UNIVERSITÉ DU QUÉBEC À MONTRÉAL

ESSAIS EN MACROÉCONOMIE ET EN ÉCONOMIE INTERNATIONALE

THÈSE

PRÉSENTÉE

COMME EXIGENCE PARTIELLE

DU DOCTORAT EN ÉCONOMIQUE

PAR

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JUIN 2024

REMERCIEMENTS

En premier lieu, mes remerciements vont à mes directeurs de recherche, les professeurs Dalibor Stevanovic et Julien Martin. Messieurs, Je vous remercie pour la liberté et la confiance que vous m'avez accordées, me permettant de m'exprimer. Merci pour les opportunités que vous m'avez offertes, qui ont enrichi et embelli mon parcours. Merci, pour votre soutien et votre bienveillance tout au long du programme et dans les moments décisifs. Je tiens également à vous remercier pour les personnesde qualité que vous êtes.

Je souhaite exprimer une gratitude particulière au professeur Kevin Moran, avec qui le premier chapitre de cette thèse a été publié, ainsi qu'au professeur Mao Takongmo (grand frère), co-auteur du deuxième chapitre de cette thèse. Merci, grand frère, pour tout.

Merci au personnel administratif, particulièrement à Martine, Julie et Karine. Mesdames, vous contribuez à créer un environnement agréable et propice à la réussite. Je remercie également les professeurs du département d'économie, notamment Alessandro Baratieri, Sophie Osotimehin, et Alain Paquet pour les conseils et suggestions.

Je suis reconnaissant d'avoir fait partie de la cohorte de 2017 avec Franck Atsiga, Komla Avoumatsodo, Mustafa Fonton, Isambert Leunga et Maxime Leroux. Chers amis, je suis heureux que chacun de nous soit arrivé au bout de cette aventure. Merci pour votre solidarité, pour les moments de travail et de qualité passés ensemble. Je vous souhaite à tous un plein et heureux succès dans vos carrières respectives.

Un grand merci aux amis de Saint-Denis, de Notre-Dame de Vie, aux fraternités de Jérusalem, notamment Sr Esther (ma très chère grande sœur) et Fr Pierre-Benoît, ainsi qu'à Papavi Agbeko, Nathan Munyaga, grand frère Konaté, grande mère Claudette, et à tous les amis et connaissances de Montréal. Merci d'avoir contribué à équilibrer et embellir socialement et spirituellement mon parcours durant ces années.

À la Grande Famille, Merci pour vos encouragements et votre soutien. Merci, Baba, pour ta bienveillance et tes conseils. Maman, comme tu le sais bien, les mots ne sauraient suffire pour exprimer ma reconnaissance et ma gratitude pour tout ce que tu fais. Merci pour tes soutiens divers et vairés tout au long de cette aventure.

PÈRE, voilà qu'après tout ce que Tu sais nous y sommes arrivés. Merci beaucoup.

Merci pour ton Amour Bienveillant, ton Précieux Pardon et ta Miséricorde qui permettent de nous relever et nous donnent assurance en Ta Présence. Merci pour ta Fidélité quelles que soient les situations, et les adversités. J 'ai appris que tu m'appelles à avancer en Toi. Merci.

À Toi, tout le mérite. Je sais que c'est Toi qui l'as fait, Grand, Fidèle et Bon Architecte. Toute imperfection étant de mon fait. Mais, je sais que nous ferons mieux.

Merci pour tout ce que Tu m'as appris durant ces années.

DÉDICACE

À Toi qui es mon PÈRE, ma Source et ma Fin ;
Mon Grand FRÈRE, mon Modèle et mon But ;
Mon Vrai SOUFFLE, mon Guide et ma Force.

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RÉSUMÉ

Cette thèse est composée de trois articles portant sur deux thèmes ayant suscité un grand intérêt parmi les économistes au cours des dernières années: l'incertitude économique et la connectivité économique. Le concept d'incertitude économique renvoie à la difficulté à former des prévisions sur le futur de l'économie, tandis que la connectivité vise à mesurer le niveau d'influence relative entre les entités économiques. Écrits en vue d'une meilleure compréhension de ces phénomènes, ces articles apportent des éléments utiles à la formulation de politiques économiques.

Le premier article construit une mesure de l'incertitude macroéconomique spécifique au Canada et évalue l'impact du choc d'incertitude associé à l'émergence de la COVID-19 sur l'économie canadienne. Pour créer cette mesure, nous appliquons la méthodologie développée par Jurado et al. (2015) à une grande de données canadiennes. Les résultats mettent en évidence une nette augmentation du niveau d'incertitude au Canada, atteignant un niveau inédit avec l'émergence de la pandémie. Cela corrobore d'autres résultats montrant des augmentations importantes de l'incertitude aux États-Unis et ailleurs dans le monde. Ensuite, l'effet d'un choc d'incertitude, calibré en fonction des variations de la mesure au cours de cette période, est estimé sur les principales variables macroéconomiques canadiennes. Les résultats montrent qu'un tel choc entraîne des ralentissements économiques, une inflation plus faible et des mesures accommodantes de la politique monétaire. D'importantes distinctions apparaissent en fonction de l'interprétation du choc comme provenant de l'incertitude aux États-Unis - auquel cas le ralentissement est profond mais relativement court - ou de l'incertitude au Canada, ce qui entraîne des déclins plus prolongés de l'activité économique.

Le deuxième article quantifie la connectivité entre économies et examine ses déterminants. Ce concept, introduit par Diebold and Yilmaz (2009, 2012), vise à mesurer le degré d'influence et d'exposition relative entre des entités économiques. Plusieurs dimensions sont envisagées : l'exposition d'une économie à une autre ou au reste du monde, l'influence d'une économie sur une autre économie ou sur le reste du monde, et la connectivité totale, qui mesure en moyenne la part de volatilité au sein des pays attribuable à la transmission de chocs entre eux. Le deuxième article associe à la méthode développée par Diebold and Yilmaz (2009, 2012), les méthodes adaptées aux données de grande dimension pour estimer la connectivité entre 28 pays développés et émergents. Les résultats révèlent que la connectivité globale entre les économies fluctue au fil du temps, augmentant lors des grandes crises mondiales. Les niveaux d'influence et d'exposition des pays changent également dans le temps.

D'autre part, cet article étudie les déterminants des différentes mesures de connectivité (influence totale, exposition totale, et connectivité bilatérale). Plus précisément, il analyse le rôle de la taille des économies, de l'ouverture commerciale et financière, ainsi que de la spécialisation des pays. Les résultats indiquent que les économies les plus influentes sont celles de grande taille en termes de production nationale. L'exposition des pays augmente avec leur niveau d'ouverture commerciale. Nous notons que l'exposition due à l'ouverture commerciale augmente avec la taille des pays. Au niveau bilatéral, la connectivité augmente avec l'intégration commerciale. L'intégration financière et les différences de spécialisation économique atténuent les effets de l'intégration commerciale sur la connectivité bilatérale. Additionnellement, nous montrons que l'appartenance à un accord commercial ou à une zone économique augmente significativement la connectivité bilatérale entre deux pays.

Le troisième article étudie le rôle de la politique monétaire et du niveau du global

de liquidité sur la connectivité internationale des prix de l'immobilier. Dans un premier temps, nous mesurons la connectivité entre les marchés immobiliers en utilisant la méthode développée par Diebold and Yilmaz (2009, 2012). Nous trouvons que la connectivité des marchés immobiliers augmente durant les périodes d'expansion globale et baisse durant les périodes de récession globale. Les États-Unis sont le pays plus influent et l'Irlande le pays le plus exposé. Ensuite nous étudions l'effet d'une variation de la liquidité au niveau global sur la connectivité. Nous montrons qu'une réduction du niveau global de liquidité réduit la connectivité entre les marchés immobiliers. Enfin nous étudions les effets d'une politique monétaire nationale restrictive sur l'exposition du marché immobilier domestique. Nous trouvons qu'une telle politique diminue l'exposition du marché immobilier domestique aux chocs étrangers.

Mots Clé: Incertitude macroeconomique, COVID-19, connectivité, contagion, réseau, intégration économique, marché immobilier, politique monétaire, liquidité globale.

INTRODUCTION

Cette thèse comprend trois articles explorant deux domaines qui ont suscité un vif intérêt parmi les économistes au cours des dernières années : l'incertitude et la connectivité. Le premier article se penche sur le thème de l'incertitude économique, tandis que les deux suivants se consacrent à la connectivité. Le concept d'incertitude économique renvoie à la difficulté à former des prévisions sur le futur de l'économie, tandis que la connectivité vise à mesurer le niveau d'influence relative entre les entités économiques.

La prévisibilité des conditions économiques futures joue un rôle crucial dans les décisions prises par différents acteurs économiques. Que ce soit la réalisation de dépenses importantes telle que l'achat d'une maison ou d'une voiture en ce qui concerne les ménages, les investissements en équipements, en personnels ou dans de nouveaux projets pour les entreprises, ou encore l'octroi de crédit à un ménage ou à une firme dans le cas des banques, ces agents économiques basent leur décision sur les prévisions qu'ils forment, et peuvent reporter ou abandonner leur projet lorsqu'il est plus difficile de prévoir.

L'émergence de la pandémie de COVID-19 a significativement accru le niveau de difficultés à former des prévisions sur l'avenir, non seulement par ses conséquences en termes de santé publique non maîtrisées par les connaissances de l'époque, par les changements qu'elle a imposés à court terme et ses implications économiques à long terme. L'augmentation de l'incertitude engendrée par la COVID-19 était certes indéniable mais difficile à quantifier et ses implications pour l'économie canadienne non totalement maîtrisée.

Dans ce contexte, le premier article apporte deux contributions. Tout d'abord, nous élaborons la première mesure d'incertitude macroéconomique spécifique au Canada. Pour ce faire, nous appliquons la méthode développée par Jurado et al. (2015) à la vaste base de données construite par Fortin-Gagnon et al. (2022). Cette mesure offre une longue perspective historique de l'incertitude macroéconomique canadienne et confirme qu'elle a atteint un niveau sans précédent lors de l'emergence de la COVID-19 (dépassant de plus 3 écart-types la moyenne historique) .

Ensuite, nous utilisons un modèle Vectoriel Autorégressif (VAR) pour estimer les répercussions économiques d'un choc d'incertitude comparable à celui survenu lors de l'arrivée de la COVID-19. Considérant le Canada comme une petite économie ouverte étroitement liée à son voisin américain, nous examinons les conséquences des chocs d'incertitude aux États-Unis et de leur contrepartie canadienne en prenant soin d'identifier et de contrôler les éventuels effets de contagion entre les incertitudes des deux pays.

Nous montrons que de tels chocs conduisent à des récessions sévères, à une baisse de l'inflation et à des politiques monétaires accommodantes. Cependant, d'importantes distinctions émergent selon que le choc d'incertitude est interprété comme provenant des États-Unis ou du Canada. Alors que dans le premier cas, les récessions causées par les chocs sont profondes mais relativement de courte durée, dans le second, les baisses de l'activité économique sont plus persistantes et ont été accentuées par le pic d'incertitude induit par la COVID.

Nous montrons que ces résultats sont robustes à divers problèmes de spécification et demeurent inchangés lorsqu'on considère différentes hypothèses relatives à l'ordonnancement (identification) des VARs ou à la stratégie de différenciation des données.

Les deuxième et troisième articles abordent le thème de la connectivité. Ce concept, introduit par Diebold and Yilmaz (2009, 2012), vise à évaluer le degré d'influence et d'exposition relative entre les entités économiques. Il comporte plusieurs aspects : l'exposition d'une économie à une autre (bilatérale) ou aux autres économies, l'influence d'une économie sur une autre ou sur le reste du monde, ainsi que la connectivité globale au sein d'un groupe de pays, mesurant en moyenne la part de volatilité dans ces économies causées par la transmission de chocs entre elles.

La plupart des régions du globe sont maintenant liées les unes aux autres par des flux de capitaux, par le commerce de biens et services, et par les mouvements de personnes. Ces interconnexions facilitent la propagation des chocs d'une économie à une autre. La crise de 2007-2009, la pandémie de la COVID-19 et plus récemment la guerre en Ukraine en sont des exemples éloquents. Au niveau microéconomique, les données de firmes étudiées par Boehm et al. (2019) montrent comment le tsunami ayant frappé le Japon en 2011 a eu des répercussions sur les États-Unis. Ainsi une crise économique ou une catastrophe naturelle dans un pays vont se propager à travers le globe selon l'importance des liens qui relient ce pays au reste du réseau.

Dès lors, la compréhension de la position d'un pays ou d'une région au sein de ce réseau global revêt une importance cruciale pour les décideurs publics en vue d'évaluer et de gérer les risques auxquels ils sont confrontés. Dans cette optique, le deuxième article propose de quantifier la connectivité en termes de production entre 28 pays (développés et émergents) et d'étudier ses déterminants, notamment le rôle de l'ouverture commerciale et financière, de la spécialisation économique et de la taille économique du pays.

Dans un premier temps, nous mesurons la connectivité entre ces 28 pays. Tandis que Diebold and Yilmaz (2015a) avait entrepris une analyse similaire pour un nombre limité de pays (6 pays du G7, à l'exception du Canada), en prenant en compte un nombre plus élevé de pays, cet article permet de contrôler les effets de second tour qui pourraient biaiser les résultats obtenus pour un groupe restreint de pays. Pour ce faire, en plus de la méthode développée par Diebold et Yilmaz (2009, 2012) nous recourons à une méthode d'estimation adaptée à des bases de données de grande dimension. Cette approche permet non seulement de contourner les limitations des méthodes standards telles que les moindres carrés ordinaires (MCO), mais aussi de sélectionner parmi un ensemble de variables (pays dans notre contexte) celles qui sont les plus pertinentes pour expliquer une variable cible. Cela permet d'obtenir des estimations plus fines des liens de connectivité entre les pays. Nos résultats révèlent que la connectivité globale entre les pays varie dans le temps, augmentant lors des périodes de crises économiques majeures à l'échelle mondiale. Nous constatons également que les niveaux d'influence et d'exposition des pays change à travers le temps.

Dans un second temps, à l'aide de modèles à effets fixes pour les données de panel, nous examinons d'une part les déterminants de la connectivité (exposition et influence) vis-à-vis des autres pays et d'autre part les déterminants de la connectivité bilatérale. Plus précisément, nous analysons le rôle de l'intégration commerciale et financière, de la spécialisation économique et de la taille des pays.

Nous trouvons que l'exposition des économies augmente avec leur ouverture commerciale au reste du monde. Plus la taille de l'économie est importante plus le lien entre ouverture commerciale et exposition est important. Nous trouvons par ailleurs que les économies les plus influentes sont les plus grandes en termes de production nationale.

Les résultats économétriques concernant la connectivité bilatérale indiquent que celle-ci augmente avec l'intégration commerciale entre deux pays. L'intégration financière et la différence de spécialisation économique dimunue l'effet du commerce sur la connectivité.

En outre, nous montrons que l'appartenance à un accord commercial ou à une zone économique renforce la connectivité entre deux pays.

Le troisième article se penche sur les marchés immobiliers. Ces dernières années ont été marquées par une augmentation des prix de l'immobilier dans plusieurs économies avancées, de manière relativement synchronisée. Parallèlement, la plupart de ces pays ont adopté des politiques monétaires très accommodantes, caractérisées par des taux d'intérêt proches de zéro et des mesures d'assouplissement quantitatif. Cela a eu pour effet d'accroître le niveau de liquidité à la fois au niveau national et à l'échelle mondiale. Il est bien établi en économie que le niveau de liquidité influe sur les prix des biens (théorie quantitative de la monnaie). En conséquence, la politique monétaire est l'instrument privilégié pour réguler l'évolution tendancielle des prix dans l'économie . Dans ce troisième article, nous examinons le rôle du niveau global de liquidité et de la politique monétaire nationale sur la connectivité des marchés immobiliers à l'échelle internationale.

Tout d'abord, nous mesurons la connectivité entre les marchés immobiliers des différents pays (connectivité totale, influence et exposition des pays, ainsi que connectivité bilatérale). Ensuite, nous analysons d'une part l'effet du niveau global de liquidité sur la connectivité totale et d'autre part l'impact de la politique monétaire nationale sur l'exposition des marchés immobiliers nationaux.

Notre échantillon de travail comprend 19 pays de l'OCDE sur la période 1970-2020. La mesure de la connectivité suit la même méthodologie que celle utilisée dans le deuxième article, combinant la méthode élaborée par Diebold and Yilmaz

(2009, 2012) avec des techniques d'estimation adaptées aux banques de données de grande dimension.

Nos résultats indiquent que la connectivité des marchés immobiliers augmente pendant les périodes d'expansion mondiale et diminue lors des récessions mondiales. Les États-Unis se distinguent en tant que pays le plus influent, tandis que l'Irlande présente la plus grande exposition. Par ailleurs, au niveau bilatéral, les marchés immobiliers les plus connectés sont ceux des pays géographiquement proches ou partageant une langue commune (ou une ethnie).

Ensuite, en utilisant un modèle vectoriel autorégressif (VAR), nous évaluons l'impact d'un choc de liquidité globale sur la connectivité totale. Nos résultats montrent qu'une réduction du niveau de liquidité mondial diminue la connectivité totale entre les pays.

Enfin, en utilisant la méthode de projection locale développée par Jordà (2005), nous montrons qu'une politique monétaire restrictive réduit l'exposition des marchés immobiliers nationaux aux chocs provenant de l'étranger.

Ces résultats suggèrent que la politique monétaire et le niveau de liquidité mondiale ont la capacité d'influencer le niveau de connectivité entre les marchés immobiliers.

CHAPTER I

MACROECONOMIC UNCERTAINTY AND THE COVID-19 PANDEMIC: MEASURE AND IMPACTS ON THE CANADIAN ECONOMY

ABSTRACT

This paper[1] constructs a measure of Canadian macroeconomic uncertainty, by applying the Jurado et al. (2015) method to the large database of Fortin-Gagnon et al. (2020). This measure reveals that the COVID-19 pandemic has been associated with a very sharp rise of macroeconomic uncertainty in Canada, confirming other results showing similar large increases in uncertainty in the United States and elsewhere. The paper then uses a structural VAR to compute the impacts on the Canadian economy of uncertainty shocks calibrated to match these recent COVID-induced increases. We show that such shocks lead to severe economic downturns, lower inflation and persistent accommodating measures from monetary policy. Important distinctions emerge depending on whether the shock is interpreted as originating from US uncertainty –in which case the downturn is deep but relatively short– or from Canadian uncertainty, which leads to more protracted declines in economic activity.

JEL classification : C53, C55, E32

[1]This Chapter is a paper written with Professor Kevin Moran and Professor Dalibor Stevanovic. It has been published at Canadian Journal of Economics/Revue canadienne d'économique, volume 55, p.379-405. https://doi.org/10.1111/caje.12551

1.1 Introduction

Many economic decisions represent bets on the future: when to make large purchases such as cars and housing, when to invest in new plants, equipment and infrastructure or whether to extend credit to entrepreneurs, households and corporations. Economic agents must forecast future conditions to make such decisions and may postpone or abandon their plans when the outlook for the future becomes harder to assess. An extensive literature has examined the quantitative implications of this intuition, by measuring economic uncertainty and analyzing the macroeconomic implications of shocks to these measures.[2]

The COVID-19 pandemic has undeniably increased the difficulty to assess the future, both because its consequences for public health are still developing and because of its possible long-term economic fallouts. As such, the pandemic likely embodies a very important increase in uncertainty and makes this literature more relevant than ever.

The present paper makes two contributions. First it constructs the first Canadian measure of macroeconomic uncertainty, by applying the Jurado et al. (2015) method to the large database of Fortin-Gagnon et al. (2022).[3] This measure

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[2]Important papers in this literature include those from Jurado et al. (2015), who measure uncertainty through the performance of a forecasting model applied to a large database; Baker et al. (2016), who use the frequency at which text incorporating words like 'economic policy uncertainty' appear in media; Bloom (2009), who identifies uncertainty with measures of volatility on financial markets, or Leduc and Liu (2016) who employ answers to future-oriented questions in the Michigan Survey. See Fernández-Villaverde and Guerrón-Quintana (2020) for a survey of this literature.

[3]The uncertainty measures constructed using the methodology described here are available and regularly updated at https://chairemacro.esg.uqam.ca/previsions-et-mesures-macroeconomiques/mesure-dincertitude/.

provides an important historical perspective about Canadian macroeconomic uncertainty and confirms it has reached unprecedented levels since the onset of the pandemic. These dramatic increases concord with those obtained with data from other countries or using other methods of measuring uncertainty (Leduc and Liu, 020a; Baker et al., 2020; Altig et al., 2020).

Second, the paper uses vector autoregressions (VARs) to compute the macroeconomic consequences of uncertainty shocks similar in size to those recorded during the COVID-19 pandemic. Considering the position of Canada as a small open economy tightly linked with its American neighbour, we analyze both the consequences of shocks to US uncertainty and to its Canadian counterpart, taking care to identify and control for the possible spillovers between these measures.

We show that such shocks lead to severe economic downturns, lower inflation and persistent accommodating measures from monetary policy. Important distinctions emerge, however, depending on whether the uncertainty shock is interpreted as originating from the US or from Canada. While in the former case, downturns caused by the shocks are deep but relatively short-lived, in the latter such declines in economic activity are more persistent and have been sharpened by the COVID-induced spikes in uncertainty. We show that these results are robust to a variety of specification issues and are unchanged under alternative assumptions about the ordering (identification) of the VARs or of the differencing strategy for the data.

Several recent papers analyze the COVID-induced spikes in uncertainty and assess their likely implications for the growth rate of output (Baker et al., 2020), unemployment and monetary policy (Leduc and Liu, 020a), economic agents' expectations about the future (Dietrich et al., 2020) or the adoption of labour-saving technology (Leduc and Liu, 020b), among several topics. These results add to the existing, pre-COVID literature establishing that increases in uncertainty lead to declines in economic activity and increases in unemployment (Bloom, 2009; Jurado et al., 2015; Caldara et al., 2016; Baker et al., 2016; Leduc and Liu, 2016; Carriero et al., 2018).

However, the great majority of research on uncertainty and its macroeconomic impacts has been conducted with US data and, when other countries do appear in this literature, the analysis usually pertains to the effect of US uncertainty on the foreign country (Colombo, 2013; Klössner and Sekkel, 2014; Kamber et al., 2016).[4] The present paper therefore constitutes the first contribution that specifically documents the interrelated movements between Canadian uncertainty, its US counterpart, and Canadian economic activity. Considering the severity of the economic downturn caused by the pandemic and the difficult road ahead towards recovery, our results are timely and policy-relevant.

The remainder of this paper is organized as follows. Section 2 describes the Jurado et al. (2015) method to measure macroeconomic uncertainty. Section 3 presents our Canadian application of this method and then compares our measure to alternatives obtained using data from other countries or other methodologies. Section 4 presents our main findings about the likely macroeconomic impacts of the recent increases in uncertainty. Section 5 concludes.

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[4] An exception is Moore (2017), which examines the domestic impacts of Australian uncertainty.

1.2 Measuring Macroeconomic Uncertainty

A simple intuition underlies Jurado et al. (2015) (JLN hereafter)'s measure of macroeconomic uncertainty : the economic future is more difficult to predict when uncertainty is high; conversely, uncertainty is high when predicting the economic future becomes more difficult.

JLN operationalize this intuition by measuring uncertainty as the performance of a macroeconomic forecasting model. To this end, they apply a factor-based approach to a large database containing dozens of time series. They compute forecasts, forecast errors, as well as the conditional volatility of these forecast errors, for each individual time series in the database and for every time period. Uncertainty at a given point of time is then defined as the weighted sum of individual conditional volatilities in forecasting errors.

Specifically, let y_t^j be the value at time t of the jth time series of the database and $\widehat{y^j}_{t+h}|_t$ the forecast of y_{t+h}^j obtained using information known as of period t, with h the forecasting horizon. The conditional volatility in the forecast error at horizon h for time series j at time t is

$$U_t^j(h) = \sqrt{E_t\left[\left(y_{t+h}^j - \widehat{y^j}_{t+h|_t}\right)^2\right]}, \tag{1.1}$$

where $E\left[y_{t+h}^j - \widehat{y^j}_{t+h|_t}\right]^2$ represents the variance in the forecasting error, conditional on information known at time t. JLN's aggregate measure of macroeconomic uncertainty is then the sum of these conditional volatilities:

$$U_t(h) = \sum_{j}^{N} U_t^j(h). \tag{1.2}$$

The measure (1.2) is flexible and can be specialized in a variety of ways. Notably, the summation can be specific to geography, using data series pertaining to a specific Canadian province, or can be conditional on sectoral criteria that retain only data about labour markets, for example. Our results below explore both of these avenues.[5]

This paper develops a Canadian measure of macroeconomic uncertainty by applying JLN's method to the database constructed and maintained by Fortin-Gagnon et al. (2020). This database contains more than 300 time series related to the Canadian economy, is available for both quarterly and monthly frequency and is updated regularly. The data begin in 1981, include both national and regional information, and cover various sectors such as production, the labour market, prices and interest rates, housing market activity and trade, among others. As is the norm for large-scale databases, individual time series are treated for seasonality, differenced when relevant and normalized. Note that the quarterly version of the database contains series drawn from Canada's National Accounts, like GDP and its various components, and thus offers a richer information set than the monthly version. We compute uncertainty measures based on both quarterly and monthly data but the impact analysis in Section 5 is based on the quarterly version because of this informational advantage.

[5]JLN also consider heterogenous weighting of the individual measures, so that (1.2) becomes $U_t(h) = \sum_j^N \omega_j U_t^j(h)$.

As indicated above in (1.1)-(1.2), measuring macroeconomic uncertainty requires that a general forecasting framework for each individual time series be established. To this end, consider the following factor model for forecasting future values of series y_j:

$$\mathbf{X}_t = \mathbf{\Lambda^F} \mathbf{F}_t + \mathbf{u_t}; \tag{1.3}$$

$$\mathbf{X}_t^2 = \mathbf{\Lambda^W} \mathbf{W}_t + \mathbf{v_t}; \tag{1.4}$$

$$y_{j,t+h} = \rho(\mathbf{L})\, y_{j,t} + \beta(\mathbf{L})\, \mathbf{F}_t + \gamma(L)\, \mathbf{F}_{1,t}^2 + \delta(\mathbf{L})\, \mathbf{W}_t + e_{j,t+h}. \tag{1.5}$$

The expressions (1.3) and (1.4) first describe how the information contained in the many hundred time series of the database are efficiently summarized. First, (1.3) describes how the vector $\mathbf{X}_t$, which contains all the database's variables, is expressed as a linear function of a small number of common factors $\mathbf{F_t}$ and idiosyncratic components $\mathbf{u_t}$.[6] Since the linear form of (1.3) limits its ability to account for possible non-linear links between the variables in $\mathbf{X_t}$, (1.4) is then added to the model to identify a second set of factors $\mathbf{W}_t$ related to the square of the variables in $\mathbf{X}_t$. Overall, (1.3) and (1.4) deliver an efficient synthesis of the information contained in more than three hundred time series, through the vectors $\mathbf{F}_t$ and $\mathbf{W}_t$ and the factor loadings $\mathbf{\Lambda^F}$ and $\mathbf{\Lambda^W}$.[7]

[6] We use the Bai and Ng (2002) test to determine the number of factors required to adequately summarize the variability in $\mathbf{X_t}$.

[7] The relevance of the non-linear terms in (1.4) is an empirical question. While Gorodnichenko and Ng (2017) find some evidence on such volatility factors in a similar setup – particularly for housing sector variables– our aggregate uncertainty measure appears less affected by them: abstracting from (1.4) leads to a measure that is very highly correlated (around

Equation (1.5) then shows how forecasts for the future values of each individual time series j are obtained on the basis of information known at time t, represented by lagged values of the factors, the variable itself and the square of the first element of $\mathbf{F}_t$.[8] This type of factor-based forecasting paradigm has become a standard in the literature (Stock and Watson, 2006).

JLN argue that it is important to distinguish between periods where time series become more volatile from episodes where they become intrinsically difficult to forecast. To that end, the variance of the residuals $e_{j,t+h}$ is assumed to be affected by stochastic volatility, so that $e_{j,t+h}$ is governed by the process $e_{j,t+h} = \sigma^y_{j,t}\,\epsilon^y_{j,t}$ with $\epsilon^y_{j,t} \overset{iid}{\sim} \mathcal{N}(0,1)$ and

$$\log \sigma^y_{j,t} = \alpha^y_j + \beta^y_j \log \sigma^y_{j,t-1} + \tau^y_j \eta_{j,t},\ \ \eta_{j,t} \overset{iid}{\sim} \mathcal{N}(0,1), \tag{1.6}$$

where $\beta^y_j > 0$ indicates that episodes of heightened volatility are persistent. In addition, autoregressive processes are specified and estimated for the factors $\mathbf{F}_t$ and $\mathbf{W}_t$ themselves, with the residuals for these processes also affected by conditional volatility similar to (1.6).

Finally, note that the predictive analysis (1.3)-(1.6) underlying the uncertainty measure consists of in-sample predictions (fitting), rather than recursive out-of-

0.98) with our benchmark.

[8]Following Jurado et al. (2015), we use four lags of y^j_t and two each for $\mathbf{F}_t$, $\mathbf{F}^2_{1,t}$ and $\mathbf{W}_t$. A robustness check conducted by allowing 4 lags of each factor in (1.5) yields uncertainty measures highly correlated (above the 0.99 mark) with our benchmark. One could alternatively use Lasso techniques to identify how many and which lags to include in (1.5), but we consider the approach with a fixed and parcimonious specification preferrable, as penalized versions of (1.5) appear not to improve the predictive power of factor models such as (1.3)-(1.5) (Goulet Coulombe et al., 2019).

sample forecasts. This follows JLN, who do compute uncertainty measures using both approaches and show they are highly correlated. This may be due to the good predictive performance of the factor model, which has been shown to be robust to structural breaks (Stock and Watson, 2002) and not be affected by overfitting (Goulet Coulombe et al., 2019).[9]

1.2.1 Adjustment of the measure to the COVID-19 Episode

The COVID-19 episode has created serious challenges to the estimation of factor and predictive models like (1.3)-(1.6), as some variables have registered such extreme observations in March and April 2020 that they could be modelled as draws from a different distribution. This situation naturally affects the measurement of macroeconomic uncertainty. Although the COVID-19 shock cannot be considered predictable, even at the one-month-ahead horizon, this regime switch ought to be taken into account going forward, when forecasting with April data in hand. Indeed, the uncertainty measure, as stated in (1.1), assumes that any forecastable component is removed before computing the conditional volatility.

In that context, Ludvigson et al. (2020) propose to model the regime switch attributable to COVID-19 as a mean-shift adjustment on every series y_j. We follow their approach and assume that the main unpredictable COVID-19 shock affected April 2020 data.[10] Hence, assuming that the shock happens in April

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[9] Rogers and Xu (2019) show that uncertainty measures like JLN have good in-sample explanatory power but low forecasting ability when assessed in real time. This lack of predictive power may therefore be related to real-time considerations instead of out-of-sample versus in-sample measurement strategies.

[10] A closer look at March and April data shows that several extreme values were recorded in April, with the aggregate unemployment rate, for example, rising to 7.8% in March but then

means that we were not able to predict the extreme magnitude of the subsequent downturn. In the case of our quarterly uncertainty measure, we assume that the main unpredictable COVID-19 shock occurred in the second quarter of 2020. Relatedly, the descriptive analysis in the next section singles out increases in uncertainty from March 2020 (monthly data) and 2020Q1 (quarterly) as the onset of the pandemic's impact on uncertainty.

Starting from April 2020 (monthly measure) and 2020Q2 (quarterly) and rolling forward, our strategy is then to compute the difference between the observed value for a series $y_{j,t}$ and its predicted value on the basis of one month (quarter)-old information. This difference is an estimate of the regime shift in the mean of each series and it is used to adjust our uncertainty measures going forward.[11] Technical details are described in Appendix A.1.

The natural question is when to stop the adjustment, if the COVID-19 shock has no permanent effect on time series. We compared the monthly uncertainty measures obtained with and without this mean-shift adjustment for the sample ending in August 2020. The correlation coefficients between the two measures are around 0.85. Hence, 4 months after the unpredictable shock, mean-shift adjustment starts losing its effect, suggesting that the shock is probably transitory.

Overall, this adjustement allows our measure to continue to be updated, while

to 13% in April. In addition, the Labour Force Survey is conducted in the third week of a month so it accidentally captured a part of the confinement. Altig et al. (2020) report that several measures of uncertainty recorded their peak in April 2020.

[11] From the modeling point of view, this is a second-best solution. A fully-specified regime-switching model would be a better choice, but the extreme values occur at the very end of the sample and in real-time, which makes this procedure infeasible.

taking into account the recent large volatility in some variables of the database and, at the same time, retaining the spirit of the JLN's method as an aggregation of the unpredictable components of these variables' evolution.

1.3 A Canadian Measure of Macroeconomic Uncertainty

Figure 1.1 reports the results of applying JLN's method to the quarterly version of Fortin-Gagnon et al. (2020)'s database. It thus depicts our Canadian macroeconomic uncertainty measure $U_t^{CAN}(h)$ for the one-quarter, two-quarter, and four-quarter-ahead horizons over the period from 1982Q1 to 2020Q2, with shaded areas representing recessions as defined by the C.D. Howe Institute (Cross and Bergevin, 2012).

Three general features of uncertainty emerge from the figure. First, uncertainty is nearly always higher for longer forecasting horizons, reflecting the fact that forecasting far away in the future is generally harder. Second, and relatedly, uncertainty is less volatile as forecasting horizons lengthen and forecasts converge to their unconditional values: this is particularly noticeable for the measure based on four-quarters-ahead forecasts. Third, the various measures are nonetheless very correlated with each other (correlation coefficients between them are all higher than 0.98) and negatively correlated to the business cycle: all three measures increase simultaneously during the early-1990s and 2008 recessions, as well as during episodes of milder turbulences such as the 2001 crash of the technology bubble and the negative oil price shock in 2015. In addition, all three measures are significantly and negatively correlated with HP-detrended GDP.

Figure 1.1 also reveals the impact of the COVID-19 pandemic. All three un-

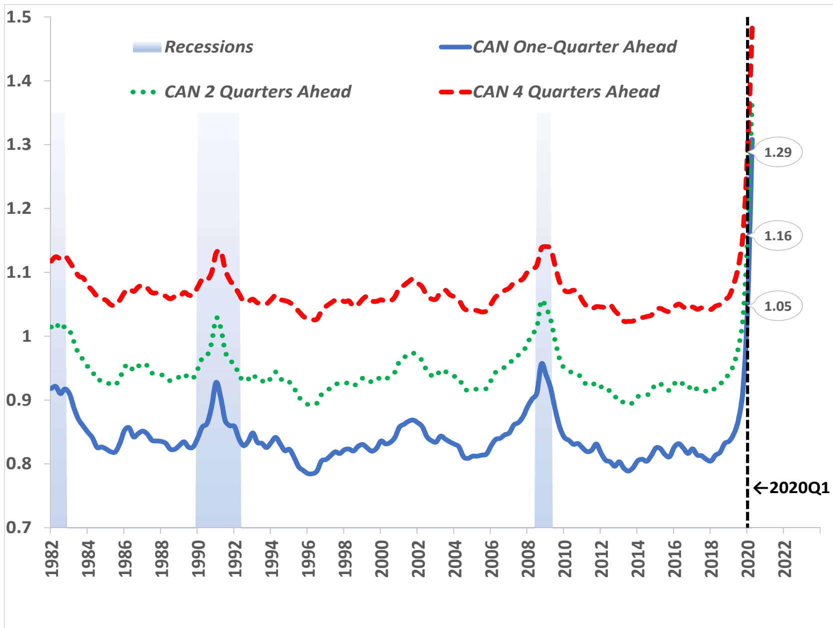

Figure 1.1: Canadian Macroeconomic Uncertainty

Note : Canadian Macroeconomic Uncertainty measured using the quarterly version of the Fortin-Gagnon et al. (2022) database.

certainty measures report very sharp increases in 2020: values for 2020Q1 –the onset of the pandemic in our interpretation of the data– indicate that they rise to 1.05, 1.16, and 1.29, respectively, 4 to 5 standard deviations away from their respective long time averages. The figure also shows that 2020Q2 uncertainty levels remain unprecedently high. Our measure therefore reveals, as expected, that COVID-19 pandemic has coincided with extremely sharp increases in Canadian macroeconomic uncertainty.

As mentioned above, uncertainty measures can be conditioned on geographic or sectoral aspects of the data underlying the forecasting model. In that context, Figure 1.2 compares the evolution of uncertainty obtained using provincial data only (Quebec, Ontario and Alberta) with the overall Canadian measure discussed so far, for the period 2000-2020.[12]

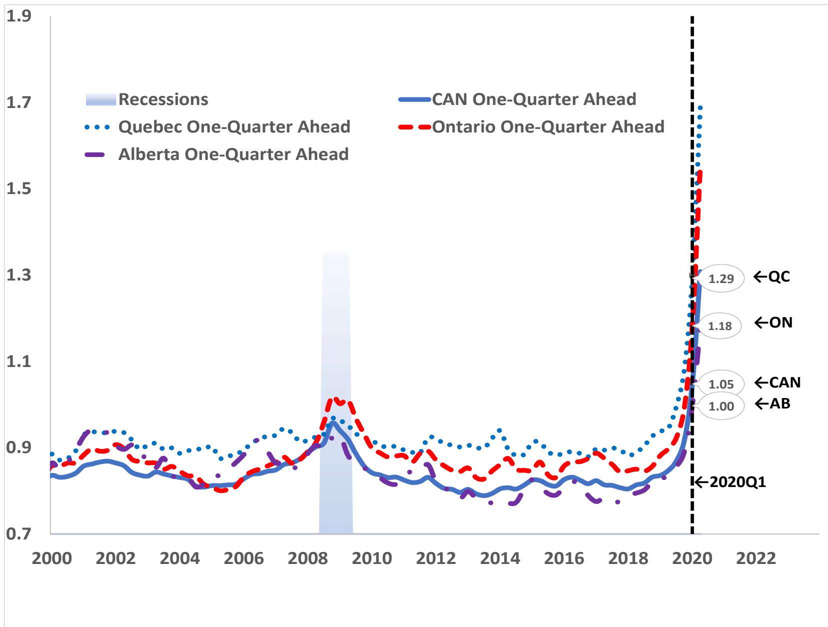

Figure 1.2: Canadian Macroeconomic Uncertainty: Provincial Measures

Note: Macroeconomic Uncertainty for Canadian provinces, measured using the quarterly version of the Fortin-Gagnon et al. (2022) database.

Figure 1.2 reveals that the various provincial measures examined are significantly correlated to overall Canadian uncertainty: correlation coefficients are above 0.9 for Ontario and Quebec but slightly lower (0.83) for Alberta. Interesting distinctions appear nonetheless: measures for Quebec and Alberta appear to have been less affected by the 2008-2009 period than Ontario, for exemple. More importantly, all measures report unprecedented increases following the onset of COVID-19, although the Quebec and Ontario-specific increases (1.29 and 1.18 for 2020$Q1$, respectively) are both higher than the Canadian average (1.05) while the one for Alberta is slightly lower (1.0).

[12]Note that provincial data for GDP and its components are not available for Alberta, which makes the data coverage less comprehensive for this province. Uncertainty measures for other provinces may also be computed, although the number of time series specific to some provinces is limited.

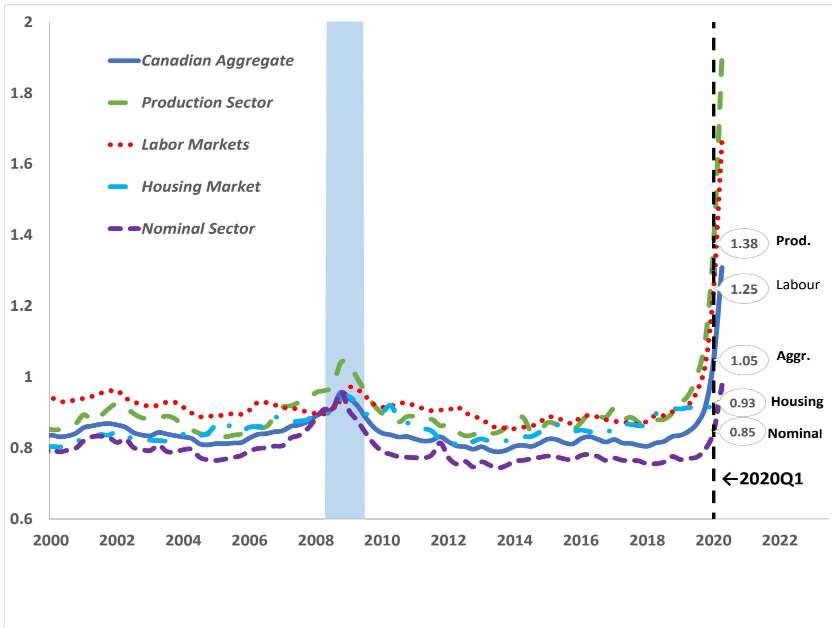

Figure 1.3: Canadian Macroeconomic Uncertainty

Note: Canadian Macroeconomic Uncertainty across sectors, measured using the quarterly version of the Fortin-Gagnon et al. (2022) database.

Next, Figure 1.3 shows how conditioning on the broad sector of economic activity can uncover different facets of uncertainty and provide clues about the likely sources for its fluctuations. To do so, the figure compares the evolution of the overall measure for Canada alongside three alternatives: the first, labelled Production Sector, is constructed from (1.1)-(1.2) using data series related to (real) GDP and its components, such as capital formation, exports and imports or manufacturing orders. The second, noted Labor Market, arises from Labour Force Survey (LFS) data and other information about labour markets. Next, the line labelled Nominal Sector relates to data on prices, interest rates, exchange rates and credit. Finally, the line denoted Housing refers to information from housing markets. Although all series are once again highly correlated, some important contrasts emerge in the wake of COVID-19: the rise in nominal uncertainty has been relatively subdued, as is that of uncertainty related to the housing sector;

by contrast the Production Sector (1.38 in 2020Q1) and Labor Market measures (1.25) have increased significantly more than the aggregate, most probably reflecting the production shutdowns that followed federal and provincial governmental directives.

1.3.1 Comparison with Alternative Measures

Jurado et al. (2015) apply their method to U.S. data and their measure is updated regularly, enabling comparisons between their results and ours. Since JLN's measure is based on monthly-frequency data, the comparison is with our monthly-frequency measure of Canadian uncertainty, which is obtained by repeating the forecasting exercise (1.3)-(1.6) using the monthly-frequency version of Fortin-Gagnon et al. (2020). Figure 1.4 reports the results, displaying the (normalized) three-months-ahead measure for both countries.[13]

The figure reports that both measures are highly correlated (the correlation coefficient is 0.82) but that the rise in US uncertainty during the 2008-2009 financial crisis was sharper than the one in Canada. Figure 1.4 once again confirms that measured uncertainty has risen importantly recently: for both Canada and the US, these increases are very significant, with the rise in the Canadian measure (5.46 in March 2020) even more significant than the one for its American counterpart. Section 5 below calibrates uncertainty shocks to match these very significant increases when assessing the likely macroeconomic impacts of such important in-

[13]As indicated above, the impact analysis of Section 5 employs the quarterly version of our measure because of its higher informational content. Nevertheless, computing and analyzing monthly-frequency versions of uncertainty measures is important as such measures respond more rapidly to unfolding events.

creases in uncertainty.

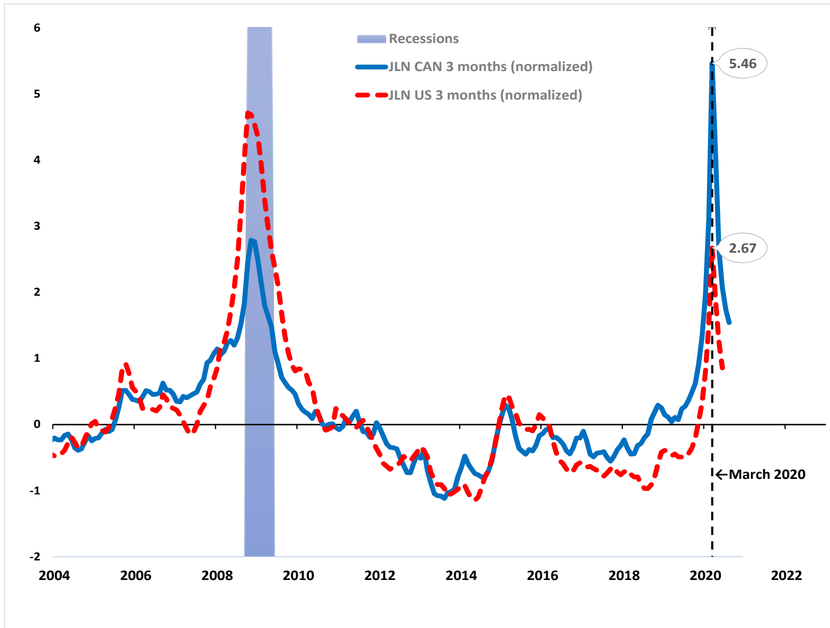

Figure 1.4: Macroeconomic Uncertainty: Canada versus the US

Note: Three-Months-Ahead Macroeconomic Uncertainty, US and Canada.

As discussed above, two popular alternatives to the macroeconomic uncertainty constructed by JLN are the economic policy uncertainty indexes (EPU), proposed originally by Baker et al. (2016), and measures of volatility in financial markets, as analyzed in Bloom (2009). To provide a comparative view of the similarities and dissimilarities between these measures, Figure 1.5 depicts the evolution of our Canadian measure of macroeconomic uncertainty (at the three-months-ahead horizon) and that of these two measures (data are once again normalized to facilitate the comparison).

Figure 1.5 reveals distinct patterns in the evolution of macroeconomic uncertainty and the two alternatives. Although all three report exacerbated levels during the 2008-2009 financial crisis and the recent COVID-19 episode, both the economic policy uncertainty and financial volatility indexes are significantly more volatile

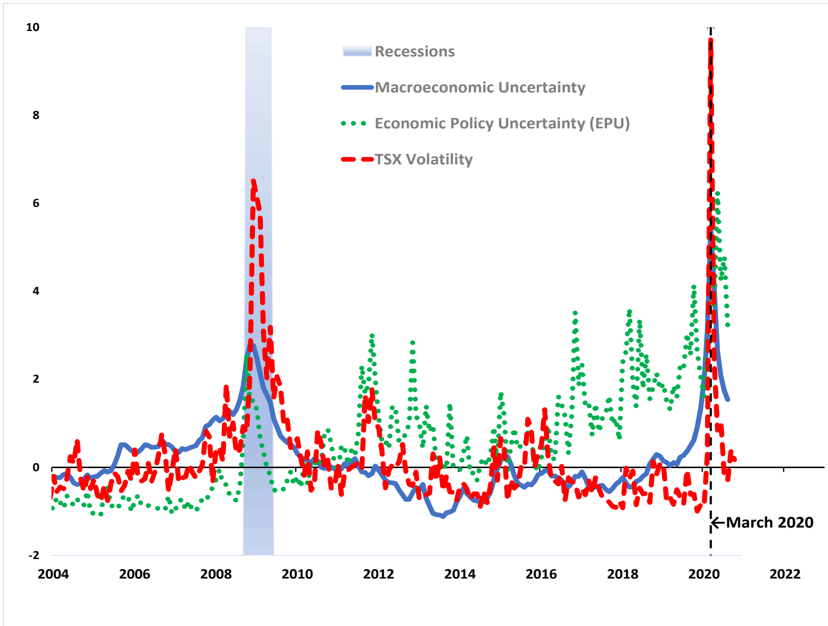

Figure 1.5: Canadian Uncertainty: Alternative Measures

Note: Comparison of three alternative measures of Canadian uncertainty : Macroeconomic, Policy and Financial.

and less serially correlated than our measure. This feature, also discussed in Jurado et al. (2015), suggests a different intuitive interpretation to the macroeconomic uncertainty measure, with its more gradual evolution more closely related to business cycle frequencies. Relatedly, correlations between these measures and ours, while still positive, are significantly smaller (0.30 and 0.56, respectively) than those between the Canadian and US macroeconomic uncertainty measures. As such, one may conclude that these three measuring strategies capture different facets of the uncertainty phenomenon.

Overall, our measure of Canadian macroeconomic uncertainty, obtained by applying JLN's method to Fortin-Gagnon et al. (2020)'s database, produces intuitive and rich information about uncertainty in Canada and shows how it affects different geographical or sectoral subsets of the economy. In addition, it reveals the extent to which the COVID-19 pandemic has coincided with unprecedented rises in uncertainty. Finally, its historical evolution is shown to be highly correlated to JLN's own US-specific measure, but less so to other measures obtained from textual analysis or financial markets' information. The next section computes the impacts of macroeconomic uncertainty shocks on the Canadian economy and applies these results to the context of the COVID-19 pandemic.

1.4 Macroeconomic Impacts of Uncertainty Shocks

As discussed above, a negative relationship between macroeconomic uncertainty and the business cycle is apparent in Figure 1.1 and confirmed by the negative (-0.3) correlation between uncertainty and (HP-detrended) GDP. This section discusses how this relationship may arise from a causal link whereby rises in uncertainty lead to decreases in activity and then computes the likely impacts of the large COVID-induced uncertainty shocks on the Canadian economy.

Bloom (2009) describes how, in a context of heightened uncertainty, firms are likely to postpone or cancel major projects and scale back hiring. In addition, households and consumers might themselves reduce their planned purchases of durables or housing. Finally, banks may choose to tighten credit availability or its terms. At the economy-wide level, Leduc and Liu (2016) argue that rises in uncertainty constitute decreases in aggregate demand and lead to reduced economic activity, higher unemployment and lower inflation. We now verify this intuition obtains in the Canadian context with our measure of Canadian macroeconomic uncertainty.

Our analysis employs structural Vector Autoregressions (SVARs) to identify and assess the impacts of uncertainty shocks. Such methods are used by much of the literature on uncertainty as well as numerous other contributions examining the impact of monetary policy shocks (Christiano et al., 2005), technology shocks (Gali, 1999) or fiscal shocks (Blanchard and Perotti, 2002), among others. In that context, consider the following six-variable VAR

$$\mathbf{Y}_t = \mathbf{A}_1\mathbf{Y}_{t-1} + \mathbf{A}_2\mathbf{Y}_{t-2} + \cdots + \mathbf{A}_p\mathbf{Y}_{t-p} + \epsilon_t, \tag{1.7}$$

where $\mathbf{Y}_t$ contains four key Canadian macroeconomic indicators (GDP, investment, inflation and the term spread), in addition to our Canadian uncertainty measure and its American counterpart as computed by JLN. The term spread, defined as the difference between 10-year government bonds and 3-month Treasury yields, is included to account for the reaction of monetary policy to economic developments: a policy of loosening rates in the wake of an adverse shock –likely to reduce short-term rates more than long-term ones– would thus show up as an increase in the term spread[14].

The data span the period of 1982Q1 - 2020Q1.[15] Nonstationary variables like GDP, investment and the GDP deflator are transformed in growth rates by taking the first difference of logs. A complete description of data sources and transformations used appears in Table A.1 of Appendix A.2. The VAR order is set to 3,

[14]It is acknowledged that empirically, the term spread can move for reasons other than the monetary policy stance

[15]We follow Lenza and Primiceri (2020) and abstract from 2020Q2 data, which contains observations for variables like investment and GDP that are outliers relative to their historical averages. These authors argue that including such outliers in a VAR calls into question the validity of parameter estimates and the appropriateness of computed impulse responses. Note that this is coherent with our choice of interpreting the spike in uncertainty recorded in 2020Q1 (March 2020 for monthly data) as the COVID-19 shock.

consistent with the Bayesian information criterion.

We use a Cholesky decomposition to identify shocks and the ordering of variables is therefore important. For our baseline results, $\mathbf{Y}_t$ is ordered as follows: US uncertainty, Canadian GDP, investment, inflation and term spread and, finally, the quarterly measure of Canadian macroeconomic uncertainty discussed above. Reflecting the small-open economy nature of Canada, US uncertainty is thus ordered first so that it may immediately affect Canadian activity and Canadian uncertainty, while the reverse is not true.

The ordering of Canadian uncertainty is potentially more controversial. One can first interpret uncertainty as an endogenous variable, which reacts to macroeconomic events and serves as a transmission mechanism for shocks. This interpretation is the one favoured by Ludvigson et al. (2021) and it suggests that Canadian uncertainty be placed last in $\mathbf{Y}_t$. Our baseline results reflect that ordering and the shocks to Canadian uncertainty analyzed below therefore do not affect any variable contemporaneously. Placing Canadian uncertainty last in $\mathbf{Y}_t$ is also a conservative strategy, limiting the extent to which fluctuations are attributed to uncertainty shocks.

An alternative vision of uncertainty stems from work by Carriero et al. (2018) and assigns it a more structural and exogenous interpretation, in the sense that innovations to uncertainty are assumed to have contemporanous impacts on the macroeconomy. This suggests placing Canadian uncertainty second in $\mathbf{Y}_t$, just after its US counterpart. We verify below that our results are robust to this assumption.[16]

1.4.1 Results

The COVID-19 pandemic constitutes a worldwide event and a first reasonable assumption is that much of the observed increases in both US and Canadian uncertainty are reflections of this global shock. Our first set of results therefore analyze the impact of a shock to US uncertainty, as a proxy for the global nature of the event. However, one can also argue that the pandemic has affected Canada in specific ways, notably because of the country's reliance on commodity exports or its small-open economy nature. We therefore also analyze the consequences of a Canadian-specific shock to uncertainty.

Figures 1.6 and 1.7 report our baseline results. Figure 1.6 depicts the macroeconomic impacts of a shock to US uncertainty whose size has been calibrated to the observed rise observed in 2020Q1, the onset of the COVID shock in our interpretation. Figure 1.7 then reports impulse response functions following a shock to Canadian uncertainty, calibrated in a similar manner. The shaded areas in both figures represent 90% confidence intervals for the responses, obtained via bootstrapping with 1000 replications.

Examine Figure 1.6 first. As indicated above, it reports the macroeconomic impacts of a positive shock to US uncertainty under the assumption that this shock can immediately affect all other variables, including Canadian uncertainty. Any

[16] The question of how best to interpret uncertainty in a VAR does not apply to the US measure for our work: whether this variable is endogenous or exogenous to the US economy, it is likely to be mostly exogenous relative to the Canadian economy, which justifies placing it first in $\mathbf{Y}_t$.

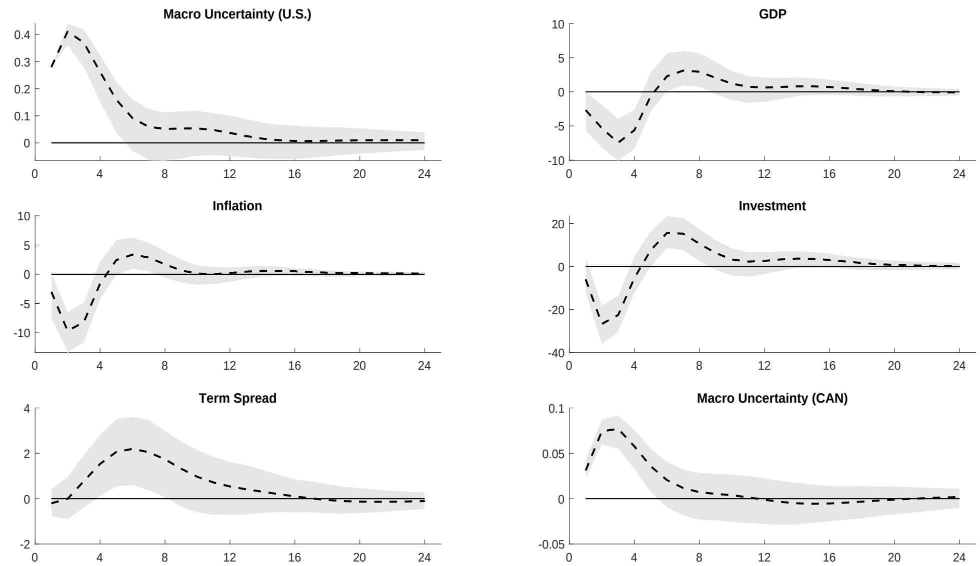

Figure 1.6: Macroeconomic Impacts of a Shock to U.S. Uncertainty

Note: Impacts of a shock to US macro uncertainty in a VAR where it is ordered first. Shaded areas represent 90% confidence bands..

contemporaneous correlation between Canadian uncertainty and the macroeconomy in the figure thus arises from the their simultaneous responses to the US shock.

Figure 1.6 shows that a spike in US uncertainty of the order of magnitude observed during 2020Q1 has important negative impacts on the Canadian economy. On the real side, investment and GDP fall by very significant margins, with GDP's decline reaching -7% in the third quarter after the shock, while investment declines by almost 20%, although it bottoms out faster. On the nominal side, inflation decreases by over 5% while the term spread increases gradually and remains elevated for a protracted period, indicating persistent loosening interventions by monetary authorities. Finally, the figure shows that spillovers from US to Canadian uncertainty are sizeable. Overall, Figure 1.6 suggests that the rise in US economic uncertainty coinciding with the 2020Q1 onset of the COVID-19 pandemic may have been one key source of the severe slowdown experienced by the Canadian economy in 2020, that these negative effects have been attenuated by the response of monetary authorities, and that the slowdown is likely to be relatively short-lived.

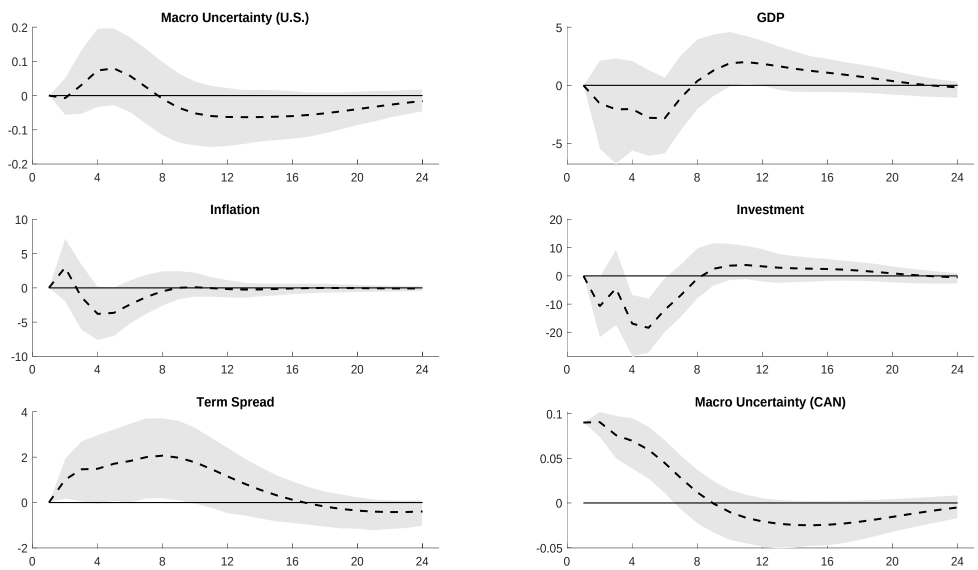

Figure 1.7: Macroeconomic Impacts of a Shock to Canadian Uncertainty

Note: Impacts of a shock to Canadian macro uncertainty in a VAR where it is ordered last. Shaded areas represent 90% confidence bands.

Next, Figure 1.7 reports the macroeconomic impacts of a positive shock to Canadian uncertainty. Our identifying assumptions imply that the responses in the figure arise from a specifically-Canadian source, after controlling for contemporaneous spillovers from US uncertainty. In addition, the ordering of Canadian uncertainty as the last variable in the vector $\mathbf{Y}_t$ entails that this shock has no immediate effects on the VAR's macroeconomic variables.

Figure 1.7 shows that the impacts of the Canadian uncertainty shock are qualitatively similar to those described above for the shock to US uncertainty, with sizeable declines in investment, GDP and inflation. In addition, monetary accomodation, as represented by the depicted increases in the term spread, is aggressive and long-lived. However, important quantitative differences emerge: the magnitude of economic responses to the shock are slightly above those in Figure 1.6 for some variables (investment, notably) and responses are generally more persistent: investment and GDP bottom out between 5 and 6 quarters after the shock and monetary accommodation persists for over two years. The more persistent nature of the impact from the Canadian-specific shock could originate because the US shock decreases demand for specific commodities that Canada exports, while the Canadian shock to uncertainty affects the economy more generally, notably the production of non-traded goods or services, which reacts more durably to shocks.

The visual impression gained from Figures 1.6 and 1.7 about the relative impacts of uncertainty shocks on the Canadian macroeconomy is confirmed by examining Table 1.1. This table reports the results of a variance decomposition exercise (from horizons $h = 1$ to $h = 24$ quarters-ahead) outlining how much of the volatility observed in our four macroeconomic aggregates and two uncertainty measures is attributable to shocks in US (Panel A) and Canadian (Panel B) uncertainty. The table shows that US uncertainty shocks explain over 25% of GDP and investment's volatility at relatively short horizons (4 quarters ahead) and that these fractions do not vary considerably as the horizons examined lengthen. By contrast, the shock to Canadian uncertainty explains a lower fraction of the aggregates' volatility at short term horizons: just over 8% for GDP at the four-quarters-ahead mark (relative to 27% for the US shock) and around 12% for Investment (27% for the US shock). However, the importance of the Canadian shock increases as the horizon

Table 1.1: Variance Decomposition

Variables	Horizon (quarters)				
	$h = 1$	$h = 4$	$h = 8$	$h = 16$	$h = 24$
	Panel A : Shock to US Uncertainty				
US Uncert.	100.00	85.48	59.36	46.94	41.11
GDP	3.71	27.27	24.95	25.18	23.90
Inflation	2.11	19.93	18.91	19.29	19.32
Investment	0.00	26.58	21.61	23.64	22.80
Term Spread	0.28	7.45	22.12	17.86	19.12
CAN Uncert.	26.66	34.64	22.08	20.41	18.80
	Panel B : Shock to CAN Uncertainty				
US Uncert.	0.00	7.01	23.09	23.8	30.83
GDP	0.00	4.965	12.31	21.96	24.69
Inflation	0.00	2.82	7.89	8.16	8.44
Investment	0.00	4.74	21.74	23.49	26.74
Term Spread	0.00	5.65	27.36	44.34	43.70
CAN Uncert.	67.10	58.07	64.0	53.09	56.22

Notes: his table presents the variance decomposition (in %) of the series included in the VAR, following shocks to US and Canadian macroeconomic uncertainty.

rises and it becomes as important a source of volatility as the US shock.

In short, the effects of US and Canadian-specific uncertainty shocks on the Canadian economic activity are intuitive, quantitatively significant, and in line with observed recent declines in GDP. During the first three quarters of 2020, Canadian real GDP has fallen by 4.4% and its level is predicted to remain between -7.1 and -5.8% under its pre-COVID levels by the end of the year, according to IMF and Consensus Forecasts (Foroni et al., 2020). Hence, the COVID-induced spike in uncertainty explains a sizeable part of the recent declines in real Canadian activity and suggest that further weaknesss in the quarters ahead, a result similar to those obtained by other reserachers working with US macroeconomic data (Baker et al., 2020).

The sensitivity of our results to the COVID-19 episode is an important issue: besides creating large increases in uncertainty, the onset of the pandemic may have also modified the dynamics of macroeconomic data, making our VAR-based analysis less robust. To assess the importance of this issue, we repeat our VAR estimation with data ending in $2019Q4$ and compute the quantitative impact of uncertainty shocks similar in size to the ones examined above. Results are presented in Appendix A.3. First, Figure A.1 shows that economic responses following a US uncertainty shock are very similar to those reported in Figure 1.6 above: notably, GDP and investment, notably, experience sizeable, but relatively short-lived declines following the shock.

By contrast, Figure A.2 shows that our view of the macroeconomic impacts of a Canadian shock to uncertainty has been affected by including the most recent data. In Figure A.2 (pre-COVID), the amplitude of the downturn created by such a shock is less significant than the one depicted in Figure 1.7 above, although its persistence remains higher than the one created by the US shock. Consistent with this finding, the variance decomposition exercise in Table A.2 now confirms that Canadian uncertainty shocks are a smaller source of macroeconomic fluctuations. Additionally, Figure 1.7, which takes into account 2020Q1 (post pandemic) data, reports that shocks to Canadian uncertainty have statistically significant and persistent impacts on their US counterpart, while Figure A.2 doesn't. This suggests that the COVID shock had a truly global impact on uncertainty that affected both the Canadian and US measures. Overall therefore, the COVID-19 pandemic was not only accompanied by a very large disturbance in measured uncertainty but appears to have sharpened our assessment of the macroeconomic consequences of these shocks.

1.4.2 The Macreconomic Impact of Alternative Measures of Uncertainty

Recall that two alternative measures of uncertainty, one derived from textual research about economic policy uncertainty (EPU) and the other related to financial markets' volatility, have been proposed and were depicted above in Figure 1.5. These measures can be used as the chosen proxies for uncertainty in alternative versions of our VAR analysis. In that context, a comparison between the responses of GDP, Inflation and Investment following similarly-sized shocks to uncertainty is provided in Figure 1.8 (for shocks to US uncertainty) and Figure 1.9 (shocks to Canadian uncertainty).

Figures 1.8 first shows that the aggregates' responses to the US shock are qualitatively similar, with a sudden increase in uncertainty leading to a deep but

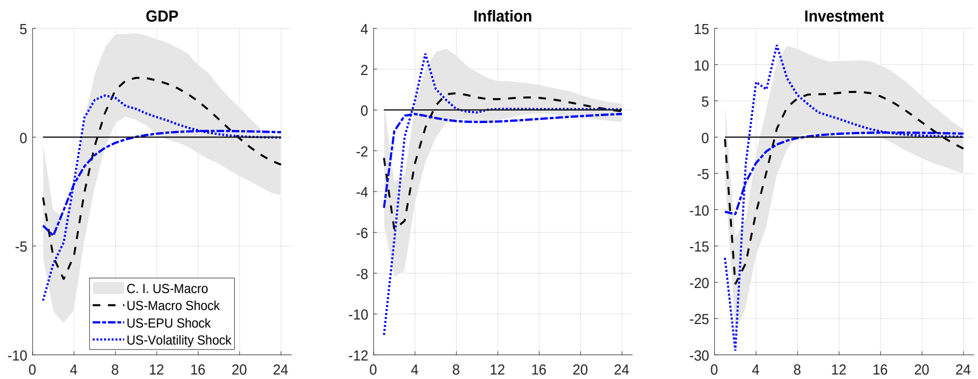

Figure 1.8: Impacts of a Shock to Canadian Uncertainty: Comparison Obtained using Alternative Measures of Canadian uncertainty

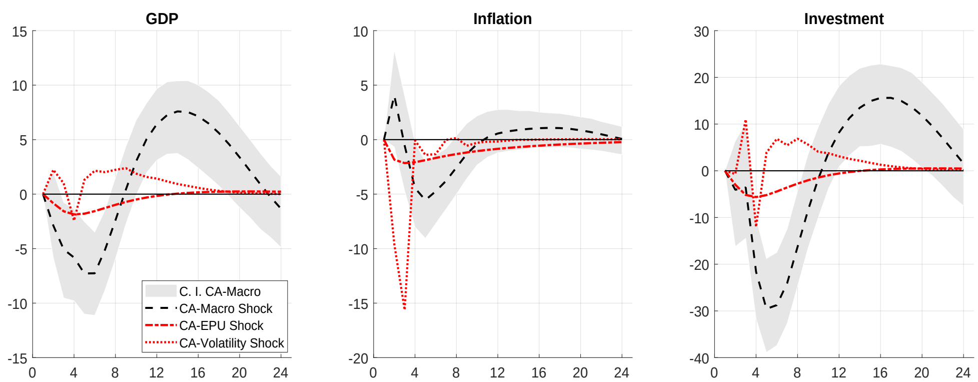

Figure 1.9: Impacts of a Shock to Canadian Uncertainty: Comparison Obtained using Alternative Measures of Canadian uncertainty

relatively short-lived economic decline. However, Figure 1.9 reports that results pertaining to the Canadian shock are not as robust. Notably, while the adverse shock to US financial markets' volatility generates a short-lived but substantial economic slowdown in Canada, the (Canadian) shock to TSX volatility does not lead to substantial dynamic responses. Specifically-Canadian shocks to financial volatility thus appear to have no impact on the Canadian economy, a result in line with those in Bedock and Stevanovic (2017) who report similar contrasts between the effects of Canadian and US shocks when estimating the macroeconomic impacts of credit shocks. This is likely due to the dominant position of the United States in financial markets.

Overall, however, the computed impacts of US and Canadian uncertainty shocks on the Canadian economy are consistent with the interpretation advanced in Bloom (2009) and Leduc and Liu (2016): sudden increases in uncertainty lead firms, households and financial intermediaries to delay or cancel plans, which depresses aggregate demand and leads to declines in economic activity, increases in unemployment and lower inflation.

1.4.3 Robustness Analysis

Several robustness checks have been considered and the results are presented in Appendix A.4. An alternative ordering of the vector $\mathbf{Y_t}$ in the VAR, with the Canadian uncertainty placed second –exogenous to the rest of Canadian variables and in the spirit of Carriero et al. (2018)– does not change the qualitative nature of our results, as shown in Figure A.3. Figure A.4 shocs that the impacts of uncertainty shocks on consumption and labour market indicators are coherent with those reported above on GDP and Investment. Interestingly, the figure also shows that consumption of durables reacts more than the aggregate measure, as expected. Finally, Figures A.5 and A.6 plot the dynamic responses when GDP, investment and GDP deflator are used in levels as opposed to the growth rates employed in our baseline specification.

1.5 Conclusion

This paper develops a measure of Canadian macroeconomic uncertainty, to help formalize discussions about uncertainty and analyze its consequences. Our measure shows that events linked to the COVID-19 pandemic have led to very sharp increases in Canadian uncertainty, in line with results obtained when using data from other countries. Our VAR analysis then reveals that uncertainty shocks similar in size to the COVID-induced spikes lead to deep slowdowns that may persist for several quarters. We also show that the macroeconomic impacts of uncertainty shocks are different whether they are assumed to affect first US uncertainty or its Canadian-specific counterpart, an interesting contrast that should be the subject of further research. In addition, the question as to whether uncertainty should be a specific input into monetary policy reaction functions remains open.

Looking past the immediate economic effects of the pandemic, analysts and policy makers are turning their attention to the long term and the road to recovery and recent work by Barrero and Bloom (2020) and Foroni et al. (2020) suggests that this recovery will be very gradual. Our results suggests that the exacerbated state of uncertainty documented here will most probably contribute to slow this return to pre-COVID economic trends. Uncertainty should therefore continue to be monitored regularly by fiscal and monetary authorities.

CHAPTER II

TRADE OPENNESS AND CONNECTEDNESS OF NATIONAL PRODUCTIONS: DO FINANCIAL OPENNESS, ECONOMIC SPECIALIZATION, AND THE SIZE OF THE COUNTRY MATTER?

ABSTRACT

Recent studies have used data from a few developed countries to show that countries with trade surpluses tend to be net recipients of connectedness shocks[1] Unlike those studies that have focused on the effects of the trade balance on net connectedness, our paper focuses on the effects of trade openness on directional and bilateral connectedness. Moreover, we use a high-dimensional approach to measure our connectedness indicators and a fixed-effect panel model for regression. We also analyze the variables that amplify the effect of trade openness. The data used in this study come from 27 OECD countries and China over the period from 1991M1 to 2017M12. We show that trade openness increases the connectedness "from other countries" and and trade integration increases the bilateral connectedness "from another country". Financial integration and differences in economic specialization dampen the effects of trade integration on bilateral connectedness "from another country", while periods of recessions amplify them.

JEL Classification: C23; C55; F02; F44.

[1]This Chapter is a paper written with Professor C-O Mao Takongmo. It has been published at Economic modelling, volume 125, August 2023, 106340, https://doi.org/10.1016/j.econmod.2023.106340.

2.1 Introduction

One of the most important topics in the international economic literature is understanding the channels by which business cycles in one country are transmitted to others (Baxter and Kouparitsas, 2005; Cravino and Levchenko, 2017; Cesa-Bianchi et al., 2019). However, in general, the indicators usually used in the literature to proxy the transmission of shocks across the border are not directional (see for example, Dées and Zorell, 2012; Ductor and Leiva-Leon, 2016; Beck, 2021; Repele and Waelti, 2021)[2].

This paper uses estimation methodology based on selection and shrinkage as proposed in Demirer et al. (2018) to estimate a high dimensional VAR and then to compute the indicators of total and directional connectedness of industrial production suggested by Diebold and Yilmaz (2015a). More specifically, Diebold and Yilmaz (2015a) compute indicators of total and directional connectedness, as well as the pairwise connectedness indicator for a relatively small VAR fitted to a proxy of real economic activity (see Diebold and Yilmaz, 2015a, Table 4). While Diebold and Yilmaz (2015a) focus on the industrial production of only six countries (G-7 except Canada)[3], in our study, we use the industrial production of 28 countries (27 OECD countries and China). Consequently, our analysis accounts for second-round effects manifesting through spillovers from a large set of

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[2] As a measure of movements of business cycles between countries, Dées and Zorell (2012) and Beck (2021) use the correlation of the cyclical components of the GDP; Ductor and Leiva-Leon (2016) used the probability that two countries share the same business cycle phase (recessions and expansions); and Repele and Waelti (2021) used the absolute value of the difference between the GDP output gaps of pairwise countries.

[3] Martin et al. (2020) examines the connectedness of nine countries including G-7, China and Mexico

countries. The second contribution is the study of the determinants of directional connectedness of industrial production.[4]

The directional connectedness indicators used in our paper estimate causality linkages as suggested by Diebold and Yilmaz (2015a) by computing the forecast error variance decomposition (FEVD) from the estimation of a VAR model. The FEVD estimation allows assessing the contribution of a shock to the dynamics of the endogenous variables in the system.

Two main fields in the literature have focused on business cycle interdependence. The first group of studies used the factor model to decompose a given country's macroeconomic variable into a common factor and an idiosyncratic factor to see whether the given country co-moves with the world economy (see, Kose et al., 2003b,a, 2012; Ductor and Leiva-Leon, 2016). Movement in the common factor represents the global business cycle.

The second contribution relative to Diebold and Yilmaz (2015a) is the analysis through fixed-effect panel regression of the determinants of the directional connectedness and pairwise connectedness indicators.

Several studies have identified the following as the main determinants of business

[4] Greenwood-Nimmo et al. (2021) estimated connectedness measures using many variables at the same time for each country with the Global VAR method. The authors considered variables in groups, and their connectedness matrix is therefore block-aggregated. One of the Global VAR drawbacks is that the corresponding connectedness measures depend on the weighting scheme used in the construction of the Global VAR model. Unlike Diebold and Yilmaz (2015a), which focus on the effects of the trade balance on net connectedness, our paper focuses more on the effects of trade openness on directional and bilateral connectedness. Diebold and Yilmaz (2015a) show that countries with trade surpluses tend to be net recipients of connectedness shocks, and countries with trade deficits are more likely to be transmitters of connectedness shocks.

cycle interdependence: trade openness (Kose et al., 2003b; Imbs, 2004; Baxter and Kouparitsas, 2005; Kose et al., 2012; Ductor and Leiva-Leon, 2016; Montinari and Stracca, 2016; Hwang and Kim, 2021), financial openness (Frankel and Rose, 1998; Kose et al., 2003b; Imbs, 2004, 2006; Kose et al., 2012; Ductor and Leiva-Leon, 2016; Montinari and Stracca, 2016; Hwang and Kim, 2021), specialization (Camacho et al., 2008; Imbs, 2004; Baxter and Kouparitsas, 2005; Kose et al., 2012; Ductor and Leiva-Leon, 2016; Hwang and Kim, 2021), and country-specific characteristics(Kose et al., 2003a; Baxter and Kouparitsas, 2005; Kose et al., 2012; Ductor and Leiva-Leon, 2016)[5], proxied in this paper by country size.

In theory, international trade interlinkages can create business cycle interdependencies. These interdependencies happen through both demand-side and supply-side effects (Kose et al., 2012). For the demand-side effect, a positive increase in gross domestic product (GDP) in one given country can increase demand for goods and services produced abroad. The supply-side effect is due to decreases in international prices induced by increases in trade intensity.

Therefore, it is easy to understand that countries with larger economies will more likely affect other countries than small countries through trade because the demand-side effect on other countries is more likely to be greater for big countries than for small countries.

In theory, trade linkages can also create industrial specialization through comparative advantages. Specialization can be assumed to be due to international trade and can also be viewed as exogenous, depending on the study's research question,

[5]That includes gravity variables such as population and total land (Baxter and Kouparitsas, 2005) or country-specific factors (Kose et al., 2003a, 2012).

and can affect business cycle interdependence either positively or negatively (see, Imbs, 2004; Kose et al., 2012). A positive effect of specialization on business cycle interdependence can be triggered, for example, by a positive global shock that pushes countries to take advantage of their specializations to generate more output. A negative effect of specialization on business cycle interdependence can be due to a country-specific shock, which can be assimilated to a sector-specific shock in the case of specialization. Suppose a shock has a positive effect on the output of a given country. In that case, this shock will not necessarily lead to an increase in output in the second country because the sectors of specialization are different in both countries. Therefore, we can expect that the effect of specialization may become small and versatile after controlling for trade.

In theory, financial interlinkages can also affect business cycle interdependencies either positively or negatively (see, Imbs, 2004; Kose et al., 2012). If financial interlinkages generate a large demand-side effect, then a positive effect is expected to happen.[6] If financial interlinkages induce greater specialization, the negative effect can in theory be observed through the reallocation of capital compatible with the countries' comparative advantages.

Two-country DSGE models also validate the economic concepts presented above. Faia (2007) show that trade openness can increase the correlation of output between two countries, while financial openness can lower it.[7]. Ambler et al. (2002)

[6]For example, suppose residents of two countries hold the same equities. In that case, a change in equity price is expected to affect the business cycle in both countries in the same direction simultaneously.

[7]The mechanism through which that result can be obtained in two-country DSGE models is as follows: a positive home country technology shock increases domestic production and investment, and also shifts demands between domestic and foreign goods. The demand shift

show that the presence of more than one sector in a two-country DSGE model, coupled with frictions in the capital market, can help explain positive co-movements of output between two countries.[8]

We therefore expect trade integration to affect pairwise connectedness positively and financial integration to affect it negatively. We also expect that financial integration will dampen the effect of trade on pairwise connectedness. Due to the versatile effects of specialization in economic theory, whether specialization could affect pairwise connectedness directly or indirectly through trade remains an empirical question.

Using simple econometric models, we test the effect of the possible determinants of business cycle interdependence mentioned above on total directional connectedness from other countries (total exposure). We also assess the impact of these potential determinants on total directional connectedness to other countries (total influence).

The data used in our study are the industrial production index for 27 OECD

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leads to a decrease in foreign inflation, foreign output, and investment. With capital flows toward the home country, this would typically lead to a negative output correlation between the two countries. However, due to sticky prices and the response of monetary authorities, the fall in foreign inflation will lead to a fall in the foreign interest rate, which will in turn boost investment and asset prices and will offset the negative impact of the demand shift on the foreign country's business cycle (Faia, 2007)

[8]The mechanism can be presented as follows: A positive technology shock in one sector of the home country leads to drawing labor and capital into that sector not only from abroad, but also from the sector in the home country that did not receive the shock. This leads to positive co-movements of output in the home sector that did not receive the shock and outputs in both sectors abroad, which in turn increases the correlation in aggregate production between the two countries (Ambler et al., 2002). The friction in the capital market reduces the size of capital inflows generated by the technology shock and reduces the negative co-movements of output related to capital inflows (Ambler et al., 2002).

countries and China. Our sample period spans from January 1991 to December 2017.

We show that global connectedness fluctuates over time. We also observe that rising periods of global connectedness are associated with periods of drastic world economic events. We also show that the most influential countries shift over time.

Our first main econometric results show that an additional increase in the trade openness of a given country increases its exposure to the rest of the world. Moreover, a larger country's size amplifies the effect of trade openness on the exposure of a given country to the world economy.

The main potential determinants that could explain changes in bilateral business-cycle co-movements have been identified in the literature as trade integration (Baxter and Kouparitsas, 2005; Ductor and Leiva-Leon, 2016; Cesa-Bianchi et al., 2019; Hwang and Kim, 2021), financial integration (Baxter and Kouparitsas, 2005; Ductor and Leiva-Leon, 2016; Cesa-Bianchi et al., 2019; Hwang and Kim, 2021), economic specialization (similarity in industrial composition) (Baxter and Kouparitsas, 2005; Ductor and Leiva-Leon, 2016; Hwang and Kim, 2021), and country-specific factors[9] (Baxter and Kouparitsas, 2005; Ductor and Leiva-Leon, 2016), also proxied in this part of the paper by country size. Most of the studies in the literature have used a non-directional measure of business cycle synchronization (usually absolute difference in GDP growth).

We also assess the impact of the potential determinants described above on our

[9]Such as gravity variables and factor endowments: labour (sometimes proxied by human capital) and capital.

indicator of pairwise directional connectedness. Our second main econometric results show that an additional increase in trade integration between two countries significantly increases the bilateral connectedness "from another country". Moreover, more financial integration and differences in economic specialization dampen the effect of trade integration on the connectedness from "from another country". On the other hand, periods of recessions amplify the effects of trade integration on the bilateral connectedness "from another country".

For robustness check, we also assess the role of economic agreements on pairwise connectedness. In theory, being part of a trade agreement or joining a currency union is expected to increase trade intensity and financial integration due to reduced trade and financial costs (Frankel and Rose, 1998), but joining a trade agreement or a currency union is also expected to increase other costs such as monetary or fiscal policy losses.

Our results show that being in the same trade agreement significantly increases bilateral connectedness. The same result is also valid when entering the same economic zone. We find that joining the European Union significantly increases the bilateral connectedness of the entering countries with existing European Union members.

We show that more financial integration or more differences in economic specialization between two countries dampens the effect of economic agreements on bilateral connectedness "from another country". Periods of recessions also amplify the impact of economic agreements on the bilateral connectedness "from another country".

The results obtained in this paper complement findings in previous literature, especially in terms of directional macroeconomic interdependence and its determinants. Policymakers can use our results depending on whether they want to reduce their country's dependency on international shock or if they want to have more influence on the global economy. Policymakers can also use our results in a bilateral economic relationship with another given economy. Our results are also important in policymakers' decisions to enter a trade agreement or a political and economic zone like the European Union.

The rest of this paper is organized as follows. Section 2 presents the methodology used to construct our measures of connectedness. We then present the static and dynamic measures obtained. In section 3, we present the data used in this study. Section 4 presents the static network representation of real output connectedness between countries. The dynamic network representations are presented in section 5. The determinants of connectedness are presented in section 6. Section 7 concludes the paper.

2.2 Methodology

Diebold and Yilmaz (2014) and Demirer et al. (2018) measured connectedness between economic entities by decomposing each series entity's forecast error variance. To obtain the Demirer et al. (2018) type connectedness measures, we followed three steps: First, we used a VAR model to capture the interaction between countries' national industrial production. Then, because we have a large number of countries, as in Demirer et al. (2018), we used the Adaptive Elastic-Net method of estimation to avoid the curse of dimensional problems. Finally, we computed connectedness measures from the estimated model using a generalized forecast error variance. In the next section, we briefly present these steps.

2.2.1 VAR Model

As in Demirer et al. (2018), our variance decomposition is based on a VAR(p) model with k variables, estimated with the Adaptive elastic-Net method (see Zou and Zhang, 2009a). The VAR(p) model can be written as follows:

$$y_t = \sum_{i=1}^{p} A_i y_{t-i} + e_t, \tag{2.1}$$

with $y_t = (y_{1,t}, y_{2,t}, \ldots, y_{k,t})'$. e_t is a white noise vector of dimension k, and $e_t \sim N(0, \Sigma)$. For each $i = 1...p$, A_i is a $k \times k$ coefficient matrice. It is assumed that this VAR (p) model is invertible. The moving average representation of model (3.2) can therefore be written as follows:

$$y_t = \sum_{i=0}^{\infty} B_i e_{t-i}, \tag{2.2}$$

where, for each i, B_i is a $k \times k$ coefficient matrice defined recursivelly as: For $i < 0$, B_i is equal to the $k \times k$ null matrix; B_0 is the $k \times k$ identity matrix; and $B_i = A_i B_{i-1} + ... + A_p B_{i-p}$, for $i > 0$. The moving average representation is used to compute the forecast error variance decomposition.

2.2.2 The Generalized Forecast Error Variance Decomposition and the Connectedness Measures

The variance decomposition indicates the amount of information each variable contributes to other variables. It determines how much of the forecast error variance at a given horizon H of each variable can be explained by exogenous shocks from other variables.

The Cholesky method is usually used to decompose the variance. Although it is easy to implement, results from the Cholesky method are nevertheless sensitive to the order in which the variables are introduced into the vector (Diebold and Yilmaz, 2015b; Demirer et al., 2018).

To estimate a forecast error variance decomposition not influenced by the order of variables, Pesaran and Shin (1998) proposed the generalized decomposition of the forecast error variance. The component of forecast error variance at horizon H, of the variable y_i, due to an innovation in the variable y_j, is given by the following formula:

$$D_{ij}^{H} = \frac{\sigma_{jj}^{-1} \sum_{l=0}^{H-1} (\iota_i' \Sigma B_l \iota_j)^2}{\sum_{l=0}^{H-1} (\iota_i' B_l \Sigma B_l' \iota_i)} \tag{2.3}$$

where σ_{jj} is the j^{rd} diagonal element of the matrix Σ and ι_i a vector of size k containing zeros except at line i, that contains 1.

Since the shares of variance do not add up to 100%, it is standard in the literature to normalize each entry of variance decomposition matrix using the sum of entries in their respective row (see, Diebold and Yilmaz, 2014). As pointed out by Caloia et al. (2019), this normalization scheme can induce errors in the sign and rankings of the net contribution of entities to the overall volatility of the system. Caloia et al. (2019) proposed scalar-based normalizations that are free of sign errors. Therefore, following Caloia et al. (2019), we normalized each entry of the variance decomposition matrix using the maximum sum of rows in the following way:

$$d_{ij}^H = \frac{D_{ij}^H}{M}, \tag{2.4}$$

where $M = max\,(r_1, r_2, ..., r_k)$ and $r_i = \sum_{j=1}^{k} D_{ij}^H$.

Connectedness Measures

Table 2.1 resumes the forecast error variance decomposition for each variable. Line i shows the variance decomposition of variable y_i. Let's call m the row that has the largest sum. Only row m sums up to 1 after the normalization. Other forecast error variance decompositions are expressed relative to the total forecast error variance decomposition of row (country) m. d_{ij}^H represents the contribution of variable j to variable i's forecast error variance at horizon H. From this table, one can compute the pairwise directional connectedness from country "j" (origin) to country "i" (destination) [in short, the bilateral or pairwise connectedness "from another country" ($C_{i\leftarrow j}^H = d_{ij}^H$)]; the overall connectedness in the network ($C^H = \frac{1}{N}\sum_{i,j=1;i\neq j}^{N} d_{ij}^H$); the total directional connectedness "from others" ($C_{i\leftarrow\bullet}^H = \sum_{j=1;j\neq i}^{N} d_{ij}^H$); and the total directional connectedness "to others" ($C_{\bullet\leftarrow j}^H = \sum_{i=1;i\neq j}^{N} d_{ij}^H$) (see, Diebold and Yilmaz, 2014).

Overall connectedness measures the average exposure of entities in the network. It gives the average proportion of the forecast error variance due to the connection between network entities. Directional connectedness "from others" measures an

Table 2.1: Connectedness Table

	y_1	y_2	$\dots$	y_N	From others
y_1	d^H_{11}	d^H_{12}	$\dots$	d^H_{1N}	$\sum_{j=1}^N d^H_{1j}, j \neq 1$
y_2	d^H_{21}	d^H_{22}	$\dots$	d^H_{2N}	$\sum_{j=1}^N d^H_{2j}, j \neq 2$
$\vdots$	$\vdots$	$\vdots$	$\ddots$	$\vdots$	$\vdots$
y_N	d^H_{N1}	d^H_{N2}	$\dots$	d^H_{NN}	$\sum_{j=1}^N d^H_{Nj}, j \neq N$
To Others	$\sum_{i=1}^N d^H_{i1}$ $i \neq 1$	$\sum_{i=1}^N d^H_{i2}$ $i \neq 2$	$\dots$	$\sum_{i=1}^N d^H_{iN}$ $i \neq N$	$\frac{1}{N}\sum_{i,j=1;i\neq j}^N d^H_{ij}$ $i \neq j$

Note: Table build based on Diebold and Yilmaz (2014) and normalized following Caloia et al. (2019).

entity's total exposure to the rest of the network. Similarly, directional connectedness "to others" measures the overall effect of a shock hitting an entity on other network entities and is obtained by adding the effects to each entity (Diebold and Yilmaz, 2014).

We also produced a connectedness time series. To accomplish this, we used a rolling window of 10 years (120 months) to estimate the model and a 12-month horizon to compute the forecast error variance decompositions. The obtained connectedness indicators were assigned to the month following the 10-year window. The window was then moved by one month to calculate the connectedness measure for the next month until the end of the work period. This provides a time series of the overall connectedness and a time series of directional connectedness for each entity.

The number of lags was fixed at $p = 12$. Due to the number of variables and the limited number of observations, the VAR model cannot be estimated using the standard ordinary least squares method. Moreover, only some variables may be necessary to fit the right dynamic for certain variables. For this reason, as in Demirer et al. (2018), we used the adaptive elastic net estimation method, which allowed us to estimate the desired VAR model parameters in our limited context and select the more informative set of variables for each regressor.

2.2.3 The Adaptive Elastic Net Estimation

An adaptive elastic net is an estimation method introduced by Zou and Zhang (2009a). That method belongs to a class of estimation methods with penalization. In order to clearly explain the main idea behind the adaptive elastic net as described by Zou and Zhang (2009a), we will present the method using a generic regression equation, as in Demirer et al. (2018). The generic regression equation is:

$$z = Xa + \epsilon, \tag{2.5}$$

where equation (2.5) represents a subsequent equation-by-equation of our VAR representation. $z = (z_1, ..., z_T)'$ is a response vector, and $x_i = (x_{i1}, ..., x_{iT})'$, $i = 1, ..., M$, are predictors.[10] $X = [x_1, ..., x_M]$ is the predictor matrix. $a = (a_1, ..., a_M)'$ is the vector of real coefficients. $\epsilon = (\epsilon_1, ..., \epsilon_T)'$ represents the errors. The errors are assumed to be i.i.d., with mean zero.

It is assumed that some variables may not be useful in approximating the dynamic of z_t. It is therefore efficient to select those variables that are informative. This selection can be done by adding some constraints to the least squares minimization.

[10]In our framework, equation (2.5) represents a subsequent equation-by-equation of our VAR representation. z is one of our $k-$variables, $x_{i's}$ are the $p-$lags of each of our variables, and M is the total number of regressors ($M = kp$).

The corresponding estimator is:

$$\hat{a} = \arg\min_{a} \sum_{t=1}^{T} \left[\left(z_t - \sum_{i=1}^{M} a_i x_{it} \right)^2 + \lambda \sum_{i=1}^{M} |a_i|^q \right]. \tag{2.6}$$

When the penalty function is concave and non-differentiable at the origin, it induces the selections, whereas smooth convex penalties (e.g., q = 2, the ridge regression estimator) lead to shrinkage estimates (see, Zou and Zhang, 2009a; Demirer et al., 2018). Hence, with some penalized estimations, one can achieve selections and shrinkage.

Tibshirani (1996), in a seminal paper, used $q = 1$ and proposed the Lasso method (least absolute shrinkage and selection operator), which combines shrinkage and selection. However, despite its popularity, that method has two significant limitations. First, it does not have the oracle property[11].

Fan and Li (2001) showed that, asymptotically, the Lasso has a non-ignorable bias for estimating the non-zero coefficients and suggests that it does not have the oracle property. This was proven by Zou (2006), who proposed an improvement to Lasso estimators. The adaptive Lasso estimator is defined as follows:

$$\hat{a}(\text{AdaLasso}) = \arg\min_{a} \left\{ \left(z_t - \sum_{i=1}^{M} a_i x_{it} \right)^2 + \lambda \sum_{i=1}^{M} \hat{\omega}_i |a_i|^q \right\} \tag{2.7}$$

where $\{\hat{\omega}_i\}_{i=1}^{M}$ are adaptive data-driven weights that can be chosen to be $\hat{\omega}_i =$

[11]An estimation method enjoys the oracle property if, for a large number of simulations, the estimates asymptotically converge in probability to the true values of parameters, and these estimates follow a normal distribution around the true value. The oracle property means that the penalized estimator is asymptotically equivalent to the oracle estimator. The oracle estimator is the ideal estimator, and it is exclusively obtained with signal variables without penalization.

$|\hat{a}_i(init)|^{-\gamma}$, where γ is a positive constant, and $\hat{a}_i(init)$ is an initial root-T consistent estimate of a_i (Zou, 2006). With the appropriate λ, the adaptive Lasso enjoyed oracle properties (see, Zou, 2006).

The second limitation of Lasso is that it displays instability in variable selection for high-dimensional data. In fact, high-dimensional data often contain groups of highly correlated variables. The problem is that Lasso tends to "arbitrarily" select one among highly correlated variables in an unstable way with no consideration regarding which one is selected (Zou and Hastie, 2005). To address this issue, Zou and Hastie (2005) proposed the elastic net (Enet) estimator, which can be written as follows:

$$\hat{a}(\text{Enet}) = \arg\min_{a} \left\{ \left(z_t - \sum_{i=1}^{M} a_i x_{it} \right)^2 + \lambda \left[\alpha \sum_{i=1}^{M} a_i^2 + (1-\alpha) \sum_{i=1}^{M} |a_i| \right] \right\} \times \left(1 + \frac{\lambda \alpha}{T} \right) \tag{2.8}$$

where α is a constant between 0 and 1. This estimator can be viewed as a linear combination of the Lasso estimator (L_1-penalty; for $\alpha = 0$) and the Ridge estimator (L_2-penalty; for $\alpha = 1$). Adding an L_2-penalty to Lasso helps to avoid arbitrary selection by encouraging a grouping effect, such that strongly correlated predictors will tend to be in or out of the model together. Zou and Zhang (2009a) proposed the adaptive elastic net estimator, which blends these two solutions. An adaptive elastic net estimator is given by

$$\hat{a}(\text{AdaEnet} = \arg\min_{a}\left\{\left(z_t - \sum_{i=1}^{M} a_i x_{it}\right)^2 + \lambda\left[\alpha\sum_{i=1}^{M} a_i^2 + (1-\alpha)\sum_{i=1}^{M}\hat{\omega}_i|a_i|\right]\right\} \times\left(1+\frac{\lambda\alpha}{T}\right) \tag{2.9}$$

where α is the weight of the Ridge penalty component and $1-\alpha$ is that of the adaptive Lasso component. If $\alpha = 1$, we get a Ridge estimation [$\hat{a}$(Ridge)], and if $\alpha = 0$, we obtain the adaptive Lasso estimation. This method performs selection and shrinkage, enjoys the oracle property, and is stable in high-dimensional data.

In this study, we used the adaptive elastic net with the following characteristics: $\alpha = \frac{1}{2}$, $\hat{\omega}_i = |\hat{a}(\text{Ridge})|^{-1}$, and λ was chosen using a 10-folds cross validation (we chose these to minimize the mean square error).

It is important to note that the shrinkage and the selection of the coefficients of our VAR(p) model do not necessarily induce sparsity in the network links, since the network links, measured using variance decomposition of the forecast errors, are nonlinear functions of the parameters and the error covariance matrix (see Demirer et al., 2018). Moreover, we did not impose any regulations on the shock covariance matrix.

2.3 Data

Connectedness was measured between 28 countries (27 OECD countries and China) using their monthly industrial production index. The industrial production index for OECD countries comes from the OECD database. China's industrial production index [12] came from the National Bureau of Statistics of China.[13]

The data used spans from January 1991 to December 2017. Connectedness between countries was measured using the annual growth rate of their monthly industrial production. This transformation helps us to obtain stationary data and to control for seasonality.

2.4 Static Estimation of the Network Connectedness

This section presents the estimated connectedness based on the full sample and 12-month forecast horizons.

Connectedness Matrix Following Caloia et al. (2019), the initial 28×28 matrix of variance decomposition was normalized using a scalar (here the maximum total forecast error variance). Using the full sample data, France had the maximum forecast error variance at horizon $H = 12$. Therefore, we normalized the matrix of variance decomposition using the France total forecast error variance. Thus, each variance decomposition matrix entry is expressed in terms of the France total forecast error variance. The results of the variance decomposition at the 12-month horizon are presented in Table B.1. This table summarizes the 28 by 28 matrix information into an easier-to-read 10 by 10 matrix by grouping the countries of the European Union (EU) together in the EU row and the EU column. The

[12] China's industrial production index is not available in the OECD database.

[13] Because China's industrial production is missing for each January, we replaced that missing data with the average between the December and February values. This is also the case with data from the Federal Reserve of Saint Louis, where the data started later, after 1990.

EU column contains the sum of connectedness from European countries with the corresponding country on the row. The total directional connectedness of these European countries is summarized in Table B.2.

Graphical Display To better analyze the results of the connectedness estimations, we use a graphical representation of these results. Following Demirer et al. (2018), we characterized the estimated network graphically using the following devices: node size, node color, node location, and link arrow sizes (two per link, because the network is directional). We used the open-source Gephi software (https://gephi.github.io/) for network visualization.

Each country is represented by a node whose respective size and color represent country influence (to others) and country exposure (from others), respectively. Precisely, we made node size a linear function of total directional connectedness (to others). Node color is a linear function of total directional connectedness (from others), ranging from light orange (the smallest) to dark red (the strongest). The color ranges are presented in figure 2.2.

We determined the node location using the ForceAtlas2 algorithm of Jacomy et al. (2014), as implemented in Gephi. This algorithm treats each node as an electrically charged particle. More precisely, nodes with the same type of charge will tend to repel each other. Connectedness links between two nodes act as attractive forces and will tend to bring them together graphically, proportional to the importance of the connectedness. The algorithm finds a steady state in which repelling and attracting forces precisely balance.

Edge size between two nodes is a linear function of the average bilateral connectedness between them, and the link arrow size indicates how big the bilateral directional connectedness is (the " from " one and the " to " one).

Network Connectedness The network for all countries in our study is presented in figure 2.1. This offers a clear view of real output connectedness between those countries.

The graphic shows that geographically closer countries are more connected. We can identify the different clusters, labeled as follows: The Asian group of countries (China, Japan, and Korea), the North American group of countries (Canada and the United States), the Central-East European group of countries (Poland, Hungary, Czech, and Slovakia), and the Western European group of countries (the United Kingdom and France, and all of France's contiguous neighbors). This result is consistent with studies that have found that geographically closer economies are associated with higher business cycle co-movements (e.g., Fidrmuc et al., 2012). We also note that the most important connectedness links are asymmetric, in the sense that for each country in a given pair of countries, the "to" connectedness is different in size than the "from" connectedness.

In this network, the most influential economies are the United Kingdom and Spain. Those two countries are mostly influential in European countries. These results are consistent with those obtained in Papadimitriou et al. (2016). Using data for European countries and the complex network approach, the authors compared the network topology and dominant countries during the pre-euro period (1986-1998) versus the post-euro period (1999-1998). Papadimitriou et al. (2016) showed that Spain was among the dominant countries in both the pre-euro period and the post-euro period. They also showed that the United Kingdom was a dominant country (see Papadimitriou et al., 2016, Fig. 5, page 115). The authors explained that the United Kingdom had completed the convergence criteria but decided not to adopt the euro for political and internal reasons. They observed that periphery countries such as Spain had become strongly correlated with many EU-dominant countries after the adoption of the euro. They concluded that Spain, in the period 1990-2011, appeared to be among the most synchronized countries (see Papadimitriou et al., 2016, page 116).

Italy was the most exposed country: 75.23 % of the volatility in the industrial production in Italy was generated by shocks from abroad. The primary component of Italy's exposure came from Western European countries, with sizable roles played by the United Kingdom and Spain. France followed Italy: 70.68% of the volatility of the industrial production in France was generated by foreign shocks, mainly from European countries.

The overall connectedness in this network is 33.77 % (see the bottom right of Table B.1). In other words, on average, 33.77 % of industrial production volatility in these countries was due to shocks from other countries. The remaining 66.23 % was due to national shocks.

2.5 Dynamic Representation of the Network Connectedness

This section presents the dynamic representation of the network connectedness. Instead of using the full sample, as is the case when measuring the static connectedness, in this section, we used a rolling window method to capture the evolution in connectedness over time. Connectedness was measured separately for each

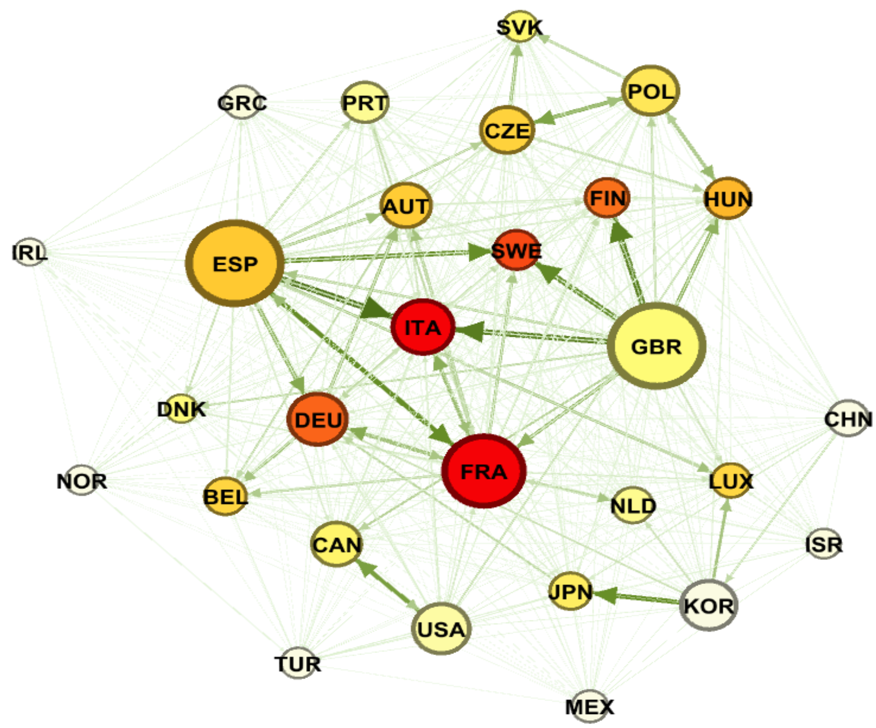

Figure 2.1: OECD country network for the period 1991-2017

Note : See section 2.4 for the graphical display method used.

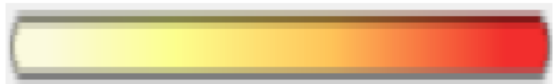

Figure 2.2: Network node colour spectrum

sub-period, using the previous T observations. T is fixed and is called the rolling window size.

Overall Dynamic Connectedness   Figure 2.5 presents the dynamic global connectivity. The global connectivity measures for each sub-period were recursively estimated using a window of 120 months and a forecast horizon of 12 months.

The result shows that connectedness between countries fluctuates over time. A similar result was also obtained in Ductor and Leiva-Leon (2016). Two phases can be distinguished from figure 2.5. The first phase spans from January 2001 to December 2007 (before the financial crisis), and the second phase from January 2008 to the end of the sample (December 2017).

We can also observe that rising periods of connectedness are associated with periods of acute economic events. We observed an increase in connectedness between 2001 and 2002, which corresponds to a period of recession in the United States, Germany, and France. The connectedness then increased during the period of the subprime crisis.[14] The connectedness displays a shelf between 2011 and 2014, which is associated with the debt crisis period in Europe. Finally, we observed an increase in 2016, when the United Kingdom voted to leave the EU. These results are consistent with that obtained in Diebold and Yilmaz (2015a), which showed that connectedness among G6 countries (G7 without Canada) usually jumped

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[14] See Mao Takongmo (2017) for predictions of DSGE models during the financial crisis.

when one or more countries experienced economic downturns. These findings are also consistent with the results obtained in Ductor and Leiva-Leon (2016). They showed that business cycle interdependence is more likely to increase during global recession periods. Ductor and Leiva-Leon (2016) used a different measure of macroeconomic interdependence than the measure used in this paper.

Network Connectedness: Before and After 2009 Financial Crisis To assess how the 2009 financial crisis affects network connectedness, we present two connectedness graphics: one before the financial crisis and another after the financial crisis (see figures 2.3-2.4). We found that the proportion of highly exposed countries had increased, and the USA's influence had importantly grown during that period. Moreover, the number of countries exposed to US shock also increased.

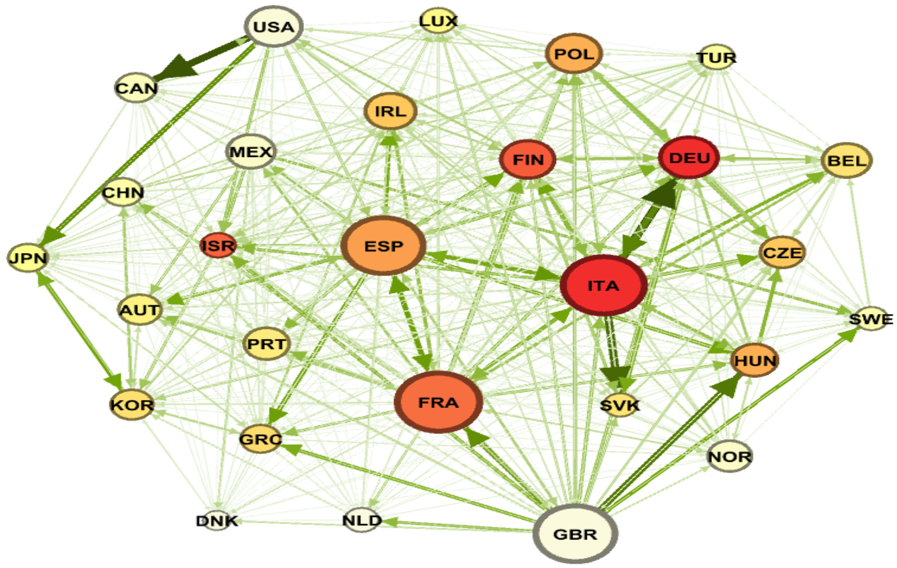

Figure 2.3: OECD country network (before the financial crisis, windows of 120 months ending on November 2007)

Note : See section 2.4 for the graphical display method used.

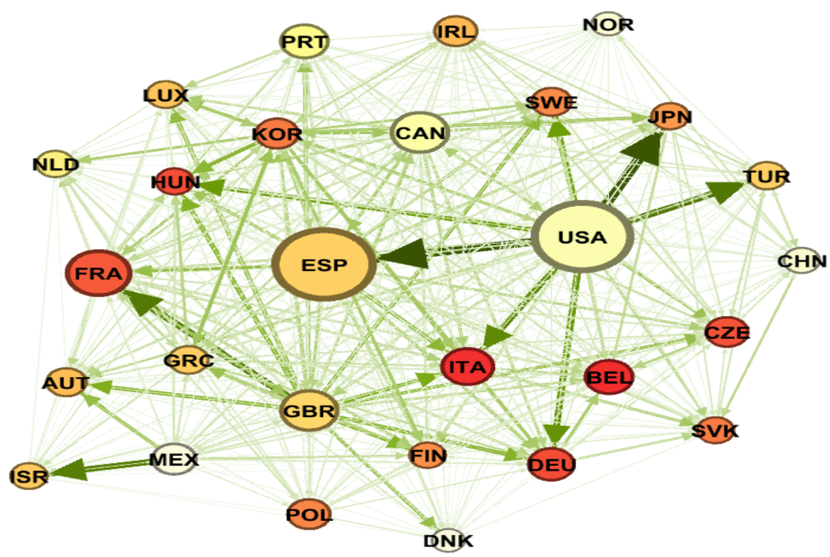

Figure 2.4: OECD country network (after the financial crisis, windows of 120 months ending on July 2009)

Note : See section 2.4 for the graphical display method used.

Directional Connectedness The total dynamic directional measure of connectedness for all countries is presented in figure B.1. It shows each country's total influence in blue bars and its total exposure in red bars. When the blue bars dominate over the red bars, the country is a net shock transmitter; otherwise, the country is a net shock receiver. A remarkable finding from this figure is the change of influential countries in the networks ("to others"). We noted a shift in influential leadership from Great Britain to China. The United States was an important shock transmitter during the subprime crisis, as shown in figure 2.6 and figure B.1. Additionally, we noted that many European countries were more exposed during the period of the financial crisis and the period of the debt crisis (see figure B.1).

In the next section, we assess the possible determinants of these connectedness measures.

2.6 The Determinants of Our Connectedness Measures

Many studies have identified the main determinants of business cycle interdependence as trade openness (Kose et al., 2003b; Imbs, 2004; Baxter and Kouparitsas, 2005; Kose et al., 2012; Ductor and Leiva-Leon, 2016; Montinari and Stracca, 2016; Hwang and Kim, 2021), financial openness (Frankel and Rose, 1998; Kose et al., 2003b; Imbs, 2004, 2006; Kose et al., 2012; Ductor and Leiva-Leon, 2016; Montinari and Stracca, 2016; Hwang and Kim, 2021), specialization (Camacho et al., 2008; Imbs, 2004; Baxter and Kouparitsas, 2005; Kose et al., 2012; Ductor and Leiva-Leon, 2016; Hwang and Kim, 2021), and country-specific characteristics(Kose et al., 2003a; Baxter and Kouparitsas, 2005; Kose et al., 2012; Ductor

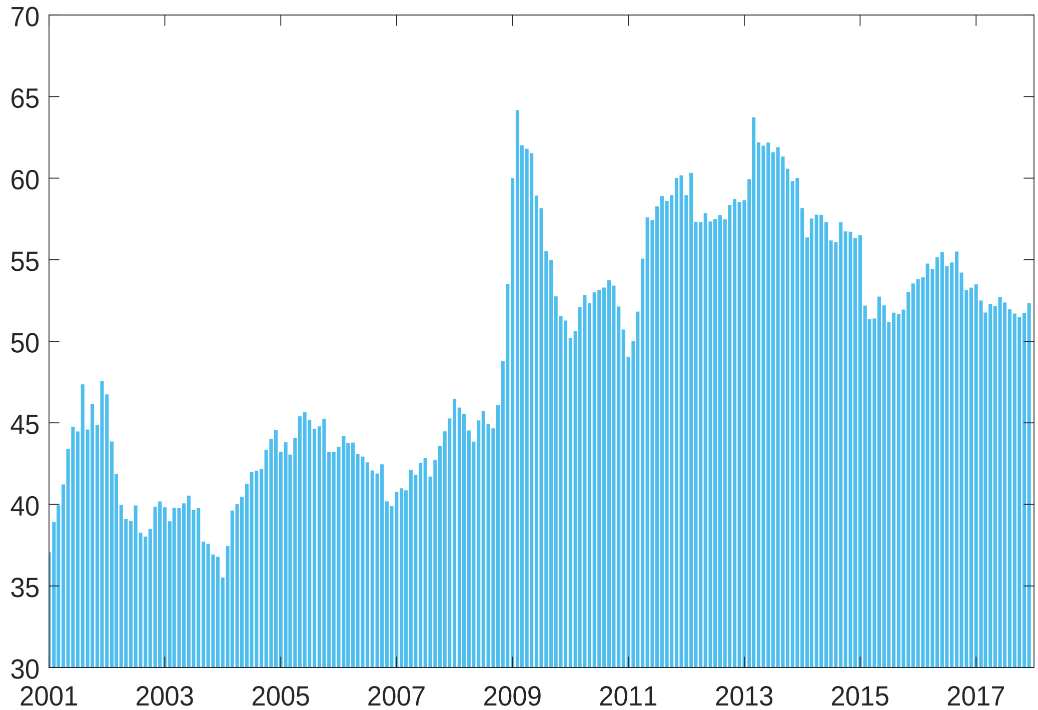

Figure 2.5: Systemwide dynamic connectedness (Jan 2001 to Dec 2017)

Note: We used a rolling window of 120 months. For instance, the first bar represents the value of total (or systemwide) connectedness in the network between January 1991 and December 2000.

and Leiva-Leon, 2016)[15], proxied in this paper by the country size.

Some studies have shown that being in the same trade agreement with another country is associated with high bilateral business cycle interdependence (e.g., Fiess, 2007). It is also well-known that being part of a trade agreement or joining a currency union can also increase trade intensity and financial integration due to reduced trade and financial costs (Frankel and Rose, 1998).

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[15]That includes gravity variables, such as population and total land (Baxter and Kouparitsas, 2005) or country-specific factors (Kose et al., 2003a, 2012).

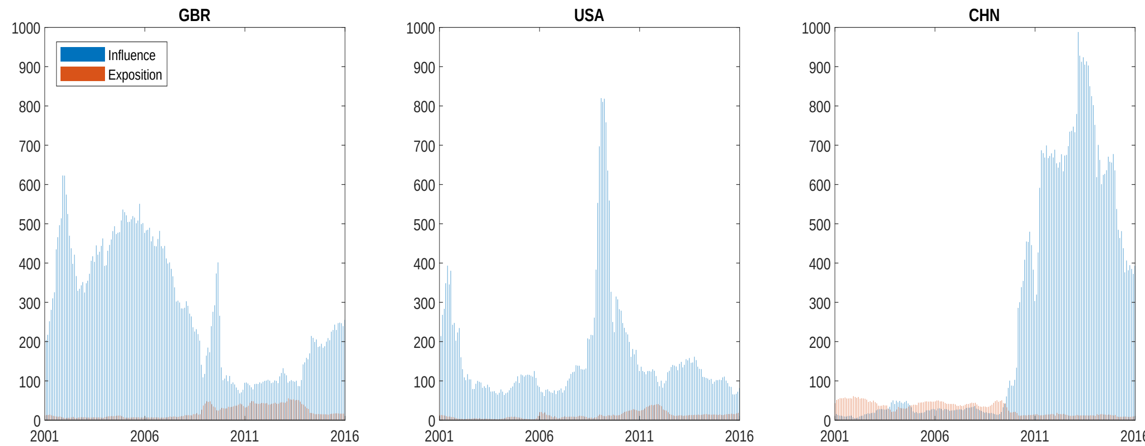

Figure 2.6: Transition in influence

Note: This figure shows the total directional connectedness for the United Kingdom, the United States, and China. The total influence (or the "to others") connectedness for each country is represented by the blue bars, and the total exposure (or the "from others") connectedness is represented by the red bars. We used a rolling window of 120 months.

Existing studies have provided excellent insights into the determinants of business cycle interdependence. However, most of them have used a set of non-directional bivariate correlations to build their measure of the business cycle interdependence.[16] They then have analyzed the effect of the listed determinants on their measure of business cycle interdependence. However, our measures are directional. In this section, we analyze the effects of the possible determinants presented above on our connectedness measures.

Our dynamic measures of connectedness can be classified into two types of indicators. The pairwise directional connectedness [from country "i" (origin) to country "j" (destination)] and the total directional connectedness [total exposure ("from others") and total influence ("to others")]. The first part of this section focuses on the determinants of total directional connectedness, and the second part assesses

[16] Usually an average across the correlations.

the determinants of pairwise connectedness.

2.6.1 Global Directional Connectedness

Many studies have used a dynamic factor model to decompose the country's macroeconomic variables into a common factor[17] and an idiosyncratic factor. They then use the common factor as a measure of the global business cycle, and the loadings (i.e., the coefficient of the factor) as a proxy of the country's business cycle link with the global economy's business cycle (e.g., Kose et al., 2003b,a, 2012; Ductor and Leiva-Leon, 2016). Unfortunately, the true loadings and the true factors cannot be separately identified without a rotation (see, Bai and Ng, 2002, 2013).[18] In fact, as also explained by Kose et al. (2012), neither the signs nor the scales of the factors and the factors loadings are separately identified. Many studies seeking to use a factor model to analyze the determinants of a country's output linkages with the global economy are therefore forced to be restricted to a schematic approach (e.g., Kose et al., 2012). In this paper, we do not face that identification problem. Moreover, unlike indicators of business cycle interdependence based on correlation, our indicator of connectedness between countries and the global economy is directional.

In this section, we test the effect of the possible determinants of business cycle interdependence mentioned above on the directional exposure of a country to the global economy. We also test the effect of these possible determinants on the

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[17] Or a common set of factors as in Kose et al. (2012).

[18] Also see Mao Takongmo and Stevanovic (2015) for problems related to the estimation of the number of factors.

directional influence of a country on the global economy. Our analysis is based on the following two generic econometric models:

$$
\begin{aligned}
C_{i \leftarrow World,t} = \quad & \beta_0 + \beta_1 \text{CountrySize}_{it} + \beta_2 \text{TradeOpeness}_{it} + \beta_3 \text{FinOpeness}_{it} \\
& + \beta_4 \text{ServiceSectorSize}_{it} + \beta_5 \text{IndustrialSectorSize}_{it} + \gamma_i + \tau_t + e_{it},
\end{aligned}
\tag{2.10}
$$

and

$$
\begin{aligned}
C_{i \rightarrow World,t} = \quad & \beta_0 + \beta_1 \text{CountrySize}_{it} + \beta_2 \text{TradeOpeness}_{it} + \beta_3 \text{FinOpeness}_{it} \\
& + \beta_4 \text{ServiceSectorSize}_{it} + \beta_5 \text{IndustrialSectorSize}_{it} + \gamma_i + \tau_t + e_{it},
\end{aligned}
\tag{2.11}
$$

where $C_{i \leftarrow World,t}$ and $C_{i \rightarrow World,t}$ are, respectively, the directional connectedness indicators of exposure to the world and the directional connectedness of influence to the world at time t.

CountrySize_{it} is the size of country i at time t. That indicator is represented by the GDP of country i relative to the average world GDP at time t. TradeOpeness_{it} is the trade openness of country i at time t. This is measured by the total international trade of country i relative to its GDP at time t (i.e., $[(Export_{it} + Import_{it})/GDP_{it}]$, (see, Montinari and Stracca, 2016)). FinOpeness_{it} is the financial openness, represented by the sum of foreign liabilities and foreign assets of country i relative to its GDP at time t (i.e., $[(Assets_{it} + Liabilities_{it})/GDP_{it}]$, (see, Montinari and Stracca, 2016)).

Two variables represent the economic specialization of country i at time t: the relative industrial sector size ($\text{IndustrialSectorSize}_{it}$) and the relative sector service size ($\text{ServiceSectorSize}_{it}$). Our proxy of the relative industrial sector size is the industrial sector size of country i at time t relative to the average world industry sector size at time t. For each country, the industry sector size is the added value of the industry sector relative to its GDP. Also, our proxy for the relative service sector size is the service sector size of country i at time t relative to the average world service sector size at time t. Where, for each country, the service sector size is the added value of the service sector relative to its GDP. γ_i is the country i fixed effect that captures all variables that are fixed over time, such as the area of the country or its geographical position, that may affect the connectedness indicator. τ_t is a year fixed effect that captures the effect of some variables, common to all countries, that evolve over time and that may affect the connectedness indicator. Those two fixed effects help reduce the omitted variable bias and endogeneity and make our analysis more causal.

We performed the Harris and Tzavalis (1999) and Im et al. (2003) unit roots tests in our panels. The details of the tests and the results are presented in the appendix. Because the Harris and Tzavalis (1999) test is a special case of that of Im et al. (2003), we mainly focus on results from Im et al. (2003). We can see from Table B.3 that, when individual trends are not taken into account (i.e., only individual fixed effects are considered), the Im et al. (2003) test results show that we cannot reject the null hypothesis of the unit roots of all variables in the table at the 5 % significance level, except for that of financial openness. We can also see from Table ?? that when heterogenous fixed effects and individual trends are both taken into account, we can now reject the null hypothesis at the 5 % significance level for all variables except country size and service sector size. These results suggest that we must be careful about the trends.

Following Ductor and Leiva-Leon (2016), we used the first-difference transformation to eliminate the country fixed effects. Time-fixed effects were eliminated by cross-sectionally demeaning the data. The results from the estimation of the two econometric models are presented in Tables (2.2–2.5). Tables (2.2–2.3) present the results for the exposures (Equation 2.10), and Tables (2.4–2.5) present the results for influences (Equation 2.11). Table (2.2) and Table (2.4) present the results with only the country fixed effects, while Table (2.3) and Table (2.5) present the results with country and year fixed effects. The results with only the country fixed effects and that with both country and year fixed effects are similar. We will, therefore, only provide comments on the results with both country and year fixed effects, because the specification with both fixed effects controls for more variables and allows for more causal interpretations. Standard errors are clustered at the country level. They are also robust to heteroskedasticity in the sense of White (1980).

An additional increase in the size of a country increases its influence (see table (2.5), column 4). In fact, influence increases by about 60 % for every additional increase of the country size by one unit. The coefficient is significantly different from zero at the 1% significance level when the country fixed effects and the time fixed effects are jointly considered. An additional increase in the size of a country decreases its exposure to international shocks (see table (2.3), column 4). An additional increase of a country size by 1 unit reduces its total exposure to international shocks by about 40 %. The coefficient is also significantly different from zero at 1% significance level.

This result is consistent with that obtained in Ductor and Leiva-Leon (2016), which used the factor loadings as a measure of the effect of the global business cycle on the country's output. Ductor and Leiva-Leon (2016) showed that the loadings associated with "Asian Tigers economies" (i.e., the group of Asiatic nations that have enjoyed a dramatic economic upswings) have experienced decreasing dynamics. This means that the more their GDP increases, the less their business cycle is affected by the global business cycle. Ductor and Leiva-Leon (2016) also showed that the loadings associated with emerging economies (i.e., countries classified by the IMF as not doing well in terms of GDP) have experienced an increasing dynamic. In other words, the less the GDP is, the more their business cycles are affected by the global business cycle.

An additional increase of a country's trade openness also increases its exposure to international shocks (see table (2.3), column 4). An additional increase of a country's trade openness by 1 unit increases its exposure to international shocks by about 1 %; the effect is significant at 10 %. However, trade openness is not a significant determinant of influence.

An additional increase of a country financial openness decreases its exposure to international shocks (see table (2.3), column 4). The effect is significant at 10 % but is not substantial. However, financial openness is not a significant determinant of influence.

An additional increase of the country services sector increase its influence (see table (2.5), column 4). The coefficient is significantly different from zero at a

5% significant level. However, the country services sector size is not a significant determinant of exposure to international shocks.

An additional increase in the country's industrial sector size also increases its influence (see table (2.5), column 4). The coefficient is significantly different from zero at the 10% significant level. An additional increase in the country's industrial sector size reduces its exposure to international shocks (see table (2.3), column 4). An additional increase in the country's industrial sector size by one unit reduces its exposure by about 120 %. The coefficient is significant at 10 %.

Do the country size and financial openness amplify or dampen the link between trade and connectedness with the global economy?

One way to understand the mechanisms through which trade openness affects the connectedness of a country to the world economy is to rely on economic theory. However, theoretical research still needs to be conducted on this important topic. We will come back to this point in the discussion section of the paper.

Another way to study the mechanisms through which the links between two variables are obtained is by analyzing the heterogeneous effects. This is usually achieved by adding interactions to the generic econometric model.[19] Table 2.3 (columns 5–8) provides the results with interaction for the exposure of a country to the world economy when both the country and the year fixed effects are considered. Table 2.5 (columns 5–8) presents the results with interactions for influence on the world economy with both country and year fixed effects.

[19]See, for example, Baier et al. (2018); Lebihan and Mao Takongmo (2019); Aman et al. (2022).

Our results suggest that a larger country size amplifies the link between trade openness and the exposure of a given country to the world economy. The interaction coefficient is significantly different from zero at 1% when the country fixed effect is considered (see Table 2.2, columns 5–8). The interaction coefficient remains positive but not statistically significant when in addition to the country fixed effects, the time fixed effects are also taken into account (see Table 2.3, columns 5–8). More financial openness dampens the link between trade openness and the exposure of a country to the world economy; however, the effect is not significantly different from zero (see Table 2.3, columns 5–8).

On the other hand, a larger country's size or more financial openness amplifies the effects of trade openness on the influence of a given country on the world economy. The interaction coefficients are statistically different from zero at 5% (see Table 2.5, columns 5–8). We delay comparing these results with those in the literature until the discussion section of the paper.

Table 2.2: Trade, country size, sectors size, financial openness, and exposure of a country to the global economy, with country fixed effects

	Dependent variable:							
	Total exposure (log)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Country Size	-0.47^{***}		-0.44^{***}	-0.42^{***}	-0.60^{***}	-0.40^{***}	-0.41^{***}	-0.57^{***}
	(0.09)		(0.08)	(0.10)	(0.06)	(0.09)	(0.10)	(0.06)
Trade openness		0.01^{**}	0.01^{***}	0.01^{***}	0.01^{***}	0.01^{***}	0.01^{***}	0.01^{***}
		(0.003)	(0.002)	(0.003)	(0.002)	(0.002)	(0.003)	(0.002)
Fin. openness				-0.01^{***}	-0.01^{***}	0.02	-0.01^{***}	0.02
				(0.002)	(0.002)	(0.01)	(0.002)	(0.01)
Service sector size				-3.15	-3.34	-3.72	-3.26	-3.81
				(2.07)	(2.01)	(2.38)	(2.10)	(2.31)
Industrial sector size				-1.48^{**}	-1.61^{**}	-1.67^{**}	-1.53^{**}	-1.80^{***}
				(0.60)	(0.59)	(0.67)	(0.59)	(0.65)
Country size × trade op.					0.01^{***}			0.01^{***}
					(0.002)			(0.001)
Fin. openness × trade op.						-0.0000^{*}		-0.0000
						(0.0000)		(0.0000)
OECD recession							-0.01	-0.09^{*}
							(0.04)	(0.05)
OECD recession × trade op.							-0.0005	0.001
							(0.0004)	(0.001)
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	No	No	No	No	No	No	No	No
Observations	448	448	448	420	420	420	420	420
Adjusted R^2	0.67	0.62	0.70	0.70	0.71	0.71	0.71	0.72

Notes: These results are obtained using the econometric model in equation (2.10), with the country fixed effects only. Robust standard errors are clustered at the country level. *, **, and *** indicate coefficient significance at 10%, 5%, and 1%, respectively. Total exposure refers to the total directional connectedness "from others" ($C^H_{i\leftarrow\bullet} = \sum^N_{j=1;j\neq i} d^H_{ij}$).

Table 2.3: Trade, country size, sectors size, financial openness, and exposure of a country to the global economy, with country and year fixed effects

	Dependent variable: Total exposure (log)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Country Size	-0.47^{***}		-0.46^{***}	-0.43^{***}	-0.53^{***}	-0.43^{***}	-0.43^{***}	-0.53^{***}
	(0.04)		(0.04)	(0.06)	(0.08)	(0.07)	(0.06)	(0.07)
Trade openness		0.005	0.003	0.01^{*}	0.01^{*}	0.01^{*}	0.01	0.01^{*}
		(0.004)	(0.003)	(0.004)	(0.004)	(0.005)	(0.004)	(0.005)
Fin. openness				-0.005^{*}	-0.005^{*}	0.004	-0.005^{*}	0.01
				(0.002)	(0.002)	(0.01)	(0.002)	(0.01)
Service sector size				-2.84	-3.04	-3.11	-2.86	-3.36
				(2.36)	(2.30)	(2.42)	(2.33)	(2.42)
Industrial sector size				-1.19^{*}	-1.35^{**}	-1.31^{**}	-1.20^{*}	-1.51^{**}
				(0.60)	(0.62)	(0.63)	(0.59)	(0.68)
Country size $\times$ trade op.					0.004			0.004
					(0.003)			(0.003)
Fin. openness $\times$ trade op.						-0.0000		-0.0000
						(0.0000)		(0.0000)
OECD recession $\times$ trade op.							-0.0001	0.0003
							(0.0004)	(0.0005)
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	448	448	448	420	420	420	420	420
Adjusted R^2	0.73	0.65	0.73	0.73	0.74	0.74	0.73	0.74

Notes: These results are obtained using the econometric model in equation (2.10), with country and year fixed effects. Robust standard errors are clustered at the country level. *, **, and *** indicate coefficient significance at 10%, 5%, and 1%, respectively. Total exposure refers to the total directional connectedness "from others" ($C^H_{i\leftarrow\bullet} = \sum_{j=1;j\neq i}^{N} d^H_{ij}$).

Table 2.4: Trade, country size, sectors size, financial openness, and influence of a country on the global economy, with country fixed effects

	Dependent variable:							
	Total influence (log)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Country Size	0.62***		0.64***	0.63**	0.23	0.62**	0.63**	0.18
	(0.21)		(0.21)	(0.23)	(0.22)	(0.24)	(0.23)	(0.21)
Trade openness		0.003	0.004	0.003	−0.001	0.002	0.002	−0.002
		(0.004)	(0.004)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Fin. openness				0.001	0.002	−0.02	0.001	−0.03
				(0.004)	(0.004)	(0.02)	(0.004)	(0.02)
Service sector size				5.82**	5.39**	6.43**	5.90**	6.13**
				(2.73)	(2.63)	(2.76)	(2.74)	(2.73)
Industrial sector size				2.90*	2.59*	3.10**	2.97*	2.88**
				(1.56)	(1.40)	(1.46)	(1.59)	(1.28)
Country size × trade op.					0.01**			0.02**
					(0.01)			(0.01)
Fin. openness × trade op.						0.0000		0.0001*
						(0.0000)		(0.0000)
OECD recession							0.07	0.14
							(0.10)	(0.11)
OECD recession × trade op.							0.0001	−0.001
							(0.001)	(0.001)
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	No	No	No	No	No	No	No	No
Observations	448	448	448	420	420	420	420	420
Adjusted R^2	0.68	0.63	0.68	0.70	0.71	0.70	0.70	0.72

Notes: These results are obtained using the econometric model in equation (2.11), with the country fixed effects only. Robust standard errors are clustered at the country level. *, **, and *** indicate coefficient significance at 10%, 5%, and 1%, respectively. Total influence refers to the total directional connectedness "to others" ($C^H_{\bullet\leftarrow j} = \sum_{i=1;i\neq j}^{N} d^H_{ij}$).

Table 2.5: Trade, country size, sectors size, financial openness, and influence of a country on the global economy, with country and year fixed effects

	Dependent variable:							
	Total influence (log)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Country Size	0.62***		0.63***	0.62***	0.21	0.58***	0.62***	0.20
	(0.17)		(0.19)	(0.21)	(0.23)	(0.19)	(0.21)	(0.22)
Trade openness		−0.0003	0.002	−0.001	0.001	−0.01	−0.001	−0.002
		(0.01)	(0.003)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Fin. openness				0.002	0.001	−0.04	0.002	−0.05*
				(0.004)	(0.004)	(0.03)	(0.005)	(0.03)
Service sector size				6.09**	5.22**	7.43***	6.14**	6.47**
				(2.67)	(2.49)	(2.66)	(2.67)	(2.46)
Industrial sector size				3.15*	2.41	3.74**	3.16*	3.02**
				(1.63)	(1.42)	(1.50)	(1.64)	(1.26)
Country size × trade op.					0.02**			0.01**
					(0.01)			(0.01)
Fin. openness × trade op.						0.0001		0.0001*
						(0.0001)		(0.0001)
OECD recession × trade op.							0.0002	−0.002
							(0.001)	(0.001)
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	448	448	448	420	420	420	420	420
Adjusted R^2	0.69	0.63	0.69	0.70	0.72	0.71	0.70	0.73

Notes: These results are obtained using the econometric model in equation (2.11), with country and year fixed effects. Robust standard errors are clustered at the country level. *, **, and *** indicate coefficient significance at 10%, 5%, and 1%, respectively. Total influence refers to the total directional connectedness "to others" ($C^H_{\bullet\leftarrow j} = \sum_{i=1;i\neq j}^N d^H_{ij}$).

2.6.2 Pairwise Connectedness

Another field of the literature focuses on bilateral business cycle interdependence over time between countries, also called synchronization. The main potential factors that could explain changes in bilateral business cycle co-movements are identified in this literature as trade integration (bilateral trade) (Baxter and Kouparitsas, 2005; Ductor and Leiva-Leon, 2016; Cesa-Bianchi et al., 2019; Hwang and Kim, 2021), financial integration (Baxter and Kouparitsas, 2005; Ductor and Leiva-Leon, 2016; Cesa-Bianchi et al., 2019; Hwang and Kim, 2021), economic specialization (similarity in industrial composition) (Baxter and Kouparitsas, 2005; Ductor and Leiva-Leon, 2016; Hwang and Kim, 2021), and country-specific factors[20] (Baxter and Kouparitsas, 2005; Ductor and Leiva-Leon, 2016), proxied in this paper by the country size. Most of the studies in the literature have used a non-directional measure of business cycle synchronization (usually the absolute difference in GDP growth).

In this section, we assess the impact of the possible determinant, presented above, on our directional measure of business cycle synchronization (our connectedness from a given country to another given country). To do that, we used the two econometric models presented below.

The first econometric model is similar to that used in Hwang and Kim (2021). Unlike Hwang and Kim (2021), who used the absolute difference in GDP growth as their measure of synchronization, we used the connectedness from a given

[20] Such as gravity variables and factor endowments: labour (sometimes proxied by human capital) and capital.

country to another given country. We also controlled for the size of the origin country and that of the destination country. This specification helps us illustrate how connectedness is affected by changes in bilateral trade, financial integration, and bilateral similarities in economic specialization, while controlling for time-invariant directional country pair characteristics and time-varying global shocks common to all pairs of countries. This econometric model will also help us shed more light on how directional connectedness is affected by the country's origin size and the country's destination size. Our first econometric model is:

$$\begin{aligned} C_{i\leftarrow j,t} = \quad & \beta_1 \text{CountrySize}_{i,t-1} + \beta_2 \text{CountrySize}_{j,t-1} + \theta_1 \text{TradeIntegration}_{ij,t-1} \\ & + \theta_2 \text{FinIntegration}_{ij,t-1} + \theta_3 \text{EconSpecialization}_{ij,t-1} + \gamma_{ij} + \tau_t + e_{ij,t}, \end{aligned} \tag{2.12}$$

where $C_{i\leftarrow j,t}$ is the connectedness from country "j" to country "i" [in short, the bilateral or pairwise connectedness "from another country"]; $\text{CountrySize}_{i,t-1}$ and $\text{CountrySize}_{j,t-1}$ are, respectively, economic size of the origin country "i" and the destination country "j". That indicator is represented by the GDP of a given country relative to the average world GDP at time $t-1$.

$\text{TradeIntegration}_{ij,t-1}$ is the trade intensity between countries "i" and "j" at time $t-1$. This is measured by the total trade between the two countries relative to their total GDP at time $t-1$ (see Frankel and Rose, 1998; Ductor and Leiva-Leon, 2016).

$$\text{TradeIntegration}_{ij,t-1} = \frac{\text{Export}_{ij,t-1} + \text{Export}_{ji,t-1}}{GDP_{i,t-1} + GDP_{j,t-1}}, \tag{2.13}$$

where $\text{Export}_{ij,t-1}$ are exports from country i to country j.

$\text{FinIntegration}_{ij,t-1}$ is the financial integration between the two countries. This is the total portfolio investment assets between the two countries, relative to the sum of their GDP at time $t-1$.[21]

$$\text{FinIntegration}_{ij,t-1} = \frac{\text{TPI}_{ij,t-1} + \text{TPI}_{ji,t-1}}{GDP_{i,t-1} + GDP_{j,t-1}}, \tag{2.14}$$

where $\text{TPI}_{ij,t-1}$ is the country i holdings of total portfolio investment assets in the year $t-1$ issued by country j. As in Hwang and Kim (2021), this amount includes equity, investment fund shares, and debt instruments.

$\text{EconSpecialization}_{ij,t-1}$ is the economic specialization index that measure the differences in industrial specialization between the country i and country j at time $t-1$.

$$\text{EconSpecialization}_{ij,t-1} = \sum_k \left| S^k_{i,t-1} - S^k_{j,t-1} \right|, \tag{2.15}$$

where $S^k_{i,t-1}$ is the GDP share of sector k in country i during the period $t-1$ (see Imbs, 2004; Ductor and Leiva-Leon, 2016).

τ_t and γ_{ij} are, respectively, time and directional country-pair fixed effects. The time fixed effect helps account for all global events (such as the 2009 financial crisis) that can affect all bilateral connectedness. Directional country-pair fixed effects help to take into account economic imbalance and asymmetries between pairs of countries (see Waugh, 2010; El Dahrawy Sánchez-Albornoz and Timini, 2021). The directional country-pair fixed effects also help control for any observable and unobservable characteristics varying at the country pair level, including gravity variables, such as distance between the two countries, contiguity, common

[21] A similar indicator is used in Montinari and Stracca (2016).

languages, or colonial relationships. As in Kalemli-Ozcan et al. (2013) and Hwang and Kim (2021), independent variables are lagged to partially account for reverse causality.

The second econometric model helps control for more variables. In the second econometric specification, we replaced the origin countries' size, the destination country size, and the time fixed effect by the origin × time and destination × time fixed effects. Doing that helped to take into account all characteristics of the origin country and destination country over time, such as GDP and population in each country (see Anderson and Van Wincoop, 2003; Yotov, 2012; Borchert and Yotov, 2017; Greaney and Kiyota, 2020; El Dahrawy Sánchez-Albornoz and Timini, 2021, for more details);

$$\begin{aligned} C_{i\leftarrow j,t} = \quad & \theta_1 \text{TradeIntegration}_{ij,t-1} + \theta_2 \text{FinIntegration}_{ij,t-1} \\ & + \theta_3 \text{EconSpecialization}_{ij,t} + \theta_4 (\text{CountrySize}_{i,t-1} / \text{CountrySize}_{j,t-1}) \\ & + \alpha_{i,t} + \alpha_{j,t} + \gamma_{ij} + e_{ij,t}. \end{aligned} \tag{2.16}$$

The results for the two econometric specifications are presented in Tables (2.6–2.7). The results for the first econometric model are presented in Table (2.6), and the results for the second econometric model are presented in Table (2.7).

As we can see in Table (2.6) (column 5), an additional increase in the country size of a given destination country reduces its exposure to shocks arising from another given country. Increasing the size of a given destination country by one unit reduces its exposure to another given country by about 46 %. The coefficient is statistically significantly different from zero at the 1% significance level. We can also see from Table (2.6) (column 5) that, after controlling for other variables, time fixed effects, and directional bilateral fixed effects, an additional increase of a given country size does not have a statistically significant impact on its influence on another given country.

An additional increase of trade intensity between two countries also significantly increases its bilateral connectedness (see Tables (2.6-2.7)). This result is consistent with that obtained in Imbs (2004), Baxter and Kouparitsas (2005), Montinari and Stracca (2016), and Hwang and Kim (2021), all of which obtained a positive effect of bilateral trade intensity on business cycles interdependence.

An additional increase in the differences of economic specialization between two countries increases the connectedness between them. Many studies have shown that an increase in differences in terms of economic specialization is associated with differences in their business cycles (e.g., Imbs, 2004; Ductor and Leiva-Leon, 2016; Hwang and Kim, 2021). Therefore, our result complements the results obtained in the literature by adding that countries affect each other more when their differences in terms of economic specialization increase.

Financial integration does not have any statistically significant impact on bilateral connectedness. This result is consistent with that obtained in many studies finding that financial integration does not have a significant effect on business cycle interdependence (e.g., Montinari and Stracca, 2016; Hwang and Kim, 2021).

Do country size, financial integration, and economic specialization amplify or dampen the effect of trade on connectedness from another country?

One way to understand the mechanisms through which trade integration affects the connectedness from the origin country to the destination country is to rely on economic theory. However, only a few theoretical studies have focused on topics close to that critical question.

Another way to understand the mechanisms through which the links between two variables are obtained is by studying the heterogeneous effects. This is achieved by adding interactions to the econometric model (see for example, Baier et al., 2018; Lebihan and Mao Takongmo, 2019; Aman et al., 2022). That will not tell us the exact story behind the link between trade integration and pairwise connectedness; however, we will have an idea about whether country size, financial integration, and economic specialization amplify or dampen the link between trade and pairwise connectedness.

Table 2.6 (columns 6–10) provides the results with interactions where both directional country pair and time fixed effects are considered. Table 2.7 (columns 4–8) presents the results obtained with interactions in the more constrained model, where both the directional country pair fixed effects and origin $\times$ time and destination $\times$ time fixed effects are taken into account.

Even if financial integration does not directly impact pairwise connectedness (see Table 2.6, columns 4), financial integration affects the link between trade integration and connectedness from the origin to the destination country. The greater the degree of financial integration with the origin country, the smaller the connectedness from the origin to the destination country that passes through trade. This dampening effect is significant at 10% (see Table 2.6, columns 7 and 10).[22]

While more differences in economic specialization positively affect connectedness from the origin to the destination country (see Table 2.6, column 4), an increase in differences in economic specialization leads to less connectedness from the origin to the destination that passes through trade integration. This dampening effect is significant at 5% (see Table 2.6, columns 8 and 10).

We also show that recession positively affects the link between trade and pairwise connectedness. Periods of recessions increase the connectedness from the origin to the destination that passes through trade integration (see Table 2.6, columns 9 and 10).

The relative size between two countries does not have any significant multiplier effect on pairwise connectedness that pass through trade integration.

In Table 2.7 (columns 4–8), we report the results when both the directional country pair fixed effects and origin $\times$ time and destination $\times$ time fixed effects are taken into account. The results confirm what we obtained when only directional country pair fixed effects and time fixed effects were considered. Note that by taking into account the origin $\times$ time and the destination $\times$ time fixed effects, we are controlling for all time series specific to each of the countries involved. Regardless, the sign of our interaction variables remains the same. While many of the coefficients associated with interaction variables lose their significance, the coefficient associated with the interaction related to economic specialization remains

[22] The variable "Financial integration $\times$ Trade" is standardized in Tables (2.6–2.7).

significantly different from zero.

Table 2.6: Trade integration, country size, economic specialization, financial integration, and pairwise connectedness from origin to destination, with directional country-pair fixed effects and time fixed effects

	Dependent variable:									
	Connectedness from origin to destination log()									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Trade integration	18.88*			22.17**	18.16*	21.32**	29.36***	31.09***	15.86	42.84***
	(9.93)			(9.57)	(10.13)	(10.16)	(10.90)	(10.36)	(10.29)	(12.89)
Destination country size		−0.42***		−0.40***	−0.46***	−0.45***	−0.46***	−0.46***	−0.46***	−0.46***
		(0.06)		(0.06)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)
Origin country size			0.56***	0.55***	−0.01	−0.01	−0.01	−0.02	−0.01	−0.02
			(0.07)	(0.07)	(0.12)	(0.12)	(0.12)	(0.12)	(0.12)	(0.12)
Financial integration					−0.25	−0.26	0.004	−0.28	−0.24	−0.04
					(0.38)	(0.38)	(0.38)	(0.39)	(0.38)	(0.38)
Econ. specialization					0.01**	0.01**	0.01**	0.01***	0.01**	0.01***
					(0.004)	(0.004)	(0.004)	(0.005)	(0.004)	(0.005)
(Dest. size / Orig. size) × Trade						−0.06				−0.04
						(0.09)				(0.09)
Financial integration × Trade							−0.16*			−0.15*
							(0.08)			(0.08)
Econ. specialization × Trade								−0.15**		−0.16**
								(0.07)		(0.07)
OECD recession × Trade									0.02*	0.02
									(0.01)	(0.02)
Dir. country-pair FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	12,015	12,096	12,096	12,015	8,918	8,918	8,918	8,918	8,918	8,918
Adjusted R^2	0.49	0.50	0.51	0.52	0.55	0.55	0.55	0.55	0.55	0.55

Notes: These results are obtained using the econometric model in equation (2.12). Robust standard errors are clustered by country pair. *, **, and *** indicate coefficient significance at 10%, 5%, and 1%, respectively.

Table 2.7: Trade integration, country size, economic specialization, financial integration, and pairwise connectedness from origin to destination, with directional country-pair fixed effects and origin × time and destination × time fixed effects

	Dependent variable:							
	Connectedness from origin to destination log()							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Trade integration	20.94***		22.78***	21.86***	26.36***	30.82***	22.51***	33.83***
	(7.46)		(8.22)	(8.44)	(8.70)	(8.76)	(8.46)	(10.12)
Dest. size div Origin country size		−0.001	−0.004**	−0.004**	−0.004**	−0.004*	−0.004**	−0.004**
		(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Financial integration			0.24	0.23	0.29	0.24	0.24	0.30
			(0.51)	(0.51)	(0.52)	(0.51)	(0.51)	(0.52)
Econ. specialization			0.01**	0.01*	0.01**	0.01**	0.01*	0.01***
			(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
(Dest. size / Orig. size) × Trade				0.02				0.03
				(0.07)				(0.07)
Financial integration × Trade					−0.04			−0.05
					(0.06)			(0.06)
Econ. specialization × Trade						−0.10*		−0.11*
						(0.06)		(0.06)
OECD recession × Trade							0.003	0.001
							(0.01)	(0.01)
Dir. country-pair FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Orig-time & dest.-time FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	12,015	12,096	8,918	8,918	8,918	8,918	8,918	8,918
Adjusted R^2	0.69	0.69	0.68	0.68	0.68	0.68	0.68	0.68

Notes: These results are obtained using the econometric model in equation (2.16). Robust standard errors are clustered by country pair. *, **, and *** indicate coefficient significance at 10%, 5%, and 1%, respectively.

2.6.3 Connectedness and Agreements

In this section, we investigate how economic agreements between countries affect their connectedness. Economic agreements can facilitate economic exchanges between signatory countries by reducing barriers. We examined the effects of being a signatory for the same multilateral agreement on bilateral connectedness. Our sample contained two important multilateral agreements: The North American Free Trade Agreement (NAFTA) and the European Union (EU) agreements. We assessed how being a signatory of these agreements affected bilateral connectedness using the following regression:

$$C_{i \leftarrow j,t} = \beta \text{Agreement} + \delta X_{ijt} + \gamma_{it} + \gamma_{jt} + \gamma_{ij} + e_{ijt} \tag{2.17}$$

where "Agreement" is a binary variable taking 1 when country "i" and country "j" are both in the same multilateral agreement (NAFTA or the EU); X_{ijt} is a vector of variables of control such as trade integration and financial integration between the pair of countries (i and j), and the difference in their economic specialization. We included in the model the origin $\times$ time and the destination $\times$ time fixed effects to control for all observable and unobservable time varying characteristics specific to the origin country and to the destination country, respectively. We also included the directional country pair fixed effect to control for all unobservable characteristic specific to each pair of countries. This specification is widely used in the literature of trade, usually to assess the effects of regional agreements on trade flow (see Yotov, 2012; Greaney and Kiyota, 2020; El Dahrawy Sánchez-Albornoz and Timini, 2021; Borchert and Yotov, 2017). The results are presented in Table 2.8.

Empirical results with interactions with economic agreements

As can be seen from Table 2.8 (column 2), two countries entering into the same agreement increased their connectedness by about 58 %. This result is consistent with that obtained by Fiess (2007), which showed that a trade agreement between Central American countries and the US made these countries more sensitive to developments in the US economy.

The results related to coefficients of interaction terms with agreements are similar to what we obtained in the previous section for coefficients associated with interactions with trade integration. Table 2.8 (columns 3–7) provides the results of interactions with economic agreements, where both the directional country pair fixed effects and origin $\times$ time and destination $\times$ time fixed effects are taken into account. We can see that, as was the case with trade integration, an increase in financial integration and an increase in differences in economic specialization between two countries both dampen the link between economic agreements and the connectedness from the origin to the destination country. Again, as was also the case for interaction with trade integration, periods of recessions amplify the positive link between economic agreements and the connectedness from the origin to the destination country (see Table 2.8, columns 6–7).

Table 2.8: Economic agreements, country sizes, economic specialization, financial integration, and pairwise connectedness from origin to destination, with directional country-pair fixed effects and origin × time and destination × time fixed effects

	Dependent variable:						
	Bilateral Connectedness log()						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Agreements	0.41***	0.58***	0.61***	0.58***	1.03***	0.51***	0.92***
	(0.11)	(0.18)	(0.18)	(0.18)	(0.18)	(0.17)	(0.18)
Trade integration		22.77***	22.61***	21.66***	19.62**	23.24***	19.63**
		(8.19)	(8.19)	(8.19)	(8.13)	(8.19)	(8.12)
Dest. size / Orig. size		−0.005**	−0.005***	−0.005**	−0.004*	−0.005**	−0.004*
		(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Financial integration		0.31	0.30	6.88	0.26	0.32	3.81
		(0.52)	(0.52)	(5.67)	(0.52)	(0.52)	(6.07)
Econ. specialization		0.01	0.01	0.01	0.02***	0.01	0.02***
		(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Agreements × (Dest. size / Orig. size)			−0.01				−0.005
			(0.01)				(0.01)
Agreements × Fin. integration				−6.53			−3.51
				(5.60)			(6.00)
Agreements × Econ. specialization					−0.02***		−0.02***
					(0.005)		(0.01)
Agreements × OECD recession						0.11	0.18***
						(0.07)	(0.07)
Orig.-time & dest.-time FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Dir. country-pair FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	12,852	8,918	8,918	8,918	8,918	8,918	8,918
Adjusted R^2	0.68	0.68	0.68	0.68	0.68	0.68	0.68

Notes: Robust standard errors are clustered by country pair. *, **, and *** indicate coefficient significance at 10%, 5%, and 1%, respectively.

2.6.4 Connectedness and new entries into the European Union

NAFTA has been in existence since 1992, and EU agreements have been in existence since 1995. While the number of NAFTA members has remained fixed since its creation, many countries joined the EU in 2004, including Poland, Czechia, Hungary, and Slovakia. We used those countries to analyze how entries into the EU affected connectedness between the entering countries and the existing members of the EU. We used the following econometric model:

$$C_{i \leftarrow j,t} = \beta_1 \text{PostEntry} + \delta X_{ijt} + \gamma_i + \gamma_j + \gamma_{ij} + e_{ijt}, \tag{2.18}$$

where $C_{i \leftarrow j,t}$ represents the connectedness between one of the four countries that entered the EU in 2004 and an existing member of the EU [“from” or “to”]. PostEntry is a year dummy indicating the post-entry period starting in 2005 (taking 1 from 2005). The vector X_{ijt} contains control variables such as trade and financial integration, differences in economic specialization, and the overall connectedness. γ_i and γ_j are origin and destination country fixed effects, respectively, and γ_{ij} are directed country-pair fixed effects.

The results for this regression are presented in Table 2.9. We found that entries into the EU increased the connectedness of the entering countries with existing members. These results remain significant when we control for individuals, pairwise characteristics, and global shocks that can affect system-wise connectedness.

Table 2.9: Entry in EU and connectedness

	Dependent variable:		
	Bilateral Connectedness log()		
	(1)	(2)	(3)
Post Entry	0.44***	0.24**	0.23**
	(0.10)	(0.10)	(0.10)
Trade Integration		45.38***	45.47***
		(15.08)	(15.05)
Financial integration		−14.90***	−14.71***
		(4.32)	(4.34)
Econ. specialization		0.02*	0.02*
		(0.01)	(0.01)
Overall Connectedness			0.49**
			(0.20)
Dir. country pair FEs	Yes	Yes	Yes
Origin & dest. FEs	Yes	Yes	Yes
Observations	1,613	1,318	1,318
Adjusted R^2	0.30	0.36	0.35

Notes: Robust standard errors are clustered by country pair. *, **, and *** indicate coefficient significance at 10%, 5%, and 1%, respectively.

2.6.5 Discussion

The main econometric results can be summarized as follows:

1. Trade openness increases connectedness from other countries.
2. A larger country's size amplifies the effect of trade openness on the connectedness from other countries.
3. Trade intensity between two countries significantly increases the bilateral connectedness "from another country".
4. Financial integration or differences in economic specialization dampens the effect of trade integration on the bilateral connectedness "from another country".
5. Recessions amplify the effect of trade integration on the bilateral connectedness "from another country".
6. The results remain the same when for robustness check, trade integration is replaced with economic agreements. In particular, financial integration or differences in economic specialization between two countries dampens the effect of economic agreements on bilateral connectedness "from another country". Recessions amplify the impact of economic agreements on the connectedness from the origin to the destination country.

The results of this paper are consistent with those obtained in economic theory. We know from theory in international trade that international trade interlinkages can create business cycle interdependencies that happen through both the demand-side and the supply-side effects (Kose et al., 2012). For the demand-side effects, a positive increase of GDP in one given country can increase demand for goods and services produced abroad. The supply-side effect is due to decreases in international prices induced by increases in trade intensity.

This implies that big countries in terms of economic size will more likely affect other countries through trade because the demand-side effects on other countries is more likely to be greater for big countries than for small countries.

International trade theory also says that trade linkages can create industrial specialization through comparative advantages. Specialization can be assumed to be due to international trade and can also be viewed as exogenous, depending on the study's research question. Regardless, specialization can affect business cycle interdependence either positively or negatively (see Imbs, 2004; Kose et al., 2012). A positive effect of specialization on business cycle interdependence can be triggered, for example, by a positive global shock that will push countries to take advantage of their specialization to generate more output. A negative effect of specialization on business cycle interdependence can be due to a country-specific shock, which is assimilated to a sector-specific shock in the case of specialization. Suppose a shock has a positive effect on the output of a given country. In that case, this shock will not necessarily lead to an increase in output in the second country because the sector of specialization is not the same in both countries. Therefore, it is easy to see that when controlling for trade, the effects of specialization may become small and versatile.

On the other hand, international finance theory says that financial interlinkages can also affect business cycle interdependencies either positively or negatively (see Imbs, 2004; Kose et al., 2012). If financial interlinkages generate a large demand-side effect, then a positive effect is expected to happen. For example, suppose residents of two countries hold the same equity. In that case, a change in equity prices is expected to affect the business cycle in both countries in the same direction simultaneously. If financial interlinkages induce greater specialization, the negative effect can in theory be observed through the reallocation of capital compatible with the countries' comparative advantages.

Using a two-country DSGE model calibrated[23] for OECD countries, Faia (2007) shows in her framework that trade openness increases the business cycle correlation between two countries and financial openness lowers it. The author also shows in her model how financial frictions could explain the positive co-movement of output, investment, and employment across countries. This idea can be summarized as follows: a positive home country technology shock increases domestic production and investment. It also shifts the demands between domestic and foreign goods. This demand shift leads to a decrease in foreign inflation, foreign output, and investment. Capital flows to the home country typically lead to a negative output correlation between the two countries. However, due to sticky prices and the response of monetary authorities, a fall in foreign inflation will lead to a fall in the foreign interest rate. The fall in interest rate will then boost investment and asset prices and will offset the negative impact of the demand shift on the foreign country's business cycle (Faia, 2007).

Another mechanism that explains the positive correlation of output between two

[23]Note that calibrating DSGE models is in general better than estimating the parameters of DSGE models using detrending data (see Mao Takongmo, 2021).

countries is also described using a two-country DSGE model with more than one sector, coupled with frictions in the capital market(see Ambler et al., 2002). The mechanism can be summarized as follows: A positive technology shock in one sector of the home country leads to labor and capital drawing into that sector not only from abroad, but also from the sector in the home country that did not receive the shock. This leads to positive co-movements of output in the home sector that did not receive the shock and outputs in both sectors abroad. This increases the correlation in aggregate production between the two countries (Ambler et al., 2002). The friction in the capital market (represented by the convex capital adjustment cost) reduces the size of capital inflow generated by the technology shock and reduces the negative co-movements of output related to capital inflows (Ambler et al., 2002).

We also know from theory that being part of a trade agreement or joining a currency union can also increase trade intensity and financial integration due to reduced trade and financial costs (Frankel and Rose, 1998).

2.7 Conclusion

This paper uses estimation methodology based on selection and shrinkage proposed in Demirer et al. (2018) to estimate a high dimensional VAR and then to compute the indicators of total and directional connectedness of industrial production suggested by Diebold and Yilmaz (2015a). More specifically, Diebold and Yilmaz (2015a) compute indicators of total and directional connectedness as well as the pairwise connectedness indicator for a relatively small VAR fitted to a proxy of real economic activity (see Diebold and Yilmaz, 2015a, Table 4). While Diebold and Yilmaz (2015a) focus on the industrial production of only six countries (G-7 except Canada), in our study, we use the industrial production of 28 countries (27 OECD countries and China). Consequently, our analysis considers the second-round effect manifesting through spillovers from a large set of countries.

The second contribution relative to Diebold and Yilmaz (2015a) is the analysis through fixed effect panel regression of the determinants of directional connectedness and pairwise connectedness indicators.

We show that global connectedness fluctuates over time. We also observe that rising periods of global connectedness are associated with periods of drastic economic world events.

Our first main econometric results show that an additional increase in the trade openness of a given country increases its exposure to the rest of the world. Moreover, a larger country's size amplifies the effect of trade openness on the exposure of a given country to the world economy.

Our second main econometric results show that an additional increase in trade intensity between two countries significantly increases the bilateral connectedness "from another country". We also show that more financial integration and differences in economic specialization dampen the effects of trade integration on the bilateral connectedness from another given country. However, periods of recession amplify the effects of trade integration on the connectedness from the origin to the destination country.

For robustness check, we also assess the role of economic agreements on pairwise connectedness. Our results are similar to those obtained with trade integration.

The results of this paper are consistent with economic theory. In fact, international trade interlinkages can create co-movement of output through both demand-side and the supply-side effects (Kose et al., 2012). It implies that big countries in terms of economic size will more likely affect other countries through trade.

Trade linkages can also create industrial specialization through comparative advantages. Specialization can affect business cycle interdependence either positively or negatively (see Imbs, 2004; Kose et al., 2012).

Financial interlinkages can also affect business cycle interdependencies either positively or negatively (see Imbs, 2004; Kose et al., 2012). If financial interlinkages generate a large demand-side effect, a positive effect is expected. If financial interlinkages induce greater specialization, the negative effect can be observed through the reallocation of capital compatible with the countries' comparative advantages (see Imbs, 2004; Kose et al., 2012).

Our results are also consistent with the predictions of two-country DSGE models.

Faia (2007) show that trade openness can increase the correlation of output between two countries, while financial openness can lower it. Two-country DSGE models with more than one sector, coupled with frictions in the capital market, can also help explain positive co-movements of output between two countries (see Ambler et al., 2002).

The results obtained in this paper complement the literature, especially in terms of directional macroeconomic interdependence and its determinants. Our results are important for policymakers and economic agents. Policymakers can adjust their trade policy and their economic activity in order to reduce their country's exposure to international shocks. Economic agents can also choose to invest in economic sectors not directly related to international trade if they want to reduce their exposure to international shocks. Our results are therefore important in policymakers' decisions to participate in trade agreements and economic zones.

CHAPTER III

INTERNATIONAL HOUSING MARKET CONNECTEDNESS AND MONETARY POLICY

ABSTRACT

This paper measures the housing market connectedness among major developed economies and the impact of monetary policy on this connectedness. We use quarterly national housing price index data, for 19 countries from Q1-1970 to Q1-2020 and apply the methodology developed by Diebold and Yilmaz (2009, 2012) to measure connectedness between the countries. Based on this methodology, we provide several measures of directional connectedness: influence of one country to another (or the rest of the countries), exposure of one country to another (or to the rest of the countries), and global connectedness. We estimate these connectedness links and provide a graphical network representation. We find that the USA is the most influential country and Ireland is the most exposed. We also measure these links over time by estimating the connectedness recursively. We find that the global housing market connectedness fluctuates, it tends to increase during global expansion periods and to decrease during global recession periods. Assessing the role of monetary policy on a country's housing market exposure, we find that a tightening monetary policy action reduces the exposure. At the global level, a tightening financial condition in the international banking system reduces global connectedness.

JEL classification : C23; C55; F02; F44.

3.1 Introduction

The interest rate is a common policy instrument used to stabilize price levels[1]. Loose monetary conditions lead to housing prices' bubbles and an increase in the interest rate is likely to reduce the price of real estate (see Jordà et al. (2015) and Goodhart and Hofmann (2008)). Real estate markets are also affected by foreign shocks. One example of this is the 2009 financial crisis, which began in the United States and had a ripple effect that spread across the world and affected the real estate and financial markets in many other countries. This suggests that the local/national dynamics of real estate markets can be influenced by foreign developments. This idea is supported by the work of Cesa-Bianchi (2013) who finds evidence of the spread of US housing demand shock to the advanced economies. Moreover, Bago et al. (2021a) and Bago et al. (2021b) find evidence of the spread of real estate bubbles between European Union countries.

In this paper, we examine the interplay between foreign influence, monetary policy, and the real estate market. We address two main questions. First, we ask how do national financial conditions (as measured by interest rates [2]) affect the connectedness of real estate markets across countries? Second, at the global level, we ask how does a tightening of financial conditions affect the total connectedness

[1] Through their effects on the cost of credit and the return on savings, and therefore on the decisions of households to save more or to make certain expenditures, changes in interest rates affect the prices of various goods in the economy, including real estate prices.

[2] It can be argued that the domestic interest rate can also be influenced by the global interest rate or foreign interest rates. To answer this question, we use panel regression. We tested our results by including an indicator of the world interest rate (London interbank offered rate - libor-). When we include this indicator in our model, we obtain virtually the same result as without it.

between countries' real estate markets?

In this work we measure the connectedness between the real estate markets of OECD countries and then we measure the effects of a tightening of financial conditions on this connectedness. We use the method developed by Diebold and Yilmaz (2014) to measure connectedness. In a set of countries, connectedness measures how innovations/shocks rising in a country affect other countries. Connectedness from country i to country j is measured by the share of country j forecast error variance associated with shocks that occur in the country i. Based on this methodology, we derive several measures of directional connectedness: influence of one country to another (or the rest of the countries)-or connectedness-"to others"-, exposure of one country to another (or to the rest of the countries)-connectedness "from others"-, and global connectedness.

We apply this methodology to 19 OECD countries using their real house price Index. Which is given by the ratio of the nominal house price index to the consumers' expenditure deflator for each country. Our sample data spans from Q1-1971 to Q1-2020. Using the full sample data, we estimate these connectedness links and provide a graphical network representation. We find that the USA is the most influential country and Ireland is the most exposed. We also find that geographically close countries and countries that share a common ethnicity are more connected. We then measure these links over time using a rolling windows estimation and find that the global housing market interdependence fluctuates over time. It tends to increase during global expansion and tends to decrease during global crisis periods.

Then, we study how national monetary policy and changes in the global financial condition affect connectedness. First, using a VAR model, we assess the effect of changes in the global financial conditions proxied by the TED spread [3] on the system-wide connectedness. We find that a tightening shock on the TED spread reduces the system-wide connectedness. Next, applying the local projection method developed by Jordà (2005) on panel regression, we evaluate the impact of monetary policy proxied by changes in national short-term interest rate, on the country's connectedness from others[4]. We find that the connectedness from others (or the country's exposure) declines by 0.83 percent after an increase of one percent in the national short-term interest rate.

Our work relates to two branches of literature. First, to the literature on measuring the effect of monetary policy on the real estate market. Many studies examine the effects of monetary policy on the housing price level (see Goodhart and Hofmann (2008) and Jordà et al. (2015)) and on the volatility of the housing market (see Engsted and Pedersen (2014)). Our contribution to this literature is to assess the effect of this policy on another aspect of the housing market: its exposure to foreign market developments. The propagation of the last financial crisis from the US to other countries' markets shows that the interplay between monetary policy and the dynamics of foreign real estate markets is of interest to policymakers who aim to stabilize the housing market.

We also contribute to the literature on the measurement of housing market con-

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[3] the TED spread is the difference between the LIBOR (London Interbank Offered Rate) and the US 3-month treasury bond. It is used to proxy the global financial conditions.

[4] Jordà et al. (2015) also use the variation of interest rate as a measure of monetary policy. Unlike us, they use a local projection with instrumental variables to estimate the effect of the monetary policy on their variables of interest, and housing price.

nectedness. Many authors have been interested in the connectedness between housing markets. between cities or regions of the same country (see Hwang and Suh (2021), Antonakakis et al. (2018), Antonakakis et al. (2021)), between cities of different countries (Alqaralleh et al. (2023)) and between countries (Lee and Lee (2018), Agyemang et al. (2021), Lee and Lee (2018)). While most of the papers in this literature focus their study at a country level or at a small number of countries, this paper analyzes the connectedness at the global level. We are similar to Agyemang et al. (2021) in that we examine housing market connectedness across a relatively large number of countries covering the 5 continents. But our work differs from Agyemang et al. (2021) by the methodology used to estimate the connectedness. We employ, the adaptive elastic net method to estimate the VAR parameters used to quantify the connectedness. This estimation method helps to perform shrinkage and selection useful for a relatively large number of variables/regressors as ours when we consider the lags in the VAR model. In addition, we bring evidence that the connectedness between countries' housing markets can be dampened by restrictive financial conditions.

The next section presents the methodology and the data used to measure connectedness. In section 3, we presents the estimated connectedness results. Section 4 analyses the impact of the changes in the global financial condition on system-wide connectedness. Section 5 examines the impact of monetary policy on national housing market exposure. And section 6 concludes.

3.2 Methodology and Data

Diebold and Yilmaz (2014) measure connectedness between economic entities by decomposing each series entity's forecast error variance. To obtain the Diebold and Yilmaz (2014) connectedness measures, first, we choose an econometric model to relate each country's information: the VAR model. Then, we estimate this VAR model using the adaptive elastic net estimation method. Finally, we compute connectedness measures from the estimated model using generalized forecast error variance. Throughout this section, we briefly present these steps and also present the data used to measure the connectedness between countries' housing markets.

3.2.1 VAR Model

The VAR model is an autoregressive model of k variables vector $Y = (y_1, y_2, \ldots, y_k)$, $(k \geq 2)$. It relates the vectors of present realizations (Y_t) to the vectors of past realizations $(Y_{t-1}, Y_{t-2}, Y_{t-3} \ldots)$ and allows us to study the dynamics that exist between the variables, as well as their past and their present realizations. A VAR(p) model is written as follows:

$$Y_t = \sum_{i=1}^{p} A_i Y_{t-i} + e_t, \tag{3.1}$$

$$or\ Y_t = A(L) Y_{t-1} + e_t, \tag{3.2}$$

where $A(L) = A_1 L + A_2 L^2 + \ldots + A_p L^p$ is a p order polynomial matrix and e_t is a white noise of dimension n, $e_t \sim N(0, \Sigma)$. L is a lag operator such that $L(Y_t) = Y_{t-1}$. The number of lags is fixed at $p = 4$.

It is assumed that this VAR(p) model is invertible and can be written as follows:

$$Y_t = B(L)(e_t), \text{with } B(L) = [I - A(L)L]^{-1}. \tag{3.3}$$

This form (equation 3.3) refers to a moving average representation of the innovations of the reduced form (3.2) of the system. This representation will later be used to compute the forecast error decomposition variance.

In our case, vector Y contains the time series of the housing market price index of all 19 countries. For a given market/country (i) this VAR relates the present realization of its price growth to its past realizations and to the past realizations of the 18 other markets' price growth up to 4 lags. Which leads to 76 regressors (parameters to be estimated) for each of the 19 markets. Due to the limited number of observations, the standard ordinary least squares method may not be suitable for estimating the parameters of this VAR model. Moreover, among the 76 regressors only some may be useful to fit the appropriate dynamics of the dependent variable. For these reasons, we use a penalized regression approach, in particular the adaptive elastic net method, which is well suited to estimate the desired VAR model parameters in our limited context and to select the more informative set of variables for each market.

3.2.2 Adaptive Elastic Net Estimation

Adaptive Elastic Net is an estimation method introduced by Zou and Zhang (2009b). It is a least square estimation method with penalization that combines two types of constraint : the Adaptive Lasso constraint and the Ridge constraint.

The combination of the two constraints helps to perform shrinkage and selection and to obtain estimators that enjoy oracle properties.

To show the adaptive elastic net estimator, let consider an equation of our VAR(p) and rewrite it as a linear model :$y_{it} = X_t A + u_t$, where $A = (A_{1,1}, A_{1,2}, \ldots, A_{k,p})'$and $X_t = (y_{1,t-1}, y_{1,t-2}, \ldots, y_{1,t-p}, y_{2,t-1}, y_{2,t-2}, \ldots, y_{2,t-p}, ..., y_{k,t-1}, y_{k,t-2}, \ldots, y_{k,t-p},)'$.

For this linear model, the adaptive elastic net estimation of A is:

$$A^{AEnet} = \arg\min_{A} \left\{ \|Y - XA\|_2^2 + \lambda \left[\alpha \sum_{j=1}^{p} \sum_{i=1}^{k} A_{i,j}^2 + (1-\alpha) \sum_{j=1}^{p} \sum_{i=1}^{k} \hat{\omega}_{i,j} |A_{i,j}| \right] \right\} \times \left(1 + \frac{\lambda\alpha}{NT} \right) \tag{3.4}$$

where α is the weight of the Ridge penalty component and $1-\alpha$ is that of the adaptive Lasso component. If $\alpha = 1$, we get a Ridge estimation, and if $\alpha = 0$, we obtain the adaptive Lasso estimation. $\hat{\omega}_i$ are adaptive data driven weights as introduced by Zou (2006) to avoid non-ignorable bias associated to standard Lasso regression. ($\hat{\omega}_{i,j} = |\hat{A}_{i,j}(Ridge)|^{-1}$) with $\hat{A}_{i,j}(Ridge)$ a ridge estimation of A. For our analysis, we use $\alpha = \frac{1}{2}$, and λ is chosen using 10 folds cross validation following Demirer et al. (2018) .

3.2.3 Connectedness Measures

The variance decomposition shows how much information each variable contributes to the variance of the other variables in the model. It determines to what extent the variance of the forecast error at the horizon h of each variable can be explained by innovations in the other variables.

The Cholesky's method is generally applied to obtain the forecast error variance decomposition. Although it is easy to implement, the results of The Cholesky's method are nevertheless sensitive to the order in which the variables are introduced in the vector (Diebold and Yilmaz, 2013).

To estimate a variance decomposition free of this constraint (influence of order), Pesaran and Shin (1998) proposed the generalized decomposition of the variance. Using the moving average representation in equation 3.3, the share of forecast error variance at horizon H, of the variable y_i, due to an innovation in the variable y_j, is given by the following formula:

$$D_{ij}^H = \frac{\sigma_{jj}^{-1} \sum_{l=0}^{H-1} (\iota_i' \Sigma B_l \iota_j)^2}{\sum_{l=0}^{H-1} (\iota_i' B_l \Sigma B_l' \iota_i)} \tag{3.5}$$

where σ_{jj} is the j^{rd} diagonal element of the matrix Σ and ι_i a vector of size k containing zeros except at line i, where there is 1.

Since the shares of variance do not add up to 100%, following Diebold and Yilmaz (2014), we normalize each entry of variance decomposition matrix using the sum of entries in their respective row, and obtain the following

$$d_{ij}^H = \frac{D_{ij}^H}{\sum_{i=1}^{k} D_{ij}^H}, \tag{3.6}$$

such that $\sum_{i=1}^{k} d_{ij}^H = 1$; and $\sum_{i,j=1}^{k} d_{ij}^H = k$.

Connectedness Measures

As in Diebold and Yilmaz (2014), the connectedness indices are derived from this variance decomposition. The connectedness from country j to country i is given by $C^H_{i\leftarrow j} = d^H_{ij}$ and measure the contribution in percent of country j to country i's forecast error variance at horizon H.

The total directional connectedness "from others", $C^H_{i\leftarrow\bullet} = \sum_{j=1;j\neq i}^{N} d^H_{ij}$, measures the share of forecast error variance of country i associated to all foreign shocks, It can be viewed as country i's total exposure to the rest of the network.

The total directional connectedness "to others", $C^H_{\bullet\leftarrow i} = \sum_{i=1;i\neq j}^{N} d^H_{ij}$ inversely measures the overall effect of a shock hitting an entity on other network entities by summing the effects on the forecast error of each.

The system-wide connectedness in the network: $C^H = \frac{1}{N}\sum_{i,j=1;i\neq j}^{N} d^H_{ij}$ measures the average exposure of entities in the network. It gives, on average, the share of the variance of the forecast errors in the network that are due to the connection between the entities.

We also produce times series of these connectedness measures. To do so, we use a rolling window of 60 quarters to estimate the model and a 4-quarter horizon to compute the forecast error variance decomposition. The obtained connectedness indicators are assigned to the quarter following the 60 quarters window. The window is then moved by one quarter to calculate the connectedness measure for the next quarter until the end of the work period.

3.2.4 Graphical display

To get a better view of the estimated connectedness, we use a network graphic representation. Following Demirer et al. (2018), we characterize the estimated network graphically using the following features: node size, node color, node location, and link arrow sizes (two per link, because the network is directional).

Each entity (country) is represented by a node whose size is a linear function of its total connectedness to others. The color of the node is a linear function of the total connectedness "from others ", from the smallest (beige) to the greatest (red). Figure 3.1 shows the range of colors in order..

We used the ForceAtlas2 algorithm of Jacomy et al. (2014), as implemented in Gephi[5] , to determine the location of the node. This algorithm treats each node as an electrically charged particle, such that they tend to repel each other. And it treats the connectedness links as attractive forces such that nodes with high connectedness tend to bring together proportionally to the importance of the estimated connectedness links. The algorithm finds a steady state in which repelling and attracting forces balance.

Each pair of nodes are linked by an Edge with two arrows. We make the thickness of this edge a linear function of the average pairwise directional connectedness. The size of the arrows indicates how important is the bilateral directional connectedness (the "from" one and the "to" one).

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[5] Gephi is an open-source software used in the paper for network visualization. This software is accessible through this website (https://gephi.github.io/).

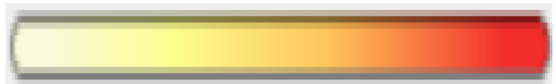

Figure 3.1: Network node colour spectrum

3.2.5 Housing Price Data

The housing prices are measured using the real house price index from the OECD database[6]. This database contains several indices related to national residential property for OECD members and non-member countries: rent price, nominal and real house price.

The real house price index is given by the ratio of the nominal house price index to the consumers' expenditure deflator for each country from the OECD national accounts database. Both indices are seasonally adjusted.

We use quarterly data spanning from Q1-1971 to Q1-2020. We use the year-over-year growth rate to control for stationarity and potential seasonality [7].

Table C.1 presents the descriptive statistic for the year-over-year growth rate of housing prices. New Zealand (NZL) shows the highest average (3.35 %) year-over-year growth rate and South Africa (ZAF) has the smallest growth rate (0.19 %). Spain is the country with the highest standard deviation (9.43%) of housing relative price growth rate and Germany is the country with the smallest variance in housing relative price growth (2.19 %).

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[6]This data can be retrieved at the OECD website

[7]We acknowledge that the use of year-over-year growth rates can lead to the potential introduction of MA(3) serial errors due to overlapping data. However, the use of 4 lags in the VAR model can help mitigate this issue.

3.3 Housing market Connectedness

3.3.1 Static connectedness

We estimate VAR using the adaptive elastic net. Then we compute the variance decomposition and corresponding connectedness measures at horizon $H = 4$ quarters, using the estimated VAR parameters. Figure 3.2 shows the graphical representation of the estimated connectedness links between the 19 countries in our sample over the period Q1-1971 to Q1-2020. We use the graphical feature explained in section 3.2.4 to get this network representation.

In this network, the most influential country or the country with highest connectedness to others ($C^H_{\bullet\leftarrow i}$) is the USA with 61.09 points of total influence. This reflects that shocks in US housing prices have the largest total contribution in the network countries' housing price forecast error variance. The most affected countries by the US shock are Ireland, Denmark, and New Zealand. The second and third most influential countries are France and Swiss with respectively 51.38 points and 41.06 points of the total impact. The Netherlands is the less influential with 3.86 points of impact.

The most exposed country or the country with highest connectedness from others (measured by $C^H_{i\leftarrow\bullet}$) is Ireland, of which 40.93 % of its forecast error variance is associated with foreign shocks. An important part of this exposure comes from the USA (14.82 points) and France (11.63 points). Germany is the least exposed country with only 2% of its forecast error variance associated with overseas housing price shocks. This low connectedness from others in the German housing market is also found by Lee and Lee (2018) and Agyemang et al. (2021). This result could

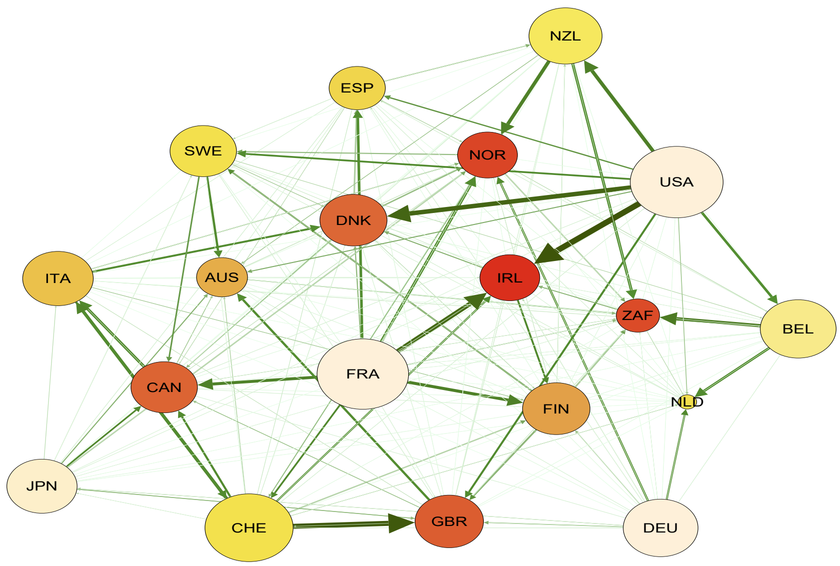


Figure 3.2: Housing Price Network

Note : This figure represents the estimated housing market connectedness based on full sample data (i.e. Q1-1971 to Q1-2020) for the 19 countries. Each country is represented by a nodes whose size represents its total connectedness “to others“ (its influence). The color of the node represents of the country’s total connectedness “from others“ (its exposure), from the smallest (beige) to the greatest (red). the importance of the bilateral connectedness connectedness between two countries are represented by the thickness of the edge and of the arrows linking their nodes. The direction of the connectedness link is showed by the arrow. For more details, see section 3.2.4.

be attributed to the high stability of the German housing market, such that it has not been affected by any global or local macroeconomic crisis during the two last decades, unlike its counterpart in the developed economy (see Agyemang et al. (2021) and Voigtländer (2014)).

The system-wide connectedness index for the full sample is 20.50 points. This means that on average 20.50% of the total forecast error variance for the 19 countries is due to the connection between them. The remaining 79.5% is associated with national housing markets shocks.

Housing connectedness, distance, and language In order to assess how the connectedness between housing markets are related to bilateral geographical, social or political characteristic of countries[8], we perform the following gravity regression:

$$C_{i \leftarrow j} = \beta_1 \text{Distance}_{ij} + \beta_2 \text{CommonBorder}_{ij} + \beta_3 \text{Colony}_{ij} + \beta_4 \text{CommonEthnicity}_{ij} + \alpha_i + \alpha_j + e_{ij} \tag{3.7}$$

Where $C_{i \leftarrow j}$ is the log of the full sample connectedness from "j" to "i". Distance_{ij} is the log of distance between countries "i" and "j". CommonBorder_{ij} and Colony_{ij} are dummy variables that take 1 when country "i" and country "j" respectively have a common border or have ever been in colonial relationship, and 0 otherwise. CommonEthnicity[9] is also a dummy variables that takes 1 if a language is spoken by at least 9% of the population in both countries and 0 otherwise. All these variables are from the GeoDist database of CEPII. We also add fixed effects origin country (α_j) and destination country (α_i).

[8] We have also tested the use of a same currency by origin and destination countries as an explanatory variable. It does not have any significant effect.

[9] We consider Ethnicity instead of the official language because European countries account for a large part of our sample and in Europe area, many countries do not have the same official language but have a significant part of their respective population that speak the same ethnicity or language. Which could lead to a close economic relationship between these countries.

The results are presented in the table 3.1. The column (1) presents the results obtained from OLS regression and the column (2) present the result with fixed effects origin and destination. We find that countries that are less distant (or geographically closed) and countries with a common ethnicity are more connected. Having a common border or ever being in colonial relationship have no significant effects on the connectedness of housing market.

This result can be explained by the fact that geographically closed countries and countries sharing the same language or the same ethnicity can experience more flows of people. Which ultimately can lead to greater economic and financial flows such as investment, trade in goods or services as documented by the literature on the determinants of trade.

3.3.2 Dynamic rolling windows estimations

Now, we study our network of housing markets dynamically. We use a 60-quarters rolling window to recursively estimate the connectedness indicators at successive points of time using the same estimation methodology described above. In this section, we analyze the evolution of the system-wide connectedness. We also analyze the total directional connectedness measures.

Figure 3.3 shows the rolling window estimation of the system-wide connectedness. We see that the connectedness among countries' housing markets fluctuates over time. It remarkably rose around the period of the last global financial crisis (and during the US real estate crisis).

Now, we look at this result in a trend-cycle setup. The trend analysis reveals two

Table 3.1: Static bilateral connectedness, distance, border, colonial relationship, and language

	Dependent variable:	
	Bilateral connectedness (log)	
	OLS	Fixed effects
	(1)	(2)
Distance	-0.18^{**}	-0.25^{*}
	(0.08)	(0.13)
Common border	-0.28	0.09
	(0.43)	(0.38)
Colony	0.25	0.29
	(0.39)	(0.40)
Common ethnicity	0.81^{***}	0.57^{*}
	(0.27)	(0.31)
Constant	0.12	
	(0.70)	
Origin and Destination FEs	No	Yes
Observations	342	342
R^2	0.04	0.36
Adjusted R^2	0.03	0.27

Note: Robust standard errors are in parentheses. *, **, and *** indicate coefficient significance at 10%, 5%, and 1%, respectively.

phases. A first weak downward trend from the beginning of our sample period to 2005 (which can be associated with the beginning of an acceleration in the USA home price). In the second phase from 2005 to the end of our sample period, we observe a steep upward trend. This finding is consistent with results of Hilbers (2020) showing that since 2006 the share of variations in the countries' residential prices explained by the common factor, measured by the principal component analysis, has augmented.

In the cycle view, we remark that the connectedness tends to increase during the period of expansion in the OECD area (e.g., the expansions preceding the 1990 recession, 1998 recession, or the 2009 global crisis), or at the end of the recession (e.g., the periods following the 1998 recession, the 2000-2003 recession, the global financial crisis, and the European debt crisis) and tends to decrease or slow down during recessions periods.

Figure C.1 shows the total directional connectedness "to others" in blue and "from others" in red of each of the 19 countries. When the blue bars dominate the red bars, the country is a net transmitter of shock. In the adverse case, it is a net receiver. The USA, Japan, and Germany are net transmitters of housing shocks almost during the sample period. Using the median as a comparative statistic, as shown by figure C.2, Germany, the USA, and Japan are the less exposed and the most influential countries. Spain, Great Britain, and South Africa are the most exposed countries and they are net receivers during almost all of the sample period.

In the following sections, we study how this connectedness is affected by monetary policy and global financial conditions.

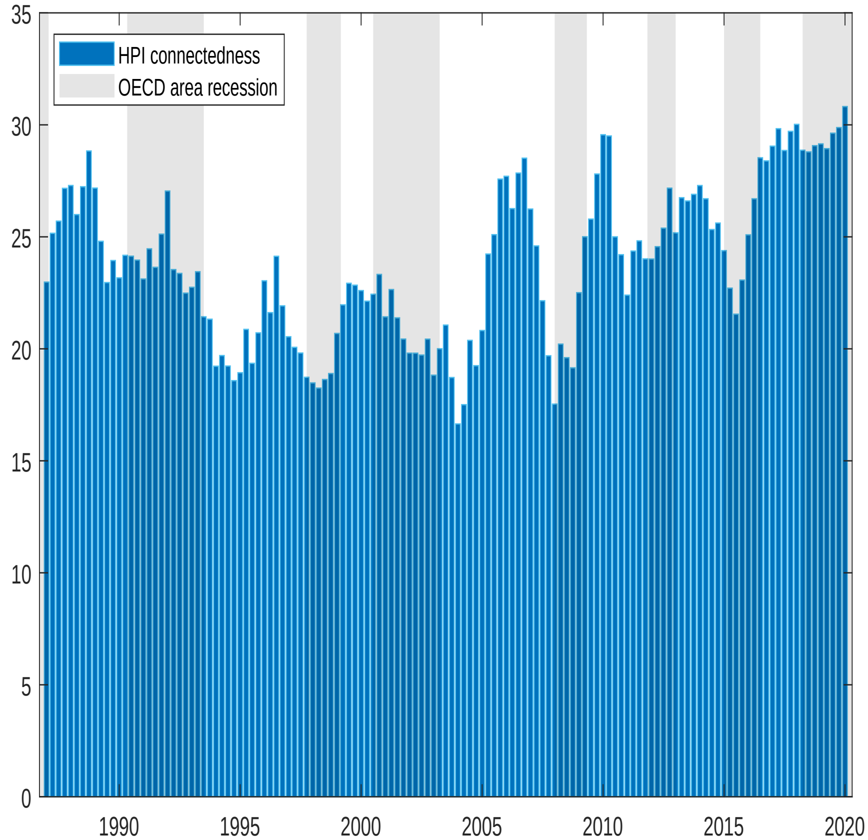


Figure 3.3: System-wide dynamic connectedness (Q1-1987 to Q1- 2020)

Note :We use a rolling window of 60 quarters. For instance, the first bar represents the value of the system-wide connectedness in the network between 1972-Q1 and 1986-Q4. The grey bars represent recession periods for the OECD area, according to turning points identified by OECD using their Composite Leading Indicators.

3.4 Global financial conditions and connectedness

In this section, we examine how global monetary and financial conditions affect system-wide connectedness. We use the TED spread, the difference between the LIBOR (London Interbank Offered Rate) and the US 3-month treasury bond as a measure of global financial and monetary conditions. The TED is a measure of credit risk in the global economy, as the US Treasury bills are seen as risk-free. It measures the risk premium that a bank is willing to receive for lending to another bank, instead of buying a risk-free bond. The higher the risk of default on that loan, the higher the yield the lender will demand. Or the lower the liquidity in the interbank market, the higher the required yield. Thus, the TED spread tends to rise during periods of lack of liquidity or during periods of high credit risk.

In addition to financial conditions, the literature identifies the household income, or the country's economic performance (captured by income, GDP per capita or GDP growth see Kishor and Marfatia (2017), Goodhart and Hofmann (2008)), and the inflation level (see Goodhart and Hofmann (2008), Apergis et al. (2003)) as key elements of housing market dynamic at the country level. Therefore, we consider their global equivalent, namely the global economic performance and the global inflation, in the model used to measure the influence of the global financial connection on the international connectedness of housing markets.

To estimate the dynamic response of the global HPI connectedness to innovation in the global financial condition, we use the following VAR model

$$Y_t = \sum_{i=1}^{p} A_i Y_{t-i} + e_t, \tag{3.8}$$

where the vector Y is defined by:

$Y =$ [GDP growth, Inflation, TED Spread, HPI connectedness]$'$.

GDP growth, Inflation are respectively the aggregate GDP growth and the aggregate inflation level for the OECD area. The number of lag p is 4. The parameters of this VAR are estimated using the OLS method.

We use the Cholesky decomposition to identify our desired shock. By making such a choice, we impose restrictions on the short-run relationships between the variables. These restrictions are related to the order in which the variables are ranged in Y. For example, by placing GDP growth first, we impose that within a quarter the economic growth does not respond to innovations in the inflation rate, in the TED spread, nor by innovations in the global connectedness, whereas a shock on the GDP growth can affect all the variables within a quarter (at its impact). Next, by placing the inflation rate in the second position, we assume that inflation can be affected by a GDP shock within a quarter but a shock on the TED spread, or on the HPI connectedness cannot affect the inflation rate at their impacts. the same logic is applied to the subsequent variables. So, by placing the TED at the third position after GDP growth and inflation, we aim to retrieve movements in the TED that are not driven by global inflation and global economic growth. Which can be more able to proxy financial condition shock in our system.

In fact, like other economic indicators related to the interest rate, the TED spread can fluctuate due to movements in the real economy or movements in inflation. For example, when the economy is overheating or under strong inflationary pressure, central banks tend to raise the policy rate, which can eventually lead to changes in the spread as well as many other interest rates. Therefore, some movements in the spread may simply be a response to global economic performance and global inflation. To identify pure movements or shocks in the financial condition, we place the Ted-spread in the third position to estimate the fluctuation in the financial condition that is independent of global economic performance and the level of global real inflation.

Figure 3.4 shows the response of all variables in the VAR to a TED shock. We will focus on the impulse responses of the HPI connectedness. The size of the shock is set to one standard deviation of the residuals. The shaded areas in the figure represent the confidence intervals of 90 % for the impulse responses, obtained using a bootstrap method with 1000 replications.

we find that a financial tightening shock reduces, at its impact the global level of Housing price connectedness by 0.25. The connectedness drops again during the second quarter and begins to increase in the following quarters. It reaches its pre-shock (or equilibrium) level in the fifth quarter and follows a positive hump shape for 10 quarters with a maximum connectedness level 0.2 above its initial level.

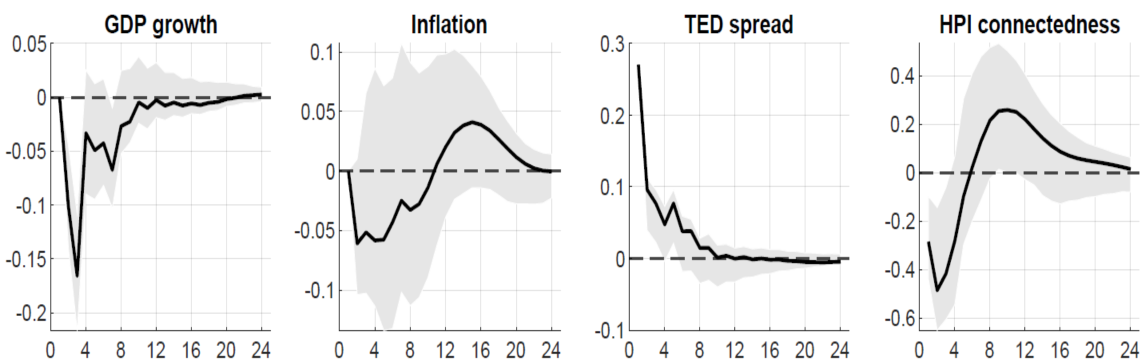


Figure 3.4: Impulse responses to TED spread shock

Note :This figure shows the impulse response of all the variables to the TED spread shock. The shaded areas represent the confidence intervals of 90 %, obtained using a bootstrap method with 1000 replications.

HPI connectedness impulse responses: an intuitive interpretation Connectedness increases when housing price developments in most countries are closely linked; to simplify, we can say that prices follow the same pattern: they rise or fall together. Connectedness decreases when price developments in most countries are less related; to simplify, we can say that there is no overall pattern, or that each country follows its own path.

The decline in connectedness in the first periods after a shock can be explained by the fact that countries react differently to a financial global shock. Indeed, a global shock may lead to different movements in housing market fundamentals such as interest rates or income, depending on the characteristics of the country (for e.g., its economic and financial development, its economic and financial openness, or its resilience to negative shocks). This may affect the evolution of housing prices differently between countries in the short run. As a result, connectedness decreases.

This finding complements the literature on the effect of the global liquidity shock on the housing market. In fact, some authors show that a tightening shock in the global financial condition (or the global liquidity) reduces significantly the housing price in the emerging economies but not the effect is not significant in the advanced economies (see Cesa-Bianchi et al. (2015), Chien and Liu (2023), and Banti and Phylaktis (2019)). Our focusing on the connectedness between the markets show that the connectedness between the markets decline. And this decline in connectedness is consistent with the divergence of reponse among countries to a global financial.

In other hand this literature supports the intuition behind the decline of the connectedness after a tightening financial conditions by providing evidence of divergence of response in housing market after the shock (see Cesa-Bianchi et al. (2015), Chien and Liu (2023), and Banti and Phylaktis (2019)) .

3.5 Connnectedness from others and monetary policy

In this section, we estimate the dynamic effect of monetary policy on the country's exposure to the foreign housing markets. Monetary policy is measured by the change in the short-term interest rate. Figure C.3 shows the short-term interest rate for each of the 19 countries. Since from 2015 the interest rate for most countries is close to zero and varies very little, we consider for this analysis the period 1990Q1-2014Q1. We can also notice that in 1999Q1, 7 countries (Belgium, Germany, Spain, Finland, France, Ireland, Italy and the Netherlands) started to have the same interest rate due to the creation of the Eurozone. We also take this fact into account in our analysis and study how the impact of monetary policy on the exposure of these countries differs between the two samples: before the Eurozone and since the Eurozone.

To assess the impact of the monetary policy on the connectedness from others we use the following panel regression model:

$$C_{i,t+h} = \alpha_i^h + \rho^h C_{i,t-1} + \beta^h \Delta r_{i,t-1} + \Gamma^h X_{i,t-1} + e_{i,t+h} \tag{3.9}$$

where $C_{i,t}$ is the country i's connectedness from others at time t, $\Delta r_{i,t} = r_{i,t} - r_{i,t-1}$ and $r_{i,t}$ is the short term interest rate. $X_{i,t}$ is the vector of the control variables including GDP growth rate, and inflation for the country i at time t. α_i is a country fixed-effect, it helps to control for any characteristic of the country that does not variate over time.

The response of connectedness to a change of interest rate is estimated using local projection and is given by: $\frac{\partial C_{i,t+h}}{\partial \Delta r_{i,t-1}} = \beta^h$ for $h = 1, ..., H$. To retrieve this impulse response we estimate the model 3.9 for $h = 1, ..., H$.

Figure 3.5 presents the dynamic response of the country's housing market exposure to a variation in interest rate. The points estimated are represented by the solid line and the grey shaded area represents the confidence interval at 90 %, obtained by the robust standard error clustered at the country level.

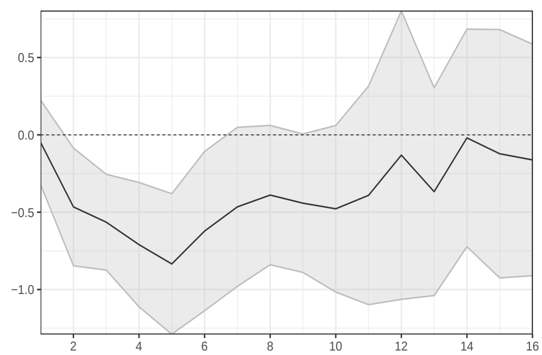


Figure 3.5: Housing market exposure impulse responses to interest rate increase

Note :This figure shows the impulse response of the connectedness from others or (housing market exposure) to positive changes in interest rates. The shaded areas represent the confidence intervals of 90 %,obtained by the robust standard error clustered at the country level.

We find that the exposure of the national housing market declines in response to an increase in interest rate. This decline is significantly different from zero from the second quarter to the sixth quarter after the shock. The decrease in connectedness peaks at 0.83 percent in the fifth quarter after the interest rate change.

Connectedness from others can be viewed as a measure of the sensitivity of the local housing market price to innovations the foreign market prices. Connectedness "from others" increases (decreases) when housing price developments abroad (or in another specific country) are more (less) likely to influence local prices. In others words, when households and business decisions related to the housing market are influenced by foreign conjectures. Let's consider a positive signal from abroad that tends to increase the incentive of economic agents to invest in the housing market. In this context, an increase in interest rate will dampen this incentive by making credit more costly. In fact, those that need credit to fulfill the desire risen by the stimulus from abroad are now retained. As consequence, the influence of this positive signal on the local housing market will be reduced, and the connectedness from others declines.

Discussion: In 1999, seven countries in our study sample joined the European Monetary Union. In doing so, they lost the independence of their monetary policy. For these countries, interest rate changes are no longer local policy decisions, but choices made by a group of countries. This fact could bias the results obtained above concerning the effect of monetary policy on the level of exposure. In order to obtain results that are free of this possible bias, we estimate the effect of the change in the interest rate for all 19 countries before they join the European Union. The results of this exercise are presented in Figure 3.6. We find that an increase in the interest rate leads to a decrease in connectedness from other countries.

In order to assess the impact of a common monetary policy on the connectedness from others, we perform the same exercise for the seven countries of the Monetary Union, considering two subperiods: before and after the entry into force of the currency area. Figure 3.7 presents the impulse responses of the connectedness from others to interest rate changes for the two periods. We find that the effect of interest rate changes on connectedness is larger before entry into the

Union. This seems to suggest that the common monetary policy has less effect on connectedness.

Note that these countries are geographically close. However, the results of Table 3.1 indicate that countries in close proximity share more connectedness. An important part of the exposure of the countries in this group would then come from the other members of the union.

The significant and negative effect of interest rate changes before the union came into effect could be explained by the fact that a higher interest rate created a more restrictive financial environment compared to all the other 18 countries in the network, especially those neighbors with which connectivity is theoretically high due to geographic proximity. This contributes to a different evolution of real estate market prices and a lower connectedness from others. On the other hand, after the entry into force of the union, the interest rate variations are the same in the countries of the union. This does not favor the decrease in connectedness between their real estate markets but encourages it. In addition, the number of countries in relation to which financial conditions change as a result of an interest rate change is fewer and more geographically distant. This makes rate hikes less impactful on total connectedness from others.

However, this result should be taken with caution because factors other than the common policy not considered in this study may have altered the effect of interest rate changes on connectivity from others.

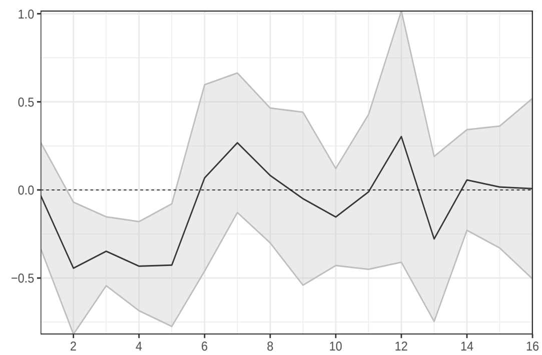


Figure 3.6: Housing market exposure impulse responses to interest rate increase before Eurozone

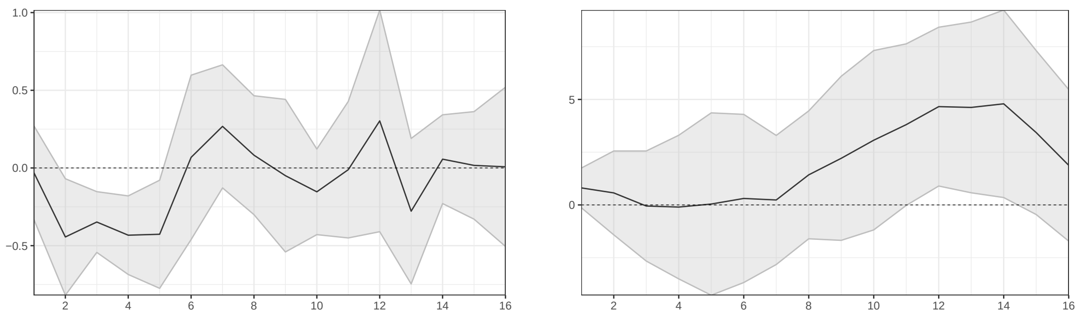
Note :This figure shows the impulse response of the connectedness from others or (housing market exposure) to positive changes in interest rates. The shaded areas represent the confidence intervals of 90 %,obtained by the robust standard error clustered at the country level.

3.6 Conclusion

This paper analyses the connectedness between the housing markets of different countries and examines the extent to which monetary policy and of global financial conditions play a role in this linkage.

We measure the connectedness between the housing markets of 19 OECD countries using the method of Diebold and Yilmaz (2014). We find that the USA is the most influential country and Ireland is the most exposed. Recursive estimation of connectedness shows that the global housing market connectedness fluctuates, it tends to increase during global expansion periods and to decrease during global recession periods.

Assessing the role of monetary policy on a country's housing market exposure, we find that a tightening monetary policy action reduces the exposure. Similarly, at the global level, a tightening financial condition in the international banking sys-



(a) before Eurozone

(b) After Eurozone

Figure 3.7: Housing market exposure impulse responses to interest rate increase for eurozone countries

Note :This figure shows the impulse response of the connectedness from others or (housing market exposure) to positive changes in interest rates, for the eurozone countries. The shaded areas represent the confidence intervals of 90 %,obtained by the robust standard error clustered at the country level.

tem reduces global connectedness. These results help to point out the usefulness of the monetary policy tool to help policymakers reduce the exposure of housing markets to foreign shock.

CONCLUSION

Cette thèse propose trois chapitres explorant deux thèmes cruciaux pour l'économie contemporaine : l'incertitude et la connectivité.

Le premier chapitre de cette thèse construit une mesure de l'incertitude macroéconomique spécifique au Canada, en s'appuyant sur la méthode développée par Jurado et al. (2015). Cette mesure révèle une augmentation considérable, sans précèdent, de l'incertitude au Canada au début de la pandémie de COVID-19. Ces résultats sont en ligne avec ceux obtenus avec les données d'autres pays, mettant en évidence que la pandémie a engendré in choc d'incertitude majeur à l'échelle mondiale.

En examinant les effets d'un tel choc d'incertitude sur l'économie canadienne, nous trouvons qu'il conduit à des recessions sévères. De plus, nous montrons que les conséquences de ce choc varient en fonction de l'hypothèse selon laquelle il affecte d'abord les Etats-Unis ou le Canada.

Il est également important de noter que notre mesure de l'incertitude, ainsi que les mesures basées sur d'autres méthodes ou des données provenant d'autres pays, montrent une augmentation de l'incertitude pendant les périodes de crises économiques. Cela souligne l'importance pour les décideurs politiques de surveiller de près l'évolution de l'incertitude dans la gestion de leur économie. De plus, cela suscite la question de savoir quelle place l'incertitude devrait avoir dans la formulation des politiques économiques ? Devrait-elle être intégrée dans la fonction de réaction des politiques monétaires? Ces questions restent ouvertes et devront être abordées dans le cadre de recherches futures.

Le deuxième article analyse la connectivité entre les économies en termes de production. Pour rappel, La connectivité vise à mesurer le niveau d'influence relative entre deux ou plusieurs économie. Cet article contribue à la littérature de ce thème a deux niveaux.

Dans un premier temps, il permet d'obtenir une mesure plus fine de la connectivité en appliquant les méthodes adaptées aux données de grandes dimensions à un échantillon de 28 pays, incluant à la fois des économies avancées et émergentes. Les résultats de cette analyse révèlent que la connectivité entre ces économies varie au fil du temps, connaissant des périodes d'augmentation, notamment pendant les évènements économiques majeurs à l'échelle internationale.

La deuxième contribution consiste à utiliser les méthodes solides de régression de panels pour étudier les déterminants de cette connectivite. Nous trouvons que l'ouverture commerciale d'un pays le rend plus exposé au reste du monde, tandis que la taille économique amplifie cet effet. De plus, une intégration commerciale plus intense entre deux pays augmente leur connectivite bilatérale. Ce lien entre la connectivité et le commerce bilatérale est atténué par des facteurs tels que l'intégration financière et la dissimilarité en termes de spécialisation économique.

Ces résultats ont des implications substantielles pour les décideurs politiques et les acteurs économiques, les aidant à gérer les risques liés à la connectivité internationale.

Le troisième chapitre analyse la connectivité entre les marches immobilières en relation avec les conditions financières et la politique monétaire.

Dans un premier temps, il mesure la connectivité entre les marchés immobiliers de 19 pays de l'OCDE. Nous avons constaté que la connectivité fluctue au fil du temps, augmentant lors des phases d'expansion économique mondiale et diminuant en période de récession. Puis, nous avons montré que la politique monétaire peut jouer un rôle essentiel pour atténuer les risques liés à cette connectivite. Lorsque'elles se resserrent, la politique monétaire nationale ou les conditions financières mondiales réduisent l'exposition des marches immobiliers nationaux aux chocs étrangers.

Cet article met aide à comprendre l'utilité de la politique monétaire et des conditions financières pour la stabilité des marches immobiliers. Il offre des outils pour les décideurs politiques cherchant à protéger leurs économies des secousses étrangères, soulignant l'impact positif de la politique monétaire sur la réduction de l'exposition aux chocs.

À ce stade, il est important de souligner une critique qui peut être faite à la mesure de la connectivité utilisée dans cette thèse. Empiriquement, la connectivité provenant de l'économie "i" vers l'économie "j" se définit par la part des erreurs de prévision de la variable de "j" qui est attribuable aux chocs frappants "i". En pratique, cette mesure présente l'inconvénient que le choc frappant l'économie "i" auquel on souhaite se référer n'est pas strictement identifié au sens structurel. En effet, il peut être difficile de distinguer ce choc d'autres chocs ayant également affecté l'économie "i" et se reflétant dans la variable d'intérêt. Pour limiter ce risque, une possibilité serait d'inclure dans le modèle plusieurs variables susceptibles d'affecter la variable d'intérêt, ou d'identifier les chocs en amont avant de mesurer la connectivité. Ces approches pourront être explorées dans les recherches futures.

En somme, ces articles par leurs contributions aident à mieux comprendre deux phénomènes qui caractérisent l'économie contemporaine: l'incertitude et la connectivité. Ils apportent potentiellement un éclairage utile à la formation de politique économique sur ces thèmes. Toutefois davantage de recherche s'avère nécessaire pour dégager plus clairement des prescriptions éventuelles

APPENDIX A

APPENDIX OF CHAPTER 1

A.1 Mean-Shift Adjustment for COVID-19 Period

As discussed in section 1.2.1, the COVID-19 shock to macroeconomic variables is so big that it potentially shifts economy to another equilibrium. We follow the procedure proposed by Ludvigson et al. (2020) and apply the mean-shift adjustment to uncertainty measurement from the second quarter of 2020 (and April 2020 for the monthly series).

Assume that the shock happens at the period $t = \tau$. Let F_t be a collection of R latent factors. Without loss of generality, consider only level factors from (1.3), the same procedure can be done with the factors from squared data in (1.4). Let $\mathbf{\Lambda}$ be the corresponding $N \times R$ matrix of factor loadings. Denote y_i, $j = 1, \ldots N$, a macroeconomic series used to form factors. The method is detailed in following steps.

1. Compute the mean and standard deviation of each series y_j with data up to $t = \tau - 1$: μ_j and σ_j.

2. $\forall t < \tau$, generate factors F_t and factor loadings $\hat{\mathbf{\Lambda}}$ using $Z_j = (y_j - \mu_j)/\sigma_j$.

Denote these matrices $\hat{\mathbf{F}}^{\tau-1}$, and $\hat{\mathbf{\Lambda}}_{\tau-1}$ such that

$$\hat{\mathbf{F}}^{\tau-1} = \mathbf{Z}\hat{\mathbf{\Lambda}}_{\tau-1}/N$$

where $\mathbf{Z} = [Z_1, \ldots, Z_j, \ldots Z_N]$ is a $T_{\tau-1} \times N$ matrix of data.

3. Denote $y_{j,\tau}$ a value of macro series y_j at time τ. Calculate conditional forecasts of each macro series $y_{j,\tau}$ on the basis of $\tau - 1$ data in $\hat{\mathbf{F}}^{\tau-1}$, and define the "mean shift" at τ as the following forecast error

$$\text{ms}_{\;j,\tau} = y_{j,\tau} - \hat{y}_{j,\tau|\tau-1}$$

where $\hat{y}_{j,\tau|\tau-1}$ is the forecast of $y_{j,\tau}$ obtained from (1.5) on the basis of data available at $\tau - 1$, including $\hat{\mathbf{F}}^{\tau-1}$.

4. Generate estimates of factors for τ, denoted by an $R \times 1$ vector $\hat{F}_\tau$, from

$$\hat{F}_\tau = \hat{\Lambda}'_{\tau-1} Z_\tau / N$$

where j^{th} row of Z_τ is

$$Z_{j,\tau} = \frac{y_{j,\tau} - \text{ms}_{j,\tau} - \mu_j}{\sigma_j}$$

Add the τ value of factors to form $\hat{\mathbf{F}}^{\tau} = \left[\hat{\mathbf{F}}^{\tau-1} \;\; \hat{F}'_\tau\right]$

5. Move forward from τ to $\tau + 1$. Calculate the corresponding mean shift as

$$\text{ms}_{\;j,\tau+1} = y_{j,\tau+1} - \hat{y}_{j,\tau+1|\tau}$$

where $\hat{y}_{j,\tau|\tau+1}$ is the conditional forecast using $\hat{\mathbf{F}}^{\tau}$.

6. Add the τ observations to $\mathbf{Z}$ and recompute the loadings matrix $\hat{\mathbf{\Lambda}}_{\tau}$. Generate the matrix of factors $\hat{\mathbf{F}}^{\tau}$ as in step 4.

7. Repeat steps 4-6 until the end of sample (or the end of COVID-19 adjustment period) to get the updated factors $\hat{\mathbf{F}}_t$, $t = 1, \ldots, \tau, \ldots T$.

8. Use updated factors to generate new forecast errors. Demean and standardize each time series $y_{j,t}$ as follows

$$
\begin{aligned}
Z_{j,t} &= \frac{y_{j,t} - \mu_j}{\sigma_j} && \text{for } t < \tau \\
Z_{j,\tau} &= \frac{y_{j,\tau} - \mu_j}{\sigma_j} && \text{for } t = \tau \\
Z_{j,t} &= \frac{y_{j,t} - \ \mathrm{ms}\ _{j,t} - \mu_j}{\sigma_j} && \text{for } \tau < t \leq T
\end{aligned}
$$

Hence, these adjustments assume that the COVID-19 shock was not predictable at time τ, but not thereafter when we take into account a regime shift in the mean of the series. Then, Use the predictive model (1.5) to obtain forecast errors (residuals) $\hat{e}_{j,t}$.

9. Given the updated forecast errors, generate uncertainty measures as described in Section 1.2.

A.2 Data

Table A.1: Data description

Series	Description	Source	Vector	Transf.
US Macro Uncertainty	Ludvigson's Website			level
GDP	Real Gross domestic product, chained (2012) $	Statcan	v62305752	log-diff.
Investment	Real Gross fixed capital formation, chained (2012) $	Statcan	v62305732	log-diff.
Inflation	Implicit price index : Gross domestic product, 2012 = 100	Statcan	v62307282	log-diff.
10-year Govt. bonds	Governmental bonds (average rate) (10+ years)	Statcan	v122487	level
3-months T. bills	Treasury bills (3 months)	Statcan	v122541	level
Term Spread	Government Bonds (10+ years) - Treasury Bond (3 months)	v122487-v122541		level
Prices	Implicit price index : Gross domestic product, 2012 = 100	Statcan	v62307282	level
Consumption	Real Final consumption expenditure, chained (2012) $	Statcan	v62305723	log-diff.
Durable Consumption	Real Final consumption expenditure, Durable goods, chained (2012) $	statcan	v62305726	log-diff.
Employment	Employment total	Statcan	v24793	log-diff.
Unemployment rate	Unemployment rate	Statcan	v2062815	log-diff.

A.3 VAR Analysis with pre-COVID Data

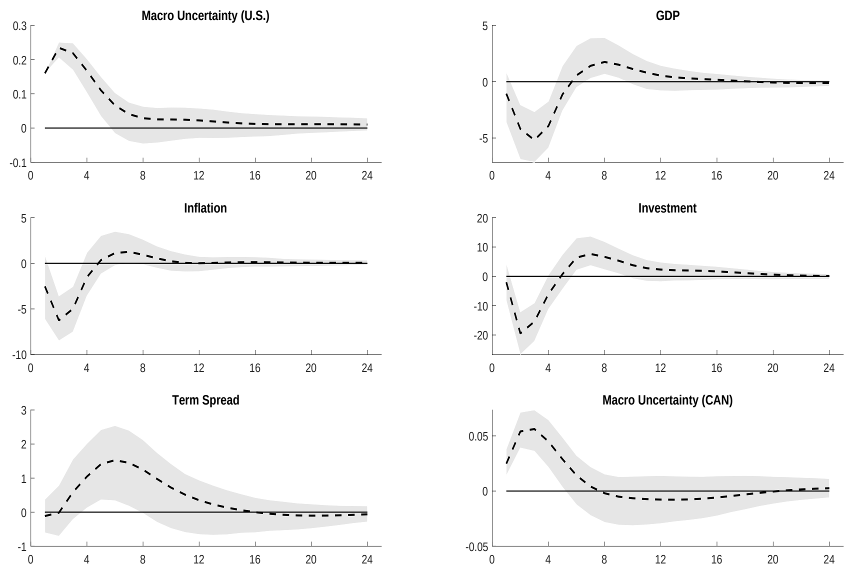


Figure A.1: Impacts of a Shock to US Uncertainty: Before COVID-19

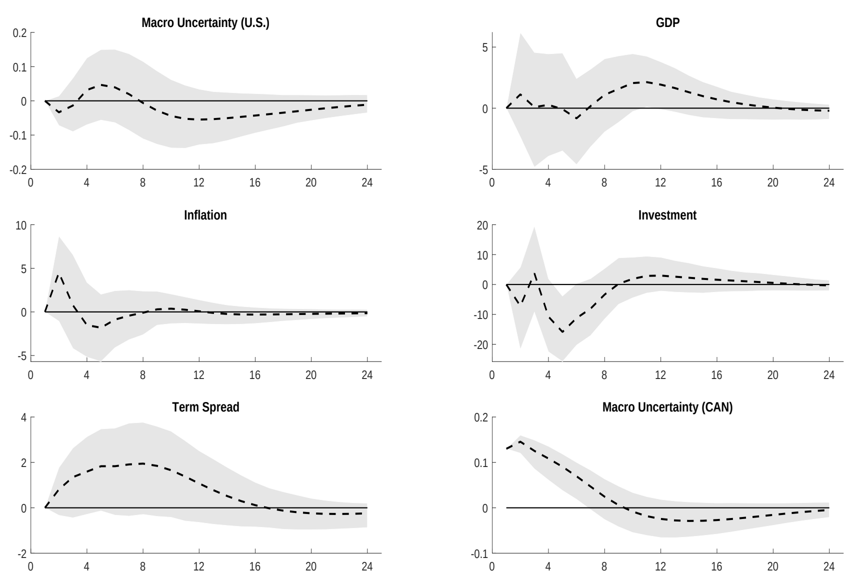


Figure A.2: Impacts of a Shock to Canadian Uncertainty: Before COVID-19

Table A.2: Variance Decomposition : Before COVID-19

Variables	Horizon (quarters)				
	$h = 1$	$h = 4$	$h = 8$	$h = 16$	$h = 24$
	Panel A : Shocks to US Uncertainty				
US Uncert.	100.00	89.99	73.21	62.23	61.22
GDP	0.52	17.21	17.58	17.83	17.80
Inflation	2.07	17.03	17.55	17.48	17.46
Investment	0.20	20.62	22.36	23.06	23.11
Term Spread	0.10	2.70	10.69	11.84	11.74
CAN Uncert.	13.73	35.50	25.44	18.05	17.67
	Panel A : Shocks to CAN Uncertainty				
US Uncert.	0.00	0.30	0.60	1.90	2.27
GDP	0.00	0.09	0.19	1.32	1.35
Inflation	0.00	1.21	1.40	1.41	1.43
Investment	0.00	1.27	3.96	3.98	3.99
Term Spread	0.00	2.09	4.85	6.83	6.83
CAN Uncert.	83.70	59.53	47.20	33.89	33.80

Notes: Variance decomposition (in %) caused by shocks to US and Canadian macroeconomic uncertainty.

A.4 Robustness Analysis

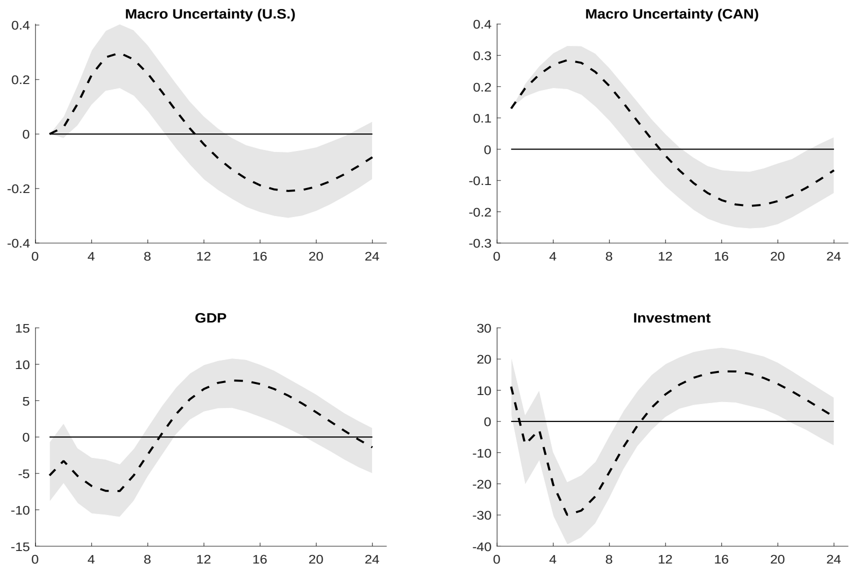


Figure A.3: Impacts of a Canadian Uncertainty Shock: Alternative Ordering

Notes: IRFs from a VAR where Canadian uncertainty is ordered second.

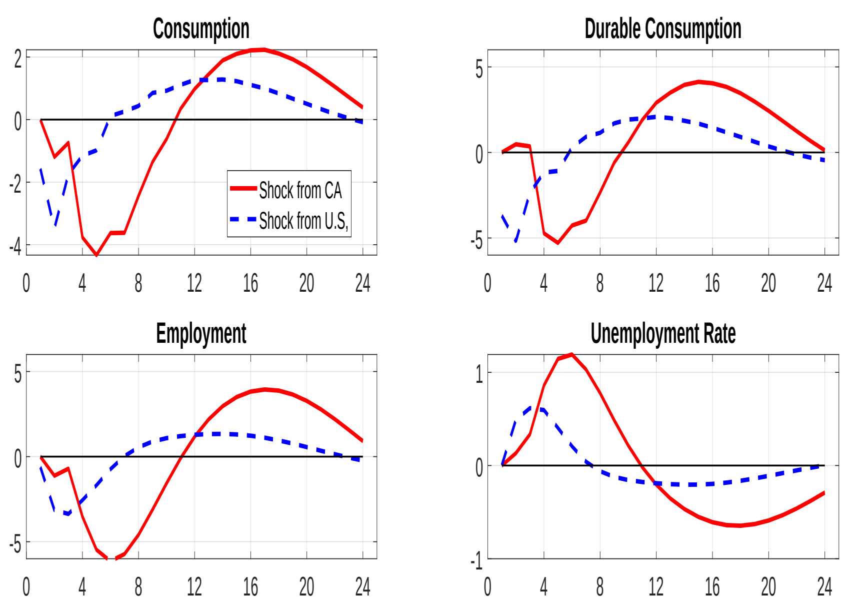


Figure A.4: Impacts of Uncertainty Shocks on Consumption and Labor

Notes: IRFs' point estimates for consumption and labour market variables.

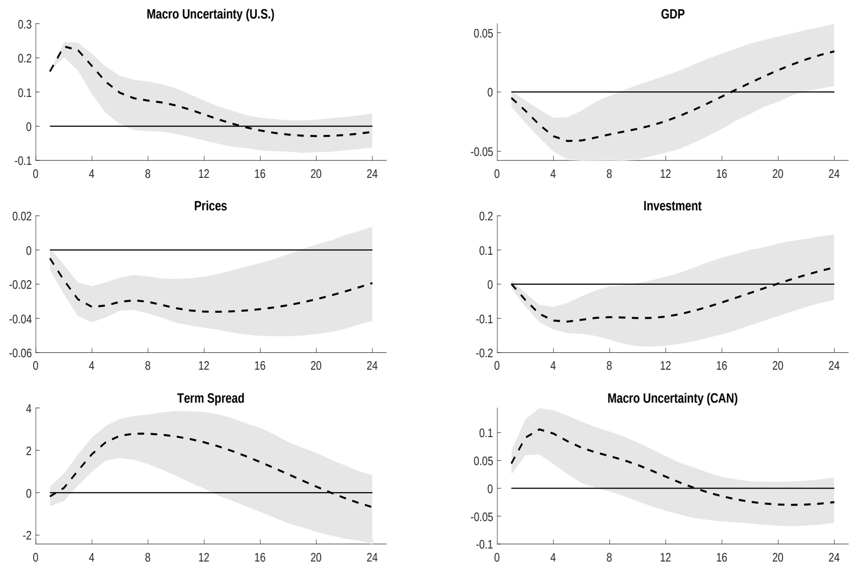


Figure A.5: Impacts of a Shock to US Uncertainty: VAR in Levels

Notes: IRFs following a US uncertainty shock: VAR containing log-levels instead of growth rates, with a linear trend included.

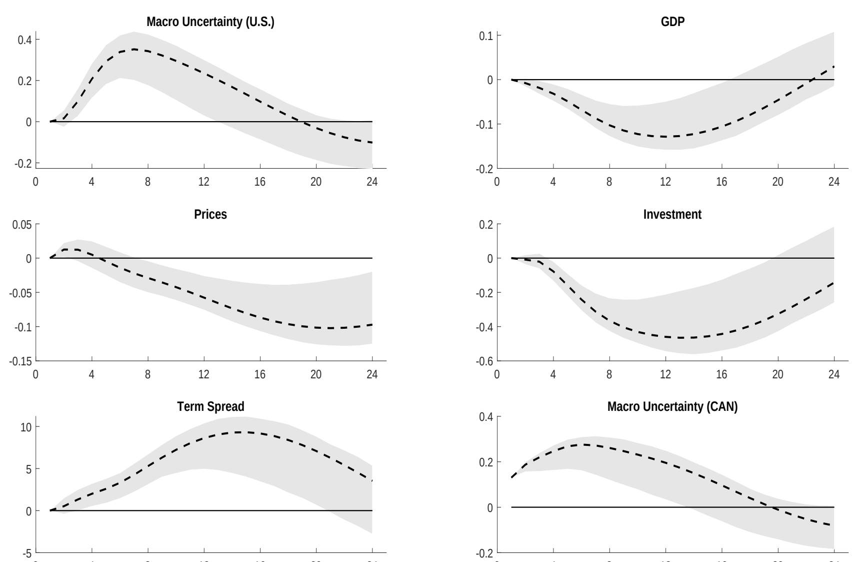


Figure A.6: Impacts of a Shock to Canadian Uncertainty: VAR in Levels

Notes: IRFs following a Canadian uncertainty shock: VAR containing log-levels instead of growth rates, with a linear trend included.

APPENDIX B

APPENDIX OF CHAPTER 2

B.1 Additional results

Table B.1: Full sample Connectedness table

	CAN	USA	MEX	GBR	E.U.	TUR	ISR	CHN	KOR	JPN	FROM
CAN	33.45	10.10	0.08	5.10	15.08	0.05	0.43	0.80	0.15	0.05	31.84
USA	6.17	35.53	0.96	1.38	10.60	0.22	0.67	0.38	1.15	0.30	21.82
MEX	0.01	0.96	35.52	0.89	2.62	0.45	0.57	0.91	0.50	0.16	7.09
GBR	1.19	0.48	0.57	35.53	22.13	0.18	0.19	0.18	0.66	1.00	28.87
E.U.	25.12	27.98	7.72	95.14	-	6.04	5.95	9.89	27.71	18.99	-
TUR	0.27	2.23	0.49	0.29	6.24	32.52	0.80	0.18	0.71	1.34	12.55
ISR	0.54	1.04	0.87	2.02	6.42	0.88	32.78	0.49	0.80	0.07	13.14
CHN	0.70	0.35	0.88	0.14	2.98	0.13	0.01	35.45	2.12	0.08	7.38
KOR	0.02	1.10	0.55	0.59	4.28	0.62	0.38	4.45	34.17	0.37	12.37
JPN	0.23	2.00	0.68	2.25	12.40	2.26	0.36	2.59	11.77	24.14	34.54
TO	35.34	47.14	13.12	107.80	-	10.82	9.37	19.86	45.58	22.35	Index
NET	3.49	25.32	6.04	78.93	-	-1.72	-3.77	12.48	33.21	-12.18	33.77

Note: Following Caloia et al. (2019), we normalized this matrix of variance decomposition by France's total forecast error variance, which is the highest forecast error variance in the system based on full sample data. As a result, each entry is expressed in a percentage of France's total forecast error variance. Each cell in the upper left 10×10 matrix gives the relative contribution of each columnar country to the variance of the row country's forecast error (in terms of France's total variance). The "FROM" column reports the share of the forecast error variance for the country in the row, attributable to other countries. It represents the exposure of the country to the world. The "TO" line reports the total contributions of the country in the column to the forecast error variance of all other countries and represents the influence of the country on the world. The "NET" reports each country's difference between its influence and its exposure. The total connectivity index in the lower right cell is the average of the items in the "TO" row (which is also the average of the "FROM" column), multiplied by 100. Let us take Canada (CAN) as an example. Its exposure is 31.84 %, its influence is 35.34 %, and the net influence is 3.49 %. The contribution of the United States to the forecast error variance of Canada's industrial production is 10.10 %, while the contribution of Canada to that of the forecast error variance of the United States is 6.17 %.

Table B.2: Full Directional Connectedness for European Union Countries

Country	TO	FROM	NET
IRL	4.33	8.65	-4.32
FRA	85.53	70.65	14.88
ESP	107.79	47.85	59.95
PRT	29.26	24.44	4.82
BEL	22.82	43.38	-20.56
ITA	54.16	75.23	-21.07
NLD	20.55	25.19	-4.64
LUX	17.24	42.86	-25.62
DEU	49.82	59.12	-9.30
DNK	6.37	28.32	-21.96
NOR	8.49	7.27	1.22
SWE	26.95	61.84	-34.88
POL	44.52	37.05	7.47
CZE	40.32	44.78	-4.46
FIN	25.71	57.91	-32.20
AUT	36.31	46.90	-10.59
SVK	10.31	30.36	-20.05
HUN	28.79	50.68	-21.89
GRC	14.92	13.50	1.42

See Table B.1 for definition of the “To” and the “From” statistics

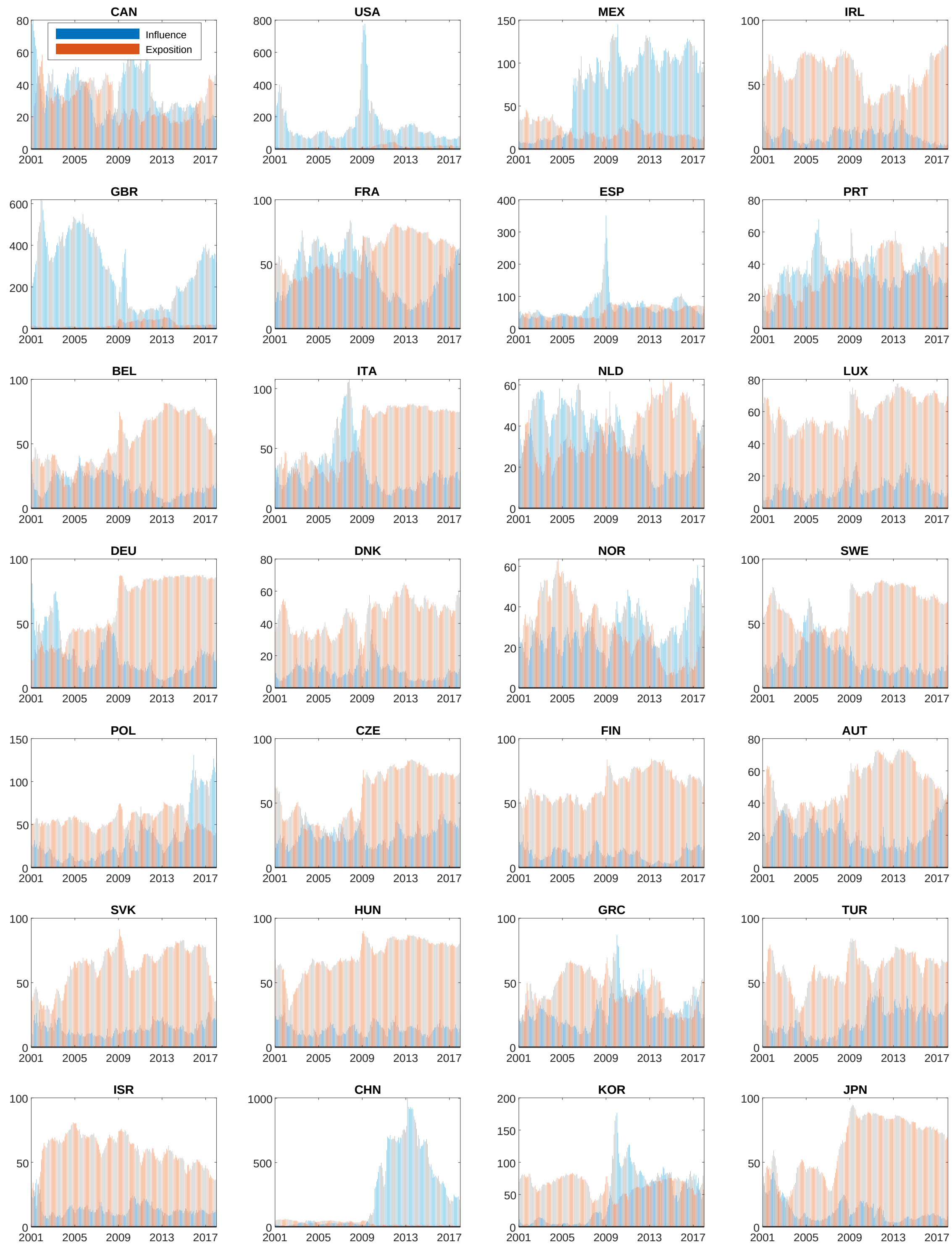


Figure B.1: Total Dynamic Directional Connectedness

Note: This figure shows the total directional connectedness. For each country, the total influence, or "to-others" connectedness, is represented by the blue bars, and the total exposure, or "from-others" connectedness, is represented by the red bars, such that when the blue bars dominate the red bars, the country is a net shock transmitter; otherwise, the country is a net receiver.

B.2 Unit roots test in our panels

We performed the Harris and Tzavalis (1999) and the Im et al. (2003) unit root tests in our panels. These two tests are suitable for panels with a relative small-time dimension Harris and Tzavalis (1999); Im et al. (2003). The Harris and Tzavalis (1999) test is based on the assumption that all panels share the same autoregressive dynamics. Im et al. (2003) allows for autoregressive parameters to differ across groups.

Harris and Tzavalis (1999) considered the two following models:

$$y_{it} = \alpha_i + \rho y_{it-1} + \nu_{it}, \tag{B.1}$$

with heterogeneous fixed effects, and

$$y_{it} = \alpha_i + \beta_i t + \rho y_{it-1} + \nu_{it}, \tag{B.2}$$

with both heterogeneous fixed effects and individual trends. $i = 1, 2, ..., N$; and $t = 1, 2, ..., T$. The null hypothesis of the unit root in Harris and Tzavalis (1999) and the alternative are:

$$\begin{aligned} &H_0 : \rho = 1, \\ &H_1 : |\rho| < 1 \end{aligned} \tag{B.3}$$

Im et al. (2003) consider the following models:

$$\Delta y_{it} = \alpha_i + \rho_i y_{i,t-1} + \sum_{j=1}^{p_i} \gamma_{ij} \Delta y_{i,t-j} + \epsilon_{it}, \tag{B.4}$$

with heterogeneous fixed effects, and

$$\Delta y_{it} = \alpha_i + \beta_i t + \rho_i y_{i,t-1} + \sum_{j=1}^{p_i} \gamma_{ij} \Delta y_{i,t-j} + \epsilon_{it}, \tag{B.5}$$

with both heterogeneous fixed effects and individual trends. $i = 1, 2, ..., N$, and $t = 1, 2, ..., T$. The null hypothesis of the unit root Im et al. (2003) and the alternative are:

$$\begin{aligned} &H_0 : \rho_i = 0 \text{ for all } i, \\ &H_1 : \rho_i < 0 \text{ for } i = 1, 2, ..., N_1; \ \rho_i = 0 \text{ for } i = N_1 + 1, N_1 + 2, ..., N \end{aligned} \tag{B.6}$$

We performed these two tests with heterogeneous fixed effects (α_i) (equations B.1 and B.4) and then with both heterogeneous fixed effects and individual trends (both α_i and $\beta_i t$) (equations B.2 and B.5). Table B.3 presents the results obtained when only heterogeneous fixed effects are included for both tests (equations B.1 and B.4); Table ?? shows the results obtained when both heterogeneous fixed effects and individual trends are taken into account (equations B.2 and B.5).

Because the Harris and Tzavalis (1999) test is a special case of that of Im et al. (2003), we used results from the Im et al. (2003) test in this paper.

As we can see in the two first columns of Table B.3, the Im et al. (2003) test results show that we cannot reject the null hypothesis of the unit roots of all variables in the table at the 5 % significant level, except for that of financial openness (TPI fin. openness). The two first columns of Table ?? show that when heterogenous fixed effects and individual trends are both taken into account (see equation B.5), we can now reject the null hypothesis at the 5 % significance level for all variables except country size and service sector size.

Table B.3: Stationary test with heterogenous fixed effects and without individual trends

Variables	Im, Pesaran and Shin		Harris Tzavalis	
	statistic	p-value	statistic	p-value
Exposure	-1.29	0.81	0.13	0.55
Influence	-1.74	0.09	0.65	0.74
Country size	-1.06	1.00	4.53	1.00
Trade openness	-1.38	0.66	1.63	0.95
Financial openness	-1.62	0.32	5.78	1.00
TPI fin. Openess	-1.90	0.02	-7.23	0.00
Industrial sector size	-1.45	0.62	-2.78	0.00
service sector size	-1.54	0.43	-1.62	0.05

Note: This table presents the Harris and Tzavalis (1999) and the Im et al. (2003) unit root tests in our panels, with heterogenous fixed effects and without individual trends.

Table B.4: Stationary test with heterogenous fixed effects and individual trends

Variables	Im, Pesaran and Shin		Harris Tzavalis	
	statistic	p-value	statistic	p-value
Exposure	-2.22	0.00	-1.56	0.06
Influence	-2.20	0.00	1.18	0.88
Country size	-1.86	0.51	3.33	1.00
Trade openness	-2.32	0.00	-1.64	0.05
Financial openness	-2.91	0.00	-4.45	0.00
TPI fin. Openess	-3.13	0.00	-12.56	0.00
Industrial sector size	-2.04	0.02	0.67	0.75
service sector size	-1.82	0.06	2.69	1.00

Note: This table presents the Harris and Tzavalis (1999) and the Im et al. (2003) unit root tests in our panels, with heterogenous fixed effects and individual trends.

APPENDIX C

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Table C.1: Descriptive statistics for annual growth of housing price

Country	Mean	Std Dev.	Median	Min	Max	Skewness	Kurtosis
AUS	2.73	6.29	2.32	-10.82	26.01	0.65	0.69
BEL	2.29	5.08	2.26	-14.57	12.43	-1.07	1.63
CAN	2.81	6.10	2.40	-18.76	22.41	-0.09	1.47
CHE	0.98	5.60	2.01	-15.15	17.84	-0.37	0.74
DEU	0.32	2.79	0.00	-5.50	7.11	0.25	-0.63
DNK	1.77	8.35	2.73	-19.26	24.19	-0.20	0.16
ESP	2.55	9.43	3.40	-19.79	30.03	0.08	0.18
FIN	1.19	8.33	0.66	-23.18	31.29	0.04	2.01
FRA	2.04	4.79	2.30	-7.52	13.07	0.04	-0.62
GBR	3.20	9.38	3.56	-19.46	32.77	0.20	0.31
IRL	2.72	9.13	3.38	-23.37	25.91	-0.37	0.24
ITA	0.93	9.30	-0.46	-19.45	43.93	1.58	4.23
JPN	0.24	5.55	-0.10	-18.28	20.84	0.28	2.46
NLD	2.22	8.16	2.79	-23.96	30.71	-0.05	2.00
NOR	2.57	6.85	1.90	-15.64	24.17	0.06	0.42
NZL	3.35	8.18	3.02	-13.51	30.79	0.30	0.39
SWE	1.87	6.61	2.54	-21.66	12.99	-0.90	0.85
USA	1.52	4.01	2.00	-13.40	7.82	-1.04	1.09
ZAF	0.19	9.00	-0.23	-24.87	24.89	0.05	1.19

Note: This table presents the descriptive statistic for the annual growth rate of housing prices. The sample period ranges from Q1-1971 to Q1-2020.

Table C.2: Total directional connectedness indicators

Country	To others	From others
AUS	8.45	23.59
BEL	23.04	11.79
CAN	15.64	31.83
CHE	41.07	17.17
DEU	22.01	2.33
DNK	16.07	31.49
ESP	10.38	18.75
FIN	16.24	25.22
FRA	51.39	2.45
GBR	16.95	32.60
IRL	11.99	40.94
ITA	18.52	21.13
JPN	18.25	6.70
NLD	3.87	17.43
NOR	11.99	35.04
NZL	20.54	15.20
SWE	15.63	17.37
USA	61.10	4.02
ZAF	6.36	34.46
Connectedness index		20.50

Note: This table presents the full sample total directional connectedness of each country and the system-wise connectedness index.

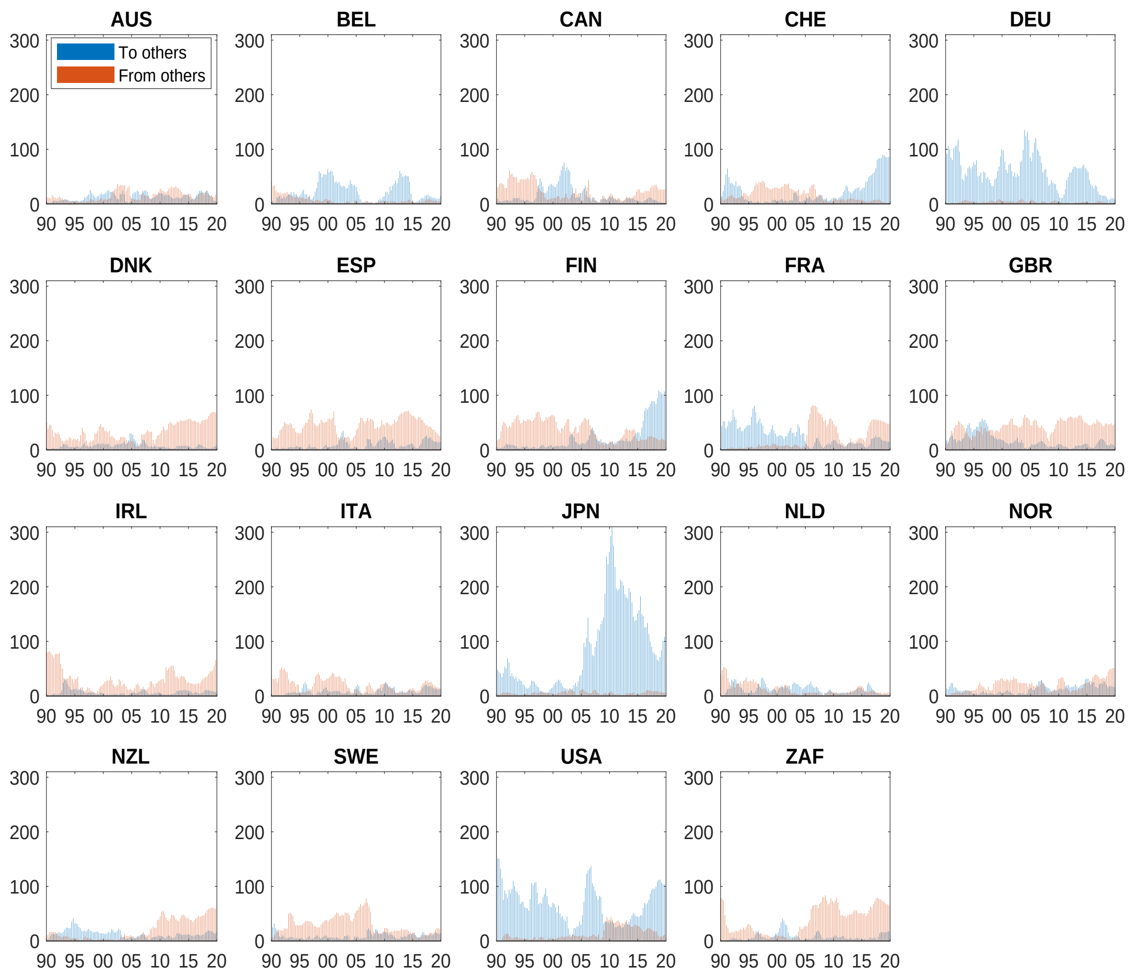

Figure C.1: Total dynamic directional connectedness (Q1-1987 to Q1-2020)

Note :This figure shows the total directional connectedness. For each country, the total influence, or "To-others" connectedness, is represented by the blue bars, and the total exposition, or "From-others" connectedness, is represented by the red bars, such that when the blue bars dominate the red bars, the country is a net shock transmitter; otherwise, the country is a net receiver.

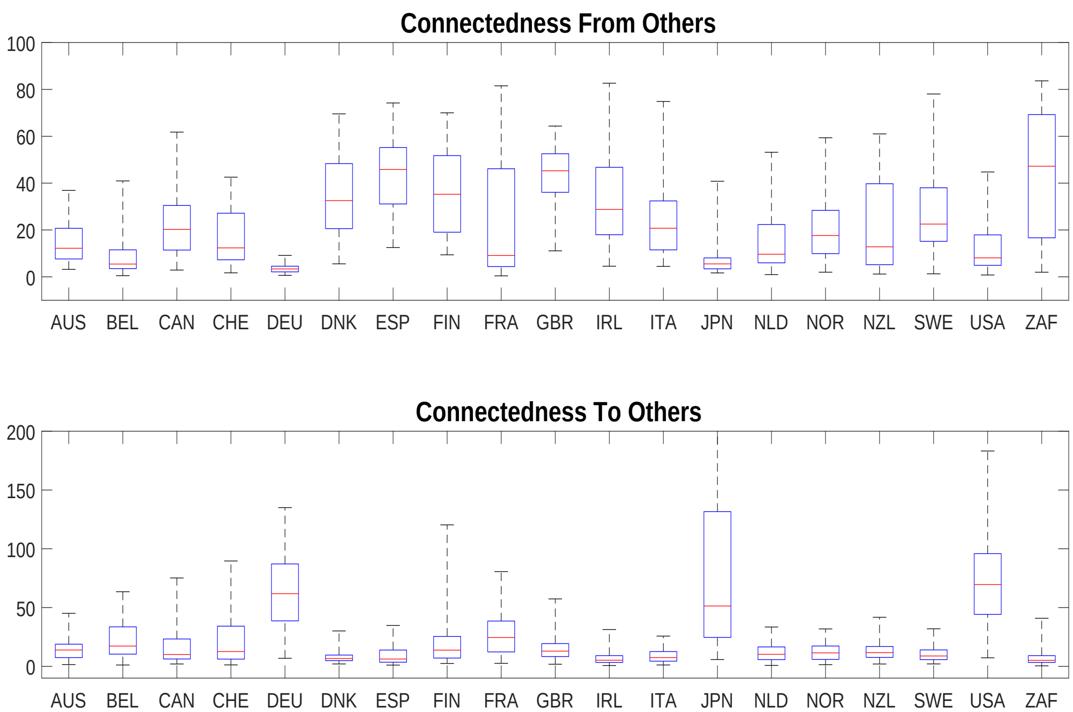

Figure C.2: Total dynamic directional connectedness boxplot

Note :This figure shows the box-plot of the total directional connectedness shown in figure C.1

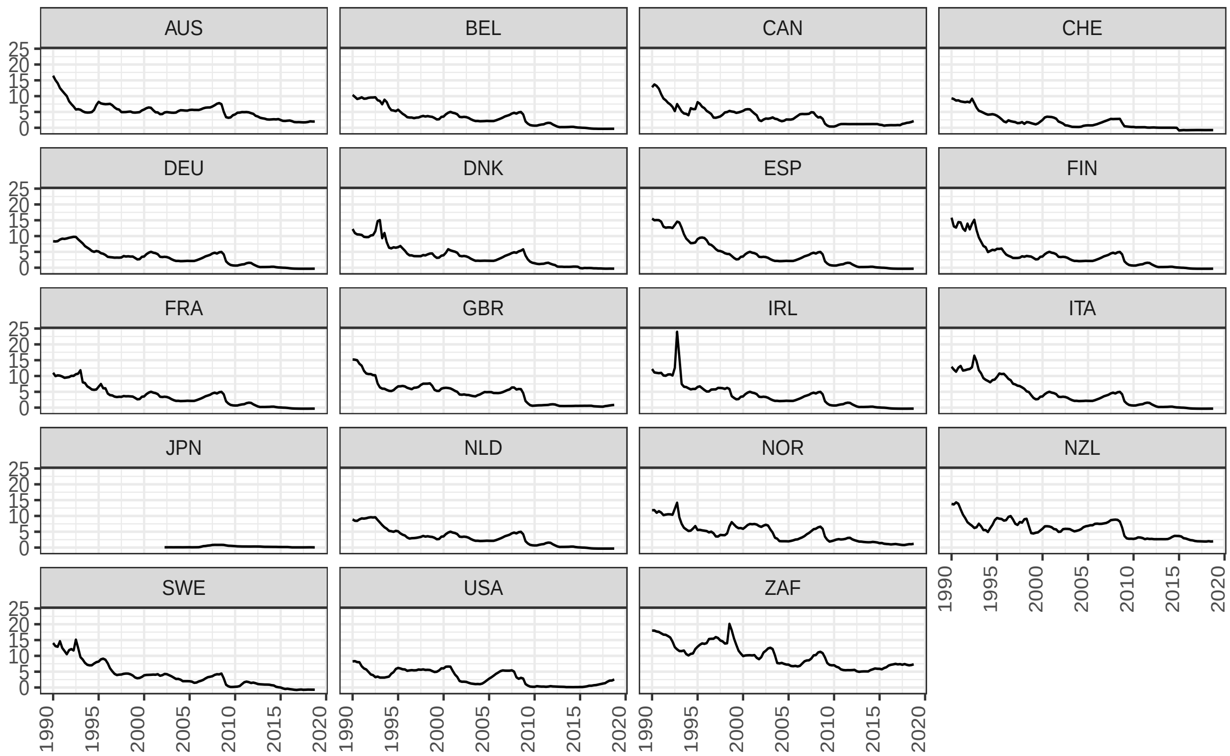

Figure C.3: Monetary policy instrument: short-term interest rate

Note : This figure shows short-term interest rate of each country. Source: OECD database.

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