use of the GARCH (1,1) volatility estimator. Figure 4.7 (down) exhibits the total volatility connectedness using the GARCH (1,1) estimator at different window sizes. As can be seen, the patterns are qualitatively similar, suggesting that the dynamic behavior of the total volatility spillover index is robust to the choice of an alternative volatility estimator. Third, we investigate the robustness of our empirical results to predictive forecast horizons (H). Figure 4.8 displays the total volatility connectedness with $H = 5, 10, 15$ and window size = 200. Also, in this case, the volatility connectedness results are robust to different choices of the forecast horizons.

Figure 4.7: Robustness tests: Rolling window estimation



Notes: Time series plot of total connectedness volatility compute with rolling window index equal to 100, 200, 250, 300, forecast horizon $H = 10$, and based on GARCH (1,1) volatility estimator. The shaded area denotes the period of Eurozone crisis based on OECD recession indicators and COVID-19 outbreak (January 2020 to now).

Figure 4.8: Robustness tests: Forecast horizon



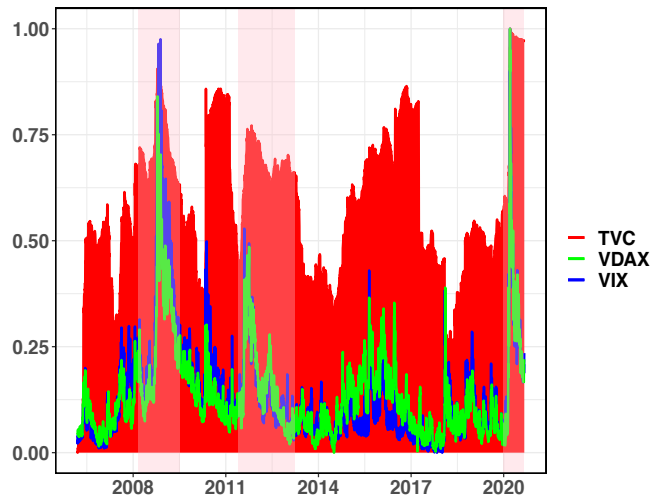
Notes: Time series plot of total connectedness volatility compute with rolling window index = 200, forecast horizon equal to $H = 5, 10, 15$, and based on GARCH (1,1) volatility estimator. The shaded area denotes the period of Eurozone crisis based on OECD recession indicators and COVID-19 outbreak (January 2020 to now).

4.6 Discussion of results

Over the last 15 years, financial markets have been affected by several significant events (from the sub-prime crisis to the COVID-19 pandemic). In this research, we analyzed the Eurozone banking sector, intending to study the structure of the volatility connections, i.e., the risk spillovers. In recent years, the Eurozone has faced several tough challenges, particularly in the financial sector. First of all, there has been the transmission of the sub-prime crisis. Originating on the US financial markets in the sub-prime mortgage segment, it has spread to the financial markets, infecting the public debt securities of

many European countries. This uncertainty has spread over to the banking system due to the close connection between sovereign risk and banks (BenSaïda, 2018; Bratis et al., 2018; Dreassi et al., 2018; Foglia and Angelini, 2020a; Malliaris and Malliaris, 2020). In this period, several conventional and non-conventional ECB monetary policy and local governments interventions contributed to reducing the volatility of the entire financial system. However, the sovereign debt crisis has had a strong impact on bank profitability and liquidity. Many companies (and households) could not repay their debts, giving rise to the NPLs crisis. In this period, we can observe how most Italian banks contributed to the greater transmission of volatility in the system (see Figure 4.5). After a period of apparent “calm”, the coronavirus outbreak (COVID-19) has disrupted social and economic life throughout the euro area and the world. Measures of market volatility (VIX), systemic stress (CISS), and financial stress index reached historic values (ECB, 2020b). In Figure 4.9, we compare the total volatility connectedness with the VIX and VDAX indexes. The pattern of indexes is qualitatively similar, but the TVC seems to be more time-responsive to shocks. All indexes can capture the salient features of events, but the total volatility connectedness index captures more information on spillover effects. To prove this, we applied a change point analysis (Bai and Perron, 2003). Thanks to this methodology, we can verify which variable best captures changes in the dynamics of financial risk. Figure .1.4 (Annex) shows the change point analysis. As we can see, the TVC index captures more (number of change points = 28) trends in behavior change than the VIX and VDAX indexes (number of change points = 18 and 22, respectively). Indeed, unlike the VIX and VDAX, the Eurozone banks’ volatility connection, while reflecting investor fear, also incorporates risk premia related to systematic financial market shocks (Hsu et al., 2020). This result testifies how this methodology manages to capture the volatility spillover in the financial markets.

Figure 4.9: TVC Vs VIX/VDAX

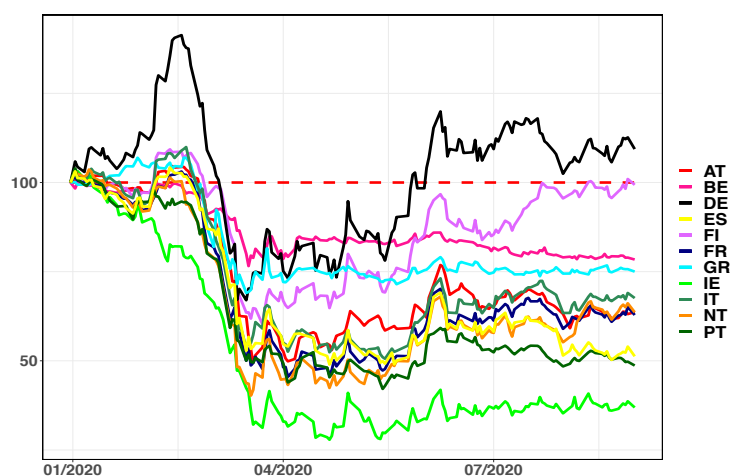


Notes: Time series plot of total volatility connectedness with VIX and VDAX variables. The shaded area denotes the period of Eurozone crisis based on OECD recession indicators and COVID-19 outbreak (January 2020 to now). Zero mean and unit variance standardize.

Indeed, in March 2020, the VIX/VDAX index reached the highest level ever recorded (82.69), as did our total volatility connectedness index (91%). This had a strong effect on European banks in anticipation of the economic impact of COVID-19 on their fundamentals (balance sheets). As we can see from Figure 4.10, bank equity indices have fallen sharply since March 2020. It should be noted that this figure is an approximation of the banking system by country—hence a total asset (2019) weighted average¹⁰. However, it helps us to understand the dynamics of risk within the Eurozone.

¹⁰Except Finland, the Netherlands and Portugal, which have only one bank in our sample.

Figure 4.10: Country banking system stocks dynamic



Notes: Time series plot of Country banking system price average stocks, indexed to 100 on 31/12/2019.

Since mid-March, only two banking systems (German and Finnish) have recovered some of their losses (perhaps due to their perceived role as “safe havens”), suggesting persistent concerns about the prospects of the Eurozone banking system. Ireland has recorded the worst performance, due to concerns regarding the real-estate sector that stem from the high values of mortgage loans and rates (Baudino, 2020). This shows how the European financial sector is very heterogeneous, i.e., a source of instability. Asymmetries can affect national systems through an asymmetrical monetary policy, and thus economic recovery (Asimakopoulos et al., 2018; Apostolakis et al., 2019). Also, the low profitability of European banks (ECB, 2020b; Aldasoro et al., 2020a) could limit their financial intermediation, thus exposing them to bank-run and credit risks. Furthermore, the high degree of interconnectedness in the Eurozone banking sector might amplify the financial impact of the shock.

The COVID-19 pandemic could again fuel financial asymmetries within the Eurozone, undermining the efforts made in recent years. Therefore, to strengthen financial stability, it is necessary to undertake a series of measures to develop greater integration between national financial markets. In a period of high uncertainty such as today, it is

necessary to secure the financial markets. Several monetary policy measures have been planned, such as the new long-term refinancing operations (LTRO and TLTRO-III), the new Pandemic Emergency Purchase Programme (PEPP), as well as a credit line of the European Stability Mechanism (ESM) to provide funding to the Member States and the much-discussed Recovery Fund¹¹. However, an action on the level of “Whatever it takes” would be welcome and reassuring for all economic operators. Besides, independent anti-COVID-19 policies should be synchronized in order to have a (hoped-for) homogeneous impact within the Eurozone, and thus on financial systems.

4.7 Conclusion

In this research, we studied dynamic volatility connectedness between 30 Eurozone banks from June 2005 to August 2020, including the COVID-19 outbreak. For this purpose, we employed the Diebold and Yilmaz (2012, 2014a) model. Thanks to this framework, we were able to analyze the interconnectedness of the banking sector by computing several network measures such as the total and net-directional volatility connectedness. Our results provide an important insight into the structure of the Eurozone banking system. Both the static and dynamic analyses highlight how the 30 Eurozone banks are highly interconnected. Moreover, the findings show the strong impact of the COVID-19 pandemic crisis on the volatility dynamics. The network structure has changed from a connectivity network dominated by the banks receiving the volatility shock to a connectivity structure dominated by the banks emitting the volatility shock. Dynamically, we find that volatility spillover connectedness increases during crises, with clear peaks during the financial crisis, the Eurozone sovereign debt crisis, the NPLs problem, and the COVID-19 era. Furthermore, the analysis points out the critical role in volatility transmission played by G-SIBs, highlighting the “too-big-to-fail” characteristic of this banking system.

The study on the impact of the COVID-19 outbreak on financial and banking stability is still at an early stage. Future work should seek to identify the causes and implications

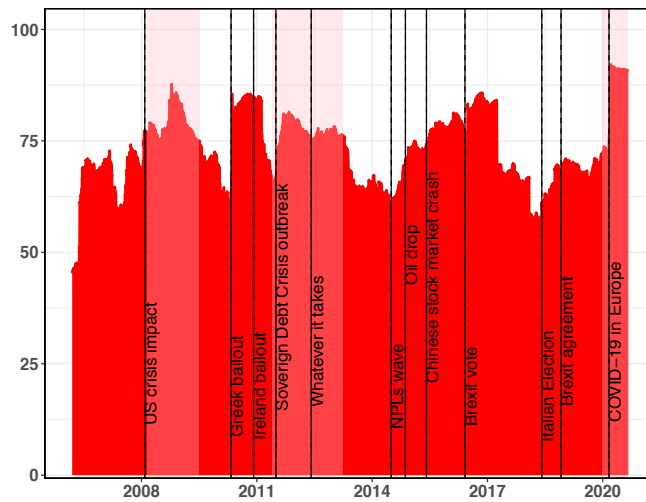
¹¹As we can see from Figure 4.10, after the announcement of the PEPP program (March 18), most bank indexes stopped their fall. However, the effect was only temporary.

of the heterogeneous financial dynamics within the Eurozone caused by the pandemic and its impact on financial and banking stability.

Annex

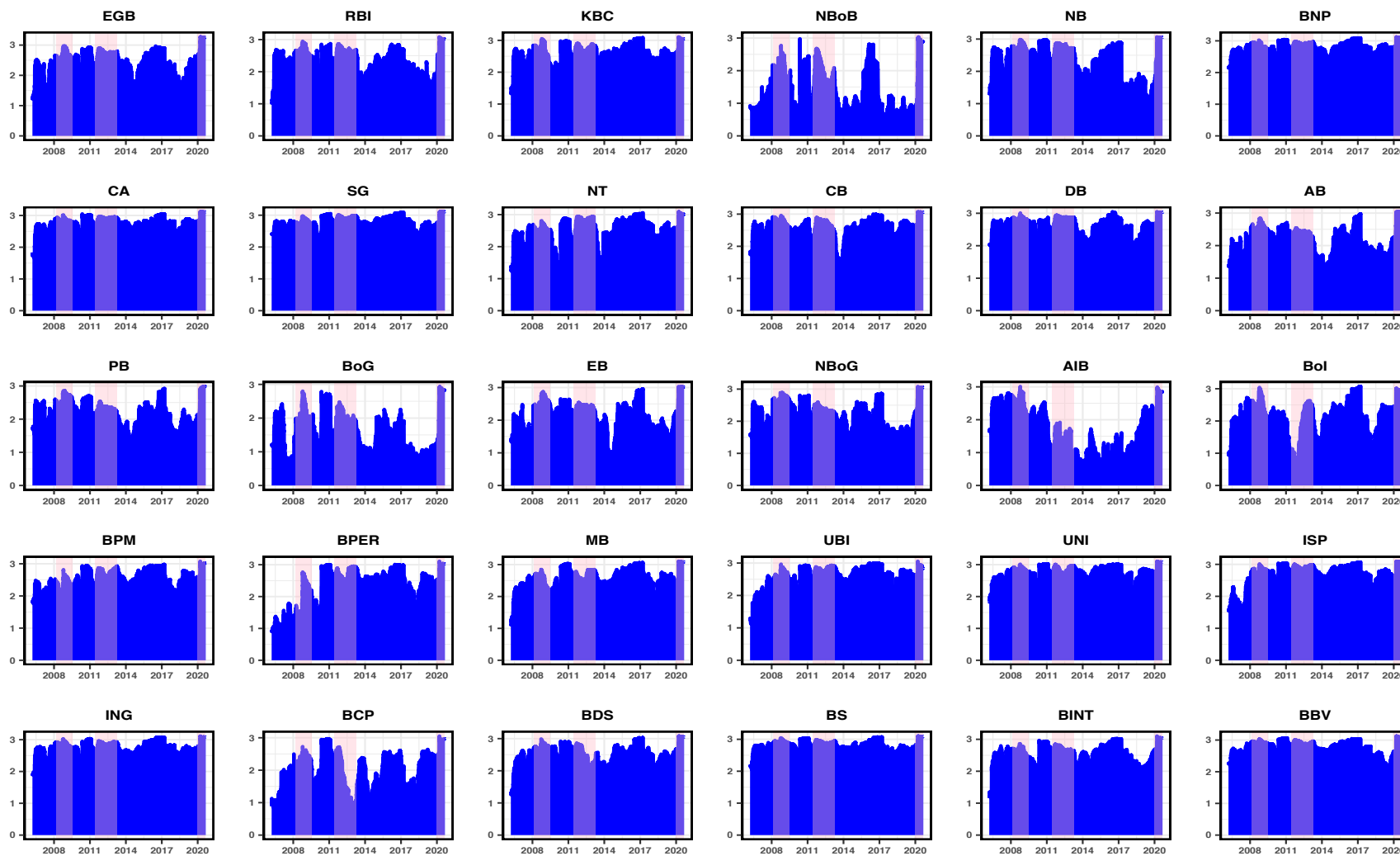
.1 Figures

Figure .1.1: TVC with events



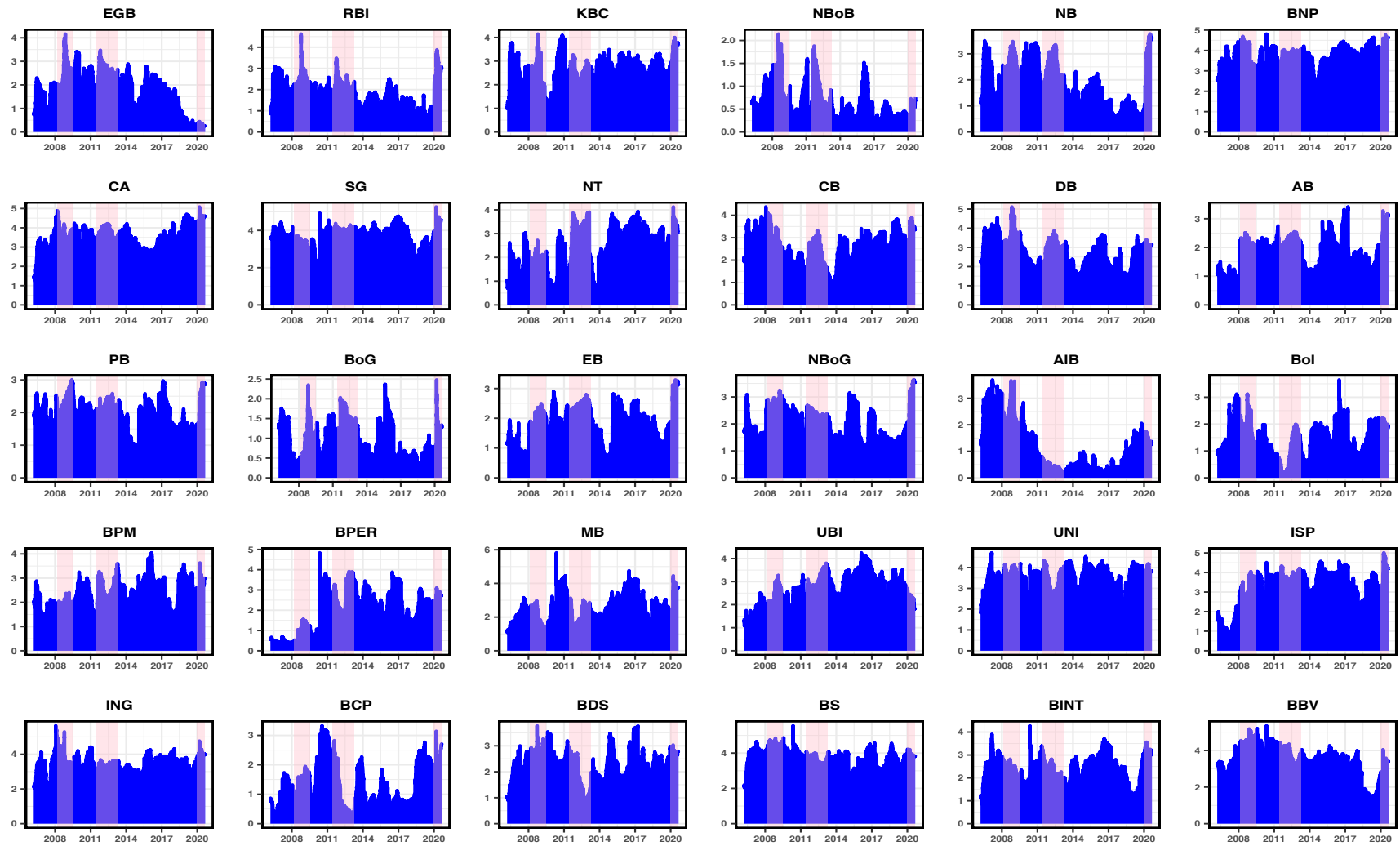
Notes: Time series plot of total volatility connectedness with financial events. It is calculated with a rolling window of 200 day and predictive horizon for the underlying variance decomposition with 10-step-ahead forecasts. The shaded area denotes the period of Eurozone crisis based on OECD recession indicators and COVID-19 outbreak (January 2020 to now).

Figure .1.2: Directional volatility: From



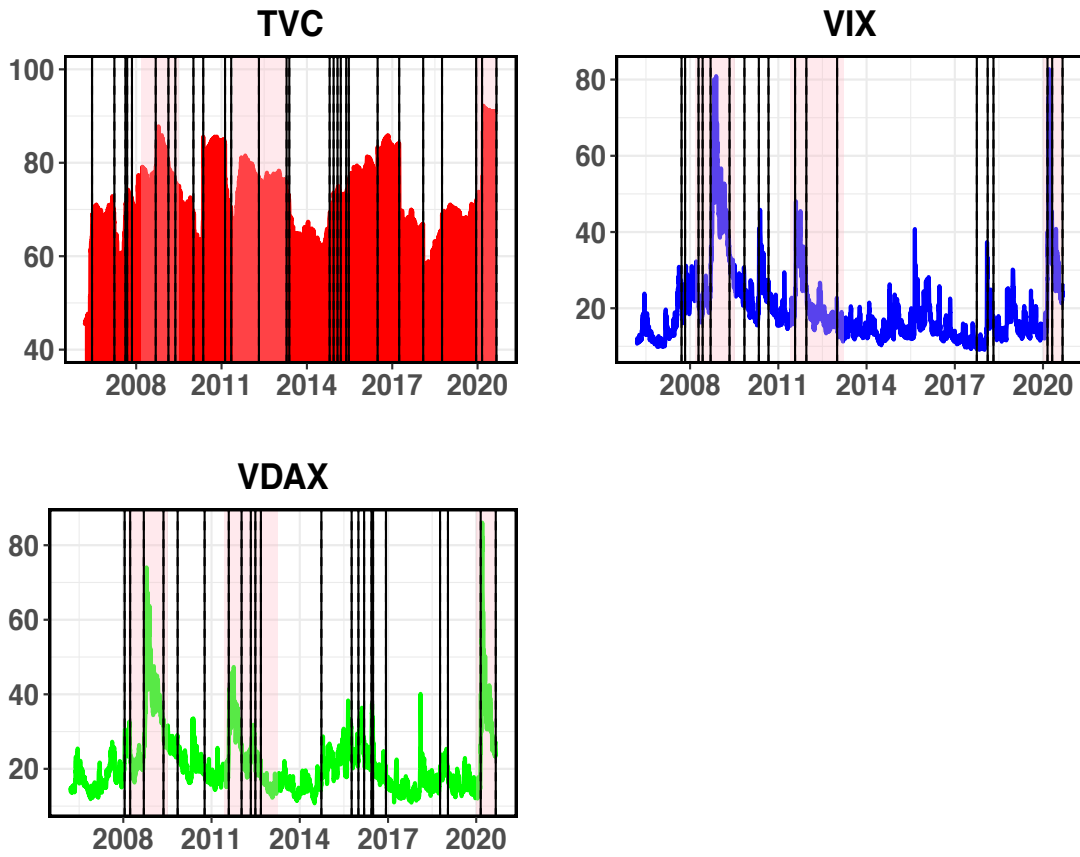
Notes: Time series plot of directional volatility contentedness from each bank i to all others. The shaded area denotes the period of Eurozone crisis based on OECD recession indicators and COVID-19 outbreak (January 2020 to now).

Figure .1.3: Directional volatility: To



Notes: Time series plot of directional volatility contentedness to each bank i to all others. The shaded area denotes the period of Eurozone crisis based on OECD recession indicators and COVID-19 outbreak (January 2020 to now).

Figure .1.4: Change-point plot



Notes: Time series plot of change-point analysis. Number of change points for TVC = 28; number of change points for VIX = 18; number of change points for VDAX = 22. The shaded area denotes the period of Eurozone crisis based on OECD recession indicators and COVID-19 outbreak (January 2020 to now).

Conclusion générale

Cette thèse propose quatre essais empiriques sur le risque systémique dans deux contextes différents : celui du système financier islamique (les banques islamiques et conventionnelles), puis celui du système financier européen. La question du risque systémique a fait l'objet de nombreux travaux, qui se sont attachés à proposer une définition conceptuelle communément admise. En dépit de toutes les investigations réalisées, le risque systémique demeure un phénomène complexe. La complexité de cette notion provient de son caractère multiforme, qui rend sa compréhension imparfaite. Les tentatives d'explication ne couvrent que quelques aspects spécifiques et, par conséquent, leurs conclusions concernant la compréhension de sa nature restent partielles. Mais, malgré des divergences sur la définition du risque systémique, les auteurs s'accordent pour avancer que la défaillance financière d'une institution est susceptible de se propager à d'autres.

Ce travail de recherche s'articule ainsi autour deux parties ; la première s'attache à étudier le risque systémique à travers une comparaison entre les banques islamiques et conventionnelles. La banque islamique, qui propose un modèle plus stable que le système conventionnel, pourrait être une alternative à ce dernier, dont les limites ont été montrées par les récentes crises. En effet, la finance islamique se base sur des principes d'éthique et propose des modes de financements censés contribuer à la stabilité financière. Néanmoins, les banques islamiques peuvent générer des risques supplémentaires en raison de la complexité de l'application des principes de la finance

islamique, de la limitation de leurs activités de financement et d'investissement et de leurs faibles moyens de gestion de risques. Cette étude des banques islamiques, en comparaison avec les banques conventionnelles, se décompose en deux chapitres.

Dans le premier chapitre, nous avons étudié l'impact de la taille sur la contribution et l'exposition au risque systémique des banques islamiques et conventionnelles. Pour cela, nous avons mesuré la contribution et l'exposition au risque systémique de 34 banques islamiques et de 70 banques conventionnelles de 12 pays de la région MENA, sur une période allant de 2006 à 2017. Dans un premier temps, nous avons analysé empiriquement l'effet de la taille sur le risque systémique des banques islamiques et conventionnelles. Dans un second temps, nous avons étudié la non linéarité de cette relation. Nos résultats ont révélé une relation positive entre la taille et le risque systémique pour les banques islamiques et conventionnelles. Nous avons également montré à partir d'un modèle Panel Smooth Threshold Regression (PSTR) et d'une approche semi-paramétrique que cette relation est non linéaire. Nos estimations ont souligné qu'en régime faible, c'est à dire lorsque la taille de la banque est inférieure à un certain seuil, cette dernière est négativement associée au risque systémique. En revanche, dans un régime fort (lorsqu'elle est supérieure à un certain seuil), la relation entre la taille et le risque systémique devient positive. Nous nous sommes parallèlement concentrés sur les différences entre banques islamiques et conventionnelles. Nous avons montré, d'une part, que les seuils obtenus à partir du modèle PSTR ont révélé un effet différentiel entre les banques islamiques et conventionnelles. Les banques conventionnelles sont plus vulnérables face au risque systémique, puisqu'elles changent de régime à un seuil inférieur à celui des banques islamiques. Les banques islamiques sont plus sensibles aux chocs systémiques étant donné qu'elles passent à un régime fort à un seuil plus bas que les banques conventionnelles. D'autre part, les résultats du modèle semi-paramétrique ont confirmé l'existence de deux régimes distincts pour les banques islamiques et conventionnelles. La relation entre le risque systémique et la taille des banques islamiques est très proche d'une relation convexe. Tandis que pour les banques conventionnelles, la relation entre

le risque systémique et la taille est plutôt de nature mitigée. Pour résumer, la mesure MES nous permet d'avancer que les banques islamiques sont plus sensibles aux chocs du marché que les banques conventionnelles, alors que la mesure de ΔCoVaR nous amène à souligner que les banques conventionnelles contribuent davantage au risque systémique.

Afin d'approfondir la question du risque systémique dans le cadre de la finance islamique, nous avons examiné à travers un deuxième chapitre les caractéristiques structurelles des interconnexions des banques islamiques et conventionnelles. En raison de leurs similitudes économiques, culturelles et environnementales, nous nous sommes concentrés uniquement sur les banques islamiques et conventionnelles des pays du Golfe étudiées dans le premier chapitre. Sur la base du modèle Tail-Event driven NETWORK risk (TENET) de Härdle et al. (2016), nous avons mis en évidence les propriétés structurelles du réseau bancaire islamique et conventionnel. Ce dernier nous a permis de mesurer l'exposition systémique de chaque banque en fonction des événements extrêmes survenus au niveau d'autres banques dans une dimension réseau. Nous avons estimé la connectivité totale et sectorielle d'une part, et la connectivité individuelle de chaque banque d'autre part. La topologie du réseau a révélé trois types d'interconnexions : intrasectorielles, intersectorielles et transfrontalières entre les différentes banques de chaque pays. Nos résultats ont également montré une asymétrie entre les banques islamiques et conventionnelles dans la transmission du risque systémique. Notre classement des banques en fonction de leur importance systémique a révélé que les banques conventionnelles contribuent davantage au risque systémique.

La complexité du phénomène de la contagion financière dans la transmission du risque systémique a fait l'objet de l'analyse que nous avons menée dans la deuxième partie de cette thèse. Cette dernière a plus particulièrement étudié le risque systémique dans le cadre du système financier européen, à travers deux chapitres.

Le premier chapitre de cette seconde partie s'est concentré sur le risque ex-

trême en tant que mécanisme de transmission du risque dans le système financier européen. Pour ce faire, nous avons examiné la contagion du risque extrême entre 183 institutions financières de la zone euro sur la période 2005-2020. L'objectif de ce chapitre était de prendre en compte l'hétérogénéité de la contagion du risque. En effet, une analyse non conditionnée par les conditions de marché est susceptible de fournir des résultats biaisés. Pour atteindre cet objectif, nous avons appliqué le test de causalité de Granger à travers les quantiles, en fonction des conditions de marché. Nos résultats ont montré, d'une part, que les conditions baissières ont une influence importante sur la transmission des « spillovers » entre les secteurs. D'autre part, nous avons considéré l'impact de l'orientation monétaire sur la stabilité financière en mettant en évidence la double stratégie pratiquée par la Banque Centrale Européenne.

Dans le dernier chapitre, nous avons examiné l'impact de la crise actuelle liée à l'épidémie de COVID-19 sur la transmission de la volatilité de 30 grandes banques de la zone euro entre juin 2005 et août 2020, en utilisant le cadre de Diebold and Yilmaz (2012, 2014a). L'objectif était d'identifier les émetteurs et les récepteurs du risque de volatilité et l'impact de la pandémie sur l'intensification du risque. Les résultats ont montré, d'une part, que toutes les banques ont contribué de manière significative à la transmission du risque de volatilité. D'autre part, nous avons mis en lumière le rôle prépondérant des banques d'importance systémique (G-SIBs) dans la transmission de la volatilité. Nous avons également montré que des événements extrêmes tels que la crise financière de 2008, la crise de la dette souveraine européenne et en particulier la crise sanitaire du COVID-19 ont eu un impact significatif sur la dynamique de la connectivité. Les résultats obtenus ont confirmé à la fois l'hypothèse selon laquelle le système bancaire de la zone euro est " too big to fail " et l'hypothèse selon laquelle le secteur bancaire de la zone euro est " too interconnected to fail ", en raison de la contribution significative des petites et moyennes banques.

Nos résultats ont un certain nombre d'implications politiques. Premièrement, les

banques islamiques et conventionnelles fonctionnent différemment, les régulateurs ne doivent pas appliquer les mêmes réglementations aux deux types de banques. Ils doivent tenir compte les spécificités structurelles des banques islamiques : leur difficulté à appliquer littéralement les principes de la finance islamique, leur refinancement et leur investissement limités, leurs faibles moyens pour gérer les risques. De plus, au-delà des risques conjoncturels et inhérents au système imposés à tous les acteurs financiers, les banques islamiques présentent des risques supplémentaires, comme le risque de retrait en cas de suspicion de non-respect des croyances religieuses des déposants. Par ailleurs, les banques islamiques doivent accompagner leur croissance rapide en développant leur gestion des risques. En effet, le développement d'une politique de gestion des risques conforme aux principes de la finance islamique jouera un rôle important pour les protéger de l'éloignement de leurs modèles théoriques. Le simple fait d'imiter les banques conventionnelles dans leurs pratiques de gestion des risques et leurs modes de fonctionnement éloigne les banques islamiques de leurs modèles d'affaires et remet en cause leur attitude de stabilité. La taille étant un déterminant majeur du risque systémique, les décideurs doivent tenir compte de l'évolution de la taille des banques lors de la conception des mesures réglementaires. En effet, les mesures réglementaires ne doivent pas uniformiser leurs exigences à toutes les banques, ces dernières doivent être adaptées en fonction de certains facteurs, en l'occurrence la taille, pour éviter de punir les banques qui ne sont pas concernées. Par ailleurs, les banques conventionnelles ont des stratégies hétérogènes, en commercialisant des produits conformes à l'éthique de la finance islamique. Ces stratégies permettent aux banques conventionnelles de se diversifier mais finissent par créer des liens, qui peuvent devenir des canaux de transmission des chocs aux banques islamiques. Étant donné les différences de capacités de gestion des risques et de poids sur le marché des banques islamiques (qui sont de petite taille par rapport aux banques conventionnelles), un choc provenant des banques conventionnelles pourrait affecter leur stabilité. À ce stade et face à un tel déséquilibre, les banques islamiques devraient limiter leurs liens avec les banques conventionnelles d'importance systémique.

Au-delà du cadre traité de la finance islamique, les résultats de la seconde partie de cette thèse permettent de dégager un certain nombre de recommandations pour le système bancaire de la zone euro. Pour commencer, l'étude des effets de débordement du risque extrême aide à mieux concevoir les politiques réglementaires, qui visent à maintenir la stabilité financière. L'étude des effets de débordement selon différents niveaux de queue extrêmes (positifs ou négatifs) permet de visualiser l'hétérogénéité non observée et de détecter ainsi le niveau de queue qui influence davantage les changements d'interconnexions. En effet, une analyse qui n'est pas conditionnée par les différentes externalités de queue pourrait conduire à des réglementations inappropriées par les décideurs politiques. Notre étude distingue la queue gauche et la queue droite, en montrant le rôle important de la queue gauche dans la transmission du risque extrême. Ces conclusions peuvent être utilisées pour guider la conception des politiques réglementaires. Par ailleurs, l'analyse du risque de queue en fonction des conditions de marché permet aux investisseurs de mieux cibler les secteurs d'investissement, en tenant compte des différents niveaux de queue, ainsi qu'aux gestionnaires de risques de mieux anticiper le risque systémique.

Enfin, nous suggérons quelques pistes de recherche pour l'avenir qui permettront d'améliorer les travaux menés dans cette recherche doctorale. Premièrement, d'autres facteurs peuvent apporter des explications supplémentaires au risque systémique, comme le risque de défaut. La littérature reconnaît que le risque de défaut d'une banque peut potentiellement affecter non seulement la stabilité de la banque mais aussi celle des autres. S'il ne se limite pas à la banque et affecte les autres banques, il est considéré comme systémique. Il peut néanmoins être idiosyncratique s'il n'affecte que la banque. A notre connaissance, la littérature existante ne s'est pas encore penchée sur l'étude des effets du risque de défaut sur la contribution et l'exposition au risque systémique global. Il serait donc pertinent de tester si le risque de défaut des banques islamiques et conventionnelles tend à être systémique ou idiosyncratique. Deuxièmement, en raison de la structure des

interconnexions entre les banques islamiques et conventionnelles et de la proximité géographique entre les banques des pays du Golfe, nous pouvons, dans le prolongement de ce travail de recherche, analyser les effets de voisinage dans la transmission du risque. Il s'agit de vérifier si le facteur de proximité géographique pourrait jouer un rôle déterminant dans la définition de la nature de la structure d'interconnexion des pays du Golfe. Troisièmement, dans le contexte actuel de COVID-19, il est souhaitable de réaliser des tests de résilience (« stress testing ») pour évaluer le niveau de résistance des banques aux chocs financiers et économiques de la crise sanitaire. Une telle analyse permettra de détecter leur fragilité afin d'agir en amont pour mieux maintenir la stabilité financière de la zone euro. Quatrièmement, pour étudier de manière exhaustive la nature de la connectivité dans la zone euro, une étude qui utilise des réseaux multicouches (la couche de débordement du rendement, la couche de débordement de la volatilité et la couche de débordement du risque extrême) peut apporter un éclairage plus global sur la nature des interconnexions au niveau des individus et du système financier dans la zone euro.

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