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Capucine Nobletz

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Membre de l'Université Paris Lumières

Capucine NOBLETZ

Rôle et responsabilité de la finance face au changement climatique

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en vue de l'obtention du doctorat de Sciences économiques de l'Université Paris
Nanterre
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0 | Introduction générale

Il est urgent de limiter le réchauffement climatique afin de réduire ses effets sur l'Homme et sur l'écosystème. En effet, la hausse anthropique des émissions de gaz à effet de serre (GES) a d'ores et déjà causé un réchauffement moyen de l'atmosphère, des océans et des terres (GIEC, 2021). Selon le rapport du « Groupe d'Experts Intergouvernemental sur l'Évolution du Climat » (2021), l'Homme serait responsable d'une hausse de la température mondiale de 1,1 °C par rapport au niveau préindustriel. Chacune des quatre dernières décennies a été successivement plus chaude que les autres depuis 1850. Par exemple, la période 2001-2020 a connu une température globale moyenne supérieure de 0,99 °C comparativement aux années 1850-1900. L'activité humaine serait également responsable d'une hausse du niveau des précipitations, d'une acidification accrue des océans, d'une élévation du niveau des mers ou encore d'une fonte accélérée des glaciers. Par ailleurs, le GIEC (2021) observe et prédit un accroissement soutenu des phénomènes météorologiques extrêmes tels que des vagues de chaleur sévères, des épisodes de fortes précipitations, des périodes de grande sécheresse météorologique et agricole, ou des cyclones tropicaux de magnitude élevée.

En réponse à cette urgence climatique, lors de la 21e Conférence des Parties en 2015, l'Accord de Paris est signé ; 196 Parties se sont engagées à limiter l'augmentation de la température mondiale à un seuil bien en deçà de 2 °C par rapport au niveau préindustriel, avec comme objectif préférentiel le seuil de 1,5 °C (UNFCCC). En novembre 2021, la Conférence des Nations Unies (COP 26) tenue à Glasgow fut l'occasion pour les gouvernements de renouveler leurs engagements climatiques, à savoir une volonté de ne pas dépasser la limite de 1,5 °C par rapport au niveau préindustriel et d'atteindre une neutralité carbone à l'horizon 2050 (UNFCCC, 2019).

Pour autant, le temps d'action qu'il nous reste est très court. En effet, d'après les dernières estimations de l' « International Energy Agency » (IEA), dans son rapport annuel « World Energy Outlook » (2021), la hausse de la température mondiale moyenne devrait excéder 1,5 °C d'ici 2030 et pourrait atteindre 2,6 °C

en 2100, si la trajectoire de nos émissions carbone reste inchangée. Dans le scénario où les engagements actuels des États seraient tenus, avec le respect des « Contributions Nationales Déterminées » (NDC) et l'objectif de neutralité carbone en 2050, la limite de 1,5 °C sera franchie en 2030, mais en 2100 la hausse de la température sera limitée à 2,1 °C. Enfin, le seuil de 1,5 °C pourrait ne pas être dépassé, si et seulement si, nous atteignons mondialement une neutralité carbone vers 2050, combinée avec une réduction des émissions de GES autres que le carbone tels que le méthane ou l'oxyde nitreux.

Par conséquent, selon la trajectoire suivie, l'horizon des conséquences sur l'Homme et l'écosystème est multiple. En effet, plus la température globale augmente, plus les risques d'évènements météorologiques extrêmes croient. Aujourd'hui, en raison de la hausse des températures observées, les épisodes caniculaires et vagues de chaleur sont trois fois plus fréquents que durant la période préindustrielle (IEA, 2021). En outre, si la trajectoire de nos émissions en carbone reste constante, l'IEA (2021) estime un accroissement des vagues de chaleur et de leurs intensités à hauteur respective de 100 % et 120 % d'ici 2050. Les épisodes de forte sécheresse sont quant à eux amenés à croître de 40 % avec une hausse de leur intensité de 100 %. Enfin, si le scénario d'émission neutre en carbone est respecté, la hausse des vagues de chaleur extrême et des sécheresses atteindrait 45 % et 20 %, respectivement.

Face à un tel constat, comment pouvons-nous expliquer la propension à l'inaction climatique de nos économies ? Les phénomènes poussant à l'inaction climatique sont bien connus dans le champ de l'économie environnementale avec notamment le concept de la « Tragédie des Communs » (Hardin, 1968). Un agent économique n'a pas d'intérêt individuel à réduire son empreinte carbone puisque le coût de la réduction est supérieur à celui de l'inaction. En d'autres termes, les comportements de maximisation d'utilité individuelle conduisent à une situation macroéconomique sous-optimale amenant la destruction de notre habitat (Hardin, 1968). De plus, Mark Carney, alors Gouverneur de la Banque d'Angleterre, dans son célèbre discours devant le « Lloyd's of London » en 2015, ajoute que le changement climatique est la « Tragédie des Horizons » : « Nous n'avons pas besoin d'une armée d'actuaire pour nous dire que les effets catastrophiques du changement climatique se feront sentir au-delà des horizons traditionnels de la plupart des acteurs – imposant aux générations futures un coût que la génération actuelle n'a aucune incitation directe à porter. » (Carney, 2015, notre traduction, page 3). Nous sommes donc en présence d'un mésalignement des horizons d'action, où les agents sont guidés par des objectifs de court terme, tandis que les défis climatiques relèvent du long terme (Finance for Tomorrow, 2019).

Ce problème de mésalignement des horizons d'action est exacerbé sur les marchés financiers. D'après

Louche et al. (2019), la logique dominante des marchés financiers constitue un frein au financement d'une économie faiblement carbonée. Ces auteurs identifient quatre grandes limites. Premièrement, la valorisation des gains de court terme limite les investissements de long terme tels que les investissements responsables. Deuxièmement, l'incertitude face aux effets du changement climatique conduit à une paralysie des acteurs financiers ; ces derniers rencontrant des difficultés de mesure pour intégrer efficacement les risques climatiques. Troisièmement, la logique d'efficience des marchés (Fama, 1970), bien que très fréquemment décriée, occulte dans son essence les enjeux climatiques. En effet, tenir compte des enjeux climatiques dans les mécanismes de prix peut se faire uniquement par l'intermédiaire de critères extra-financiers, revenant alors à supposer que les prix d'actifs ne reflètent pas l'ensemble des informations disponibles. Dernièrement, la logique de maximisation rendement/risque tend à négliger les risques non-financiers tels que les risques climatiques futurs, d'autant qu'ils sont difficilement quantifiables.

Pour autant, les marchés financiers sont nécessaires au financement de la transition énergétique et écologique, avec notamment un fort pouvoir d'action dans l'orientation des flux de capitaux vers des projets responsables. En effet, selon l'IEA (2021), vivre dans un monde où la température n'excède pas 1,5 °C demanderait d'accroître les investissements verts à hauteur de 4 000 milliards de dollars par an d'ici 2030. Le « Programme des Nations-Unies pour l'Environnement » (UNEP, 2015) définit trois missions pour assurer une finance responsable. Premièrement, le système financier doit reconnaître les coûts et les risques associés aux secteurs d'activité fortement émetteurs en carbone. Deuxièmement, le secteur financier doit permettre l'allocation de ressources vers des actifs faiblement carbonés. Enfin, le secteur financier doit s'assurer de la résilience des institutions financières et des consommateurs aux chocs climatiques, tels que les catastrophes naturelles.

Notre thèse s'articule autour de ces trois axes. **L'objectif de la thèse est ainsi d'analyser le rôle de la finance dans le processus de transition énergétique en nous consacrant plus particulièrement à l'étude de la responsabilité du secteur financier face au changement climatique.** Dans notre premier chapitre « Green energy indices & financial markets : An in-depth look », nous construisons une nouvelle base de données sur les indices boursiers énergétiques verts et nous analysons les caractéristiques de ces indices face aux indices boursiers de référence. Dans notre deuxième chapitre « Return spillovers between green energy indices and financial markets : a sectoral approach » nous analysons comment ces indices énergétiques verts interagissent avec les autres secteurs économiques tels que les secteurs de l'industrie, des matériaux ou des énergies fossiles. Ces deux premiers chapitres

ont pour objectif d'accroître la transparence autour des produits financiers verts et de comprendre leurs intégrations sur les marchés financiers ; des conditions qui nous semblent nécessaires dans la perspective d'une réorientation massive des flux de capitaux vers des projets responsables. Notre troisième chapitre « Large-scale natural disasters & credit market risks » s'intéresse à la résilience des institutions financières et des consommateurs aux chocs climatiques. À cette fin, nous mesurons l'impact des catastrophes naturelles sur les risques de crédit des ménages et des entreprises aux États-Unis, ainsi que la réponse des investisseurs institutionnels à ces chocs.

0.1 Financer une économie bas carbone

0.1.1 Contexte

Comme énoncé précédemment, l'urgence climatique doit nous amener à repenser le fonctionnement de nos économies. Un des secteurs clef est le secteur énergétique, étant responsable à lui seul des trois-quarts des émissions de carbone ayant causé une hausse de la température de 1,1 °C (GIEC, 2021). Pour ce faire, l'IEA (2021) préconise plusieurs voies d'actions avec notamment le développement de l'électricité verte, la hausse de l'efficacité énergétique, et l'investissement massif dans les innovations vertes. Il est donc nécessaire de s'interroger sur les produits financiers verts et leurs capacités à financer des investissements faiblement carbonés. Plusieurs produits financiers verts existent, tels que les actions ou les obligations vertes.

0.1.1.1 Les obligations vertes

Bien qu'il n'existe pas de définition consensuelle sur les obligations vertes, nous pouvons les définir comme des instruments obligataires ayant pour vocation de financer ou refinancer des projets verts (ICMA, 2021). La définition de ce qu'est un « investissement vert » est également débattable. Cependant, la littérature s'accorde pour identifier les secteurs des énergies renouvelables, de la gestion des eaux usées et de l'efficacité énergétique comme étant « verts ». Les secteurs du nucléaire et de l'hydroélectricité font l'objet d'une plus grande controverse, tandis que les secteurs des biocarburants et du gaz de schiste suscitent un changement de consensus (Inderst et al., 2012). La première émission d'obligations vertes a eu lieu en 2007 par la Banque Européenne d'Investissement (BEI), suivie de la Banque Mondiale. Au cours des dernières années, malgré la pandémie, le marché des obligations vertes a enregistré une très forte

croissance, avec une accélération notable depuis 2014 ([Climate Bonds Initiative](#)). En effet, en matière de volume d'obligations vertes émises, nous sommes passés de 40 milliards de dollars en 2015, contre 170 milliards en 2018 et plus de 500 milliards en 2021 (Figure 0.1). En 2021, les principaux émetteurs étaient l'Europe, l'Asie du Pacifique et l'Amérique du Nord, et les trois premiers pays étaient les États-Unis, la Chine et l'Allemagne. La France est arrivée en quatrième position. En outre, en 2021, la majorité des émissions provenait d'entreprises non-financières avec en tête « China Three Gorges Corporation » et « Iberdrola ». Dans la suite du classement, nous avons les entreprises financières avec « China Development Bank » et « ICBC », et pour finir, les émetteurs souverains avec comme leader la France (Figure 0.2). Enfin, les obligations vertes ont majoritairement été émises afin de financer des projets dans les secteurs de l'énergie, du bâtiment et du transport ([Climate Bonds Initiative, 2021](#)).

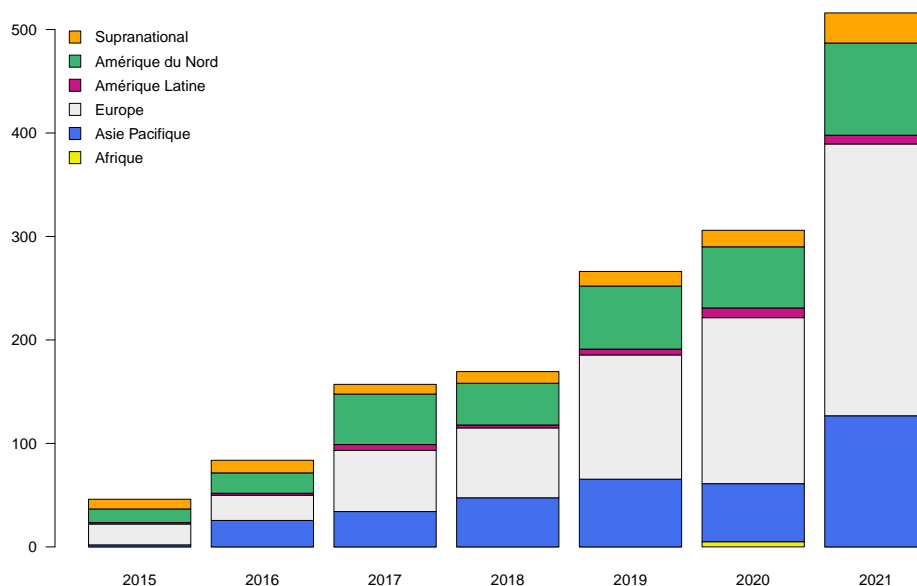


Figure 0.1 – Volume des émissions d'obligations vertes dans le monde, par région (en milliards de US dollars).

Source : [Climate Bonds Initiative \(2021\)](#)

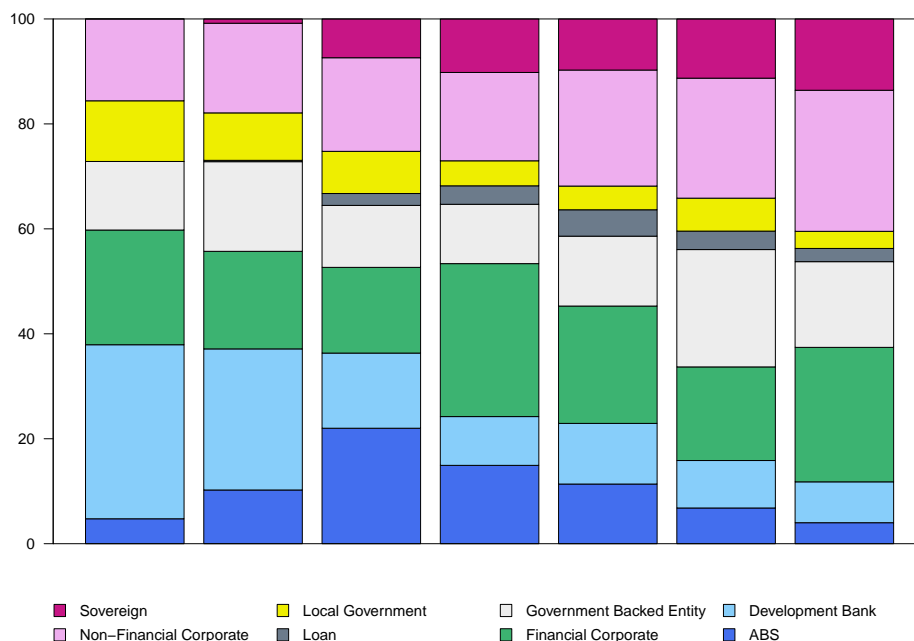


Figure 0.2 – Volume des émissions d’obligations vertes dans le monde par type d’émetteurs (en %). Source : Climate Bonds Initiative (2021).

Source : [Climate Bonds Initiative \(2021\)](#)

Toutefois, il est nécessaire de préciser qu’à ce jour le volume d’obligations vertes émises reste infinitésimal face au volume d’émission d’obligations « classiques » au niveau international. Par ailleurs, il n’existe pas de standard contraignant permettant de définir si une obligation est verte ou non ; l’émetteur peut ainsi auto-déclarer son obligation comme « verte ». Sur ce point, la [Climate Bonds Initiative \(2021\)](#) souligne une tendance à la hausse du recours à la certification « verte » des obligations dans le temps. Par exemple, en 2021, 86 % des émetteurs d’obligations vertes ont eu recours à des évaluations externes. Un constat qui reste à mitiger, puisque deux tiers des émissions d’obligations vertes non-évaluées sont originaires des États-Unis (45 %) et de la Chine (22 %), les deux plus gros émetteurs.

À ce jour, diverses lignes directrices non-contraignantes servent de cadre pour définir ce qu’est une obligation verte ; toutefois, les « Green Bond Principles » (GBP) élaborés en 2014 par l’ « International Capital Market Association » (ICMA) font office de référence internationale. Les GBP reposent sur quatre piliers fondamentaux : (1) l’utilisation des fonds, (2) le processus de sélection et d’évaluation des projets, (3) la gestion des fonds, et (4) le « Reporting ». Concernant (1) l’utilisation des fonds, les GBP préconisent une

description claire de l'utilisation des fonds levés et de leurs bénéfices environnementaux. Pour cela, les GBP définissent les catégories de projets verts éligibles, tels que les projets d'adaptation et d'atténuation au changement climatique¹. En ce qui concerne (2) le processus de sélection et d'évaluation du projet, l'émetteur est encouragé à fournir aux investisseurs les objectifs et les avantages environnementaux du projet, les critères indiquant qu'il s'agit d'un projet vert, ainsi que des informations complémentaires sur les méthodes d'évaluation du projet (par exemple, internes ou externes). Concernant (3) la gestion des fonds, cette dernière doit être formelle et transparente; les fonds doivent être crédités sur un compte distinct ou un portefeuille financier secondaire, doivent être alloués le plus rapidement possible au projet, et le recours à des auditeurs internes ou externes est fortement recommandé. Enfin, le (4) « Reporting » consiste à fournir le maximum d'informations sur les projets financés, tels que les méthodes d'évaluation de ces derniers (des mesures pouvant être quantitatives ou qualitatives) ([ICMA, 2021](#)).

Notons que l'Europe, ainsi que d'autres zones géographiques (par exemple, la Chine et le Japon), disposent de leur propre standard d'évaluation des projets verts. La taxonomie européenne, « EU Taxonomy » est l'une des plus développées; elle fût publiée le 22 juin 2020 au Journal Officiel de l'Union Européenne (JOUE) et est entrée en vigueur le 12 juillet 2020. La taxonomie européenne fournit un système de classification permettant de définir quels sont les secteurs d'activité écologiquement responsables, se traduisant par des obligations d'informations et des labels officiels pour les produits financiers ([Commission Européenne](#); [ICMA, 2021](#)).

Le financement de la transition énergétique par l'émission d'obligations vertes présente donc plusieurs avantages. Pour en citer quelques-uns, les obligations vertes représentent une nouvelle source de financement pour les investisseurs, permettent de financer des projets verts sur une longue période, et poussent les entreprises à se sensibiliser aux questions climatiques et environnementales ([OECD, 2017](#)). En outre, la littérature identifie majoritairement une prime de prix négative pour les obligations vertes; les émetteurs d'obligations vertes se financent à des coûts plus faibles (taux d'intérêt plus bas) qu'avec des obligations standards ([Sartzetakis, 2021](#), pour un état de l'art). Cependant, ce marché a également ses limites; il manque d'encadrement, l'émission obligataire ne s'applique qu'aux grandes entreprises, excluant les petites et moyennes firmes, pourtant déterminantes sur le marché de la transition énergétique. Les obligations vertes seules ne suffisent donc pas à financer la transition bas carbone, il est nécessaire d'utiliser en parallèle d'autres types de produits financiers.

1. Nous renvoyons le lecteur au rapport [ICMA \(2021\)](#) pour une description exhaustive des projets verts.

0.1.1.2 Les fonds communs de placement verts

Rappelons brièvement qu'un fonds commun de placement (ou encore, un Organisme de Placement Collectif, OPC) est un organisme de gestion collective d'épargne permettant aux agents d'investir dans des valeurs mobilières (actions ou obligations) tout en bénéficiant d'un portefeuille diversifié, même si le montant investi est faible (AMF). Il n'est donc pas surprenant de noter un développement à la hausse des fonds communs de placement « verts » ; des fonds dont les titres sélectionnés répondent à des critères environnementaux (Silva and Cortez, 2016). Au niveau européen, ces fonds ont connu une première expansion entre 2006 et 2008 ; une hausse pouvant s'expliquer par le développement substantiel des industries vertes, soutenu par des subventions gouvernementales élevées et s'inscrivant dans un contexte de hausse significative des prix du pétrole. Ensuite, la croissance de ces fonds fut ralentie par les différentes crises financières avec la crise globale de 2008 et celle de la dette souveraine de 2011, ne repartant qu'à la hausse depuis la signature des Accords de Paris en 2015 (Novethic, 2017, 2018). En termes de volume de marché, les encours de fonds verts européens sont passés de 19 milliards d'euros en 2015 à 59 milliards en 2019, et ont atteint 381 milliards en juin 2021 (Figure 0.3). Bien que ces fonds bénéficient d'une forte croissance, les encours « verts » restent minimes face à la gestion d'actifs traditionnels, puisqu'ils ne représentent que 1,3 % des encours totaux. Notons également que le déploiement des fonds verts n'est pas uniquement européen bien qu'étant plus marqué dans les pays développés qu'en développement (Novethic, 2021).

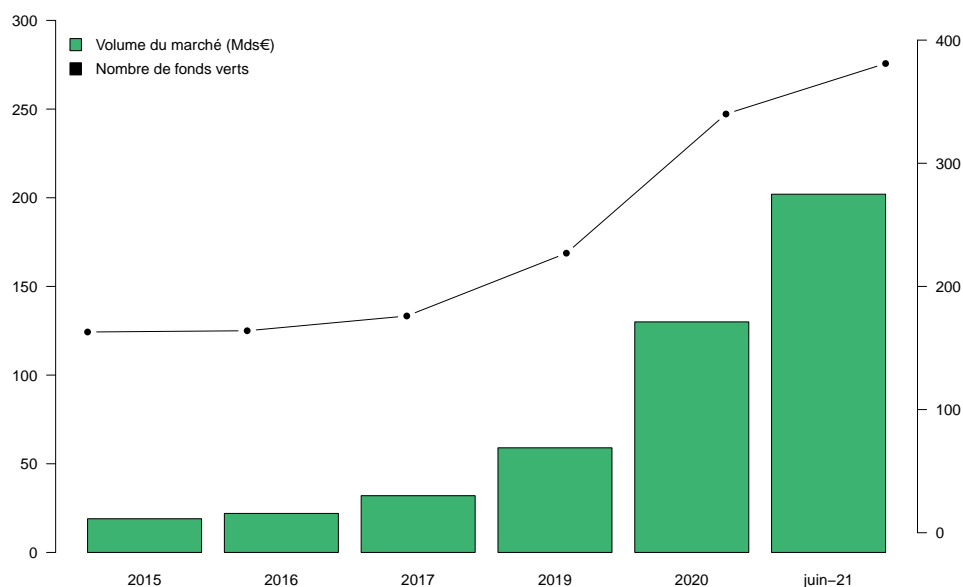


Figure 0.3 – Encours des fonds verts au niveau européen de 2015 à 2021 (axe de gauche, volume du marché en milliards d’euros ; axe de droite, nombre de fonds verts).

Source : [Novethic \(2021\)](#).

Les fonds verts peuvent en réalité être définis comme une sous-famille des fonds d’Investissement Socialement Responsable (ISR) ; ces derniers se distinguant des fonds standards par la prise en compte de critères extra-financiers tels que les critères ESG (Environnementaux, Sociaux, et de Gouvernance) ([AMF](#)). Les stratégies des fonds ISR sont très hétérogènes ; elles peuvent concerner tout ou partie du fonds considéré, ne sont pas mutuellement exclusives, et peuvent changer d’un fonds à l’autre. Nous recensons cinq grandes stratégies d’investissement responsable : l’approche « best-in-class », l’exclusion, l’investissement thématique, l’engagement actionnarial et l’investissement d’impact. L’approche « best-in-class » consiste à sélectionner les entreprises ayant les meilleurs scores ESG dans chaque secteur d’activité (« screening » positif). En revanche, la méthode d’exclusion consiste à exclure les entreprises qui ne répondent pas à des critères environnementaux et sociaux minimaux, tels que la vente de tabac, d’alcool ou d’armement (« screening » négatif). Les portefeuilles d’investissement thématique ciblent des secteurs environnementaux spécifiques tels que les secteurs des énergies renouvelables ou de l’efficacité énergétique. Enfin, les stratégies d’engagement actionnarial reviennent à recourir aux droits des actionnaires pour inciter les entreprises à mieux intégrer les critères ESG, tandis que les stratégies d’investissement d’impact consistent

majoritairement à investir dans des entreprises non-cotées en bourse recherchant un fort impact social et environnemental ([Eurosif, 2018](#)).

Au niveau européen sur la période 2009-2017, la stratégie d'investissement ayant rencontré le plus de succès est la stratégie d'exclusion, avec en tête la Suisse et le Royaume-Uni, suivie de l'engagement actionnarial avec le Royaume-Uni et la Suède, respectivement. La prépondérance de ces deux stratégies envoie un signal fort : les investisseurs sont de plus en plus soucieux des enjeux environnementaux et sociétaux. Une autre démarche en plein essor est l'approche « best-in-class » avec une hausse annuelle de 20 % entre 2009 et 2017. À l'exception de la Suède, tous les pays européens ont connu une augmentation de cette approche, la France étant leader dans ce domaine. Cette stratégie a plusieurs avantages, elle permet d'encourager les « bons » comportements des entreprises dans tous les secteurs et de proposer aux investisseurs un portefeuille diversifié ([Eurosif, 2018](#)). Cependant, en sélectionnant les meilleurs comportements dans tous les secteurs, nous n'excluons pas, par définition, les secteurs les plus polluants tels que les secteurs des énergies fossiles ou de l'industrie, ces derniers pouvant alors composer les fonds « verts ». Sur ce point, [Novethic \(2021\)](#) souligne que l'exclusion des énergies fossiles des portefeuilles financiers verts ne fait pas consensus au niveau européen ; une partie importante du marché souhaite continuer à financer ces entreprises lorsqu'elles entament leur transition énergétique. Par exemple, en 2021, seule la moitié des fonds verts excluait le charbon et seulement 40 % d'entre eux le pétrole. Parmi les fonds qui ont exclu les activités pétrolières, deux tiers l'ont fait, car ils y étaient tenus, soit en raison d'un label rigoureux ou de la réglementation en vigueur.

Ainsi, même si la définition de l'investissement responsable reste similaire entre les pays, il existe une grande hétérogénéité dans sa mise en œuvre. Cette hétérogénéité européenne devrait progressivement s'estomper grâce au développement de la taxonomie. Cependant, elle reste encore très présente aujourd'hui, comme en témoigne la multiplicité des labels européens et leurs critères de choix d'actifs. En France, nous avons deux labels soutenus par des ministères différents avec le label ISR spécialisé dans la gestion des fonds ESG et le label Greenfin dédié à l'investissement thématique. Notons que le label ISR est le seul des neuf principaux labels européens (FNG-Siegel, LuxFLAG ESG, Towards Sustainability, Umweltzeichen, Nordic Swan Ecolabel, LuxFLAG Environment, Greenfin) à ne pas exclure les énergies fossiles ([Novethic, 2022](#))².

2. Nous renvoyons le lecteur au rapport [Novethic \(2022\)](#) pour plus d'informations sur les critères de sélection d'actifs propres aux différents labels européens.

0.1.2 Chapitre 1 : « Green energy indices & financial markets : An in-depth look »

Face à ce contexte, il est nécessaire d'accroître la lisibilité autour de l'ensemble des produits financiers verts, si l'on veut pouvoir atteindre la neutralité carbone d'ici 2050. Un produit financier reste particulièrement opaque et est pourtant en pleine expansion : les indices boursiers verts. En effet, ces derniers sont particulièrement appréciés par les investisseurs souhaitant investir dans les « Exchange-Traded Funds » (ETF) correspondants ; les ETF ont pour objet la réplique du cours d'un indice de référence, à la hausse et à la baisse, renvoyant à une gestion passive du fonds. Sur ce point, [Novethic \(2021\)](#) souligne une montée en puissance de la gestion passive des fonds indiciels européens, avec une hausse qui a plus que doublé en un an et demi. En effet, en décembre 2019, seuls 8 % des fonds étaient gérés passivement, contre 21 % en juin 2021. Ces fonds de gestion passive sont en moyenne plus gros que les autres.

Dans notre premier chapitre, nous cherchons alors à accroître la lisibilité des indices boursiers verts. Pour ce faire, nous (i) proposons une méthode de sélection des indices verts, (ii) fournissons une nouvelle base de données présentant les composantes des indices verts retenus dans le temps, et (iii) comparons les caractéristiques de ces indices à des benchmarks.

Tout d'abord, nous identifions les indices qui répondent au mieux aux enjeux environnementaux et aux exigences en matière de finance responsable. Ainsi, nous sélectionnons les indices boursiers verts qui fournissent un maximum d'informations sur leur choix de titres, leur composition et leur méthode de pondération. La méthode de sélection d'actifs se doit d'être exclusive (voir discussion dans la section précédente) et la liste de ces actifs doit être accessible.

Nous retenons deux indices boursiers verts : l'indice américain, « WilderHill Green Energy Index » (ECO) et l'indice mondial, « WilderHill New Energy Global Innovation Index » (NEX). Après un traitement exhaustif des données, nous fournissons une liste des composantes de ces indices de leur date d'émission (ECO : 2005, NEX : 2006) à 2021. Notons que les rapports avec les listes d'entreprises, en l'état, ne sont pas exploitables pour une analyse temporelle ; selon le rapport trimestriel, la graphie de l'entreprise peut changer, de même que les informations fournies sur cette dernière (exemples : son poids dans l'indice, sa localisation, ou son secteur environnemental). Ainsi, à l'aide de techniques de « web scraping », nous avons récupéré l'ensemble des rapports trimestriels et recoupé toutes les informations afin de reconstruire une série fournissant le nom de l'entreprise, son poids, sa géolocalisation et son secteur environnemental pour chaque année. La contribution de cette base de données est d'améliorer la compréhension des dynamiques

propres aux marchés des énergies vertes. En effet, mieux nous comprendrons ces marchés, plus nous serons en mesure d'investir massivement dans les activités vertes. Nous répondons donc aux questions suivantes : quelles sont les entreprises leaders dans le secteur des énergies vertes ? Quels sont les pays ou les zones géographiques les plus actifs ? Quels sont les sous-secteurs environnementaux les plus développés ? Et comment ces tendances ont-elles évolué ?

En concentrant notre analyse descriptive sur le NEX, nous constatons que l'indice mondial suit correctement les différentes tendances propres aux secteurs des énergies vertes. L'indice reflète l'expansion du marché vert, le rôle croissant de la région Asie-Pacifique et le leadership des entreprises chinoises, européennes et américaines sur ce marché. L'indice souligne également la croissance des secteurs des énergies solaires et éoliennes. En outre, la composition de cet indice met en évidence le caractère « jeune » des secteurs environnementaux ; l'indice a une composition très volatile avec par conséquent un grand nombre d'entrées et de sorties d'entreprises dans le temps. Nous pouvons expliquer ce phénomène par la plus grande propension des entreprises environnementales à faire défaut, à fusionner avec un groupe plus important, ou à rencontrer des problèmes de capitalisation d'une année sur l'autre, ne répondant donc plus aux critères d'entrée de l'indice.

Enfin, nous comparons les composantes de notre indice boursier vert mondial avec celles d'un benchmark, le S&P Global 1200. Nous montrons que peu d'entreprises composent conjointement les deux indices au cours du temps. Ce résultat est double, puisqu'il souligne que la méthode de l'indice a bien exclu les entreprises potentiellement polluantes. Cependant, il montre également la faible représentation des entreprises énergétiques vertes mondiales dans les indices de référence ; ces derniers étant représentatifs de la répartition sectorielle économique actuelle.

En résumé, cette étude fournit davantage d'informations sur les indices boursiers verts. Notre recherche est donc tout indiquée pour les investisseurs souhaitant mieux comprendre le positionnement des indices verts par rapport aux benchmarks, afin de réaliser des choix d'investissement. Notre étude nous amène également à appeler une nouvelle fois les pouvoirs publics de se saisir du problème de manque de taxonomie autour des produits financiers verts, ainsi que de la surpondération des entreprises carbonées dans les indices de référence. Enfin, notre base de données sur le NEX et l'ECO peut ouvrir le champ à de nouvelles études académiques. Sur ce point, nous proposons dans notre article une application de la base ; nous mesurons l'interconnexion entre les indices boursiers verts et les différents indices économiques sectoriels au niveau mondial. En effet, ayant montré que peu d'entreprises composent simultanément les

indices boursiers verts et les indices de référence, il est possible de mesurer leur interdépendance sans craindre de capturer une dépendance artificielle entre ces variables. Cette application est une synthèse des principaux résultats de notre chapitre 2.

0.1.3 Chapitre 2 : « Return spillovers between green energy indices and financial markets : a sectoral approach »

Notre chapitre 2 s'interroge sur l'interdépendance du secteur des énergies vertes avec les autres secteurs économiques tels que ceux de l'industrie, des matériaux ou des énergies fossiles. En effet, nous faisons le postulat que pour effectuer une transition vers une économie bas carbone, nous devons appréhender comment le secteur des énergies vertes s'intègre aux autres marchés. En d'autres termes, comment le développement du secteur des énergies vertes peut-il impacter les autres secteurs économiques ? Et comment des politiques publiques visant à réduire l'empreinte carbone des secteurs les plus polluants peuvent-elles avoir un effet de rétroaction sur les entreprises vertes ? À notre connaissance, nous sommes les premiers à fournir une analyse intersectorielle, et cela constitue notre principale contribution.

En nous appuyant sur la méthode de décomposition de la variance des erreurs de prévision d'une spécification VAR, nous construisons des indicateurs mesurant les effets d'interconnexion entre l'indice mondial de l'énergie verte (NEX) et les indices économiques sectoriels (indices sectoriels du S&P Global 1200) de 2006 à 2020, en journalier. Nous utilisons également des fenêtres roulantes pour tenir compte de la variation temporelle de nos indices d'interconnexion et, ainsi, fournir une analyse dynamique.

Nos principaux résultats sont les suivants. L'analyse statique révèle que le secteur des énergies vertes a une ouverture financière significative et reçoit plus de chocs qu'il n'en transmet aux autres secteurs économiques. En effet, la demande croissante d'actifs verts favorise l'intégration du secteur des énergies vertes sur les marchés financiers, accroissant ainsi sa propension à transmettre des chocs. Cependant, ce secteur reste « jeune » avec des problèmes de capitalisation ou de liquidité plus élevés que les autres secteurs économiques. Il n'est donc pas surprenant d'identifier que le secteur des énergies vertes reçoit plus de chocs qu'il n'en transmet aux autres marchés, en moyenne. Par ailleurs, nous identifions une interconnexion plus forte entre les entreprises du secteur des énergies vertes et celles appartenant aux secteurs de l'industrie et des matériaux. Deux facteurs peuvent expliquer ce phénomène. Premièrement, les secteurs de l'industrie et des matériaux sont fortement intégrés (plus une entreprise échange avec le reste du monde, plus elle est à même de recevoir ou de transmettre des chocs). Secondement, les entreprises

dans le secteur des énergies vertes et celles dans les secteurs de l'industrie et des matériaux produisent des biens similaires. Citons, par exemple, la production de turbines pour le secteur éolien ou encore de matériels photovoltaïques pour le secteur de l'énergie solaire. Ce résultat est intéressant, car il signale que les politiques publiques visant à réduire les émissions en carbone dans les secteurs des matériaux ou de l'industrie devront tenir compte des effets de rétroaction sur l'industrie verte. Un autre résultat notable est l'interconnexion plus faible entre le secteur des énergies vertes avec les secteurs de la santé, du service public et des biens de consommation courante. Ainsi, les gestionnaires d'actifs souhaitant investir dans les énergies vertes peuvent considérer ces indices sectoriels pour diversifier leurs portefeuilles et donc minimiser les risques de perte en capital.

En passant à l'analyse dynamique, nous montrons que l'interconnexion entre le secteur des énergies vertes et les autres secteurs économiques varie et semble suivre les épisodes d'incertitudes économiques. Par exemple, nous identifions une hausse de l'interconnexion avec le secteur des énergies vertes durant la pandémie, pouvant illustrer le phénomène de « fuite vers la liquidité ». En période de crise, les investisseurs retirent leurs investissements à risque tels que les actifs financiers verts et les redirigent vers des actifs plus sûrs tels que des obligations souveraines ou des métaux précieux. En outre, alors que la relation entre le secteur des énergies vertes et celui des énergies fossiles ne joue pas un rôle prépondérant dans l'analyse statique, l'étude dynamique révèle un schéma variable dans le temps. En effet, depuis la prise de conscience des enjeux climatiques (2014-2015), les effets de rétroaction des industries vertes sur les énergies fossiles ont augmenté. En résumé, les rendements des énergies vertes impactent ceux des énergies fossiles.

0.2 Risques financiers climatiques

0.2.1 Contexte

Comme souligné dans le « Programme des Nations-Unies pour l'Environnement » ([UNEP, 2015](#)), le système financier doit s'assurer de la résilience des institutions financières et des ménages aux chocs climatiques, tels que les catastrophes naturelles.

Dans son discours, en 2015, Mark Carney définit pour la première fois les trois principaux risques financiers climatiques avec (i) le risque de responsabilité, (ii) le risque de transition, et (iii) le risque physique. Le risque de responsabilité est le risque encouru si les Parties ayant subi des pertes ou des dommages dus au

réchauffement climatique demandent réparation aux agents qu'elles tiennent pour responsables (Carney, 2015). Ce type de procédure judiciaire est de plus en plus fréquent ; selon le rapport de Setzer and Higham (2022), le nombre de recours en justice a plus que doublé depuis 2015, atteignant un total d'environ 2 000 affaires déposées. La majorité de ces affaires ont eu lieu aux États-Unis, mais cette démarche tend à s'exporter à l'ensemble des régions du globe. Aujourd'hui, la plupart des recours en justice sont attentés contre les gouvernements pour inaction climatique. Par exemple, en France, « l'Affaire du Siècle » a débuté en 2018 ; quatre organisations françaises avec la « Fondation Nicolas Hulot », « Greenpeace France », « Notre Affaire à tous » et « Oxfam France » ont assigné l'État français en justice pour inaction contre le réchauffement climatique. Leur objectif est de faire reconnaître par les juges, l'obligation de l'État à agir pour limiter la hausse de la température à 1,5 °C (L'affaire du siècle). Par ailleurs, les plaintes déposées contre les grands extracteurs de combustibles fossiles ou d'autres entreprises polluantes continuent de se multiplier avec notamment 13 recours en Europe contre les grands émetteurs de carbone, ou deux recours en Australie contre la compagnie gazière Santos (Setzer and Higham, 2022).

Le deuxième risque financier climatique est le risque de transition, pouvant être défini comme les risques financiers encourus pendant le processus d'ajustement vers une économie faiblement carbonée. En effet, les changements dans les politiques économiques, les technologies ou les sentiments de marché peuvent entraîner une large réévaluation d'actifs, susceptible de mettre le système financier en difficulté. Un exemple spécifique au risque de transition est celui du « carbone non-brûlable » ; afin de limiter le réchauffement climatique, une grande partie des réserves de combustibles fossiles devra rester « non-brûlée » (Scott et al., 2017). Selon le dernier rapport du « think tank » CarbonTracker (2022), 60 % des réserves de combustibles fossiles découvertes devront rester dans le sol pour éviter un dépassement de la température à 2 °C. Or, les réserves déjà acquises par les grandes compagnies de pétrole, de gaz et de charbon dépassent déjà le budget carbone restant. La majorité de ces réserves est détenue par des sociétés cotées en bourse sur les places financières mondiales. La Chine est en tête, détenant à elle seule plus de 70 % du budget carbone restant pour un seuil à 1,5 °C. Ce risque pourrait se matérialiser non seulement au niveau des grands groupes pétroliers et gaziers avec plus de 1 000 milliards de dollars de pertes d'actifs (CarbonTracker, 2022), mais aussi auprès des secteurs fortement dépendants des énergies fossiles et/ou émetteurs en carbone, tels que les secteurs de l'industrie, des matériaux ou des transports (Scott et al., 2017). Rappelons également que la majorité des actifs des entreprises de combustibles fossiles sont cotés en bourse avec environ 600 milliards de dollars (CarbonTracker, 2022), suggérant ainsi qu'une dépréciation

en valeur de ces titres provoquerait des effets en chaîne ne s'arrêtant pas aux frontières des agents impliqués. Par exemple, la dépréciation de la valeur de ces actifs pourrait lourdement affecter les compagnies d'assurance ou le bilan des banques (Scott et al., 2017).

Troisièmement, les risques physiques sont les risques pour la sphère économique et financière dus au changement climatique et à l'augmentation des événements météorologiques. Citons par exemple, l'accroissement des événements naturels extrêmes avec des vagues de chaleur de forte intensité, des précipitations intenses ou des cyclones tropicaux de forte magnitude (Batten et al., 2016).

Notre troisième chapitre s'intéresse aux risques physiques. C'est pourquoi, nous développons particulièrement ce point dans la section suivante.

0.2.2 Risques physiques

Tout d'abord, nous pouvons définir les événements météorologiques extrêmes comme des événements présentant des valeurs extrêmes dans leurs taux d'occurrence, leurs intensités, leurs durées temporelles, leurs échelles spatiales ou leurs dépendances mutuelles (Stephenson, 2008). D'un point de vue économique, une catastrophe naturelle est alors un événement générant des perturbations sévères dans le fonctionnement de nos économies avec un impact significativement négatif sur différents agrégats macroéconomiques tels que la production, l'emploi ou la consommation (Hallegatte and Przyluski, 2010). Stephenson (2008) ajoute qu'une catastrophe naturelle génère de larges pertes dans plusieurs dimensions : une dimension humaine (par exemple, le nombre de morts, de blessés ou de personnes touchées), physique (destruction de capital) et/ou environnementale (destruction de la biodiversité).

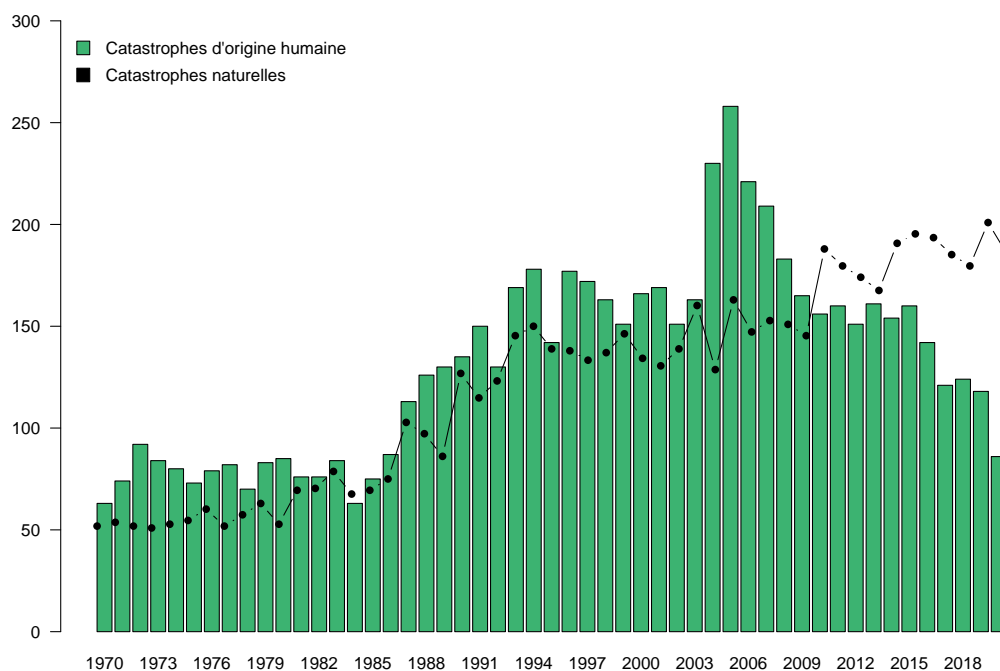


Figure 0.4 – Nombre de catastrophes naturelles et d’origine humaine au niveau mondial entre 1970 et 2020.

Source : [SwissRe \(2021\)](#).

Aujourd’hui, nous observons que la fréquence et l’intensité des catastrophes naturelles croient dans le temps et touche l’ensemble des régions du globe. En effet, la Figure 0.4 souligne distinctement une tendance à la hausse des catastrophes naturelles, tandis que celles d’origine humaine (exemples : catastrophes maritimes et ferroviaires) décroissent dans le temps. Ainsi, les dommages économiques totaux augmentent, et ce, en raison de catastrophes plus fréquentes, combinées avec une accumulation du capital humain et physique dans le temps ([SwissRe, 2021](#)). La Figure 0.5 met également en exergue le problème de « défaillance de protection » ; les pertes non-assurées sont supérieures à celles assurées. Cette « défaillance de protection » est non-homogène en fonction des régions ; les régions en cours de développement (l’Afrique, l’Amérique Latine et l’Asie) ont un déficit assurantiel plus fort que les régions développées (l’Amérique du Nord, l’Europe et l’Océanie) ([SwissRe, 2021](#)).

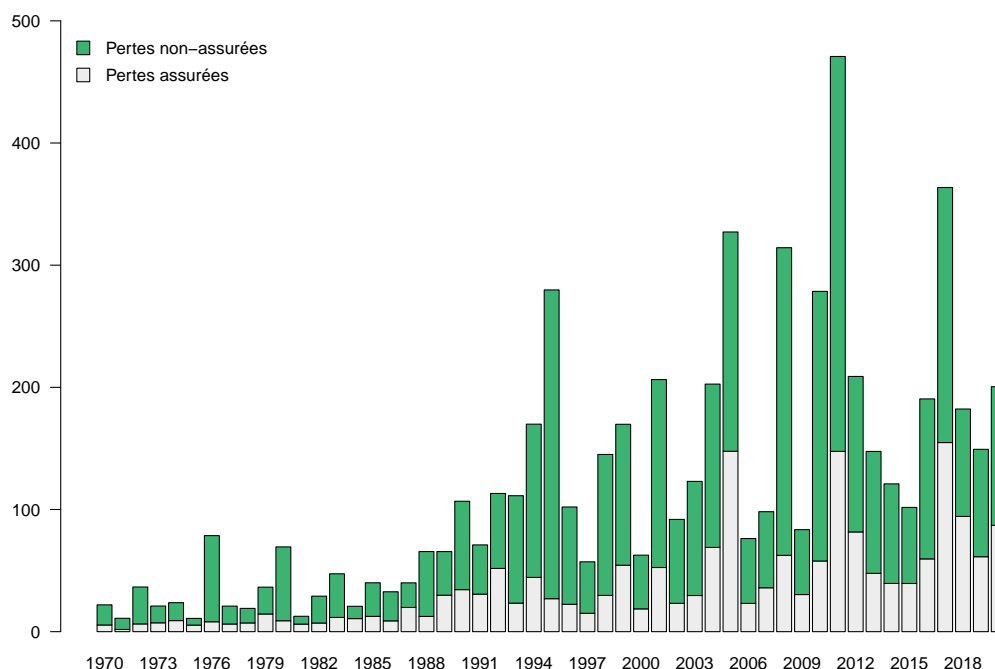


Figure 0.5 – Pertes assurées et non-assurées des catastrophes naturelles au niveau mondial, entre 1970 et 2020.

Source : [SwissRe \(2021\)](#).

Ainsi, les catastrophes naturelles peuvent avoir un impact sur la stabilité du système financier, notamment dans le cas d’une défaillance de couverture assurantielle ([Peter et al., 2012](#)). Sur ce point, notons que les assurances ayant subi de lourdes pertes à la suite d’une catastrophe naturelle peuvent réagir en augmentant leur prime de risque ([Angbazo and Narayanan, 1996](#)) ou en décidant de ne plus assurer certaines zones définies comme « trop risquées » ([Peter et al., 2012](#)). Le risque sous-jacent est donc l’accroissement d’une « défaillance de protection » exacerbant les effets négatifs des catastrophes. En effet, les catastrophes naturelles peuvent avoir un impact négatif sur les bilans des entreprises et des ménages ([Batten et al., 2016](#)). Les entreprises peuvent subir une destruction d’actifs avec un arrêt partiel ou total de leurs activités, entraînant une baisse de la production et du niveau d’emploi ([Dafermos et al., 2018](#)). Les ménages sont principalement exposés au risque de destruction de patrimoine, entraînant une diminution de leurs revenus et de leurs niveaux de consommation ([Karim and Noy, 2016](#)). De plus, ces pertes peuvent se propager au niveau des banques *via* une augmentation des prêts non-performants,

notamment si les actifs détruits sont utilisés comme collatéraux (Batten et al., 2016). La stabilité financière des banques peut donc être menacée (Landon-Lane et al., 2011; Lamperti et al., 2019); ces dernières peuvent réagir en réduisant leur offre de crédits (Berg and Schrader, 2012; Brei et al., 2019), exacerbant alors les conséquences macroéconomiques initiales de la catastrophe. Notons toutefois que les banques des pays développés et en développement peuvent réagir différemment. Par exemple, certains travaux identifient qu’après une catastrophe naturelle de grande ampleur aux États-Unis, les banques ne réduisent pas leur offre de crédit, mais se couvrent contre la montée des risques en titrisant ces « nouveaux » prêts (Chavaz, 2016; Schüwer et al., 2019). En outre, une catastrophe naturelle est susceptible de modifier les préférences de liquidité des investisseurs, conduisant à une restructuration de leurs portefeuilles financiers avec une baisse de la détention d’obligations d’entreprises et une hausse d’achats souverains (Dafermos et al., 2018). La littérature identifie également qu’une catastrophe naturelle conduit à un effet négatif à court terme sur les prix, les rendements et la volatilité des actions (Shelor et al., 1990; Carpentier and Suret, 2015; Bourdeau-Brien and Kryzanowski, 2017, pour n’en citer que quelques-uns).

Au niveau national, les gouvernements peuvent être confrontés à une augmentation de leur niveau d’endettement en raison d’une hausse des dépenses publiques couplée à une baisse des recettes fiscales (Ouattara and Strobl, 2013; Klomp, 2017). Ce gonflement de la dette peut menacer la viabilité de l’émetteur souverain, entraînant potentiellement d’importantes sorties de capitaux et davantage de contraintes de liquidité *via* la hausse des taux d’intérêt obligataires (Klomp, 2015). Ce phénomène est essentiellement observable pour les économies en développement (Klomp, 2015; Kling et al., 2018, 2021). Pour autant, la viabilité de la dette dépend également des réactions des banques centrales à ces catastrophes. La banque centrale d’un pays peut réduire son taux d’intérêt pour soutenir le niveau de la production, mais en cas de fortes pressions inflationnistes, elle peut aussi y répondre en augmentant son taux d’intérêt (Klomp, 2017). Klomp (2020) souligne que la réponse monétaire d’une banque centrale aux chocs de catastrophes naturelles dépend de sa liberté d’action face à son mandat. Dans le cas où la banque centrale a un mandat strict tel que le maintien d’un taux de change fixe, elle sera plus susceptible de répondre en augmentant son taux d’intérêt. À l’inverse, une banque centrale disposant d’une plus grande liberté d’action sera plus susceptible de soutenir la croissance et l’emploi en abaissant le taux d’intérêt. L’auteur souligne que le second effet semble l’emporter sur le premier. Concernant l’inflation, les effets sont ambigus. Parker (2018) met en évidence une augmentation de l’inflation pour les pays en développement, alors que l’impact sur les pays développés est négligeable. L’auteur pointe également une hétérogénéité selon les désastres ou les

sous-indices de prix. Par exemple, l'inflation des prix alimentaires est significativement positive, tandis que l'inflation des prix immobiliers est négative. Enfin, la littérature identifie un impact négatif des catastrophes naturelles sur le niveau de croissance. Klomp et Valckx (2014) conduisent une méta-régression et identifient ce résultat tout en soulignant que les effets divergent selon la catastrophe, la période d'étude ou le pays.

0.2.3 Chapitre 3 : « Large-scale natural disasters & credit market risks »

Comme indiqué précédemment, des catastrophes naturelles de forte intensité peuvent entraîner des pertes importantes pour le système financier, notamment en cas d'absence de couverture assurantielle.

Bien que ce déficit de protection soit plus prononcé pour les pays en développement, les pays développés ne sont pas exempts de risques ; ces derniers ayant des systèmes financiers significativement développés et interconnectés. Par exemple, le « Small Business Credit Survey » (2017) mené par plusieurs banques fédérales américaines, montre que les catastrophes naturelles survenues sur le territoire américain en 2017, comme les ouragans Harvey et Irma, ont induit des pertes pour 40 % des petites à moyennes entreprises situées dans les zones sinistrées. Parmi les entreprises touchées, 61 % ont subi des pertes allant de 1 à 25 000 dollars, et 35 % ont subi des pertes supérieures à 25 000 dollars. En outre, 27 % des entreprises affectées n'avaient aucune couverture assurantielle, et seulement 17 % étaient couvertes en cas de cessation d'activité (c'est la source de perte la plus importante pour les entreprises après une catastrophe).

Ainsi, nous proposons une analyse dynamique des chocs de catastrophes naturelles sur les « spreads » de crédit des entreprises et des ménages aux États-Unis. Nous poussons cette analyse en analysant la réponse des investisseurs institutionnels à ces chocs. Enfin, nous mettons en lumière différents mécanismes de transmission, selon que la catastrophe naturelle est de « court » ou de « long » terme. Ces trois points sont nos principaux apports à la littérature.

Plus spécifiquement, nous retenons les catastrophes naturelles de grande ampleur aux États-Unis, sur la période allant de 1990 à 2019, avec une fréquence mensuelle. À l'aide d'un modèle VAR, nous réalisons une analyse de réponse impulsionnelle (IRF) et nos principaux résultats sont les suivants. Nous constatons que les catastrophes naturelles augmentent les « spreads » de crédit des ménages et des entreprises américaines avec des effets persistants dans le temps. Nous montrons également qu'à la suite d'une catastrophe naturelle, le risque de défaut des entreprises augmente, induisant une plus grande aversion au risque des investisseurs institutionnels, conduisant alors au resserrement des conditions d'octroi de crédits.

Sur ce dernier point, nous constatons que seules les catastrophes de longue durée, telles que les sécheresses ou les inondations, induisent un resserrement de crédit, et non les événements de courte durée comme les ouragans ou les tempêtes. Pour autant, les deux catégories de catastrophes induisent une augmentation des défauts attendus des entreprises. Nous pouvons expliquer ce phénomène *via* la différence de couverture médiatique et, donc, des pressions gouvernementales à octroyer des crédits aux agents endommagés. Par exemple, nous pouvons supposer que les ouragans sont des événements plus médiatisés que les sécheresses, induisant de fortes pressions gouvernementales auprès des investisseurs à soutenir par le crédit les zones sinistrées.

Dans l'ensemble, nos résultats soulignent que les catastrophes naturelles aux États-Unis ont des effets ne s'arrêtant pas aux frontières des zones impactées, générant aussi un impact au niveau fédéral. Ces effets risquent de s'aggraver à mesure que la température mondiale croît, pouvant alors profondément déstabiliser le système financier dans son ensemble.

1 | Green Energy Indices & Financial Markets :

An In-Depth Look[†]

Abstract

This chapter builds a new database on green energy stock indices, over the 2006-2020 period. We show that green energy indices follow different patterns than benchmark stock indices. Moreover, only a few firms simultaneously compose the green and benchmark indices. This could be an indication that the current leading financial indices might not be structured to finance a low-emissions economy.

Keywords : Financial markets, Green energy indices.

JEL codes : G15, Q42.

[†]. This chapter has been published as [Nobletz, C. \(2022\), "Green energy indices and financial markets: An in-depth look", International Economics 171, 80-109.](#)

Introduction

Scientific researchers are unanimous : it is urgent to curb climate change to minimize its effects on the ecosystem and humankind. The rising temperatures, precipitation, increasing ocean acidification, and melting ice caps have profoundly disrupted the earth and marine environments. Humans are affected ; global warming threatens food security, risks aggravating health problems, or generating severe migratory movements. Climate change also undermines economic activities with a negative impact on growth, agricultural production, or labor productivity (Dell et al., 2014). In response to the climate emergency, 196 Parties adopted the Paris Agreement in 2015 and committed to limiting global warming below two degrees above pre-industrial levels. At COP 26 in Glasgow in 2021, countries pledged to keep their efforts not to exceed the 1.5°C threshold (UNFCCC). Several mitigation pathways are achievable to meet these commitments, but all require substantial reductions in greenhouse gas emissions (IEA, 2021). For example, with an equivalent carbon footprint, global temperature is expected to exceed 1.5°C by 2030 and 2.6°C by 2100. If humanity does not want to cross the 1.5°C line, countries must achieve zero net carbon emissions by 2050 (IEA, 2021).

Given these issues, it is essential to rethink the functioning of the energy sector, responsible for three-quarters of the emissions causing global warming of over 1.1°C (IPCC, 2021). The IEA (2021) proposes three main lines of action : (i) considerably develop green electricity, (ii) increase energy efficiency, and (iii) invest massively in green innovations. Indeed, living in a world below 1.5°C would require annual investments in the green energy sectors of \$4 trillion by 2030 (IEA, 2021). Several financial instruments can finance green projects, including issuing grants, equities, bonds, or credits. However, these products lack readability, especially the green equity market, as there is high heterogeneity in Sustainable and Responsible Investment (SRI) strategies.¹ For example, some indices (or mutual funds) follow a *best-in-class* approach, selecting the *best* companies in all sectors. Conversely, other indices follow an *exclusion* strategy, excluding companies that do not meet minimum social and environmental criteria from the investment universe. Green indices can also focus on specific environmental sectors such as wind or solar, thus entering the *sustainability-themed* process (Eurosif, 2018).² The metric in green asset selection can vary as some follow quantitative or qualitative criteria. Therefore, the definition of a green company is

1. SRI is "a long-term oriented investment approach that integrates ESG [Environmental, Social, and Governance] factors in the research, analysis, and selection process of securities within an investment portfolio. [...]"(Eurosif, 2018, p.18).

2. There are other SRI strategies ; we present them in Section 1.2.1.

not consensual and also differs depending on the country and regulations (Inderst et al., 2012).

Consequently, it appears necessary to increase the readability of green energy indices. The paper's contribution is to assume this cost by (i) proposing a selection method for green indices, (ii) providing a new database with the constituents of the green indices selected over time, and thus (iii) enabling to highlight features of green indices relative to a financial benchmark.

First, we select the *best* green indices on the following criteria : (i) the index transparency, (ii) the index constituents' availability over time, and (iii) an *exclusion* process as an SRI strategy – we select this method rather than the *best-in-class* process because the latter selects the *best* companies for each economic sector and therefore includes the most polluting ones like energy or industry. Hence, we build a new database listing all companies in the green indices selected – the NEX and the ECO. Our contribution through this database building is to improve our understanding of the green energy market dynamics. Indeed, a better knowledge of this market might be necessary to develop and invest massively in these activities. Specifically, our database answers the following questions : Which companies are leaders in the green energy sector ? Which countries or geographical areas are the most involved ? Which environmental sectors are the most developed ? And how have all these trends evolved ? The provision of this database required significant data processing. First, we scraped the quarterly index reports to extract the company names and any available information on the latter, such as geographic location, environmental sector, or company weight. As this information is not homogeneous between the reports (and not always available), we matched and harmonized this data to construct the series for each year.

Second, we compare the constituents of a benchmark index, the S&P Global 1200, with the worldwide green index, the NEX. The constitution of the green index is much more volatile than the financial benchmark, highlighting the youthful nature of environmental markets. Green companies are more likely to bankrupt, merge, or fail to meet the index's capitalization requirements from year to year. We also show that few firms jointly compose the two indices over time. This result is ambiguous as, on the one hand, it highlights that the selected index excludes many potentially polluting firms, but on the other hand, it emphasizes the low representation of green firms in the benchmark.

Therefore, this study allows investors to assess the green indices with a benchmark better and, consequently, optimize their investment behavior. It also launches a new call to public authorities to restructure the benchmarks, whose current construction leads to an overweighting of high-carbon-emitting companies.

Finally, the NEX and ECO time components database might open doors for further academic studies. We run an application by studying the interconnection between green energy and sectoral economic indices. Indeed, since few firms jointly compose the NEX and the S&P Global 1200, we can perform spillover analyses without risking creating dependence between variables artificially. This application succinctly explains the considerations and main results obtained in [Nobletz \(2021\)](#). Using this database, one could also in-depth analyze the relationship between green energy and fossil energy sectors – we find no joint companies between both indices. This issue is appealing as there is no consensus in the literature; there appears to be a weak substitution effect between green and fossil energy markets ([Henriques and Sadorsky, 2008](#)). However, some authors identify a positive relationship ([Kumar et al., 2012](#); [Managi and Okimoto, 2013](#)), while others do not ([Ferrer et al., 2018](#)).

The chapter is organized as follows. Section 1.1 describes green energy investment trends. Sections 1.2 and 1.3 present the green energy and the benchmark index selected. Section 1.4 outlines the main results by comparing the green and sectoral indices' components. Section 1.5 provides an application of the database, and Section 1.6 concludes the chapter.

1.1 Green investment trends

Green financial assets belong to the green investment family, namely investments in productive sectors that improve the economic system’s environmental sustainability (Campiglio, 2016). Therefore, it is challenging to be aware of green stock characteristics without considering the trends in green energy investments. For example, how are green energy investments evolving? Are green assets playing a key role in financing green projects? Or, who are the dominant leaders? We answer these questions by providing a descriptive analysis in this section.

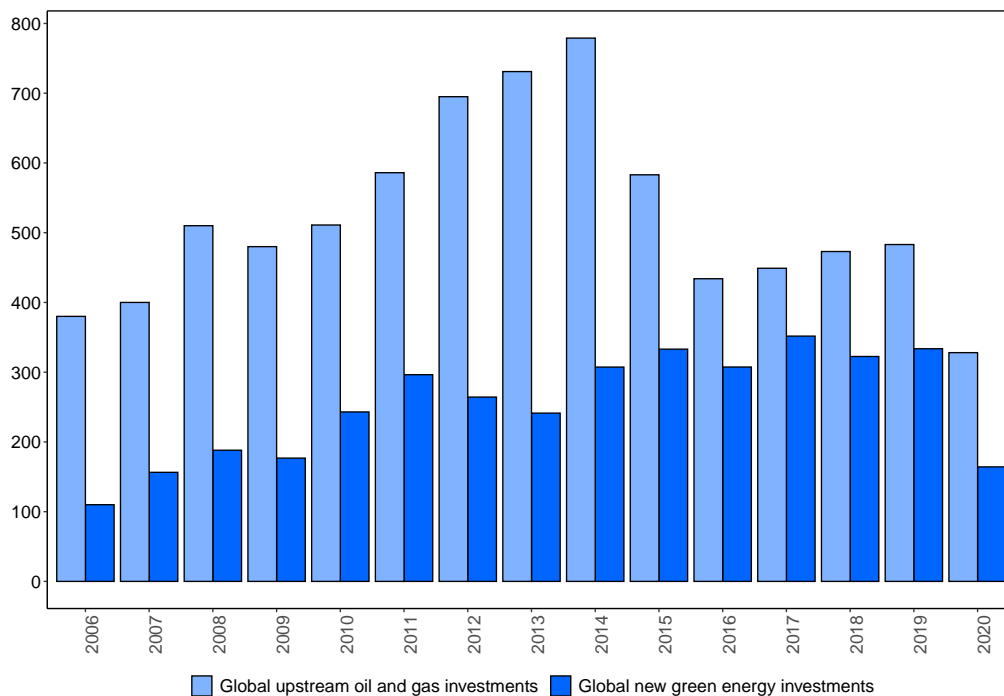


Figure 1.1 – Investments in global green energy and upstream oil and gas sectors (\$bn)

Source : Blue – IEA (2016, 2020) ; Dark blue – BloombergNEF (2020)

As highlighted in Figure 1.1, fossil fuels investments have remained higher than green energy investments over time. Nevertheless, since 2014, oil and gas investments have decreased, notably due to the fall of oil prices while, on the contrary, the green energy investments worldwide have continued to grow. This rise of green investments sends positive signals, but we need more to move toward low-carbon economies.

Besides, looking at the pandemic period, both investments in green and fossil sectors have fallen sharply ;

–32.09% for fossil energy and –51% for green energy sectors, between 2019 and 2020. Indeed, oil demand decreased to almost a standstill during the Great Lockdown, and producers faced barrel storage capacity problems. This phenomenon created a panic in the WTI (West Texas Intermediate Crude Oil) futures market, causing oil prices to fall into negative territory, from \$18 to \$–37 a barrel (Mignon, 2020b). For green companies, the investments’ fall has even been more pronounced as they mainly bear their project execution risks by financing them through internal balance sheets, loans, or equity. This way of financing is represented in Figure 1.2 by the asset finance category and shows, for instance, that in Q2 2020, new investments in asset finance (excluding large hydro) amount to \$52 billion against \$13 billion in small scale solar, \$1 billion in public markets, and \$1 billion in venture capital and private stock (VC&PE).³

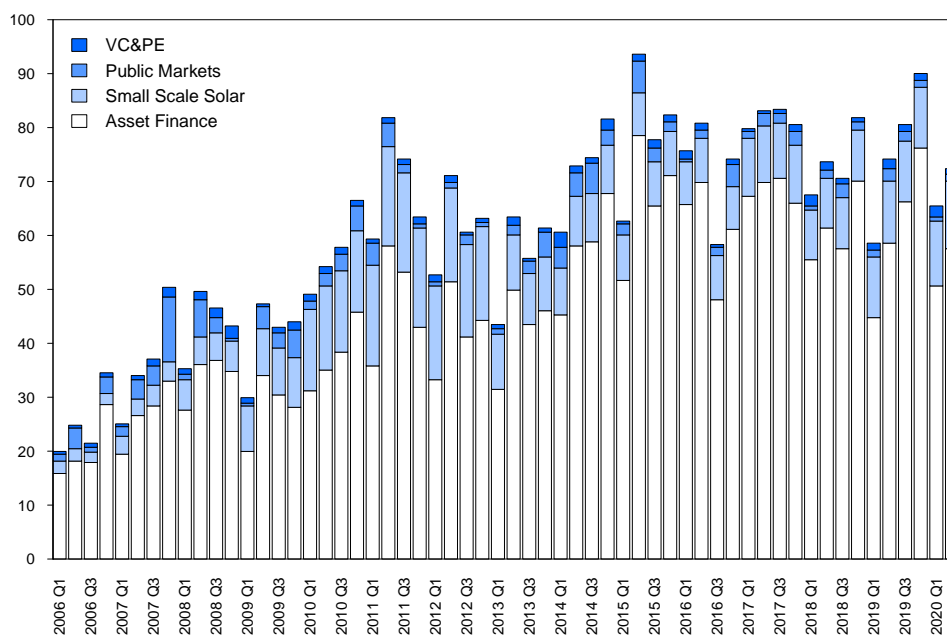


Figure 1.2 – New global green energy investments by asset class (\$bn)

Source : BloombergNEF (2020).

Note : For asset class definitions, see BloombergNEF (2020)’s report.

Hence, in regular times, government incentives with feed-in tariffs, tax incentives, or green certificates secure green projects’ revenues by improving future cash flows’ predictability and thus, encouraging lenders

3. For exact definitions of asset classes, we refer readers to the following reports : BloombergNEF (2020), and Frankfurt School-UNEP Centre (2020).

like banks or shareholders to provide debts ([Frankfurt School-UNEP Centre, 2020](#)). However, green companies' performance is uncertain in times of crisis, even if government incentives are maintained. Investors are inclined to pull their investments out of green assets that are considered risky and move into safer investments such as sovereign bonds or gold. This phenomenon is the *fly to liquidity effect* ([Longstaff, 2004](#)). Lastly, from an ethical view, investors are more prone to finance the environmental transition in periods of expansion, whereas financial concerns prevail in times of crisis.

These phenomena shed light on why the decline in new green energy investments has been so sharp and has affected all geographic areas (Figure 1.3). These investment declines have been severe in the United States (-60.36%) and China (-52.58%), while in Europe, the decrease has been more moderate (-33.66%) (Figure 1.4). Europe even saw a rebound in green energy investments in Q2 2020, led by offshore wind projects. Indeed, four of the top asset finance deals were European in 2020, with the Netherlands and the UK in first and second place, followed by France in fourth and fifth place ([BloombergNEF, 2020](#)).⁴

Over time, the leaders of green energy investments have been APAC (Asia Pacific Region), EMEA (Europe Middle East and Africa region), and AMER (North Central and South America regions) with China, Europe, and the United States, respectively ([BloombergNEF, 2020](#)). Nevertheless, the top position has shifted several times between these three markets (Figure 1.4). Europe was the dominant player until 2013, dethroned by China. Indeed, in 2011, Europe's green investments decreased due to a slowdown in the solar boom for Germany and Italy, while at the same time, China increased its investments in solar PV (photovoltaic) and wind ([Frankfurt School-UNEP Centre, 2020](#)). Since then, China has remained the leader in green energy investments but witnessed a drop in its investments in 2016 due to the financial crisis. China's dominant position can be explained notably by its internal energy independence policy ([Zou et al., 2020](#)). In addition, United States' green investment had moved closer to European investments and rebounded in 2019 as "developers rushed to qualify for tax credits before they expire" ([Frankfurt School-UNEP Centre, 2020](#), p.22).

4. First, the *Vattenfall Hollandse Zuid Offshore Wind Portfolio* with \$3,850 million. Second, the *SSE Seagreen Offshore Wind Portfolio Phase I* with \$3,839 million. Third, the *CIP Changhua Zone Changfang Xidao Offshore Wind Portfolio* with \$3,632 million. Fourth, the *EDF and Enbridge Fecamp Offshore Wind Farm* with \$2,713 million. Fifth, the *Iberdrola St Brieuc Offshore Wind Farm* with \$2,664 million ([BloombergNEF, 2020](#)).

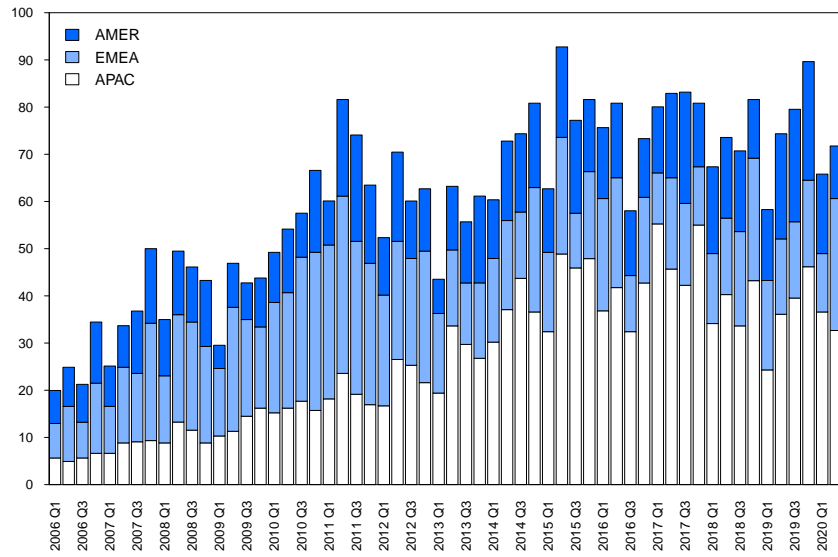


Figure 1.3 – By geographical zones

Source : BloombergNEF (2020).

Note : APAC, Asia-Pacific region, EMEA, Europe Middle East and Africa region, and AMER, North Central and South-America region.

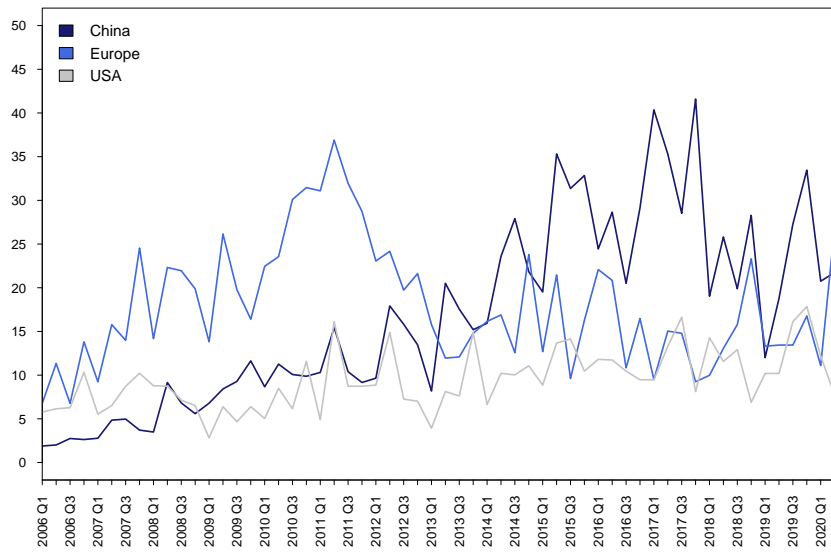


Figure 1.4 – By country

Source : BloombergNEF (2020).

Finally, the leaders in the environmental sectors have been solar and wind over time (Figure 1.5), reflecting the declining cost of electricity generation for these energies since 2010 (Figure 1.6; all costs are in real terms, adjusted to 2020\$).

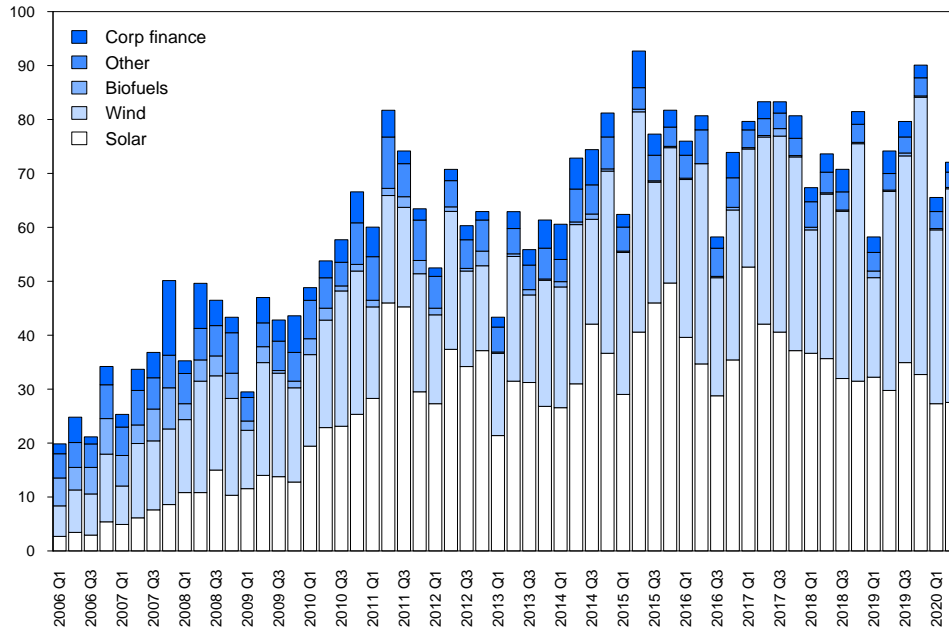


Figure 1.5 – Global new green energy investments by sectors (\$bn)

Source : BloombergNEF (2020).

From Figure 1.6, the decline in electricity costs has been substantial for the solar sectors; for concentrating solar power, the Levelized Cost Of Electricity (LCOE) declined from \$0.34/kWh in 2010 to 0.11/kWh in 2020. Similarly, the solar PV electricity cost decreased from \$0.38/kWh in 2010 to \$0.06/kWh in 2020. We also noticed the reduction in LCOE values for offshore wind, but those were more moderate than those for solar; we went from \$0.16/kWh in 2010 to \$0.08/kWh in 2020. In contrast, the cost of electricity for onshore wind remained almost stable, with already very low costs; we went from \$0.09/kWh in 2010 to \$0.04/kWh in 2020.

The declines in electricity costs for green energy might reflect, on average, lower total installed costs and technology improvements. The decline in solar PV is primarily due to the lower total installed costs, while the drop in LCOE for concentrating solar power is also due to higher capacity factors, lower capital costs, and reduced costs for operation and maintenance. In the wind sector, onshore wind has a lower LCOE

due to the reduced total installed costs, lower average turbine prices, and technological improvements. These technological improvements also lead to lower costs for offshore wind electricity, like larger turbines or longer blades (IRENA, 2021). Consequently, in 2019, two-thirds of the world’s population lived in a country where solar and wind electricity was the cheapest source (Frankfurt School-UNEP Centre, 2020). However, the economic recovery from the Covid lockdowns is challenging today’s economic system with rising prices for natural gas, coal, and electricity markets (IEA, 2021).

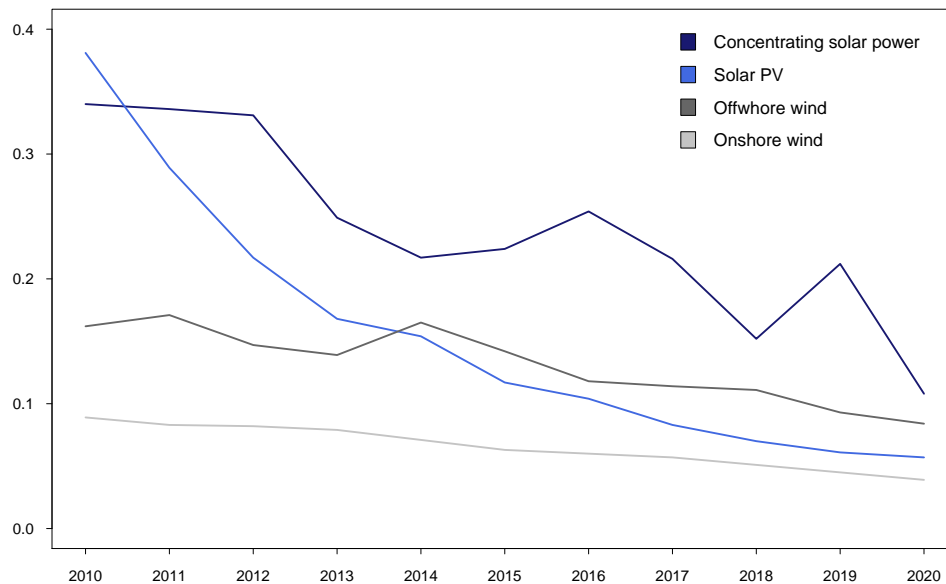


Figure 1.6 – Levelised cost of electricity (LCOE) for green energies (2020 \$/kWh)

Source : IRENA (2021).

Note : The data are for the year of commissioning. The data represent the global weighted average LCOE value derived from individual plants commissioned each year. For more information on LCOE measurement, we refer readers to the IRENA (2021, Annex I, p.164)’s report.

In sum, green investments have increased over time. Companies’ funding of green projects is mainly self-financed through loans or equities. Several macroprudential policies can be put in place to support green lending, such as a *brown-penalizing factor* requiring banks to hold more capital for carbon-intensive assets or a differentiated reserve requirement adjusting to green lending and accounting for country-specific characteristics, e.g., developing or developed countries (D’Orazio and Popoyan, 2019). This issue is gaining momentum in the literature, while there has been limited coverage on green stocks. As noted in the introduction, encouraging investors to invest in green companies through mutual funds or ETFs

(Exchange Traded Fund) that replicate green indices calls for more transparency. This section illustrates that a suitable green index must follow green investment trends, as both are closely related. Therefore, in the next section, we present the criteria for picking the green benchmark.

1.2 The green energy index

Selecting a green financial index is not simple as the definition of a green asset is plural, and SRI (Sustainable and Responsible Investment) strategies are heterogeneous. First, we review the different SRI strategies and explain why we choose the *exclusion* approach. Second, we outline the other criteria that led us to select the *WilderHill New Energy Global Innovation Index* (NEX) as the green benchmark. Finally, we perform a descriptive analysis of this green energy stock index.

1.2.1 Sustainable and Responsible Investment (SRI) strategies

Green financial products are heterogeneous in their SRI strategies. The main and opposite methods of selecting companies for a portfolio confront the *positive* and *negative* screening process with the *best-in-class* and *exclusion* methods, respectively. The *best-in-class* strategy involves selecting companies with the *best* ESG scores across all sectors.⁵ In contrast, the *exclusion* approach is the oldest strategy and consists of excluding companies that do not meet minimum social and environmental criteria, such as tobacco, alcohol, or nuclear energy. In addition, *thematic investing* portfolios target specific environmental sectors, and *engagement and voting* strategies use shareholder rights to push companies to integrate ESG criteria better. Finally, *impact investing* strategies involve investing in primarily unquoted companies seeking strong social and environmental impacts (Eurosif, 2018).

First, we decide to exclude indices based on ESG criteria, as we focus on financial indices funding green projects, and it is difficult to identify the share of environmental, social, or governance practices, respectively (Inderst et al., 2012). Hence, we exclude *engagement and voting* strategies and the *best-in-class* approach; the latter by definition includes all sectors and potentially polluting sectors with energy, industry, or materials. As Eurosif (2018) points out, some portfolios "may not differ significantly from non-SRI portfolios" (Eurosif, 2018, p.17). Second, we exclude the *impact investing* strategy, as we focus on listed companies, and the *thematic investing* strategy, as we want an index representing all environmental sectors

5. Environmental, Social and Governance (ESG) criteria belong to Socially Responsible Investing (SR) and constitute the main pillars of extra-financial analysis (Novethic).

to analyze their index weights over time. Finally, based on all these arguments, the *best* SRI strategy for this issue is the *exclusion* one, in particular, as this investment strategy is the closest to the definition of a *green activity*. Even if this definition is not consensual in the literature, activities related to renewable energy, energy efficiency, and wastewater management are commonly considered *green* (Inderst et al., 2012).

1.2.2 Which green energy index ?

We select green indices that meet the following criteria. As stated above, the green index must provide a comprehensive representation of environmental sectors and follow an *exclusion* approach. It must apply an equal weighting method to avoid companies topping the index. The index company lists must be available for each year. In this way, we can delve deeper into the characteristics of green indices and verify that they correctly track the green investment trends identified in Section 1.1.

Two green energy indices meet these criteria : the WilderHill Green Energy Index (ECO) and the WilderHill New Energy Global Innovation Index (NEX), focusing on the United States and the world market, respectively.⁶ We pick the NEX as the benchmark green index, as we prefer to focus on a global level before drilling down to a finer level. Therefore, we make an exhaustive presentation of the NEX only, but for the sake of completeness, we provide the ECO index constituents in the appendix (Table 1.A.3).

The NEX includes companies that focus on innovative clean energy, conservation, efficiency, and advanced renewable energy technologies. It is calculated by Solactive using a *modified equal-weighted* methodology, is quarterly restructured, and no single stock can exceed 5% of the total weight.

The eligibility criteria are as follows : (i) at least half of the companies are listed outside the United States stock market, (ii) a minimum of 10% of the companies' market value must be related to their green activities, and this index favors *pure play* – 50% of companies' market value comes from green activities, (iii) small and medium-sized companies can play a leading role in the index, while larger companies make up the index if they have a growing activity in green sectors or if they are a benchmark, and (iv) the conglomerates' number is limited to 20% of the index composition. Besides, the selection process imposes that companies have to be listed on a national stock exchange or primary market. They must have a three-month average market capitalization of at least \$100 million and a high volume of transactions.

6. The S&P Global Green Energy Index has not been selected due to availability issues regarding its components (only its ETF components are available).

Finally, several subsectors compose the index : Energy Conversion, Energy Efficiency, Power Storage, Renewables – Biofuels and Biomass, Renewable – Other, Renewable Solar, and Renewable – Wind (NEX, 2020).⁷

1.2.3 The NEX

One of the goals is to provide better readability of the green energy indices ; thus, we build a database listing all the companies in the NEX over time. The adding value of this database is to apprehend green energy characteristics, answering the following questions : Which green energy firms lead the market ? Which countries or regions are frontrunners ? Or which green energy sectors are the most developed ? Improving our understanding of the green energy market might be necessary if we want to redirect finance toward a less carbon-intensive economy.

Thus, we retrieve the NEX composition each quarter from 2006, when it was launched, to 2020. The reports with the NEX constituents are available on the [index website](#) and provide notably the company list. However, as it stands, these reports are not usable for temporal analysis. Indeed, depending on the quarterly report, the spelling of the companies differs, and the weights, localizations, or environmental sectors associated with each company are not always available. Therefore, we scrape each quarterly report and extract company names with all available additional data. Then, by matching and harmonizing all this information, we reconstruct a list of companies making up the index with their weights, geographic localization, and environmental sectors for each year. Note that there might be variations in the NEX composition between quarters ; thus, we take the first quarter of each year as the baseline.⁸

First, Table 1.A.2 shows the list of companies making up the NEX between 2006 and 2020. The index has 95 firms, on average. While the company numbers have increased over time, illustrating the growth in green investment, we dropped from 109 to 91 companies during the pandemic, reflecting the contraction in global demand. In addition, 309 companies made up the index over the entire period, highlighting the high volatility of company outflows and inflows. Environmental companies are young, and therefore more likely to merge, go bankrupt, or fail to achieve sufficient capitalization from one year to the next.

Second, Tables 1.A.4 and 1.A.5 are the index's geographical distribution, i.e., the percentage of companies making up the index according to their country or geographical area.⁹ On average, the top three countries

7. We provide the definitions of environmental sectors in Table 1.A.1 in the appendix.

8. For the years 2006 and 2007, the benchmark is the fourth quarter due to the still young nature of the index.

9. [U.N. standards](#) determine the country's assimilation to a geographical area.

in the index are the United States, Germany, and Japan – 32.40%, 8.44%, and 6.74%, respectively. China appears in fourth place, followed by Hong Kong – 6.43% and 5.26%, respectively. However, what is interesting is how the countries' representation evolves; does the index follow green investment trends, or is it biased towards specific regions? Over time, the leading roles of the United States and Germany have declined, while the leadership of Asian companies has grown, including China, Hong Kong, Taiwan, and South Korea. Indeed, U.S. companies accounted for 43.21% of the index' companies in 2006, compared to 24.18% in 2020. In contrast, Chinese companies represented 2.27% of the index' companies in 2007 and reached 10.99% in 2020. At last, European countries' position, driven by Northern European companies, has risen in the index. Overall, the NEX's geographical composition is in line with the green energy markets' development, including the growing role of Asian companies.

Third, Table 1.A.6 shows the NEX's environmental sector breakdown (see Table 1.A.1 for the environmental sector definitions).¹⁰ The energy efficiency, wind, and solar sectors made up the bulk of the index, with 27.23%, 23.73%, and 23.34% of the firms, respectively. On the contrary, energy conversion and storage companies play a minor role, with 1.82% and 5.33%, respectively. Biofuels sectors account for 10% of the firms, but this share has declined over time, from 14.26% in 2008 to 8.80% in 2020. This result highlights the changing consensus for these energies; the biofuels' impacts on greenhouse gas emissions are not consensual, depending on the feedstock or farming practices. The net outcome can be unfavorable due to deforestation, overexploitation of land and water resources, or biodiversity destruction. The growing demand for biofuels has also contributed to rising food prices, threatening the food security of the poorest (FAO, 2008). Moreover, we note a recent rise in energy conversion companies; we went from 1.40% in Q2 2019 to 5.70% in Q2 2020. This increase is driven mainly by companies investing in fuel cells and green hydrogen businesses. At last, wind and solar companies have also increased over time, emphasizing the recent green investment trends.

Finally, as Table 1.A.7 points out, the companies' weight is, on average, about 1% in the index, with a minimum of 0.25% and a maximum of 2%. The risk of some companies topping the index is minimal.

In sum, we select the *WilderHil New Energy Global Innovation Index* (NEX) as the global green benchmark. The NEX constituents highlight that : (i) green energy indices are highly volatile, (ii) green energy markets' changes are well tracked, and (iii) there is a minimal risk that some companies drive the

10. Before 2008, sector names were different. For further details, see : <https://nexindex.com/>

index.

1.3 The financial benchmark

Regarding the green index selected, we pick a financial benchmark that provides a global and sectoral representation of the world stock market. Indeed, we want to compare the constituents of the green energy and benchmark indices to better apprehend the green markets' specificity. Are the benchmark components as volatile over time as NEX ? Are there similar companies between these indices ? If so, in which economic sectors are they located ?

1.3.1 Which sectoral stock indices ?

Selecting sectoral equity indices requires choosing an Industry Classification System (ICS). The two main industrial classifications are the following. The *production-oriented* classification sorts companies by firms' activities in identifying similar production processes. The best known is the NAICS (North American Industry Classification System, 1997), reflecting North American economic activity. In contrast, the *market-oriented* classification selects firms meeting similar demands and operating in the same markets. This classification is followed by the financial community, especially for stock screening, index building, risk management, or sector identification. The best known are the GICS (Global Industry Classification Standard, 1997) and ICB (Industry Classification Benchmark, 2001) (Phillips and Ormsby, 2016, for a survey).

We select the *market-oriented* classification as it provides a more reliable representation of the sectoral concentration (Hrazdil and Zhang, 2012) and performs to explain comovements in stock returns (Bhojraj et al., 2003). Within this family, we select the GICS as more suitable for a global analysis.¹¹ The GICS is produced by Standard & Poor's (S&P) and MSCI. It is the first *market-oriented* classification, is revised annually, and contains four hierarchical classifications – 11 sectors, 24 industry groups, 69 industries, and 158 sub-industries. We focus on the *sectors* because there is a risk of losing key information by going down to a finer level.

Therefore, the subindices selected are the following : S&P Global 1200 Communications Services, Consumer Discretionary, Consumer Staples, Energy, Financials, Health Care, Industrials, Information Techno-

11. The Dow Jones and the FTSE provide the ICB ; the indices are mostly European.

logy, Materials, Real Estate, and Utilities. The S&P Global 1200 is a global index capturing 70% of the world's market capitalization covering seven regions and thirty countries. It is composed of seven sub-indices : S&P 500 (U.S.), S&P Europe 350, S&P TOPIX 150 (Japan), S&P/TSX 60 (Canada), S&P/ASX All Australian 50, S&P Asia 50, and S&P Latin America 40. Each company in the index must meet liquidity requirements, and each region has a corresponding sectoral representation. Moreover, each region's weight corresponds to its relative size in the global stock market based on a *float-adjusted market value* method. The restructuring is quarterly, and the launch date is in 1999 ([S&P Dow Jones Indices](#)).

1.3.2 The S&P Global 1200

We retrieve on Datastream the S&P Global 1200 sectoral indices' compositions from 2006 to 2020 ; we get the companies' names with their introduction year, asset class, exchange market, sector, and sub-sector. We do not have companies' weights in the indices. Besides, before analyzing the S&P Global 1200 compositions, we assess the impact of the 2018 GICS restructuring on this index.¹² The communications services sector, earlier the telecommunications services, includes companies formerly belonging to the consumer discretionary and information technology sectors (MSCI). We notice that 33 companies over 1200 have changed sectors, which is negligible (Table 1.A.8).

First, Table 1.A.9 highlights that the index composition grows over time, 1073 companies in 2006 versus 1219 in 2020, but is much less volatile than the NEX. The S&P Global 1200 is older than the NEX, and companies have greater capitalization and liquidity. Second, Table 1.A.10, representing the country distribution of the S&P Global 1200, emphasizes that the top three countries in the index are the United States, Japan, and the United Kingdom – 41.36%, 12.79%, and 7.70%, on average. Canada and France follow with 4.78% and 4.49%, respectively. Moreover, after Japan, the leading Eastern Asian country is Hong Kong, and China does not have a predominant role in this index. The analysis by geographical areas identifies the same results (Table 1.A.11) : North American companies lead, followed by European companies, and then by Asian firms. These outcomes have not changed over the years. Finally, Table 1.A.12 shows the sectoral economic distribution of the S&P Global 1200 ; the sectors with the highest weight are industry (16.25%), finance (16.16%) and discretionary consumption (12.26%), while the energy, real estate, and communication services are the sectors with the lowest weights – 4.93%, 4.94%, 5.44%, respectively. The S&P Global 1200 composition reflects the heterogeneities among the world's economic

12. We cannot provide the S&P Global 1200 companies' list as we retrieved the data from the paid software Datastream.

sectors.

In summary, we select the S&P Global 1200 as a financial benchmark ; it follows a *market-oriented* classification, has a long history, serves as a reference for investors, and its composition is available over time. We show that the composition of the S&P Global 1200 has increased over time without volatility in its constituents. The leading companies are the U.S., Japan, and U.K. companies, and the prevailing sectors are the industrial and finance sectors.

1.4 The green index vs. the benchmark

This section compares the NEX and the S&P Global 1200 in this first step of asset composition. The objective is to better understand green equities' characteristics and identify eventual similar companies between the two indices. Indeed, the lack of or few similar components might be a first signal that current financial benchmarks are not designed to direct financial flows towards a world of no more than 1.5°C.

1.4.1 Two different dynamics...

First, the S&P Global 1200 is less volatile in its index constitution than the NEX. Indeed, the S&P Global 1200 includes the world's leading companies ; these firms are more capitalized and liquid than those in the environmental sector. This result is consistent with the youthful nature of the environmental markets, as companies are more likely to go bankrupt, merge, or encounter capitalization issues from one year to the next.

Second, the geographic distribution between the financial and green benchmarks does not follow the same pattern. For instance, China has played an increasing role in the green energy markets while not in the benchmark. In contrast, the U.S. has dominated the global stock market, while its position has declined in the NEX – in absolute terms, U.S. companies outnumber Chinese companies.

The rise of the Chinese leading position in green energy markets could highlight its internal energy independence policy, even if it stays a prevailing consumer of fossil energies (oil, natural gas, and coal). For instance, in 2020, the share of worldwide consumption in oil, natural gas, and coal was around 15.7%, 8.6%, and 54.3%, respectively (BP, 2021).¹³ For its part, the North American region, notably the United

13. China leads in coal production ; in 2020, it produced 50.7% of global coal production (BP, 2021).

States, is a dominant leader in fossil fuel production, following the Middle East. In 2020, the U.S. world oil, natural gas, and coal productions were 18.6%, 23.7%, and 6.7%, respectively (BP, 2021). The United States has had an ambivalent stance on climate agreements : recall that during the presidency of Donald Trump, the United States withdrew from the Paris Agreement designated as job-destroying (announced on November 4, 2019, and effective on November 4, 2020). The new presidency with President Joe Biden has reversed that decision by depositing the instrument of the Paris Agreement acceptance on his first day in office, January 20, 2021 (UNTC).

Finally, regarding the sectoral concentration, the dominant sectors in the S&P Global 1200 are the industrial and financial sectors, while the energy sector plays a minor role. Therefore, in the following section, we regard the overlapping firms between the green and the benchmark index, wondering if there are many similar companies and, if yes, in which economic sectors they are related.

1.4.2 ...and few overlapping companies

Table 1.1 displays all similar components between the NEX and the S&P Global 1200 : we consider a group and its subsidiaries as identical, e.g., *brookfield renewable energy* and *brookfield asset man*. If a company is in both indices, we report its economic sector, entry and exit dates, and its weight in the NEX – such data are not available for the S&P Global 1200.

Twenty-two companies are in both the NEX and the S&P Global 1200. In ascending order, six are in utilities, five in industrials, four in materials, two in consumer discretionary and financials, and one in consumer staples, health care, and information technology. These 22 companies made up the S&P Global 1200 each year, but 22 out of roughly 1200 remains a modest share. Moreover, in the NEX, the period during these 22 companies have composed the index is volatile and weak. For example, ten of these companies have been in the index for less than two years, and only three each year : *Kingspan Group*, *Novozymes*, and *Vesta's wind systems*. The latter companies have a moderate weight, with 1.46%, 1.39%, and 1.73%, respectively (average over all years).

The interpretation of this result is twofold : first, since there are few overlapping firms in the indices, it implies that the selected green index excludes many potentially polluting firms. Second, it highlights a low representation of large green energy companies in the corresponding benchmark. Benchmarks, such as the S&P Global 1200, are particularly followed by the financial community to assess the performance of other financial indices or asset portfolios (active portfolio management). Alongside, there is an intensive

demand growth for ETF products (passive portfolio management), aimed at replicating the performance of an underlying index. [Stephens et al. \(2018\)](#) point out that key benchmarks are not structured to finance low-emissions economies : benchmark portfolio investments with the S&P 500, MSCI World Index, MSCI Europe, CAC 40, or Barclays Euro Aggregate Corporate follow trajectories toward global warming of about five degrees Celsius. These indices are characterized by high capitalization and liquidity requirements, resulting in a bias towards carbon-intensive companies. The responsibility does not lie with the index management, representing current economic activities and sector concentration with benchmarks.

Company names		Economic sectors	Entry and exit dates		Weight
NEX	S&P Global 1200	S&P Global 1200	S&P	NEX	NEX
aisin seiki	"	consumer discretionary	2006-2020	2006-2007	1.48
archer daniels midland	"	consumer staples	2006-2020	2006	1.52
brookfield renewable energy	brookfield asset man.'a' ltd.vtg.shre.	financials	2006-2020	2012-2013	1.87
credit suisse real estate fund	credit suisse group	financials	2006-2020	2019-2020	0.88
green property	edf	utilities	2006-2020	2007-2011	2.08
edf energies nouvelles	edf	utilities	2006-2020	2006-2015	1.68
fortum oyj	"	utilities	2006-2020	2006-2011	2.34
iberdrola renovables sa	iberdrola	utilities	2006-2020	2006-2011	2.34
johnson controls inc	johnson controls intl.	industrials	2006-2020	2009-2016	1.60
johnson matthey	"	materials	2006-2020	2006	0.91
kingspan group	"	industrials	2006-2020	2007-2020	1.46
marubeni	"	industrials	2006-2020	2006	3.41
novozymes a/s series	novozymes b	materials	2006-2020	2006-2020	1.39
nrg yield inc	nrg energy	utilities	2006-2020	2017-2018	1.65
orsted	"	utilities	2016-2020	2018-2020	1.39
rwe	"	utilities	2006-2020	2006	1.36
samsung sdi co	samsung electronics	information technology	2006-2020	2016/2018-2020	1.29
sekisui chemical ltd	sekisui house	consumer discretionary	2006-2020	2006	0.98
siemens gamesa renewable	siemens	industrials	2006-2020	2018-2020	1.35
signify nv (philips lighting nv)	philips eltn.koninklijke	health care	2006-2020	2017-2020	1.52
sociedad quimica y minera de chile	"	materials	2006-2020	2019-2020	1.34
umicore	"	materials	2006-2020	2006-2009	1.52
vestas wind systems	"	industrials	2006-2020	2006-2020	1.73

Table 1.1 – Companies in both NEX and S&P Global 1200

Sources : Datastream and the WilderHill New Energy Global Innovation Index.

Note : This table shows all companies in both the NEX and the S&P Global 1200 over time – a group and its subsidiaries are considered being similar. The date and weight columns are, respectively, the years in which the companies make up the index and their average weight (in %). The S&P Global 1200 companies' weights are not available.

1.5 Application

Our database with time variations of NEX and ECO components might allow further studies. As an illustration, we use the database to measure the interconnectedness between the green and sectoral equity indices. Indeed, since few firms belong to both indices, it is feasible to measure their interconnection without artificially creating dependence. The application provides an overview of the motivations and results obtained in [Nobletz \(2021\)](#).

1.5.1 Return spillovers between green energy indices and financial markets

Due to the increasing demand for green assets, we wonder about their interconnection with different economic sectors. Are green indices closely interconnected with financial markets? Are they more immune to external financial shocks? Are they net donors or net receivers of shocks? Finally, do they tend to be more interconnected with specific economic sectors, and how explain it? To address these questions, we analyze the returns spillovers between NEX and sectoral stock indices from 2006 to 2020 (daily frequency). Our main contribution to the existing literature is to pay particular attention to the sectoral dimension.

Regarding methodology aspects, we apply the [Diebold and Yilmaz \(2014\)](#) method; we compute the generalized VAR variance decomposition of [Koop et al. \(1996\)](#) and construct spillover indices. Then, to ensure model consistency, we construct confidence intervals for the variance decomposition matrix with a fixed-effect wild bootstrap dealing with conditional heteroscedasticity of the residuals.

The main results are as follows. The green energy index has a significant degree of financial openness, but on average, it receives more shocks than it gives to other economic sectors. In addition, the green energy index is closely interconnected with the materials and industrial sectors. Indeed, the green energy sectors and the material/industrial sectors produce similar outputs, such as turbines for wind energy or photovoltaic panels for solar energy. Finally, green energy's spillover power varies over time and appears to respond to economic and financial uncertainties. For example, its spillover effect has increased during the pandemic, reflecting the *fly to liquidity* mechanism ([Longstaff, 2004](#)). In times of crisis, investors shift from risky assets, such as green energy stocks, to safer products like gold or Treasury bonds.

1.5.2 Empirical data

As noted earlier, we consider the NEX and the S&P Global 1200 Communication Services, Consumer Discretionary, Consumer Staples, Energy, Financials, Health Care, Industrials, Information Technology, Materials, Real Estate, and Utilities. Data comes from Datastream, and the period runs from 2006-03-06 (NEX launch date) to 2020-06-19 daily.

All variables are in first logarithmic difference (Figure 1.A.1) to deal with non-stationarity issues (Table 1.A.13).¹⁴ Moreover, all indices exhibit the usual properties of financial series (Table 1.A.14) : (i) the mean of asset returns are zero, (ii) the skewness of the series is less than zero – with minimums of -1.08 and -0.67 reached by the energy and NEX indices, (iii) the series have skewed distributions spreading to the left – the tails of the distributions are ticker than those of the normal law, implying a higher probability of extreme points, and (iv) the null hypothesis of normality is rejected at the 5% significance level.

Finally, Figure 1.7 provides a graphical representation of the NEX and the S&P Global 1200 sectoral indices (in logarithm). The variables co-move strongly and suffer significant drops during the crisis, e.g., 2008 and 2020. The NEX is more volatile than the S&P Global 1200 sectoral indices, related to the *fly to liquidity* effect (investors have withdrawn their investments in favor of safer products) and the green index volatile constitution (Sections 1.1 and 1.2, respectively). Looking deeper into NEX, its prices were high between 2007 and 2008 ; during this period, global demand was strong, oil prices were high, and government subsidies for environmental sectors were significant. Its prices fell during the global financial crisis, never returning to pre-crisis levels. In 2013, the index prices started to rise again until the pandemic crisis led to a market crash ; this decline seems temporary as NEX prices have returned to their pre-pandemic levels. On this last point, it is still early to estimate the effects of the pandemic on the financial sphere.

14. According to Augmented Dickey-Fuller – ADF (Dickey and Fuller, 1981), Kwiatkowski-Phillips-Schmidt-Shin test – KPSS (Kwiatkowski et al., 1992), and Phillips-Perron – PP (Phillips and Perron, 1988) tests, all series in logarithm are non-stationary at conventional levels. In the first log difference, all tests conclude that all series are stationary at 5%.

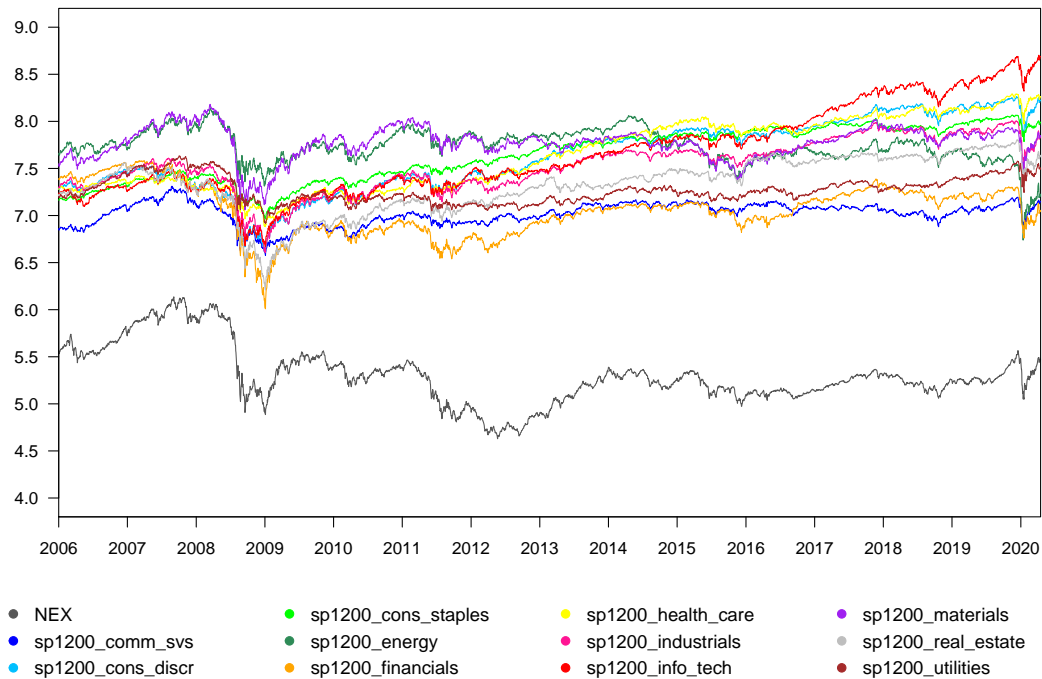


Figure 1.7 – NEX and the S&P Global 1200 sectoral indices (in logarithm)

Source : Datastream.

1.6 Conclusion

Since the 2015 Paris Agreement, the demand for green investments has increased, but they remain insufficient to achieve global warming below 1.5°C above preindustrial levels (IEA, 2021). The lack of transparency around green energy assets is a drag on green project financing. Green energy assets lack readability, although they are a dominant source of financing through mutual funds or indices. This chapter aims to fill this gap by providing a new database to clarify green energy indices and enable future studies.

We select green indices based on specific criteria : index transparency, an *exclusion* approach as an SRI strategy, and the index components' availability over time. After extensive data processing, we provide a database listing all components of the selected indices over time – the NEX and the ECO. Focusing on the worldwide green energy index, the NEX tracks green energy market trends, and its composition

emphasizes the youthful nature of environmental markets : volatility in the inflows and outflows of index companies. We deepen this analysis by selecting a financial benchmark, recovering its constituents over time, and comparing them with the green index components. We find few overlapping companies in the green and financial indices. This result is twofold as it highlights that the index selection methodology excluded many potentially polluting companies. However, it also underscores the low representation of world green energy companies in the benchmarks, providing a current economic representation. One course of action might be to restructure these benchmarks, widely followed by the financial community, to redirect financial flows towards a low-emissions society.

In this regard, we provide an empirical application of the database to understand better the positioning of green indices in financial markets. This application, which synthesizes [Nobletz \(2021\)](#)'s paper on the interconnection between green and sectoral stock indices worldwide, shows notably that green indices are not free of market risks. Besides, further studies through the database might be feasible. For example, since we do not find overlapping companies between the green energy and fossil energy sectors, it would be interesting to analyze the relationship between these two sectors further. This question is all the more relevant as there is no consensus in the literature on this topic. It seems that there is a weak substitution effect between these two sectors ([Henriques and Sadorsky, 2008](#)) ; in other words, an increase in fossil fuel prices has small repercussions on green energy prices (and, respectively). However, some authors find a positive relationship between the two ([Kumar et al., 2012](#); [Managi and Okimoto, 2013](#)), others a negative relationship ([Ferrer et al., 2018](#)), and others a time-varying one ([Inchauspe et al., 2015](#); [Reboredo, 2015](#); [Reboredo et al., 2017](#)).

Appendix 1.A

NEX sectors	Abb	Definitions
Energy Conversion	ECV	"The Energy Conversion sector covers conversion technologies and fuels. Hydrogen & fuel cell technology for example is included, from production and storage of hydrogen, to distribution as well as related technologies. [...] Advanced turbines, and lower-carbon fuel systems may also be covered in this sector, as well as potentially whole systems such as alternative fuel vehicles allowing renewables to power new greener transportation."
Energy Efficiency	EEF	"Companies in this sector are working to deliver step-change improvements in efficiency of existing generation and distribution systems. Important technologies include software to improve electricity demand management or reduce grid losses, as well as breakthroughs in motor or generator design. This sector could also include technologies for combined heat and power (i.e. those which enable the capture and use of waste heat from power generation). [...] We may include in this sector technologies that reduce use of energy in homes, retail and commercial buildings. These may include building components that reduce energy use, intelligent systems for managing power consumption and technologies that more efficiently use power. Note : Nuclear power is not considered green energy for purpose of this Index, and it is thus Excluded (very minor tangential involvement will not disqualify a company)."
Energy Storage	ENS	"We include here too newly emerging storage technologies, and also extant mechanical technologies like flywheels and components like ultra-capacitors, which are potentially complimentary with batteries. Systems built around large-scale storage such as EVs (Electric Vehicles) like electric cars, electric buses and trucks, electric ships, trains and planes etc. might potentially be included here as well."
Renewables, Biofuels, and Biomass	RBB	"Liquid transportation fuels including biodiesel and bioethanol can be derived from a range of biomass sources, including sugar cane, rapeseed/canola, soybeans, and importantly ahead as being greener, cellulosic biomass. The Index may include suppliers of biofuels, of the processing technologies and equipment, logistics and distribution players, manufacturers of energy systems specially adapted for the use of biofuels and products. The Index may also include companies involved in production and consumption of solid or gaseous fuels derived from biomass. Solid biomass can also consist of crop residues such as straw. [...]"
Renewables, Other	ROH	"This sector allows coverage of companies active in renewable categories other than main ones of solar, wind. For example, geothermal power has long played a part in the energy mix of countries with natural geothermal resources, such as Iceland and Japan. [...] Hydroelectric too is seeing some new use as the world shifts to new energy solutions, but with understandable controversies about its ecological impacts and so sustainability of large-scale hydroelectric power projects; that said there's interesting advances in smaller-scale, low-head hydro and even micro-scale, the latter technologies generally preferred for this Index."
Renewables, Solar	RSR	"The Solar sector covers all technologies that capture energy directly from the sun, either using a photovoltaic (PV) material, or via solar thermal technologies such as concentrators, stirling engines etc. The solar energy sector is already substantial - and growing quickly. [...]"
Renewables, Wind	RWD	"Wind is a major and growing renewable technology that's had relatively large impacts on (green) energy usage over the past few decades. [...] This Wind sector includes components, parts and subassemblies for wind turbines, as well as manufacturers of turbines themselves. Also new fields relating to wind are starting up. And a big portion too of this sector increasingly consists of related developers, generators, utilities and engineering firms that have sprung up to exploit opportunities to build wind farms around the world."

Table 1.A.1 – Definitions of the environmental sectors in the NEX index

Source : [WilderHill New Energy Global Innovation Index](#).

Note : ECV : Energy Conversion, EEF : Energy Efficiency, ENS : Energy Storage, RBB : Renewables - Biofuels & Biomass, ROH : Renewables - Other, RSR : Renewable - Solar, RWD : Renewable - Wind.

	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	Σ
5n plus inc	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	2
a123 systems inc	0	0	0	0	1	1	1	0	0	0	0	0	0	0	0	3
abengoa sa	0	1	1	1	1	1	1	1	1	1	1	0	0	0	0	10
acciona sa	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0	9
actelios spa	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	3
active power	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
acuity brands inc	0	0	0	0	0	0	1	1	1	1	1	1	1	1	0	8
advanced battery technologies	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	1
advanced lithium electrochemistry	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	2
aerovironment inc	0	0	0	0	0	1	1	1	1	1	1	0	0	0	0	6
aisin seiki co	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	2
aixtron se	0	0	0	0	0	0	0	1	1	1	1	0	0	0	0	4
akenerji elektrik uretim	0	0	0	0	0	0	0	1	1	1	1	1	0	0	0	5
albioma sa	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	7
ameresco inc	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	10
american superconductor	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	8
amyris inc	0	0	0	0	0	1	1	1	0	0	0	0	0	0	0	3
anhui bbca biochemical	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	2
ao smith corp	0	0	0	0	0	1	1	1	1	1	1	0	0	0	0	6
apollo solar energy	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	2
archer daniels midland	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
arima optoelectronics corp	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	2
atlantica yield plc	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	4
ats automation tooling	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
audax renovables sa	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	2
aventine renewable energy	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	3
avista	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
ayen enerji	0	0	0	0	0	1	1	1	0	0	0	0	0	0	0	3
babcock & brown	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	4
baldor electric co	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	5
ballard power systems	1	1	1	1	0	0	0	0	1	1	1	1	1	1	1	11
baoding tianwei bao	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
bcpq pcl	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1
bharat heavy elect	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
bkw fmb energie	0	1	1	1	0	0	0	0	0	0	0	0	0	0	0	3
bloom energy corp	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	2

blue solutions	0	0	0	0	0	0	0	0	0	1	1	1	0	0	0	0	3
boralex inc	0	0	0	1	0	0	0	0	0	0	0	1	1	1	1	1	6
brasil ecodiesel industria	0	1	1	0	0	1	0	0	0	0	0	0	0	0	0	0	3
broadwind energy inc	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	2
brookfield renewable energy	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	2
byd co ltd	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	15
canadian hydro developers	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	4
canadian solar inc	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	7
canvest environmental protection	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	4
capital stage ag	0	0	0	0	0	0	0	0	0	0	1	1	1	1	0	0	4
capstone turbine corp	1	1	1	1	1	0	0	0	0	1	1	0	0	0	0	0	7
caverion corp	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	4
centrotec sustainable ag	0	1	1	0	0	0	0	0	0	1	1	1	0	0	0	0	5
centrotherm photovoltaics ag	0	0	0	1	1	1	1	0	0	0	0	0	0	0	0	0	4
china datang corp	0	0	0	0	0	1	1	1	1	1	1	0	0	0	0	0	6
china everbright international	0	0	0	0	0	0	1	1	1	1	1	1	1	0	0	0	7
china high speed	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	12
china longyuan electric	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	1
china longyuan power	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	0	9
china ming yang	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	1
china power green	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	1
china power new	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0	2
china singyes solar	0	0	0	0	0	0	0	0	1	1	1	1	1	1	0	0	6
china suntien green	0	0	0	0	0	1	1	1	1	0	0	0	0	0	0	0	4
china titans energy	0	0	0	0	0	0	0	0	0	0	0	1	1	1	0	0	3
china windpower group	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	2
chugai ro co	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2
clearway energy inc	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1
climate exchange plc	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	2
comverge inc	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	2
conergy ag	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	4
contact energy ltd	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	15
cosan sa industria	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	9
covanta holding corp	0	0	0	1	1	1	1	1	1	1	1	0	0	0	0	0	8
credit suisse real	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	2
cree inc	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	15
cropenergies ag	0	1	0	0	0	0	0	0	0	0	0	0	0	1	1	1	4
cs real estate	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	1

cs wind corp	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	2
dalian east new	0	0	0	0	0	0	1	1	1	1	0	0	0	0	0	4
daqo new energy	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	3
dialight plc	0	0	0	0	0	0	0	1	1	1	1	1	1	0	0	6
distributed energy	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
diversa	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
dong energy a/s	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	1
drax group plc	0	0	0	0	0	0	0	0	0	0	0	1	1	1	0	3
eaga plc	0	0	0	1	1	1	0	0	0	0	0	0	0	0	0	3
ebara corp	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	3
echelon corp	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	7
ecopro co ltd	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	2
edf energies nouvelles	0	1	1	1	1	1	0	0	0	0	0	0	0	0	0	5
edp renovaveis sa	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	12
ef-on inc	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	2
elster group se	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	2
emcore	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
encavis ag	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	2
enel green power	0	0	0	0	0	1	1	1	1	1	1	0	0	0	0	6
ener1 inc	0	0	0	1	1	1	0	0	0	0	0	0	0	0	0	3
energy absolute pcl	0	0	0	0	0	0	0	0	1	1	1	1	1	1	0	6
energy conversion devices	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	6
energy development corp	0	0	0	1	1	0	1	1	1	1	1	1	1	0	0	9
energy developments	1	1	1	1	0	1	0	0	0	0	0	0	0	0	0	5
enernoc inc	0	1	1	1	1	1	1	1	1	1	1	1	0	0	0	11
enphase energy inc	0	0	0	0	0	0	0	0	1	1	1	0	1	1	1	6
envitec biogas ag	0	1	1	1	0	0	0	0	0	0	0	0	0	0	0	3
eolus vind ab	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1
epistar corp	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	12
equipment group	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	1
erex co ltd	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	3
ersol solar energy	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	3
evergreen solar inc	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	4
everlight electronics co	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	5
falck renewables spa	0	0	0	0	0	0	1	1	1	1	1	0	0	1	1	7
fdg electric vehicles	0	0	0	0	0	0	0	0	0	1	1	1	1	1	0	5
first solar inc	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	14
fortum oyj	1	1	1	1	1	1	1	1	1	1	0	0	0	0	0	10

fuel systems solutions	0	0	0	1	1	1	1	1	1	0	0	0	0	0	6
fuelcell energy inc	1	1	1	1	1	1	1	1	1	1	1	0	0	0	11
gamesa corporacion tecnologica	1	1	1	1	1	1	1	1	1	1	1	1	0	0	12
gcl poly energy	0	0	0	0	1	1	1	1	1	1	1	1	1	1	10
gcp infrastructure investments	0	0	0	0	0	0	0	0	0	1	1	1	1	1	5
gevo inc	0	0	0	0	0	0	1	0	0	0	0	0	0	0	1
gigasolar materials corp	0	0	0	0	0	0	0	0	0	1	1	1	1	1	5
goldpoly new energy	0	0	0	0	0	0	0	0	1	0	0	0	0	0	1
green energy technology	0	0	0	0	1	0	0	0	0	0	0	0	0	0	1
green plains inc	0	0	0	0	0	0	0	0	0	1	1	1	1	1	5
greencoat uk wind	0	0	0	0	0	0	0	0	0	1	1	1	1	1	5
greentech energy systems	0	1	1	1	0	0	0	0	0	0	0	0	0	0	3
gs yuasa corp	1	1	1	1	1	1	1	1	1	1	1	1	1	1	15
gt advanced technologies	0	0	0	0	0	0	1	1	1	0	0	0	0	0	3
gt solar international	0	0	0	1	1	1	0	0	0	0	0	0	0	0	3
gurit holding ag	0	1	1	1	1	1	0	0	0	0	0	0	0	1	7
gushan environmental energy	0	0	0	1	1	0	0	0	0	0	0	0	0	0	2
hanergy solar group	0	0	0	0	0	0	0	1	1	0	0	0	0	0	2
hanergy thin film	0	0	0	0	0	0	0	0	0	1	0	0	0	0	1
hannon armstrong sustainable	0	0	0	0	0	0	0	0	0	0	1	1	1	1	4
hansen transmissions international	0	0	1	1	1	1	0	0	0	0	0	0	0	0	4
harris & harris	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1
hexcel corp	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1
huaneng renewables corp	0	0	0	0	0	0	0	0	1	1	1	1	1	1	6
hydrogenics corp	1	0	0	0	0	0	0	0	0	1	0	0	0	0	2
iberdrola renovables sa	1	1	1	1	1	1	0	0	0	0	0	0	0	0	6
infigen energy	0	0	0	0	1	1	0	0	0	0	0	0	0	0	2
infinis energy plc	0	0	0	0	0	0	0	0	0	1	0	0	0	0	1
innergex renewable energy	0	0	0	0	0	0	1	1	1	1	1	1	1	1	9
intelligent energy holdings	0	0	0	0	0	0	0	0	0	1	1	0	0	0	2
international rectifier corp	1	1	1	1	1	1	1	1	1	1	0	0	0	0	10
itron inc	1	1	1	1	1	1	1	1	1	1	1	1	1	1	15
ja solar holdings	0	1	1	1	1	1	1	1	1	1	1	1	1	0	12
japan wind development	0	1	1	1	1	0	0	1	1	0	0	0	0	0	6
jinkosolar holding co	0	0	0	0	0	0	0	0	0	0	0	1	1	1	3
johnson controls inc	0	0	0	1	1	1	1	1	1	1	1	0	0	0	8
johnson matthey plc	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1
kandi technologies group	0	0	0	0	0	0	0	0	0	0	0	1	1	1	4

kingspan group plc	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	14
kior inc	0	0	0	0	0	0	1	1	1	0	0	0	0	0	0	3
landis+gyr group ag	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	3
ldk solar co	0	1	1	1	1	0	0	0	0	0	0	0	0	0	0	4
lextar electronics corp	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	2
linear technology	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
lsb industries inc	0	0	0	0	0	1	1	1	1	1	0	0	0	0	0	5
lsi industries inc	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	2
lynas corp ltd	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	2
marubeni corp	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
maxwell technologies inc	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	14
medis technologies	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	3
meidensha corp	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	15
memc electronic materials	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	8
mercury nz ltd	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	4
meridian energy ltd	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	2
meyer burger technology	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	11
mgp ingredients	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
mighty river power	0	0	0	0	0	0	0	0	1	1	1	0	0	0	0	3
molycorp inc	0	0	0	0	0	1	1	1	0	0	0	0	0	0	0	3
motech industries inc	0	0	0	0	0	0	1	1	1	1	1	1	1	1	0	8
nel asa	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	3
neo-neon holdings ltd	0	0	0	0	1	1	1	1	0	0	0	0	0	0	0	4
neo solar power	0	0	0	0	0	1	1	1	1	1	1	1	1	1	0	9
neoen sa	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	2
nexolon co ltd	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	2
nibe industrie-b	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	1
nibe industrier ab	0	0	0	0	0	0	1	1	1	1	1	1	0	1	1	8
nio inc adr	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	2
nordex ag	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	15
northland power inc	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1
novozymes a/s series	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	15
npc inc	0	0	0	0	1	1	1	0	0	0	0	0	0	0	0	3
nrg yield inc	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	2
odelic co ltd	0	0	0	0	0	0	0	0	0	0	1	1	1	0	0	3
opower inc	0	0	0	0	0	0	0	0	0	1	1	0	0	0	0	2
ormat technologies inc	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	15
orsted a/s	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	3

osram licht ag	0	0	0	0	0	0	0	0	0	1	1	0	1	1	1	0	5
pacific ethanol inc	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	3
panda green energy	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	1
pattern energy group	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	0	6
phoenix solar ag	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	2
plug power inc	1	1	1	1	0	0	0	0	0	0	1	1	1	1	1	1	10
pne ag	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1
pnoc energy development	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	2
polypore international inc	0	0	0	0	1	1	1	1	1	1	0	0	0	0	0	0	6
power-one inc	1	1	1	1	0	1	1	1	0	0	0	0	0	0	0	0	7
power integrations inc	0	0	1	1	1	1	1	1	0	0	0	0	0	0	0	0	6
powercell sweden ab	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1
powersecure international inc	0	0	0	0	0	0	0	0	1	1	1	0	0	0	0	0	3
praj industries ltd	1	1	0	1	1	1	1	1	0	0	0	0	0	0	0	0	7
puget energy	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
pvc crystalox solar	0	0	0	1	1	1	0	0	0	0	0	0	0	0	0	0	3
pvc crystalox wi	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1
q-cells se	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	7
quantum fuel	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
quimica y minera	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	1
rec silicon asa	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	0	6
rec solar asa	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	2
renewable energy corp	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	8
renewable energy group	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	8
renewables infrastructure group	0	0	0	0	0	0	0	0	1	1	1	1	0	1	1	1	6
renova inc	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	2
repower systems ag	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	2
ricardo plc	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	7
rockwool international a/s	0	0	0	1	1	1	1	1	1	1	1	0	0	0	0	0	8
roth & rau	0	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	5
rubicon technology inc	0	0	0	0	0	1	1	1	1	0	0	0	0	0	0	0	4
rwe st class	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
saeta yield sa	0	0	0	0	0	0	0	0	0	0	1	1	1	0	0	0	3
saft groupe sa	1	1	1	1	1	1	1	1	1	1	1	1	0	0	0	0	11
saltx technology holding	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	1
samsung sdi co	0	0	0	0	0	0	0	0	0	0	1	0	1	1	1	1	4
sanyo electric co	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	5
sao martinho s/a	0	0	0	1	1	1	1	1	1	1	1	1	1	0	0	0	9

scatec solar asa	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	2
schmack biogas ag	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	2
scottish & southern	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	3
sechilienne sidec	0	0	1	1	1	1	1	1	0	0	0	0	0	0	0	6
sekisui chemical ltd	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
senvion sa	0	0	0	0	0	0	0	0	0	0	0	1	1	1	0	3
seoul semiconductor co	0	0	0	0	0	1	1	1	1	1	1	0	1	1	1	9
sgl carbon ag	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
sharp corp	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	4
shunfeng international green	0	0	0	0	0	0	0	0	0	1	1	1	1	0	0	4
shunfeng photovoltaic international	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	1
siemens gamesa renewable	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	3
signify nv	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	4
silver spring networks	0	0	0	0	0	0	0	0	1	1	1	1	0	0	0	4
sino-american silicon products	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	8
sinopoly battery ltd	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	1
sky solar holdings	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	1
sma solar technology	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	12
sociedad quimica y	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	2
solar millennium ag	0	1	1	1	1	1	0	0	0	0	0	0	0	0	0	5
solarcity corp	0	0	0	0	0	0	0	0	1	1	1	0	0	0	0	3
solaredge technologies inc	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	5
solaria energia y	0	1	1	1	1	0	0	0	0	0	0	0	0	0	1	5
solarworld ag	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	8
solazyme inc	0	0	0	0	0	0	1	1	1	1	1	0	0	0	0	5
solon se	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	5
spcg pcl	0	0	0	0	0	0	0	1	1	1	1	1	1	1	0	7
str holdings inc	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	2
sunedison inc	0	0	0	0	0	0	0	0	1	1	1	0	0	0	0	3
sunnova energy international	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1
sunpower corp	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	15
sunrun inc	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	4
suntech power holdings	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	7
sunways ag	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
super energy corp	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1
superblock pcl	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	2
suzlon energy ltd	1	1	0	0	0	0	0	0	1	1	0	0	0	0	0	4
taewoong co ltd	0	0	0	0	0	1	1	1	1	1	1	0	0	0	0	6

takuma co ltd	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	14
tanaka chemical corp	0	0	0	0	1	1	0	0	0	0	0	1	1	1	0	5
techem ag	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1
terraform power inc	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	6
tesla inc	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	10
the renewables infrastructure	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	1
theolia sa	0	1	1	1	0	0	0	0	0	0	0	0	0	0	0	3
tilt renewables ltd	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1
toho tenax	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
tpi composites inc	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	4
transalta renewables inc	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	6
trina solar ltd	0	0	0	0	0	1	1	1	1	1	1	0	0	0	0	6
trony solar holdings	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	2
ultralife batteries inc	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	4
umicore sa	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	4
unison co ltd/south	0	0	0	0	0	0	0	1	0	0	0	0	0	1	0	2
united photovoltaics group	0	0	0	0	0	0	0	0	0	1	1	1	0	0	0	3
united renewable energy	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1
universal display corp	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	11
utilitywise plc	0	0	0	0	0	0	0	0	0	1	1	1	0	0	0	3
vanguardia agro sa	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	1
veeco instruments inc	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	9
verasun energy corp	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	3
verbio ag	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	1
verbio vereinigte bioenergie	0	1	1	0	0	0	0	0	0	0	0	1	0	1	1	5
verbund ag	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	14
verenium corp	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	2
vestas wind systems	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	15
vivint solar inc	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	6
voltabox ag	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1
w-scope corp	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1
wacker chemie ag	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
wasion group holdings	0	0	0	0	0	1	1	1	1	1	1	1	1	1	0	9
west holdings corp	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	7
willdan group inc	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	2
woongjin energy co	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	1
xinjiang goldwind science	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	12
xinjiang tebian	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1

xinyi energy holdings	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1
xinyi solar holdings	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	6
yingli green energy	0	1	1	1	1	1	1	1	1	1	0	0	0	0	0	9
zhejiang yankon group	0	1	1	1	1	1	0	0	0	0	0	0	0	0	0	5
zoltek cos inc	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	8
Σ	81	88	86	89	86	100	97	94	102	107	104	97	105	109	91	

Table 1.A.2 – NEX index composition for all years

Source : WilderHill New Energy Global Innovation Index.

Note : This table represents the list of companies (rows) that composed or made up the NEX index between 2006 and 2020. For each year (columns), if the company belongs to the index, the value is 1 and 0 otherwise.

	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	Σ
a123 systems inc	0	0	0	0	0	1	1	1	0	0	0	0	0	0	0	0	3
active power inc	1	1	1	1	0	0	1	0	0	0	0	0	0	0	0	0	5
advanced battery tech	0	0	0	0	1	1	1	0	0	0	0	0	0	0	0	0	3
advanced energy industries	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	7
air products	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	16
aixtron se	0	0	0	0	0	1	1	1	1	1	1	0	0	0	0	0	6
albemarle corp	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	3
amer power conversion	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2
amer superconductor	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
ameresco inc	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	10
american superconductor corp	0	1	1	1	1	1	1	1	1	1	0	0	1	1	1	1	13
amerigon inc	0	0	0	1	1	1	1	1	0	0	0	0	0	0	0	0	5
amtech systems inc	0	0	0	0	0	0	0	1	0	0	1	0	0	1	1	0	4
amyris inc	0	0	0	0	0	0	1	1	1	1	1	1	0	0	0	0	6
applied materials	0	0	1	1	1	1	1	0	0	0	0	0	0	0	0	0	5
aqua metals inc	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	2
ascent solar technologies	0	0	0	1	1	1	1	0	0	0	0	0	0	0	0	0	4
atlantica yield plc	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	4
ballard power systems	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1	15
beacon power corp	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	2
bloom energy corp	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	2
boc group ads	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2
broadwind energy inc	0	0	0	0	0	1	1	0	0	1	1	0	0	0	0	0	4
calpine corp	1	0	0	0	1	1	1	1	1	1	1	0	0	0	0	0	8
canadian solar inc	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	10
capstone turbine corp	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	3
cd technologies	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
central vt pub	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
china bak battery	0	0	0	1	1	1	1	0	0	0	0	0	0	0	0	0	4
china ming yang	0	0	0	0	0	0	1	1	1	1	1	1	0	0	0	0	6
china wind systems	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	1
comverge inc	0	0	0	1	1	1	1	0	0	0	0	0	0	0	0	0	4
cosan ltd	0	0	0	1	1	1	1	1	1	1	0	0	0	0	0	0	7
cpfl energia sa	0	0	0	0	1	1	1	1	1	0	0	0	0	0	0	0	5
cree inc	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	16
cypress semiconductor	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	2

cytec industries inc	0	0	0	0	0	0	0	0	0	1	1	0	0	0	0	2
daqo new energy	0	0	0	0	0	0	0	1	0	0	1	1	1	1	1	7
distributed energy sys	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	3
echelon corp	1	1	1	1	1	1	1	1	1	1	1	0	0	0	0	11
emcore corp	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	6
ener1 inc	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	2
energy conversion devices	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	7
energy focus inc	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	1
enernoc inc	0	0	0	0	0	0	0	1	1	1	1	1	1	0	0	6
enphase energy inc	0	0	0	0	0	0	0	0	1	1	1	1	0	0	1	6
esco technologies inc	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
evergreen	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	1
evergreen solar inc	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	6
first solar inc	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	14
fuel systems solutions	0	0	1	1	1	1	1	1	1	1	1	0	0	0	0	9
fuelcell energy inc	1	1	1	1	1	1	1	1	1	1	1	0	1	1	0	13
general cable corp	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	1
gentherm inc	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	8
gevo inc	0	0	0	0	0	0	0	1	1	1	0	0	0	0	0	3
gt advanced technologies	0	0	0	0	0	0	0	1	1	1	0	0	0	0	0	3
gt solar international	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	2
gushan environmental energy	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	2
hanwaha q cells	0	0	0	0	0	0	0	0	0	0	1	1	1	1	0	4
hanwaha solarone co	0	0	0	0	0	0	0	1	1	1	0	0	0	0	0	3
hexcel corp	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	5
hydrogenics corp	1	1	1	0	0	0	0	0	0	1	1	1	1	1	1	9
idacorp inc	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0	9
impco technologies	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	2
intermagnetics general	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	2
international rectifier corp	1	1	1	1	1	1	1	1	1	1	0	0	0	0	0	10
itc holdings corp	0	0	0	0	0	0	0	1	1	1	1	1	0	0	0	5
itron inc	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	16
ja solar holdings	0	0	0	1	1	1	1	1	1	1	1	1	1	1	0	11
jinkosolar holding co	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	3
kaydon corp	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	2
kior inc	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0	2
kyocera corp adr	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	3
lime energy co	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	1

livent corp	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1
lsi industries inc	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	0	3
magnetek inc	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2
maxwell technologies inc	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	15
mechanical technology	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2
medis technologies ltd	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	4
memc electronic materials	0	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	8
mgp ingredients inc	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	3
molycorp inc	0	0	0	0	0	0	1	1	1	0	0	0	0	0	0	0	3
myr group inc	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	3
nio inc adr	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	2
nova biosource fuels	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	1
ocean power technologies	0	0	0	1	1	1	1	0	0	0	0	0	0	0	0	0	4
om group inc	0	0	1	1	1	1	1	1	1	1	1	0	0	0	0	0	9
opower inc	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0	0	2
orion energy systems	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	1
ormat technologies inc	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	16
pacific ethanol inc	0	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	3
pattern energy group	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	0	6
plug power inc	1	1	1	1	1	1	0	0	0	0	1	1	1	1	1	1	12
polypore international inc	0	0	0	0	0	0	1	1	1	1	1	0	0	0	0	0	5
portland general electric	0	0	0	1	1	1	0	0	0	0	0	0	0	0	0	0	3
power integrations inc	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2
power-one inc	0	0	0	0	0	0	1	1	1	0	0	0	0	0	0	0	3
powersecure international inc	0	0	0	0	0	0	0	1	1	1	1	1	0	0	0	0	5
praxair inc	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	3
puget energy	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1
quanta services inc	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	12
quantum fuel systems	1	1	1	0	1	1	0	0	0	1	1	0	0	0	0	0	7
rare element resources	0	0	0	0	0	0	1	1	1	1	0	0	0	0	0	0	4
raser technologies inc	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	2
renesola ltd ads	0	0	0	0	0	0	0	1	1	1	1	1	0	0	0	0	5
renewable energy group	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	7
rubicon technology inc	0	0	0	0	1	1	1	1	1	1	1	0	0	0	0	0	7
satcon technology corp	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	2
scottish power ads	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2
semileds corp	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	1
silver spring networks	0	0	0	0	0	0	0	0	0	1	1	1	1	0	0	0	4

sky solar holdings	0	0	0	0	0	0	0	0	0	0	1	1	1	1	0	0	4
sociedad quimica minera	0	0	0	0	1	1	1	1	1	1	1	0	1	1	1	1	11
sola international inc	0	0	0	0	1	1	1	0	0	0	0	0	0	0	0	0	3
solarcity corp	0	0	0	0	0	0	0	0	0	1	1	1	0	0	0	0	3
solaredge technologies inc	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	5
solazyme inc	0	0	0	0	0	0	0	1	1	1	1	1	0	0	0	0	5
spire corp	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	2
str holdings inc	0	0	0	0	0	0	1	1	1	1	0	0	0	0	0	0	4
sunedison inc	0	0	0	0	0	0	0	0	0	1	1	1	0	0	0	0	3
sunnova energy international	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1
sunpower corp	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	15
sunrun inc	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	5
suntech power holdings	0	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	8
terraform global inc	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0	2
terraform power inc	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	6
tesla motors inc	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	10
tpi composites inc	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	3
trina solar ltd	0	0	0	1	1	1	1	1	1	1	1	1	0	0	0	0	9
ultralife batteries inc	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	5
universal display corp	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	14
uqm technologies inc	1	1	1	1	0	1	1	1	0	0	0	0	0	0	0	0	7
us geothermal inc	0	0	0	0	1	1	1	0	0	0	0	0	0	1	0	0	4
valence technology inc	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	2
veeco instruments inc	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	4
verasun energy corp	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	2
verenium corp	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	2
vivint solar inc	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	1	2
willdan group inc	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	2
woodward inc	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1
workhorse group inc	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1
yingli green energy	0	0	0	1	1	1	1	1	1	1	1	0	0	0	0	0	8
zoltex companies inc	1	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	9
Σ	38	40	39	42	51	54	57	56	50	53	53	42	37	40	39	39	

Table 1.A.3 – ECO index composition for all years

Source : WilderHill Clean Energy Index.

Note : This table represents the list of companies (rows) that composed or made up the ECO index between 2005 (its launch date) and 2020. For each year (columns), if the company belongs to the index, the value is 1 and 0 otherwise.

	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	Mean
australia	2.47	2.27	2.33	2.25	1.16	1.00	1.03	1.06	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.90
austria	0.00	1.14	1.16	1.12	1.16	1.00	1.03	1.06	0.98	0.93	0.96	1.03	0.95	0.92	1.10	0.97
belgium	1.23	1.14	1.16	1.12	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.38
bermuda	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.06	0.00	0.00	0.00	0.00	2.86	0.00	0.00	0.26
brazil	1.23	2.27	2.33	2.25	2.33	3.00	3.09	2.13	1.96	0.93	0.96	1.03	0.00	0.00	0.00	1.57
canada	4.94	2.27	2.33	4.49	1.16	0.00	2.06	1.06	1.96	4.67	4.81	5.15	4.76	4.59	6.59	3.39
cayman	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	10.48	0.00	0.00	0.70
chile	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.95	0.92	0.00	0.12
china	0.00	2.27	2.33	3.37	2.33	12.00	11.34	9.57	0.98	10.28	9.62	9.28	3.81	8.26	10.99	6.43
denmark	2.47	3.41	3.49	4.49	3.49	3.00	3.09	3.19	2.94	2.80	2.88	3.09	2.86	2.75	3.30	3.15
finland	1.23	1.14	1.16	1.12	1.16	1.00	1.03	1.06	0.98	0.93	0.00	1.03	0.95	0.92	1.10	0.99
france	1.23	3.41	4.65	4.49	3.49	3.00	2.06	2.13	2.94	2.80	2.88	1.03	0.95	1.83	2.20	2.61
germany	12.35	17.05	15.12	11.24	10.47	9.00	6.19	4.26	4.90	5.61	4.81	6.19	5.71	8.26	5.49	8.44
hong kong	1.23	1.14	1.16	2.25	6.98	6.00	6.19	7.45	14.71	8.41	7.69	9.28	1.90	4.59	0.00	5.26
india	3.70	2.27	0.00	1.12	1.16	1.00	1.03	1.06	0.98	0.93	0.00	0.00	0.00	0.00	0.00	0.88
ireland	0.00	1.14	1.16	1.12	1.16	1.00	1.03	1.06	0.98	0.93	0.96	1.03	0.95	0.92	1.10	0.97
israel	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.96	1.03	0.00	0.92	0.00	0.19
italy	1.23	1.14	1.16	0.00	0.00	1.00	2.06	2.13	1.96	1.87	1.92	0.00	0.00	0.92	1.10	1.10
japan	12.35	10.23	8.14	6.74	8.14	5.00	4.12	4.26	4.90	3.74	4.81	6.19	7.62	8.26	6.59	6.74
luxembourg	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.95	0.00	0.00	0.06
netherlands	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.03	0.95	0.92	1.10	0.27
new zealand	1.23	1.14	1.16	1.12	1.16	1.00	1.03	1.06	1.96	1.87	1.92	2.06	1.90	2.75	4.40	1.72
norway	1.23	1.14	1.16	1.12	1.16	1.00	1.03	1.06	1.96	0.93	0.00	0.00	1.90	1.83	2.20	1.18
philippines	0.00	1.14	1.16	1.12	1.16	1.00	1.03	1.06	0.98	0.93	0.96	1.03	0.95	0.00	0.00	0.84
portugal	0.00	0.00	0.00	1.12	1.16	0.00	0.00	0.00	0.98	0.00	0.00	0.00	0.00	0.00	0.00	0.22
shanghai	2.47	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.16
singapore	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.93	0.00	0.00	0.00	0.00	0.00	0.06
south korea	0.00	0.00	0.00	0.00	0.00	2.00	4.12	4.26	1.96	1.87	2.88	0.00	1.90	4.59	4.40	1.87
spain	3.70	5.68	5.81	5.62	5.81	5.00	4.12	4.26	2.94	2.80	3.85	4.12	2.86	3.67	5.49	4.38
sweden	0.00	0.00	0.00	0.00	0.00	0.00	1.03	1.06	0.98	0.93	0.96	1.03	1.90	0.92	3.30	0.81
switzerland	0.00	2.27	2.33	2.25	2.33	2.00	1.03	1.06	0.98	0.93	0.96	1.03	2.86	3.67	4.40	1.87
taiwan	0.00	1.14	1.16	1.12	2.33	2.00	3.09	4.26	3.92	3.74	5.77	7.22	5.71	6.42	6.59	3.63
thailand	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.06	1.96	1.87	1.92	3.09	2.86	3.67	0.00	1.10
turkey	0.00	0.00	0.00	0.00	0.00	1.00	1.03	2.13	0.98	0.93	0.96	1.03	0.00	0.00	0.00	0.54
uk	2.47	1.14	3.49	4.49	4.65	2.00	0.00	1.06	2.94	5.61	6.73	7.22	6.67	4.59	4.40	3.83
usa	43.21	34.09	36.05	34.83	36.05	35.00	37.11	35.11	36.27	31.78	29.81	25.77	23.81	22.94	24.18	32.40

Table 1.A.4 – NEX index composition by country (in %)

Source : WilderHill New Energy Global Innovation Index.

Note : The percentage of companies making up the NEX index by country.

	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	Mean
America	49.38	38.64	40.70	41.57	39.53	38.00	42.27	39.36	40.20	37.38	35.58	31.96	42.86	28.44	30.77	38.44
Caribbean	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	10.48	0.00	0.00	0.70
Northern America	48.15	36.36	38.37	39.33	37.21	35.00	39.18	37.23	38.24	36.45	34.62	30.93	31.43	27.52	30.77	36.05
South America	1.23	2.27	2.33	2.25	2.33	3.00	3.09	2.13	1.96	0.93	0.96	1.03	0.95	0.92	0.00	1.69
Asia	19.75	18.18	13.95	15.73	22.09	30.00	31.96	35.11	31.37	33.64	35.58	38.14	24.76	36.70	28.57	27.70
Eastern Asia	16.05	14.77	12.79	13.48	19.77	27.00	28.87	29.79	26.47	28.04	30.77	31.96	20.95	32.11	28.57	24.09
Southern Asia	3.70	2.27	0.00	1.12	1.16	1.00	1.03	1.06	0.98	0.93	0.00	0.00	0.00	0.00	0.00	0.88
South Eastern Asia	0.00	1.14	1.16	1.12	1.16	1.00	1.03	2.13	2.94	3.74	2.88	4.12	3.81	3.67	0.00	1.99
Western Asia	0.00	0.00	0.00	0.00	0.00	1.00	1.03	2.13	0.98	0.93	1.92	2.06	0.00	0.92	0.00	0.73
Europe	27.16	39.77	41.86	39.33	36.05	30.00	23.71	23.40	26.47	27.10	26.92	27.84	30.48	32.11	36.26	31.23
Northern Europe	7.41	7.95	10.47	12.36	11.63	8.00	7.22	8.51	10.78	12.15	11.54	13.40	15.24	11.93	15.38	10.93
Southern Europe	4.94	6.82	6.98	6.74	6.98	6.00	6.19	6.38	5.88	4.67	5.77	4.12	2.86	4.59	6.59	5.70
Western Europe	14.81	25.00	24.42	20.22	17.44	16.00	10.31	8.51	9.80	10.28	9.62	10.31	12.38	15.60	14.29	14.60
Oceania	3.70	3.41	3.49	3.37	2.33	2.00	2.06	2.13	1.96	1.87	1.92	2.06	1.90	2.75	4.40	2.62

Table 1.A.5 – NEX index composition by geographical area (in %)

Source : WilderHill New Energy Global Innovation Index.

Note : According to the United Nations standards, the percentage of companies making up the NEX index by geographical area.

	ECV	EEF	ENS	RBB	ROH	RSR	RWD
2008 Q1	3.93	13.56	2.94	14.26	6.99	30.00	28.34
2008 Q2	3.81	17.85	2.81	14.32	6.47	27.03	27.71
2008 Q3	3.31	20.03	3.33	13.14	6.54	27.27	26.39
2008 Q4	2.25	23.93	3.57	12.09	6.48	26.63	25.05
2009 Q1	2.77	15.14	5.29	14.19	8.25	25.70	28.68
2009 Q2	2.42	12.89	4.79	12.21	6.49	30.57	30.63
2009 Q3	2.59	13.77	5.38	10.76	6.81	29.24	31.45
2009 Q4	2.25	15.20	7.10	11.26	7.10	27.51	29.58
2010 Q1	2.04	16.93	8.65	12.25	6.73	25.03	28.36
2010 Q2	1.90	17.29	8.53	12.36	6.58	24.29	29.05
2010 Q3	1.97	20.31	8.86	11.70	6.59	24.42	26.16
2010 Q4	1.79	24.32	8.80	11.21	6.02	24.16	23.71
2011 Q1	1.50	26.95	6.99	10.50	9.46	24.59	20.00
2011 Q2	1.50	23.34	8.06	10.69	9.53	25.76	21.04
2011 Q3	1.28	22.72	6.24	10.17	10.49	24.60	24.32
2011 Q4	1.14	25.06	4.12	12.13	11.63	26.48	19.45
2012 Q1	1.60	28.01	4.01	13.85	14.70	20.83	17.00
2012 Q2	1.34	28.14	4.16	14.61	13.98	22.00	15.96
2012 Q3	2.32	28.30	6.70	14.22	8.35	21.17	19.00
2012 Q4	1.50	33.93	2.97	14.50	14.50	19.59	13.04
2013 Q1	1.31	33.43	2.63	15.42	14.05	15.90	14.14
2013 Q2	1.31	33.43	2.63	15.42	14.05	17.54	15.62
2013 Q3	1.25	35.04	2.35	14.61	13.06	19.10	14.58
2013 Q4	1.28	35.26	2.28	14.02	12.47	19.58	15.10
2014 Q1	1.17	33.13	2.34	12.17	10.33	23.95	16.91
2014 Q2	1.11	34.20	2.00	12.16	9.86	23.16	17.52
2014 Q3	1.42	33.42	2.30	12.44	9.09	23.78	17.56
2014 Q4	1.42	33.67	2.26	12.31	8.45	24.67	17.22
2015 Q1	1.68	33.88	2.14	11.54	6.84	24.86	19.06
2015 Q2	1.22	33.68	2.26	9.55	6.90	24.88	21.50
2015 Q3	0.95	32.97	3.18	8.05	4.52	24.65	25.67
2015 Q4	0.95	33.54	3.09	9.19	5.19	20.40	27.65
2016 Q1	1.01	34.83	3.61	9.38	4.26	20.14	26.77
2016 Q2	1.02	32.18	3.69	7.15	5.18	21.60	29.18
2016 Q3	1.12	31.00	4.54	7.76	5.87	21.09	28.61
2016 Q4	0.71	32.00	3.58	8.48	5.20	18.84	31.19
2017 Q1	1.00	31.83	5.64	9.03	5.43	17.92	29.14
2017 Q2	0.67	33.68	6.50	8.75	4.92	18.73	26.75
2017 Q3	0.76	30.88	5.91	9.11	4.55	18.80	29.98
2017 Q4	1.14	29.36	6.75	8.21	4.68	20.58	29.28
2018 Q1	1.00	30.67	7.64	7.74	3.92	23.37	25.66
2018 Q2	0.80	30.50	8.80	7.90	3.90	22.50	25.50
2018 Q3	0.79	29.62	8.48	6.60	3.71	23.67	27.12
2018 Q4	1.05	30.25	9.00	7.94	3.63	21.78	26.34
2019 Q1	1.42	30.07	9.36	8.48	4.49	20.72	25.46
2019 Q2	1.40	29.72	9.11	6.13	4.41	21.75	27.49
2019 Q3	3.77	22.64	9.43	9.43	5.66	26.41	22.64
2019 Q4	4.00	23.00	8.00	10.00	6.00	26.00	23.00
2020 Q1	5.50	23.10	6.60	8.80	6.60	27.50	22.00
2020 Q2	5.70	23.00	6.90	8.00	6.90	26.40	23.00
Mean	1.82	27.23	5.33	10.92	7.56	23.34	23.73

Table 1.A.6 – Sector weights of the NEX index after 2008 (in %)

Source : [WilderHill New Energy Global Innovation Index](#).

Note : ECV : Energy Conversion, EEF : Energy Efficiency, ENS : Energy Storage, RBB : Renewables - Biofuels & Biomass, ROH : Renewables - Other, RSR : Renewable - Solar, RWD : Renewable - Wind. Before 2008, the names (and classification) of the sectors were different.

	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	Mean
Mean	1.21	1.13	1.16	1.14	1.16	1.00	1.03	1.03	0.98	0.93	0.96	1.03	0.95	0.92	1.10	1.05
Min	0.29	0.15	0.15	0.26	0.40	0.28	0.18	0.15	0.15	0.13	0.19	0.25	0.18	0.22	0.70	0.25
Max	3.60	2.50	2.09	2.54	1.97	1.70	1.94	1.79	1.64	1.84	1.74	1.83	1.60	1.73	1.64	2.01

Table 1.A.7 – NEX index component weights (in %)

Source : WilderHill New Energy Global Innovation Index.

Note : This table represents the minimum, mean, and maximum company weight composing the NEX index for each year.

Company name	Country	Sector before 2018	New sector
activision blizzard inc	USA	Information Technology	Communication Services
akamai technologies inc	USA	Information Technology	Information Technology (new subsectors)
alphabet inc	USA	Information Technology	Communication Services
charter communications inc	USA	Consumer Discretionary	Communication Services
comcast corp	USA	Consumer Discretionary	Communication Services
delivery hero ag	DEU	Information Technology	Consumer Discretionary
dentsu inc	JPN	Consumer Discretionary	Communication Services
dish network corp	USA	Consumer Discretionary	Communication Services
disney (walt) co	USA	Consumer Discretionary	Communication Services
ebay inc	USA	Information Technology	Consumer Discretionary
electronic arts inc	USA	Information Technology	Communication Services
facebook inc	USA	Information Technology	Communication Services
fuji media holdings inc	JPN	Consumer Discretionary	Communication Services
grupo televisa sab	MEX	Consumer Discretionary	Communication Services
informa plc	GBR	Consumer Discretionary	Communication Services
interpublic group of cos	USA	Consumer Discretionary	Communication Services
itv plc	GBR	Consumer Discretionary	Communication Services
live nation entertainment	USA	Consumer Discretionary	Communication Services
naver corp	KOR	Information Technology	Information Technology (new subsector)
netflix inc	USA	Consumer Discretionary	Communication Services
news corp	USA	Consumer Discretionary	Communication Services
nintendo co ltd	JPN	Information Technology	Communication Services
omnicom group	USA	Consumer Discretionary	Communication Services
pearson plc	GBR	Consumer Discretionary	Communication Services
publicis groupe sa	FRA	Consumer Discretionary	Communication Services
ses sa	LUX	Consumer Discretionary	Communication Services
shaw communications inc-cl b	CAN	Consumer Discretionary	Communication Services
shopify inc	CAN	Information Technology	Information Technology (new subsector)
tencent holdings ltd	CHN	Information Technology	Communication Services
twitter inc	USA	Information Technology	Communication Services
ubi soft entertainment sa	FRA	Information Technology	Communication Services
united internet ag	DEU	Information Technology	Communication Services
verisign inc	USA	Information Technology	Information Technology (newsubsector)
viacom inc	USA	Consumer Discretionary	Communication Services
vivendi sa	FRA	Consumer Discretionary	Communication Services
wpp plc	GBR	Consumer Discretionary	Communication Services
discovery communications inc	USA	Consumer Discretionary	Communication Services

Table 1.A.8 – GICS restructuring (2018) and the S&P Global 1200

Source : StructureReviewChanges2018 (MSCI) and Datastream.

Note : This table shows all companies in the S&P Global 1200 Index that have changed sectors (or subsectors) with the 2018 GICS reclassification.

		2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	Σ
#####	financials	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	15
#####	industrials	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	15
#####	industrials	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	15
#####	industrials	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	15
#####	industrials	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	15
#####	health care	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	15
#####	health care	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	9
#####	health care	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	15
#####	financials	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	6
#####	info tech	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	15
#####	cons discr	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	15
#####	industrials	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	15
#####	comm services	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	15
#####	industrials	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	15
#####	cons discr	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	15
#####	financials	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	15
#####	info tech	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	15
#####	industrials	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	15
#####	cons discr	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	15
#####	info tech	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	15
#####	info tech	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	3
#####	financials	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	15
#####	industrials	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	6
#####	cons staples	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	15
#####	utilities	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	15
#####	financials	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	15
#####	industrials	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	15
#####	financials	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	15
#####	health care	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	15
#####	utilities	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	15
#####	materials	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	15
#####	financials	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	11
#####	materials	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	15
#####	industrials	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	15
#####	cons discr	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	15
#####	cons staples	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	15
#####	info tech	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	15
#####	materials	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	15
#####	industrials	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	15
...
Σ		1073	1091	1097	1109	1127	1140	1147	1164	1177	1190	1196	1201	1209	1217	1219	

Table 1.A.9 – S&P Global 1200 composition from 2006 to 2020

Source : Datastream.

Note : This table represents the list of companies (rows) that composed or made up the S&P Global 1200 index between 2006 and 2020. For each year (columns), if the company belongs to the index, the value is 1 and 0 otherwise.

	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	Mean
australia	3.82	3.76	3.74	3.70	3.73	3.86	3.84	3.78	3.91	3.95	3.93	3.91	3.97	3.94	3.94	3.85
austria	0.19	0.18	0.18	0.18	0.18	0.18	0.17	0.17	0.17	0.17	0.17	0.17	0.17	0.16	0.16	0.17
belgium	0.84	0.82	0.82	0.81	0.80	0.79	0.78	0.77	0.76	0.76	0.75	0.75	0.74	0.74	0.74	0.78
brazil	1.30	1.47	1.46	1.44	1.42	1.40	1.39	1.37	1.36	1.34	1.34	1.33	1.32	1.31	1.31	1.37
canada	4.75	4.77	4.74	4.87	4.88	4.82	4.80	4.73	4.76	4.79	4.77	4.75	4.80	4.77	4.76	4.78
chile	0.75	0.73	0.73	0.72	0.71	0.70	0.70	0.69	0.68	0.67	0.75	0.75	0.74	0.74	0.74	0.72
china	0.65	0.64	0.64	0.63	0.62	0.61	0.61	0.60	0.59	0.59	0.59	0.58	0.58	0.58	0.57	0.61
colombia	0.19	0.18	0.27	0.27	0.27	0.26	0.26	0.26	0.25	0.25	0.25	0.25	0.25	0.25	0.25	0.25
denmark	0.93	0.92	0.91	0.90	1.06	1.05	1.05	1.03	1.02	1.01	1.09	1.08	1.08	1.07	1.07	1.02
finland	1.03	1.01	1.00	0.99	0.98	0.96	0.96	0.95	0.93	0.92	0.92	0.92	0.91	0.90	0.90	0.95
france	4.57	4.58	4.65	4.60	4.61	4.56	4.53	4.47	4.42	4.45	4.43	4.41	4.38	4.35	4.35	4.49
germany	3.63	3.57	3.56	3.52	3.55	3.51	3.49	3.61	3.65	3.70	3.68	3.75	3.72	3.70	3.69	3.62
hong kong	3.08	3.02	3.01	3.16	3.28	3.25	3.23	3.18	3.14	3.28	3.26	3.25	3.56	3.53	3.53	3.25
ireland	0.47	0.55	0.55	0.54	0.53	0.53	0.52	0.52	0.51	0.50	0.50	0.50	0.50	0.49	0.49	0.51
italy	1.21	1.28	1.28	1.35	1.33	1.32	1.31	1.46	1.44	1.43	1.51	1.50	1.49	1.48	1.48	1.39
japan	13.33	13.11	13.04	12.98	13.13	12.98	12.99	12.80	12.74	12.61	12.54	12.49	12.41	12.33	12.31	12.79
luxembourg	0.19	0.18	0.18	0.18	0.18	0.18	0.17	0.17	0.17	0.17	0.17	0.17	0.17	0.16	0.16	0.17
mexico	1.49	1.47	1.46	1.44	1.42	1.58	1.57	1.72	1.70	1.68	1.67	1.67	1.65	1.64	1.64	1.59
netherlands	1.40	1.37	1.37	1.35	1.33	1.32	1.31	1.29	1.36	1.43	1.42	1.42	1.49	1.56	1.56	1.40
new zealand	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.08	0.08	0.08	0.08	0.08	0.08	0.03
norway	0.65	0.64	0.64	0.63	0.62	0.61	0.61	0.60	0.59	0.59	0.59	0.58	0.58	0.58	0.57	0.61
portugal	0.19	0.18	0.18	0.18	0.18	0.18	0.17	0.17	0.17	0.17	0.17	0.17	0.17	0.16	0.16	0.17
singapore	0.75	0.73	0.73	0.72	0.71	0.70	0.70	0.69	0.68	0.67	0.67	0.67	0.66	0.66	0.66	0.69
south korea	1.12	1.10	1.09	1.08	1.06	1.05	1.05	1.03	1.02	1.01	1.00	1.00	0.99	0.99	0.98	1.04
spain	1.30	1.37	1.37	1.35	1.42	1.49	1.48	1.46	1.44	1.60	1.59	1.58	1.57	1.56	1.56	1.48
sweden	2.33	2.29	2.28	2.25	2.22	2.19	2.18	2.15	2.12	2.10	2.09	2.16	2.32	2.30	2.30	2.22
switzerland	3.26	3.21	3.19	3.25	3.19	3.16	3.14	3.09	3.06	3.03	3.01	3.00	2.98	3.04	3.04	3.11
taiwan	2.05	2.02	2.01	1.98	1.95	1.93	1.92	1.89	1.87	1.85	1.84	1.83	1.82	1.81	1.80	1.90
united kingdom	7.92	7.97	7.93	7.84	7.81	7.81	7.85	7.73	7.65	7.56	7.53	7.49	7.44	7.48	7.47	7.70
united states	40.63	40.79	40.93	41.03	40.82	41.05	41.24	41.67	41.80	41.68	41.72	41.80	41.60	41.74	41.84	41.36

Table 1.A.10 – S&P Global 1200 composition by country (in %)

Source : Datastream.

Note : The percentage of firms making up the S&P Global 1200 index by country.

	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	Mean
America	49.11	49.40	49.59	49.77	49.51	49.82	49.96	50.43	50.55	50.42	50.50	50.54	50.37	50.45	50.53	50.06
Central America	1.49	1.47	1.46	1.44	1.42	1.58	1.57	1.72	1.70	1.68	1.67	1.67	1.65	1.64	1.64	1.59
Northern America	45.39	45.55	45.67	45.90	45.70	45.88	46.03	46.39	46.56	46.47	46.49	46.54	46.40	46.51	46.60	46.14
South America	2.24	2.38	2.46	2.43	2.40	2.37	2.35	2.32	2.29	2.27	2.34	2.33	2.32	2.30	2.30	2.34
Asia	20.97	20.62	20.51	20.56	20.76	20.53	20.49	20.19	20.05	20.00	19.90	19.82	20.02	19.88	19.85	20.28
Eastern Asia	20.22	19.89	19.78	19.84	20.05	19.82	19.79	19.50	19.37	19.33	19.23	19.15	19.35	19.23	19.20	19.58
South Eastern Asia	0.75	0.73	0.73	0.72	0.71	0.70	0.70	0.69	0.68	0.67	0.67	0.67	0.66	0.66	0.66	0.69
Europe	30.10	30.16	30.08	29.94	29.99	29.82	29.73	29.64	29.48	29.58	29.60	29.64	29.69	29.75	29.70	29.79
Northern Europe	13.33	13.38	13.31	13.17	13.22	13.16	13.16	12.97	12.83	12.69	12.71	12.74	12.82	12.82	12.80	13.01
Southern Europe	2.70	2.84	2.83	2.89	2.93	2.98	2.96	3.09	3.06	3.19	3.26	3.25	3.23	3.20	3.20	3.04
Western Europe	14.07	13.93	13.95	13.89	13.84	13.68	13.60	13.57	13.59	13.70	13.63	13.66	13.65	13.72	13.70	13.75
Oceania	3.82	3.76	3.74	3.70	3.73	3.86	3.84	3.78	3.91	4.03	4.01	4.00	4.05	4.03	4.02	3.89

Table 1.A.11 – S&P Global 1200 composition by geographic area (in %)

Source : Datastream.

Note : According to the United Nations standards, the percentage of firms making up the S&P Global 1200 index by geographical area.

	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	Mean
communication services	5.31	5.32	5.38	5.41	5.32	5.26	5.32	5.50	5.52	5.55	5.52	5.50	5.46	5.59	5.58	5.44
consumer discretionary	12.21	12.19	12.12	12.26	12.33	12.28	12.21	12.29	12.32	12.18	12.29	12.32	12.32	12.33	12.31	12.26
consumer staples	7.83	7.70	7.75	7.75	7.63	7.63	7.59	7.56	7.48	7.56	7.61	7.66	7.69	7.64	7.63	7.65
energy	4.75	4.77	4.83	4.87	4.88	5.00	5.14	5.07	5.01	4.96	4.93	5.00	4.96	4.93	4.92	4.94
financials	16.12	16.41	16.32	16.32	16.50	16.32	16.30	16.07	16.23	16.13	16.05	15.99	15.88	15.86	15.83	16.16
health care	9.13	8.98	8.93	8.84	8.87	8.86	8.89	8.93	8.84	8.74	8.70	8.66	8.60	8.63	8.61	8.81
industrials	16.31	16.32	16.23	16.14	16.06	16.32	16.30	16.32	16.31	16.22	16.22	16.24	16.29	16.19	16.32	16.25
information technology	9.32	9.35	9.39	9.47	9.58	9.47	9.50	9.45	9.60	9.75	9.70	9.66	9.84	9.78	9.76	9.58
materials	8.39	8.52	8.48	8.39	8.43	8.42	8.37	8.25	8.16	8.32	8.28	8.33	8.35	8.55	8.53	8.38
real estate	4.94	4.86	4.83	4.78	4.70	4.82	4.80	4.98	5.01	5.13	5.10	5.08	5.05	5.01	5.00	4.94
utilities	5.68	5.59	5.74	5.77	5.68	5.61	5.58	5.58	5.52	5.46	5.60	5.58	5.54	5.51	5.50	5.60

Table 1.A.12 – S&P Global 1200 composition by economic sector (in %)

Source : Datastream.

Note : The percentage of firms making up the S&P Global 1200 index by economic sector according to the 2018 GICS classification.

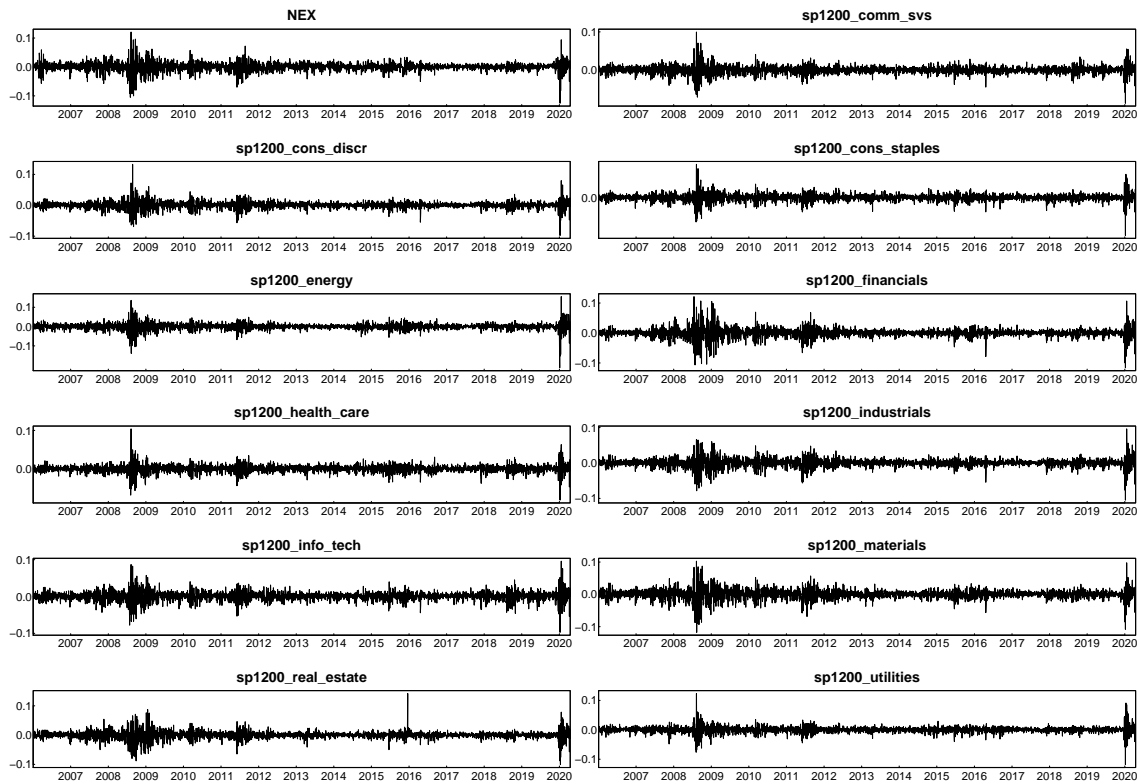


Figure 1.A.1 – Data in first logarithmic difference

Source : Datastream.

	ADF	PP	KPSS
NEX	-0.21 ³	-0.19 ³	4.67 ¹
sp1200_comm_svs	0.44 ³	-2.54 ²	1.68 ¹
sp1200_cons_discr	1.13 ³	1.23 ³	3.17 ¹
sp1200_cons_staples	1.59 ³	1.65 ³	2.56 ¹
sp1200_energy	-0.49 ³	-0.48 ³	1.78 ¹
sp1200_financials	-0.45 ³	-0.44 ³	4.77 ¹
sp1200_health_care	1.58 ³	1.69 ³	4.13 ¹
sp1200_industrials	0.55 ³	0.63 ³	2.96 ¹
sp1200_info_tech	1.92 ³	2.01 ³	5.47 ¹
sp1200_materials	-3.10 ²	-3.07 ²	0.71 ¹
sp1200_real_estate	0.38 ³	0.41 ³	3.64 ¹
sp1200_utilities	0.39 ³	0.44 ³	5.04 ¹
Δ NEX	-38.27 ³ *	-50.02 ³ *	0.12 ² *
Δ sp1200_comm_svs	-23.74 ³ *	-58.47 ³ *	0.04 ² *
Δ sp1200_cons_discr	-40.59 ³ *	-52.26 ³ *	0.09 ² *
Δ sp1200_cons_staples	-44.67 ³ *	-58.22 ³ *	0.06 ² *
Δ sp1200_energy	-33.73 ³ *	-58.46 ³ *	0.11 ² *
Δ sp1200_financials	-41.01 ³ *	-53.98 ³ *	0.12 ² *
Δ sp1200_health_care	-43.34 ³ *	-58.55 ³ *	0.13 ² *
Δ sp1200_industrials	-40.46 ³ *	-52.36 ³ *	0.06 ² *
Δ sp1200_info_tech	-42.74 ³ *	-58.61 ³ *	0.24 ² *
Δ sp1200_materials	-41.22 ³ *	-50.46 ³ *	0.04 ² *
Δ sp1200_real_estate	-39.33 ³ *	-54.78 ³ *	0.08 ² *
Δ sp1200_utilities	-44.93 ³ *	-56.75 ³ *	0.08 ² *

Table 1.A.13 – Unit root tests

Note : ADF, the Augmented Dickey-Fuller test (Dickey and Fuller, 1981), PP, the Phillips-Perron test (Phillips and Perron, 1988), and KPSS, the Kwiatkowski-Phillips-Schmidt-Shin test (Kwiatkowski et al., 1992). In the text core, the unit root test coefficients, and in superscript, the selected models with *one* for *trend and constant*, *two* for *constant*, and *three* for *no trend or constant*. The *star* indicates the stationarity of the series. All variables are non-stationary in level at conventional thresholds – 5% for all series, except the S&P Global 1200 materials non-stationary at 1% with ADF and PP. All variables in log difference are stationary at all thresholds.

	NEX	Comm Svs	Cons Discr	Cons Staples	Energy	Financials
Mean	0.00	0.00	0.00	0.00	0.00	0.00
Median	0.00	0.00	0.00	0.00	0.00	0.00
Maximum	0.12	0.10	0.13	0.08	0.16	0.12
Minimum	-0.13	-0.09	-0.10	-0.09	-0.21	-0.12
Std.Deviation	0.01	0.01	0.01	0.01	0.02	0.01
Skewness	-0.67	-0.17	-0.12	-0.54	-1.08	-0.34
Kurtosis	12.38	13.07	15.83	15.69	23.17	14.96
Jarque-Bera	13958.87	15760.80	25603.13	25218.83	63951.65	22294.53
p.value	0	0	0	0	0	0
	Health Care	Industrials	Info Tech	Materials	Real Estate	Utilities
Mean	0.00	0.00	0.00	0.00	0.00	0.00
Median	0.00	0.00	0.00	0.00	0.00	0.00
Maximum	0.10	0.10	0.10	0.10	0.14	0.12
Minimum	-0.08	-0.10	-0.10	-0.12	-0.10	-0.12
Std.Deviation	0.01	0.01	0.01	0.01	0.01	0.01
Skewness	-0.30	-0.55	-0.28	-0.51	-0.15	-0.23
Kurtosis	13.78	12.29	10.74	11.91	15.41	21.32
Jarque-Bera	18129.78	13586.55	9363.89	12498.63	23937.98	52159.32
p.value	0	0	0	0	0	0

Table 1.A.14 – Descriptive statistics

Note : All variables are in first logarithm difference. The [Jarque and Bera \(1980\)](#)'s test allows testing the null hypothesis of normality distribution. For all variables, normality is rejected.

2 | Return spillovers between green energy indices and financial markets : a sectoral approach[†]

Abstract

This chapter assesses the return spillovers between green energy and other economic sectors. We show that the green energy sector has significant financial openness and is closely interconnected with sectors producing similar goods such as materials or industrials. Therefore, we encourage public policies aimed at reducing carbon emissions in these high-emitting sectors to consider feedback effects on green energy firms. We also point out that green energy spillovers vary over time, e.g., green spillovers increased during the pandemic, illustrating the "fly to liquidity" mechanism. Finally, since climate awareness (2014-2015), the net return spillovers from green industries to fossil energy have risen.

Keywords : Financial markets, Green energy stocks, Sectoral indices, Spillovers, Networks.

JEL codes : C32, G15, Q42.

[†]. A first version of this chapter has been published as [Nobletz, C. \(2021\), "Return spillovers between green energy indexes and financial markets: a first sectoral approach", *EconomiX Working Paper 2021-21*](#), and is currently under revision in *Finance*. The author would like to thank Valérie Mignon, Elena Dumitrescu, Gilles de Truchis, and Anthony Paris, for their valuable comments to improve the article.

Introduction

Since 1950, societies have faced intensifying extreme weather and climate events, such as increased global warming, heightened ocean acidification, or higher ice caps melting. According to [IPCC \(2014\)](#), human activities are the leading cause, mainly through greenhouse gas emissions. In response, several governments have committed to addressing this climate emergency, resulting in the Paris Agreement (2015). The 196 Parties committed to limiting global warming to well below two degrees above pre-industrial levels, with a target of 1.5°C ([UNFCCC](#)). At COP26 in Glasgow (2021), countries pledged again to continue their efforts to reach this threshold ([UNFCCC](#)), but the path is still long if societies want to transition to low-emissions economies successfully. Indeed, we have already crossed the 1.1°C level, where three-quarters of carbon emissions come from the energy sectors ([IPCC, 2021](#)). The [IEA \(2021\)](#) advises rethinking the energy sectors by developing the green energy sector with green electricity, green innovations, and better energy efficiency. Therefore, investments in green energy should increase by \$4 trillion per year by 2030 to reach the 1.5°C targets ([IEA, 2021](#)).

In this context, our paper analyzes the return spillovers between green energy and the other economic sectors. Indeed, we assume that achieving this transition requires an awareness of (i) how the green energy sector's development might affect other economic sectors, and (ii) how policies to reduce greenhouse gases from polluting sectors (e.g., energy, industry, or materials) might affect the green energy one. This issue is all the more relevant as investments in green energy worldwide are already growing, and the predominant sources of financing are financial assets (stocks, bonds, credits) ([BloombergNEF, 2020](#)). To our best knowledge, we are the first to provide a cross-sectoral analysis, and there lies our main contribution.

Relying on the VAR forecast errors' variance decomposition methodology, we construct return spillover indices and analyze the return spillovers between the global green energy index (NEX) and sectoral economic indices (S&P Global 1200 sectoral indices) from 2006 to 2020. We also use rolling windows to account for the temporal variation of the spillover indices and, thus, provide a dynamic analysis.

Our main results are as follows. The static analysis highlights that the green energy sector has significant financial openness but receives more shocks than it transmits to other economic sectors. Indeed, the growing demand for green assets drives the green energy sector's integration and its propensity to transmit shocks. Nevertheless, environmental markets are still young, facing more capitalization or liquidity issues than more developed economic sectors, explaining why they receive more shock returns on average. In

addition, we note stronger interconnections between green energy companies with those in industry and material. Two factors can explain this phenomenon : (i) the industrial and material sectors are highly integrated, and (ii) they also produce similar goods as green energy firms. For example, the wind sectors have turbine manufacturers, and the solar sectors produce photovoltaic materials. This result is interesting as it highlights that public policies aimed at reducing carbon emissions in the material or industrial sectors should consider feedback effects on green industries. Another noteworthy finding is that return spillovers from green energy are lowest in the health care, utilities, and consumer staples sectors. Simply put, asset managers looking to invest in green energy can consider these sector indices to diversify their portfolios. Turning to dynamic analysis, we show that green energy return spillovers vary and appear to follow economic uncertainties ; green spillovers increased during the pandemic, illustrating the "flight to liquidity" effect. Investors pull their investments out of risky assets such as green financial products into safer assets. Additionally, whereas the relationship between the green and fossil energy sectors does not play a prominent role in the static analysis, the dynamic study reveals a time-varying pattern. Indeed, since the rising awareness of climate issues (2014-2015), the net spillovers from green industries to fossil energy have increased. In sum, green energy returns impact those of fossil energy.

The chapter is organized as follows. Section 2.1 provides a brief overview of the existing literature. Sections 2.2 and 2.3 present the data and the methodology used, respectively. Section 2.4 outlines the empirical results. Section 2.5 is devoted to the robustness tests, and Section 2.6 sets out the main conclusions.

2.1 Literature review

2.1.1 Green asset definition

As noted in the introduction, investments in green energy are primarily financed through green energy assets' emissions. Therefore, before reviewing the links identified in the literature between green energy and other economic sectors, we first focus on the green stocks' features. On this last point, the literature is scarce.

A "green stock" is a company share whose core activity is not "harmful" to the environment. Defining what is not "harmful" is far from simple, as there is no consensus on what is "green" or not. The "green"

attribute depends on the SRI (Sustainable and Responsible Investment) process.¹ With the "best-in-class" approach, the "best" companies in each sector are selected, while the "exclusion" approach consists of excluding companies that do not meet socio-environmental criteria (e.g., armament, nuclear)(Eurosif, 2018). Greenness measures also depend on the criteria used, i.e., qualitative or quantitative. Furthermore, the definition varies between countries and their respective governmental policies. However, the literature generally identifies renewable energy, wastewater management, or energy efficiency as "green" activities. The nuclear and hydropower sectors are controversial, and the biofuels or shale gas drive consensus shifts (Inderst et al., 2012).

As a result, the lack of clarity around green assets makes us wonder why they are so popular. Inderst et al. (2012) highlight several reasons for investing in green assets (e.g., stock or bonds) : (i) financial motivations (return, risk, and portfolio diversification criteria), (ii) extra-financial motivations (e.g., ecological, scientific, ethical), (iii) reputational motivations (reputation of the investor or company, political pressures, and marketing tools) or (iv) compliance and fiduciary obligations (e.g., national laws and regulations, international conventions).

2.1.2 Green energy indices & financial markets

To our best knowledge, we are the first to analyze the return spillovers between green energy and "all" other economic sectors. Indeed, most studies analyzing relationships with green energy focus on specific sectors, especially fossil energy and high-tech ones.

Overall, the literature highlights that (i) high-tech sectors impact significantly and positively green energy sectors, while (ii) fossil energy sectors play minor roles. On the first point, the literature puts forward several hypotheses to explain this relationship : (i) the returns of high-tech stocks drive those of green energy through a "price signal" (Henriques and Sadorsky, 2008; Kumar et al., 2012; Sadorsky, 2012; Managi and Okimoto, 2013; Inchauspe et al., 2015; Ferrer et al., 2018), and (ii) these two assets "compete for the same inputs," such as highly skilled engineers and researchers, semiconductors, or thermoelectric materials (Inchauspe et al., 2015). On the second point, substitution effects between the green and the fossil energy sectors appear to be weak (Henriques and Sadorsky, 2008) : an increase in oil prices has only small repercussions on the green energy demand and, consequently, on their prices (the reverse is true). Nevertheless, there is no clear consensus about this relationship; some authors find a positive

1. "Sustainable and responsible investment ("SRI") is a long-term oriented investment approach that integrates ESG factors in the research, analysis, and selection process of securities within an investment portfolio. [...]"(Eurosif, 2018, page 18).

relationship (Kumar et al., 2012; Managi and Okimoto, 2013), while others do not (Ferrer et al., 2018). Some researchers answer this issue by showing that this relationship is time-varying (Inchauspe et al., 2015; Reboredo, 2015; Reboredo et al., 2017; Ahmad and Rais, 2018). According to Reboredo et al. (2017), this dependence is weak in the short term but strengthens in the long term.

In a broader sense, the literature identifies strong connectivity between green energy assets and financial markets. Henriques and Sadorsky (2008), Kumar et al. (2012), Managi and Okimoto (2013), and Bondia et al. (2016) find a positive relationship between interest rates (measured with the three-month US Treasury Bill) and green energy indices. Inchauspe et al. (2015) underline that the MSCI World Index and the global green energy index are highly correlated. Ferrer et al. (2018) highlight that renewable energy indices are net transmitters of return and volatility spillovers on the US financial market.

Finally, turning to methodological considerations, several various approaches are used. Henriques and Sadorsky (2008), and Kumar et al. (2012) estimate a vector autoregressive model (VAR) to compute generalized impulse response functions (GIRF) and Granger causality tests. Others use Diebold and Yilmaz's (2012; 2014) methodology (Ahmad, 2017; Ahmad and Rais, 2018; Pham, 2019) or its extension introduced by Baruník and Křehlík (2018) in the frequency domain (Ferrer et al., 2018). Several papers also employ a model belonging to the ARCH-GARCH family (Broadstock et al., 2012; Sadorsky, 2012; Wen et al., 2014; Ahmad, 2017; Ahmad and Rais, 2018; Dutta et al., 2018; Pham, 2019; Dutta et al., 2020). Some use copula methods (Reboredo, 2015; Reboredo and Ugolini, 2018; Elie et al., 2019). At last, Managi and Okimoto (2013) and Inchauspe et al. (2015) employ, respectively, the state-space multi-factor asset pricing model with time-varying coefficients and Markov-switching vector autoregressive models. Reboredo et al. (2017) rely on continuous and discrete wavelets.

2.2 Data

2.2.1 Data selection process

Concerning data, the main challenge we face is to select green and sectoral indices for which we have access to their compositions each year.² Indeed, we want to verify that no or few firms simultaneously make up the green and the sectoral indices, as the risk is to create a dependency between them artificially. For the green energy index, we select the "WilderHill New Energy Global Innovation Index" (NEX), which is composed of companies focusing on innovative technologies on cleaner energy, conservation, efficiency,

2. See Nobletz (2022) for more information.

and the advancement of renewable energy (NEX, 2020). The NEX provides an overall presentation of the environmental sectors, and an "exclusion" approach is applied to select firms. It has a long history, is a reference for investors and academics, and its constituents are accessible each year.³ From 2006 to 2020, the NEX index composition has been highly volatile. The index includes about 100 global green companies, but 309 have comprised the index in all years. This result highlights the youth of the environmental market ; green companies are more likely to go bankrupt, merge, or have capitalization issues that prevent them from being included in the index from year to the next. Moreover, the NEX composition tracks the green energy market changes : the Asia-Pacific companies' role has grown, like the wind and solar industries. Finally, given the limited weights of companies in the index, it is unlikely that some firms drive index changes.

For sectoral stock indices, we select a "market-oriented" rather than a "production-oriented" classification. Indeed, the "market" classification is followed by the financial community (Phillips and Ormsby, 2016), allows to explain the comovements of stock returns (Bhojraj et al., 2003), and depicts a more reliable representation of the sector concentration (Hrazdil and Zhang, 2012). Moreover, belonging to this classification family, we select the GICS (Global Industry Classification Standard, 1997) over the ICB (Industry Classification Benchmark, 2001), as we pick the S&P Global 1200 for our worldwide analysis.⁴ There are eleven "sectors" in the S&P Global 1200 : Communication Services, Consumer Discretionary, Consumer Staples, Energy, Financials, Health Care, Industrials, Information Technology, Materials, Real Estate, and Utilities. We focus on the sectors and not on the 24 industry groups, 69 industries, or 158 sub-industries as the risk of going down to a more advanced level is to drowning in information. At last, we retrieve these indices' compositions for all years and check the GICS 2018 restructuring impact on the sectoral indices. We find that 33 companies over 1200 have changed sectors, which is negligible.

Finally, comparing the NEX and S&P Global 1200 components, we identify 22 joint companies. In ascending order, six are in utilities, five in industrials, four in materials, two in consumer discretionary and financials, and one in consumer staples, health care, and information technology. Twenty-two companies are marginal for the S&P Global 1200 but are more substantial for the NEX. On the latter, ten companies have been in the index for less than two years, and only three have been in the index for all years. Therefore, these results highlight the low risk of creating multicollinearity between indices.

3. Reports with NEX components are available for free on the index website. However, in their current state, these reports are unusable for temporal analysis as the information provided is not harmonized (e.g., company names, weight, or geographic location availability). We had to combine and harmonize all information for each year (quarter by quarter) and between these years.

4. MSCI and Standard & Poor's (S&P) produce the GICS, while Dow Jones and FTSE provide the ICB. The former is, therefore, more relevant for a global study.

2.2.2 Selected data

As noted previously, we consider the NEX and the S&P Global 1200 Communication Services, Consumer Discretionary, Consumer Staples, Energy, Financials, Health Care, Industrials, Information Technology, Materials, Real Estate, and Utilities.⁵ Data comes from Datastream, and the period runs from 2006-03-06 (NEX launch date) to 2020-06-19 daily. All variables are expressed in USD and are in logarithmic first difference (Figure 2.A.1) to address non-stationary issues.⁶

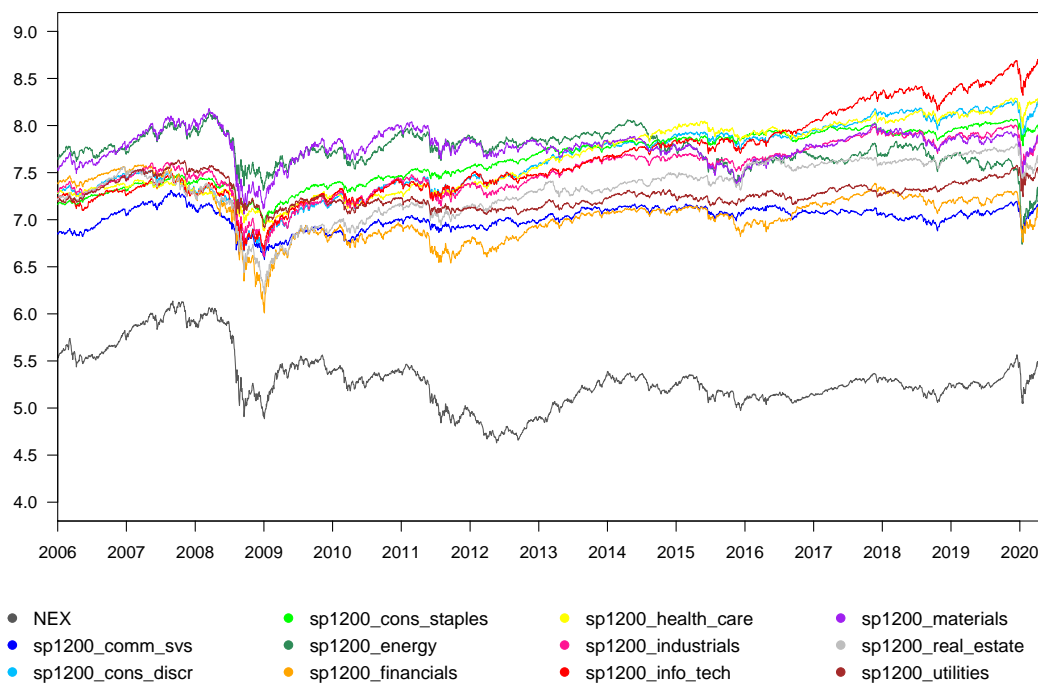


Figure 2.2.1 – The NEX and the S&P Global 1200 sectoral indices (log)

Source : Datastream

Figure 2.2.1 shows that NEX and S&P Global 1200 sectoral indices (in logs) co-move strongly and positively. A positive trend characterizes these indices, even if they have experienced substantial drops during crisis periods, e.g., 2008 and 2020. For example, during the Covid-19 crisis, markets collapsed,

5. In the model, we do not include the VIX (Figure 2.A.2 in Appendix) as it has statistical properties incompatible with returns (high persistence), leading to inconsistent estimates (Sun, 2004). Likewise, we omit public environmental expenditures, as these data are not available at the global level with daily frequency.

6. According to the ADF (Dickey and Fuller, 1981), KPSS (Kwiatkowski et al., 1992), and PP (Phillips and Perron, 1988) tests, all logarithmic series are non-stationary at conventional levels. In first log difference, all tests conclude to the series' stationary at 5% (Table 2.A.1). Table 2.A.3 provides descriptive statistics on these series.

followed by a rapid recovery in index prices. Moreover, NEX appears to be more volatile than the S&P Global 1200 sectoral indices. Indeed, in times of crisis, investors are more likely to withdraw their green financial investments and move to safer assets, such as 10-year sovereign bonds. This phenomenon is known as "fly to liquidity" effect (Longstaff, 2004). At last, from an ethical point of view, agents are more willing to finance the environmental transition in times of expansion, while financial concerns prevail in times of crisis.

Finally, we perform Granger causality tests (Table 2.A.2) to check whether there is a causal relationship between the aggregated variables before going down to a sectoral level. We identify a bi-directional Granger causality between the S&P Global 1200 and the NEX at 5%. There is a feedback effect : the S&P Global 1200 returns contribute to the forecasts of the NEX returns (and conversely). Since these two variables contribute to each other's prediction, performing a network analysis at a more advanced level is relevant. This analysis no longer focuses on the VAR's coefficients but on the VAR forecast errors' variance decomposition. We explain this methodology in detail in the following section.

2.3 Methodology

2.3.1 Connectedness measures

Different connectedness measures exist, such as the Marginal Expected Shortfall (MES) (Acharya et al., 2016, 2012), the CoVaR (Adrian and Brunnermeier, 2016), the pairwise Granger causality (Billio et al., 2012), or the equi-correlation (Engle and Kelly, 2012). In a series of papers (2008, 2012, 2014), Diebold and Yilmaz use forecast error variance decomposition of VAR(p) model to compute spillover indices ; we follow this methodology. Indeed, the Marginal Expected Shortfall and Expected Capital Shortfall approaches analyze firm sensitivity to extreme market risks (financial markets \rightarrow firm) while the CoVaR approach measures the firm systemic nature to financial markets (firm \rightarrow financial markets). Diebold and Yilmaz spillover indices mix these two approaches ; the directional spillover indices allow measuring whether an asset is more receiver or transmitter of shocks in the system. Besides, this methodology provides greater granularity, as we can analyze pairwise spillovers between all system assets (Diebold and Yilmaz, 2014).

Diebold and Yilmaz have refined their method over time. In the 2008 paper, the Cholesky factorization achieves orthogonality. Hence, the variance decomposition depends on the variables' ordering. We could compute the VAR models corresponding to all possible permutations of variables (Faust, 1998), but this

solution is too time-consuming. Moreover, it would be hazardous to justify a specific order in the variables as we have established bidirectional causality between the S&P Global 1200 and the NEX. In 2012 and 2014 papers, Diebold and Yilmaz address this issue by implementing the generalized VAR framework of Koop et al. (1996); this approach allows innovations (shocks) to be correlated but takes them into account appropriately using the historically observed error distribution.

Therefore, we use the methodology of Diebold and Yilmaz (2014) and construct the confidence intervals/distributions of the variance decomposition matrix using the fixed-effect wild bootstrap. This residual resampling method accounts for conditional heteroskedasticity of unknown form leading to valid inference (Gonçalves and Kilian, 2004).⁷

2.3.2 Spillover indices

To compute spillover indices, we apply the Diebold and Yilmaz (2014) methodology based on the generalized VAR variance decomposition of Koop et al. (1996).

First, consider a covariance stationary N -variable VAR(p) :

$$x_t = \sum_{i=1}^p \Phi_i x_{t-i} + \varepsilon_t \quad (2.3.1)$$

where ε is a N -vector of identically and independently distributed (i.i.d.) errors with zero mean and covariance matrix, Σ . We transform the model into its moving average representation :

$$x_t = \sum_{i=0}^{\infty} A_i \varepsilon_{t-i} \quad (2.3.2)$$

where A_i is a $N * N$ coefficient matrix and has the following form : $A_i = \Phi_1 A_{i-1} + \Phi_2 A_{i-2} + \dots + \Phi_p A_{i-p}$. A_0 is a $N * N$ identify matrix with $A_i = 0$ for $i < 0$.

Second, we calculate the generalized h -step-ahead forecast error variance decomposition, $\theta_{ij}^g(H)$:

$$\theta_{ij}^g(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} (e_i' A_h \sum e_j)^2}{\sum_{h=0}^{H-1} (e_i' A_h \sum A_h' e_i)} \quad (2.3.3)$$

with Σ , the error vector variance matrix; σ_{jj} , the standard deviation of the error term for the j^{th} equation, and e_i the selection vector, a vector which takes the value of one at the i^{th} element and zero otherwise.

7. The bootstrapping residuals $\hat{\varepsilon}_t^*$ take the following form : $\hat{\varepsilon}_t^* = \hat{\varepsilon}_t \cdot \eta_t$ where $\hat{\varepsilon}_t = \hat{\Phi}(L)y_t$ are the estimated residuals of the OLS model and η_t is an i.i.d sequence with mean zero and variance one (Gonçalves and Kilian, 2004).

As there is no error orthogonalization, the sum of each variable's forecast error variances (the sum of the error variances by row) is not necessarily equal to one : $\sum_{j=1}^N \theta_{ij}^g(H) \neq 1$. Therefore, we normalize each variance of the matrix by the row sum, equal to the number of variables, N .

$$\tilde{\theta}_{ij}^g(H) = \frac{\theta_{ij}^g(H)}{\sum_{j=1}^N \theta_{ij}^g(H)} \longrightarrow \sum_{i,j=1}^N \tilde{\theta}_{ij}^g(H) = N \quad (2.3.4)$$

Third, we measure the total spillover index, and as the covariance matrix is independent of the variable ordering, we also compute the directional and the net spillovers.

The Total Spillover Index (TSI) measures the system's overall connectedness :

$$S^g(H) = \frac{\sum_{i,j=1, i \neq j}^N \tilde{\theta}_{ij}^g(H)}{\sum_{i,j=1}^N \tilde{\theta}_{ij}^g(H)} * 100 = \frac{\sum_{i,j=1, i \neq j}^N \tilde{\theta}_{ij}^g(H)}{N} * 100 \quad (2.3.5)$$

The directional spillovers are spillovers transmitted by a variable to all others ($S_{.i}^g(H)$) and spillovers received by a variable from all others ($S_i^g(H)$).

$$S_{.i}^g(H) = \frac{\sum_{j=1, j \neq i}^N \tilde{\theta}_{ji}^g(H)}{\sum_{i,j=1}^N \tilde{\theta}_{ji}^g(H)} * 100 = \frac{\sum_{j=1, j \neq i}^N \tilde{\theta}_{ji}^g(H)}{N} * 100 \quad (2.3.6)$$

$$S_i^g(H) = \frac{\sum_{j=1, j \neq i}^N \tilde{\theta}_{ij}^g(H)}{\sum_{i,j=1}^N \tilde{\theta}_{ij}^g(H)} * 100 = \frac{\sum_{j=1, j \neq i}^N \tilde{\theta}_{ij}^g(H)}{N} * 100 \quad (2.3.7)$$

The net spillovers (net) are the difference between the "to" and "from" indices. Therefore, if $S_{.i}^g(H) > 0$, the variable is a net transmitter of shocks, and if $S_i^g(H) < 0$ it is a net receiver of shocks.

$$S_i^g(H) = S_{.i}^g(H) - S_i^g(H) \quad (2.3.8)$$

The net pairwise spillover between the variables x_i and x_j , is the difference between the pairwise spillover of i to j ($x_i \rightarrow x_j$), and the pairwise spillover of j to i ($x_j \rightarrow x_i$).

$$S_{ij}^g(H) = \left[\frac{\tilde{\theta}_{ji}^g(H)}{\sum_{i,k=1}^N \tilde{\theta}_{ik}^g(H)} - \frac{\tilde{\theta}_{ij}^g(H)}{\sum_{j,k=1}^N \tilde{\theta}_{jk}^g(H)} \right] * 100 \quad (2.3.9)$$

$$S_{ij}^g(H) = \left[\frac{\tilde{\theta}_{ji}^g(H) - \tilde{\theta}_{ij}^g(H)}{N} \right] * 100$$

Finally, to analyze these spillover indices in a static setting, we compute the spillover table (Table 2.3.1) :

Table 2.3.1 – Spillover table

	x_1	x_2	x_3	...	x_N	from
x_1	p_{11}	p_{12}	p_{13}	...	p_{1N}	$\sum_{j=1, j \neq 1}^N p_{1j}$
x_2	p_{21}	p_{22}	p_{23}	...	p_{2N}	$\sum_{j=1, j \neq 2}^N p_{2j}$
x_3	p_{31}	p_{32}	p_{33}	...	p_{3N}	$\sum_{j=1, j \neq 3}^N p_{3j}$
...
x_N	p_{N1}	p_{N2}	p_{N3}	...	p_{NN}	$\sum_{j=1, j \neq N}^N p_{Nj}$
to	$\sum_{i=1, i \neq 1}^N p_{i1}$	$\sum_{i=1, i \neq 2}^N p_{i2}$	$\sum_{i=1, i \neq 3}^N p_{i3}$...	$\sum_{i=1, i \neq N}^N p_{iN}$	$TSI = \frac{1}{N} * \sum_{i,j=1, i \neq j}^N p_{ij}$

The "own-spillovers" are the matrix's diagonal elements (without the TSI) ; p_{ii} is the share of forecast error variance that x_i transmits to itself. The "pairwise-spillovers" are, therefore, elements of the off-diagonal matrix (without "to" and "from" indices) ; p_{ij} is the share of variance that x_i received from x_j . Besides, the from (to) indices are the row (column) sum for each variable minus its own-variance share. Finally, the TSI is the sum of the pairwise spillovers divided by N (Diebold and Yilmaz, 2012; Diebold and Yilmaz, 2014).

2.4 Results

This section analyzes the return spillovers in a static sample, capturing the average behaviors. Then, we observe how the return spillovers between sectors vary over time.

2.4.1 Full-sample static analysis

We run the 12-VAR(1) model, transform it into its moving average form, and compute the 10-step-ahead forecast error variance decomposition. To avoid over-parametrization, we select the SIC over the AIC criterion – one versus six lags. In addition, the VAR model is stable, and we pick a 10-forecast horizon as it is consistent with "risk management considerations" (Diebold and Yilmaz, 2014, page 4).⁸ Finally, we do inference on the estimated parameters using bootstrap adapted to the residuals' conditional heteroscedasticity ; the bootstrap number is 5000. Hence, we provide Efron percentile confidence intervals for the estimated parameters of the variance decomposition matrix (Table 2.A.4) and plot the spillover indices' distributions (Figures 2.A.5, 2.A.6).⁹ All estimated coefficients fall within their respective confidence intervals.

8. Our results are robust to the number of lags and the forecast horizon selected. Results are available upon request to the author.

9. The Efron percentile confidence intervals are the quantiles of the distributions at 2.5% and 97.5%.

To ease the reading of the spillover table (Table 2.A.4), we compute a network graph of pairwise spillovers (Figure 2.4.1) using the ForceAtlas2 algorithm of Jacomy et al. (2014).¹⁰ Nodes' size denotes the assets' interconnectedness degree : the larger the node, the more the asset is connected in the system. Nodes' location and links indicate the "to" and "from" pairwise spillovers : their sizes are proportional to the percentage variance of the error predictions they transmit or receive from other assets. The nodes' color indicates the "to-degree" : the darker the color, the more the asset transmits shocks in the system.

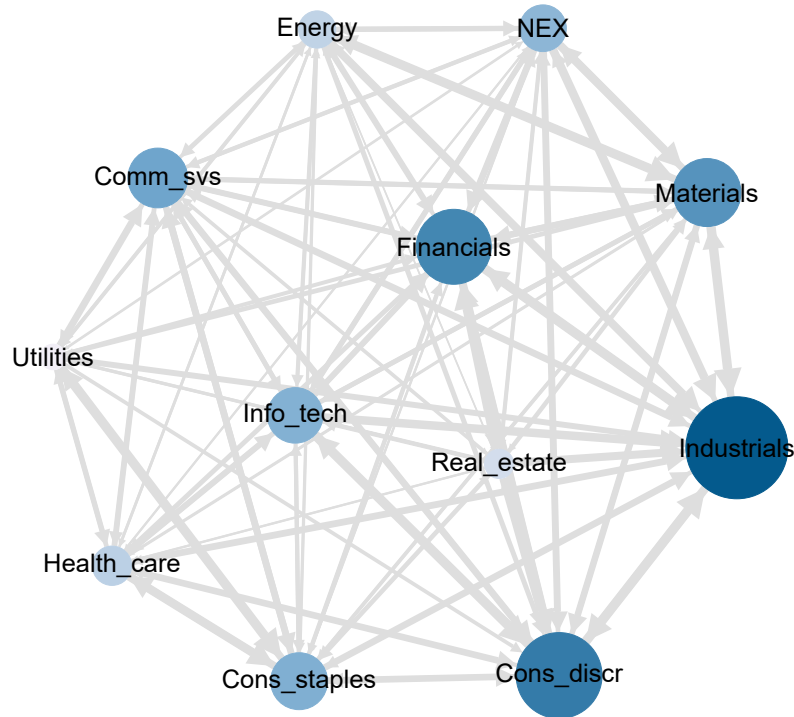


Figure 2.4.1 – Network graph

Note : Networks have been computed with Gephi software. The nodes' position between networks can change slightly ; there is no single representation of the system as it depends on the initial state. Nevertheless, each node's location depends on the others ; thus, the valid visual representation of the structure is not affected (Jacomy et al., 2014).

10. The ForceAtlas2 algorithm is a "force-direct layout. [...] It simulated a physical system in order to spatialize a network. Nodes repulse each other like charged particles, while edge attracts their nodes, like springs" (Jacomy et al., 2014, page 2).

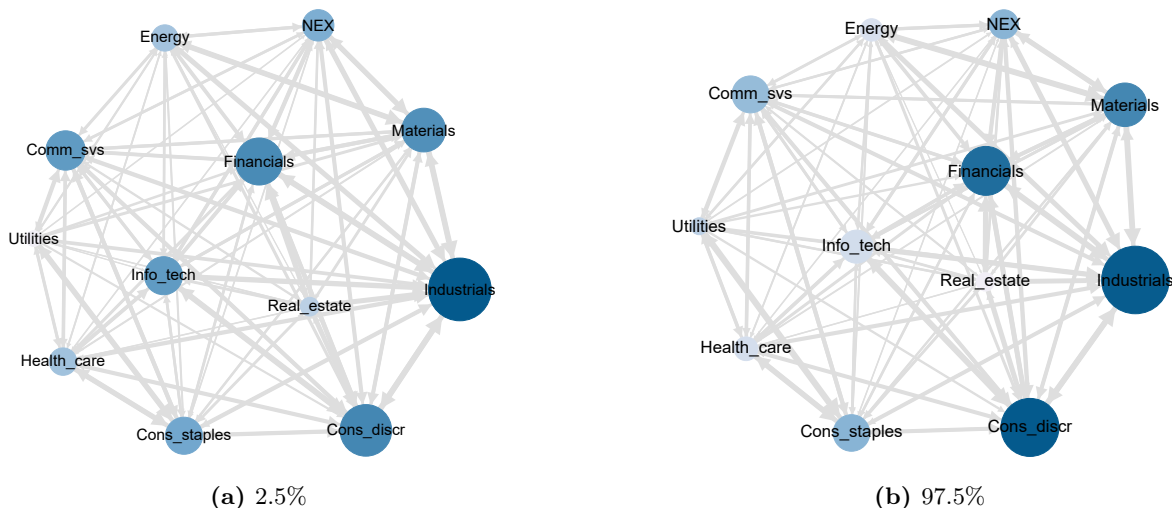


Figure 2.4.2 – Efron percentile confidence intervals

Note : The Efron percentile confidence intervals are the quantiles of the 2.5% and 97.5% distributions.

First, Figure 2.4.1 shows that sectoral indices are highly interconnected, underlining substantial sectoral integration. According to the TSI, the cross-sectoral spillovers explain 86.51% of the variance of forecast errors. Moreover, sectoral indices are more likely to transmit shocks across their markets than toward other sectors – their own-spillovers are higher than their pairwise-spillovers (Table 2.A.4).

Second, the most interconnected sectoral indices are industrial, consumer discretionary, and financial sectors, while the least are utilities, real estate, health care, and energy. These results are consistent with the empirical literature; Balli et al. (2021) also identify "consumer goods," financials, and industrials as primary shock donors (the findings also hold for dominant receivers). In particular, they point out that net sectoral market spillovers depend positively on firms' capitalization ratio and liquidity position, while they depend negatively on the debt level. The S&P Global 1200's composition is in line as this index aims to provide an "appropriate sector concentration" (S&P, 2021, Factsheet, page 1). This index shows that the leading economic sectors are industrial, financial, and consumer discretionary, while the less preponderant are utility, real estate, and energy (Table 2.A.5).

Third, the net return spillover of the green energy index (NEX) is in an intermediate position (Figure 2.A.3). Indeed, the green energy sector has a significant degree of financial openness (approximated by the sum of its pairwise spillovers). However, on average, green energy sectors receive more shocks than they transmit to others. Indeed, the demand for green energy assets is growing, but the environmental market is young and could face capitalization or liquidity issues. Therefore, we can assume two conflicting forces here : on the one hand, the growing demand for green energy pushes its market integration and

thus its propensity to give shocks. On the other hand, capitalization or liquidity issues negatively impact the sectoral return spillovers (Balli et al., 2021).

Fourth, the green energy sector is more interconnected with the material and industrial sectors. This result may reflect the financial openness of the former, but also the similarity of goods produced between the green, materials, and industrial sectors. For example, the wind energy sector includes turbine manufacturers, and the solar energy sector comprises firms producing photovoltaic materials or solar thermal technologies, e.g., concentrators and Stirling engines. This result is interesting as it highlights that public policies aimed at reducing greenhouse gas emissions from polluting sectors such as industry or material have to consider feedback on green industries. In addition, the green energy index appears less interconnected with the health care, utility, and consumer staple sectors. As green energy stocks are volatile, it would be feasible to support green energy investments while reducing the risk of capital loss by diversifying portfolios with sectoral assets, e.g., the less interconnected.

Finally, the returns spillovers are weak between the green energy and fossil energy sectors, suggesting that substitution effects are not the primary driver. This result is consistent with the literature (Henriques and Sadorsky, 2008). Nevertheless, the dynamic analysis in the following section reveals that this relationship is time-varying.

2.4.2 Dynamic analysis

We run rolling windows on the model with a 250-day width (a business year) to analyze the spillover indices variations. The primary advantage of this method is its ease of implementation and the application of a consistent framework (Diebold and Yilmaz, 2014). We also perform 200 wild bootstraps to construct confidence intervals for the dynamic spillover indices.¹¹

2.4.2.1 Dynamic analysis of the global connectedness

As shown in Figure 2.4.3, there are substantial variations in overall system connectivity. Global interconnectedness follows the level of worldwide uncertainty; it rises in times of global economic or political shocks and falls in times of lull. Candelon et al. (2021) support these findings by matching the Diebold and Yilmaz (2008) methodology with a non-linear effect – threshold VAR. In the following paragraphs, we propose a reading of this graph by analyzing, in a non-exhaustive way, the events that may have caused these variations.

11. We are not able to run more than 200 bootstraps as we face computational limitations.

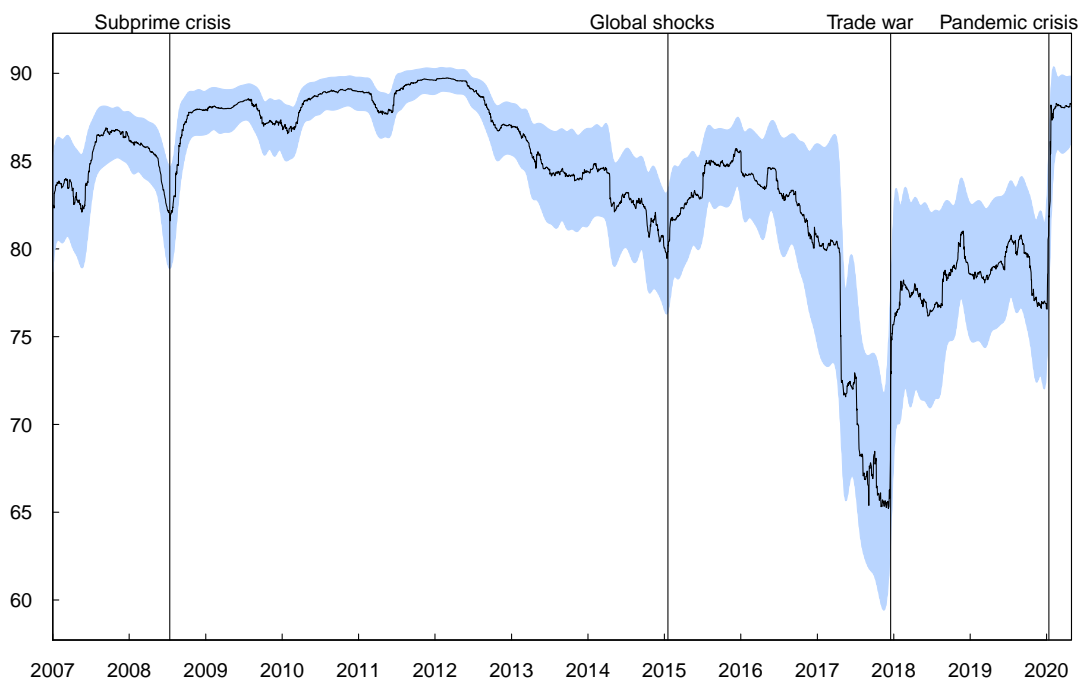


Figure 2.4.3 – TSI over time

Note : This figure depicts the variations in the Total Spillover Index, estimated with 250-day width rolling windows. On the x-axis, each point represents the ending of the rolling windows. We construct Efron percentile confidence intervals with 200 fixed-effect wild bootstraps. Smoothing splines are also applied to these intervals to improve their graphical readability. For more details on the smoothing method, see [Green and Silverman \(1993\)](#).

First, we observe an increase in system connectivity around 2008, 2015, 2018, and 2020. In 2008, the global financial crisis occurred, which led to significant disruptions in the financial markets. Numerous shocks also hit the years between 2015 and 2016. In 2015, we had the end of the Swiss franc's peg to the euro, the Chinese economic crisis, the Greek bankruptcy, and the easing of monetary policies worldwide, combined with the rise in federal funds rates. Add to this the terrorist attacks and the refugees' crisis. In 2016, China's stock market crashed, OPEC announced cuts in oil production, Donald Trump became President of the United States, and Brexit was announced. Anxiety rose again in 2018-2019 with the trade war between China and the United States or the tensions over the nuclear negotiations between South Korea and the United States. Finally, in 2020, the pandemic crisis provoked the Great Lockdown and exacerbated the already high uncertainty ([Mignon, 2020a](#)). The financial markets crash then took place, aggravated by a drastic drop in oil prices.

Second, this figure highlights a sharp decline in financial interconnectedness in 2017. This year was indeed characterized by low uncertainty, e.g., the VIX nearly hit its floor value (Figure 2.A.2). The upholding growth, the rising interest rates, or the flourishing year for the financial markets could explain this finding.

2.4.2.2 Dynamic analysis of the NEX pairwise spillovers

Let us now analyze the evolution of net spillovers between green energy and other economic sectors.

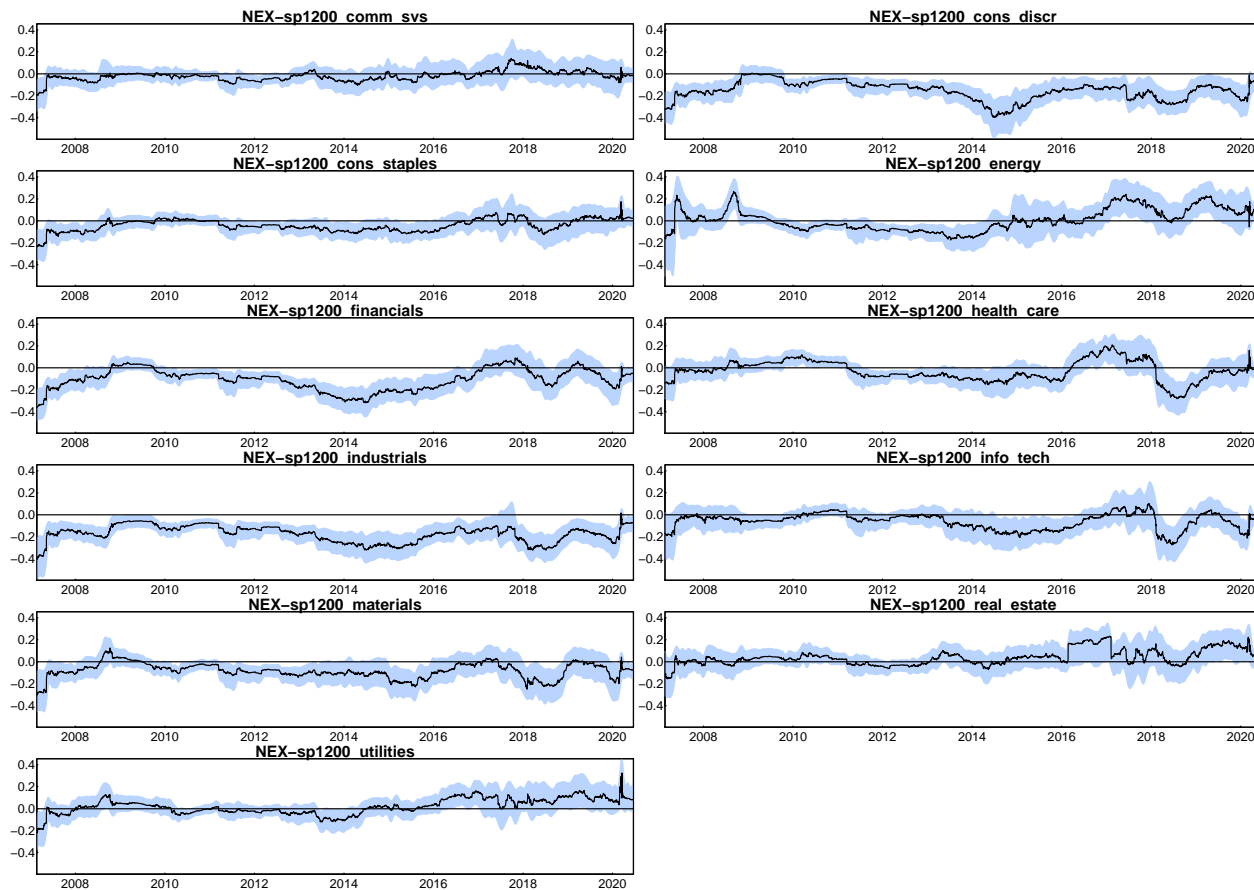


Figure 2.4.4 – NEX pairwise spillover indices

Note : This figure depicts the variations of the NEX pairwise spillover indices, estimated with 250-day width rolling windows. On the x-axis, each point represents the ending of the rolling windows. We construct Efron percentile confidence intervals with 200 fixed-effect wild bootstraps. Smoothing splines are also applied to these intervals to improve their graphical readability. For more details on the smoothing method, see [Green and Silverman \(1993\)](#).

Figure 2.4.4 shows that green energy sectors are mainly net receivers of shocks from other economic sectors – the NEX’s pairwise indices are below zero, on average ($net_{NEX} < 0$). Simply saying, the green energy sectors receive more shocks than they transmit to other economic sectors over time. However,

the green energy sectors have varying return spillovers after significant economic or financial events. For instance, NEX's spillovers rose in 2007, highlighting strong global demand, increased government subsidies in environmental markets, or higher oil prices. Moreover, green energy spillovers rose again during the pandemic and could be linked to the "fly to liquidity" effect. In times of crisis, investors withdraw their risky investments, such as green assets, toward safer financial products. Finally, an interesting result stands out when considering net spillovers between green energy and fossil energy sectors. Since 2014, the green energy sector has witnessed increasing spillovers to fossil energy and has become a net donor of shocks to the latter in several periods.¹² This result could reflect increased climate awareness and thus increased return spillovers from green energy to fossil fuel companies.

2.5 Robustness

The use of different specifications backs up our findings. We use the LASSO model to check that multicollinearity problems do not bias our results, as the instantaneous correlations between the variables are strong (Figure 2.A.10a).¹³ We found that our spillover tables with and without shrinkage are very similar (Tables 2.A.4, 2.A.6). For example, the TSI is 86.51 with VAR-OLS and 86.41 with VAR-LASSO. We further investigate the multicollinearity issue and show that the correlation coefficients between the model variables – the endogenous and lagged endogenous variables – are weak (Figure 2.A.10b). The VIF (Variance Inflation Factor) also highlights the result of no or weak multicollinearity; for all regressions, the VIFs barely exceed 1.¹⁴ Finally, we provide readers with boxplots of the estimated parameters of the OLS-VAR model (Figure 2.A.11), pointing out that all coefficients belong to their confidence intervals and that several variables are significant, e.g., discretionary consumption.¹⁵

12. No company composes the NEX and the energy index jointly. We refer readers to Section 2.2.2.

13. Shrinkage methods with LASSO, ridge, or elastic-net allow to recover degrees of freedom and deal with potential multicollinearity problems by imposing constraints on the model coefficients (Friedman et al., 2008). By minimizing the variance forecast errors, we select the LASSO model with a constraint equal to 0.00123 (Figure 2.A.9).

14. Detailed results are available upon request.

15. One could consider inference in the VAR-LASSO model based on recent bootstrap method specific to shrinking models (Dezeure et al., 2017). This is left for future research.

2.6 Conclusion

As the demand for green investments increases, especially green financial products, we assess the return spillovers between green energy and other economic sectors. First, the green energy sector has a significant degree of financial openness, and it receives more shocks than it transmits to other sectors. The green energy sector's interconnections are higher with the material and industrial sectors. Hence, we encourage public policies aimed at reducing carbon emissions from these polluting sectors to consider their feedback effects on green energy industries. Second, spillovers of green energy are lower in the healthcare, utilities, and consumer staples sectors. Therefore, asset managers seeking to invest in green energy may consider these sectoral indices for portfolio diversification, minimizing capital loss risk. Third, the green energy sector is a net receiver of shocks from other economic sectors over time. However, green energy spillovers vary and have, for example, increased during the pandemic crisis, reflecting the "fly to liquidity" mechanism. The interconnections between green and fossil energies are, also, time-varying. Since the climate awareness with the Paris Agreement, the net spillovers from green energy to fossil energy have increased.

Appendix 2.A

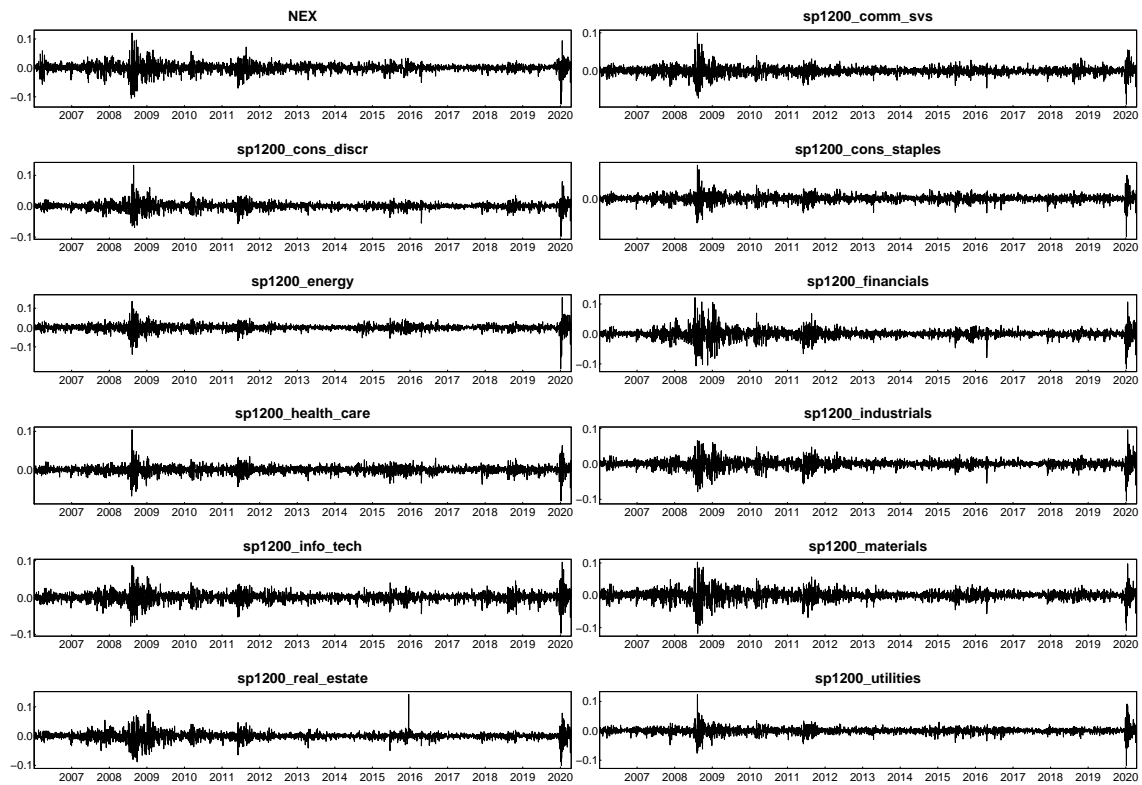


Figure 2.A.1 – Data in first logarithmic difference

Source : Datastream

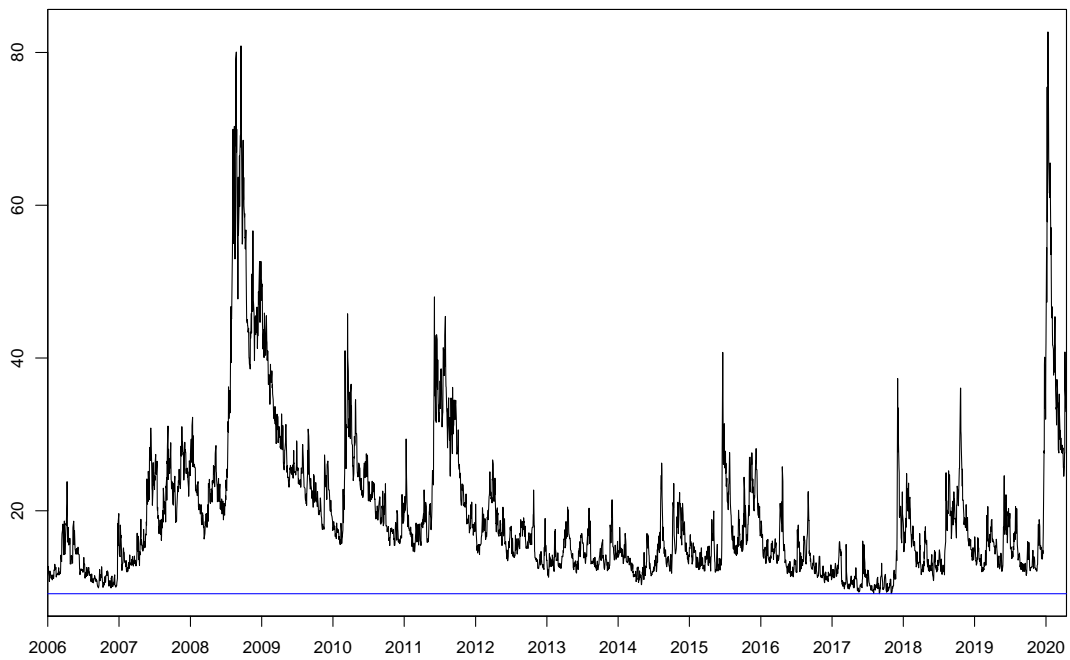


Figure 2.A.2 – VIX (in level)

Note : The VIX is the volatility index of the S&P500 constructed by the CBOE (Chicago Board Options Exchange), and the blue line is drawn from the minimum point.

	ADF	PP	KPSS
NEX	-0.21 ³	-0.19 ³	4.67 ¹
sp1200_comm_svs	0.44 ³	-2.54 ²	1.68 ¹
sp1200_cons_discr	1.13 ³	1.23 ³	3.17 ¹
sp1200_cons_staples	1.59 ³	1.65 ³	2.56 ¹
sp1200_energy	-0.49 ³	-0.48 ³	1.78 ¹
sp1200_financials	-0.45 ³	-0.44 ³	4.77 ¹
sp1200_health_care	1.58 ³	1.69 ³	4.13 ¹
sp1200_industrials	0.55 ³	0.63 ³	2.96 ¹
sp1200_info_tech	1.92 ³	2.01 ³	5.47 ¹
sp1200_materials	-3.10 ²	-3.07 ²	0.71 ¹
sp1200_real_estate	0.38 ³	0.41 ³	3.64 ¹
sp1200_utilities	0.39 ³	0.44 ³	5.04 ¹
Δ NEX	-38.27 ^{3*}	-50.02 ^{3*}	0.12 ^{2*}
Δ sp1200_comm_svs	-23.74 ^{3*}	-58.47 ^{3*}	0.04 ^{2*}
Δ sp1200_cons_discr	-40.59 ^{3*}	-52.26 ^{3*}	0.09 ^{2*}
Δ sp1200_cons_staples	-44.67 ^{3*}	-58.22 ^{3*}	0.06 ^{2*}
Δ sp1200_energy	-33.73 ^{3*}	-58.46 ^{3*}	0.11 ^{2*}
Δ sp1200_financials	-41.01 ^{3*}	-53.98 ^{3*}	0.12 ^{2*}
Δ sp1200_health_care	-43.34 ^{3*}	-58.55 ^{3*}	0.13 ^{2*}
Δ sp1200_industrials	-40.46 ^{3*}	-52.36 ^{3*}	0.06 ^{2*}
Δ sp1200_info_tech	-42.74 ^{3*}	-58.61 ^{3*}	0.24 ^{2*}
Δ sp1200_materials	-41.22 ^{3*}	-50.46 ^{3*}	0.04 ^{2*}
Δ sp1200_real_estate	-39.33 ^{3*}	-54.78 ^{3*}	0.08 ^{2*}
Δ sp1200_utilities	-44.93 ^{3*}	-56.75 ^{3*}	0.08 ^{2*}

Table 2.A.1 – Unit root tests

Note : ADF, the Augmented Dickey-Fuller test (Dickey and Fuller, 1981), PP, the Phillips-Perron test (Phillips and Perron, 1988), and KPSS, the Kwiatkowski-Phillips-Schmidt-Shin test (Kwiatkowski et al., 1992). In the text core, the unit root test coefficients, and in superscript, the selected models with "one" for "trend and constant," "two" for "constant," and "three" for "no trend or constant." The "star" indicates the stationarity of the series. All variables are non-stationary in level at conventional thresholds – 5% for all series, except the S&P Global 1200 materials non-stationary at 1% with ADF and PP. All variables in log difference are stationary at all thresholds.

Granger causality H0 : the S&P Global 1200 does not Granger-cause the NEX Index
F-Test = 17.668, df1 = 3, df2 = 3722, p-value = 0

Granger causality H0 : the NEX Index does not Granger-cause the S&P Global 1200
F-Test = 10.679, df1 = 3, df2 = 3722, p-value = 0

Table 2.A.2 – Granger causality tests

Note : The variables are in first logarithmic difference, as they are integrated of order one. We compute the bivariate VAR model with three lags, selected according to the Akaike criterion. Each F-test follows a Fisher law with $(p, T - 2 * p - 1)$ degrees of freedom ; $T = 3729$, $p = 3$. The critical values for these models are 2.606 and 3.784 at 5% and 1%, respectively.

	NEX	Comm_svs	Cons_discr	Cons_staples	Energy	Financials
Mean	0.00	0.00	0.00	0.00	0.00	0.00
Median	0.00	0.00	0.00	0.00	0.00	0.00
Maximum	0.12	0.10	0.13	0.08	0.16	0.12
Minimum	-0.13	-0.09	-0.10	-0.09	-0.21	-0.12
Std.Deviation	0.01	0.01	0.01	0.01	0.02	0.01
Skewness	-0.67	-0.17	-0.12	-0.54	-1.08	-0.34
Kurtosis	12.38	13.07	15.83	15.69	23.17	14.96
Jarque-Bera	13958.87	15760.80	25603.13	25218.83	63951.65	22294.53
p.value	0	0	0	0	0	0
	Health_care	Industrials	Info_tech	Materials	Real_estate	Utilities
Mean	0.00	0.00	0.00	0.00	0.00	0.00
Median	0.00	0.00	0.00	0.00	0.00	0.00
Maximum	0.10	0.10	0.10	0.10	0.14	0.12
Minimum	-0.08	-0.10	-0.10	-0.12	-0.10	-0.12
Std.Deviation	0.01	0.01	0.01	0.01	0.01	0.01
Skewness	-0.30	-0.55	-0.28	-0.51	-0.15	-0.23
Kurtosis	13.78	12.29	10.74	11.91	15.41	21.32
Jarque-Bera	18129.78	13586.55	9363.89	12498.63	23937.98	52159.32
p.value	0	0	0	0	0	0

Table 2.A.3 – Descriptive statistics

Note : All variables are in first logarithm difference. The [Jarque and Bera \(1980\)](#)'s test allows testing the null hypothesis of normality distribution. For all variables, normality is rejected.

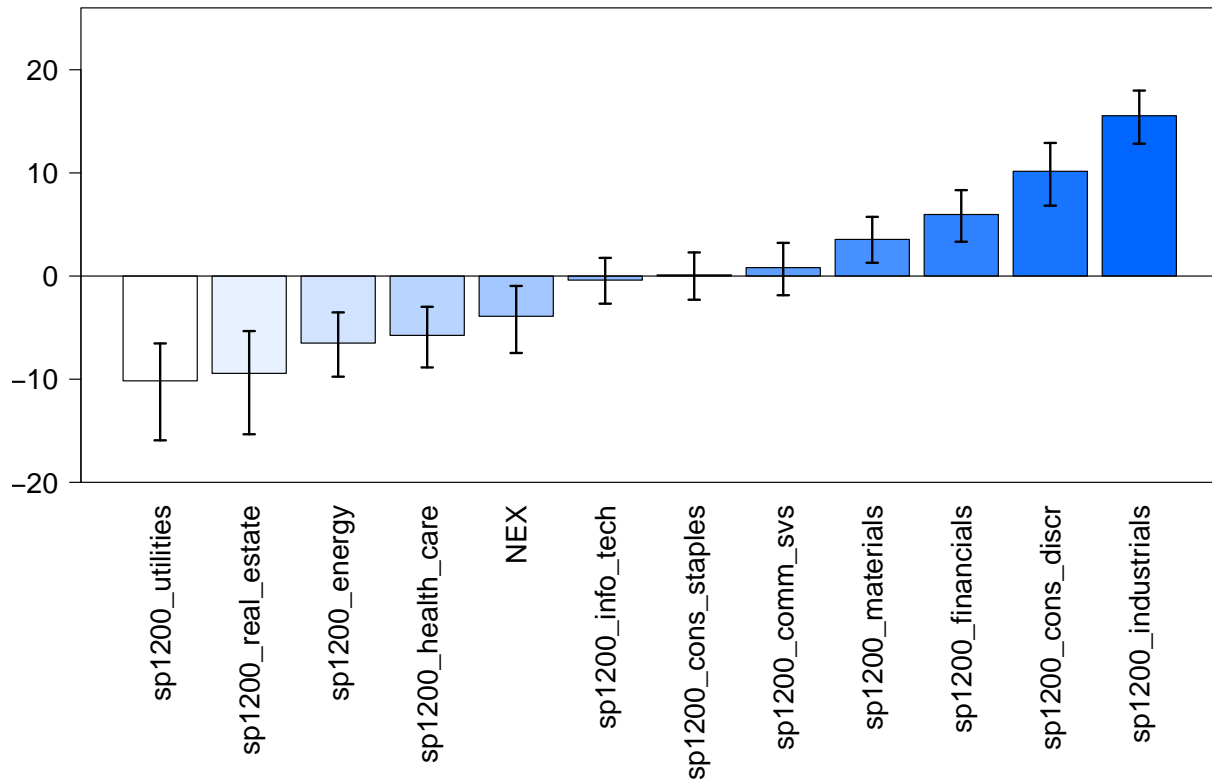
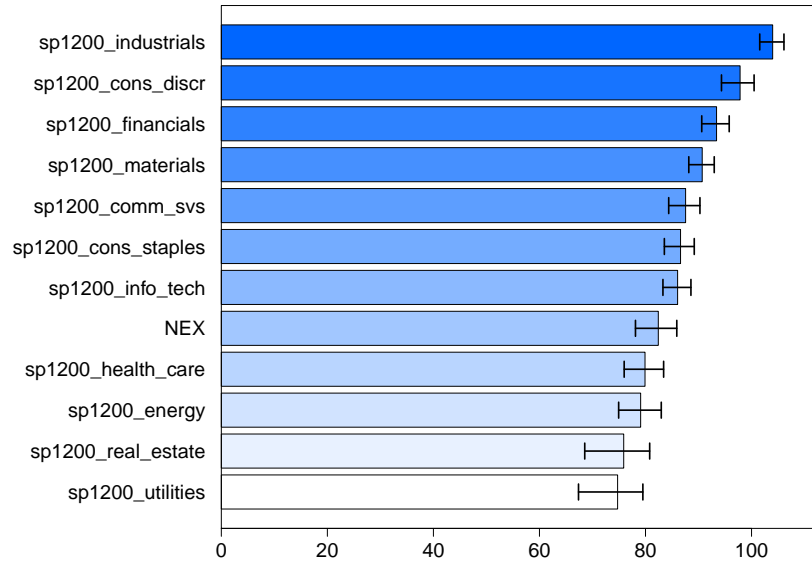
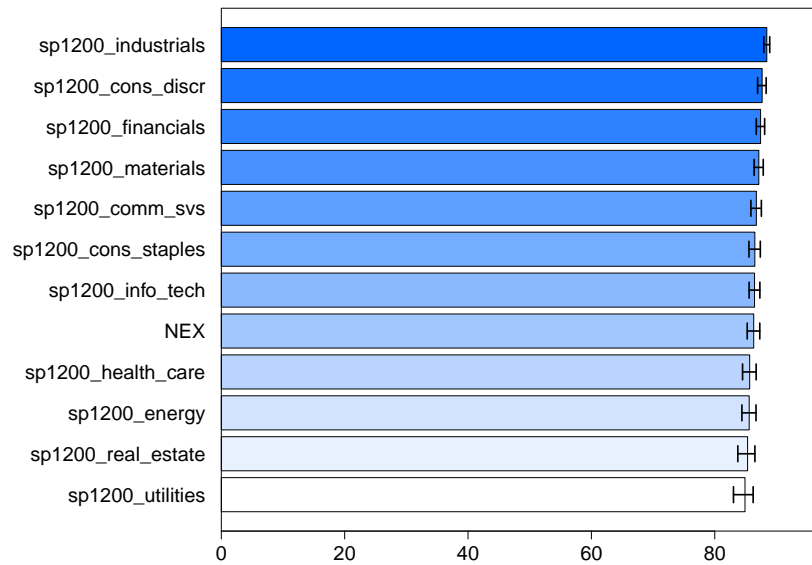


Figure 2.A.3 – Net indices

Note : This figure displays the net spillover indices measured as the difference between the "to" and "from" indices. If $net > 0$, the variable is a net transmitter of shocks, and if $net < 0$, the variable is a net receiver of shocks. The black lines depict the Efron percentile confidence intervals of these indices, estimated with 5000 wild bootstraps.



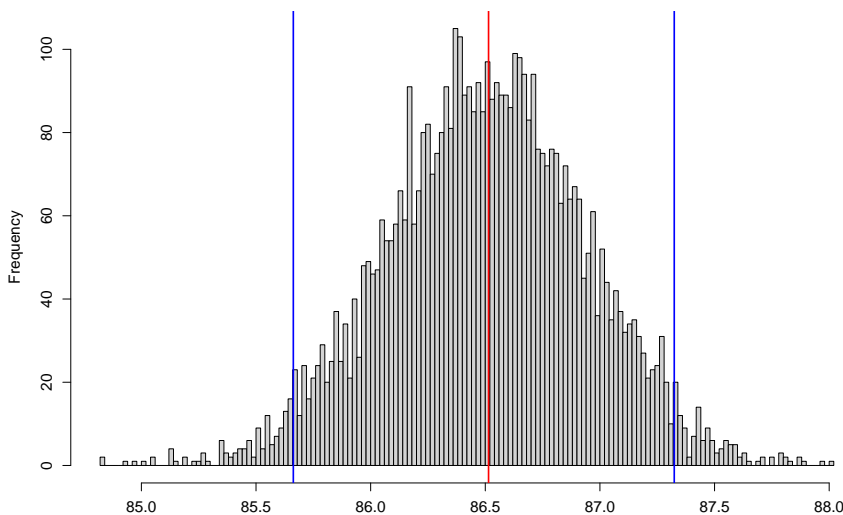
(a) To indices



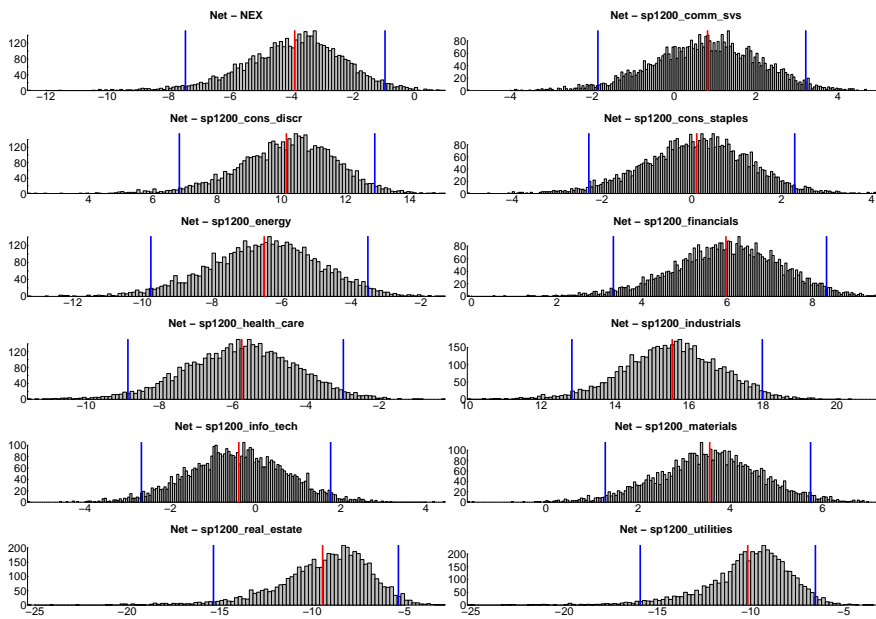
(b) From indices

Figure 2.A.4 – Directional spillover indices

Note : These figures display the directional spillover indices. The "to" indices are the variance shares that variables transmit to others. Conversely, the "from" indices are the variance shares that variables receive from others. The black lines represent the Efron percentile confidence intervals around these indices, estimated with 5000 wild bootstraps.



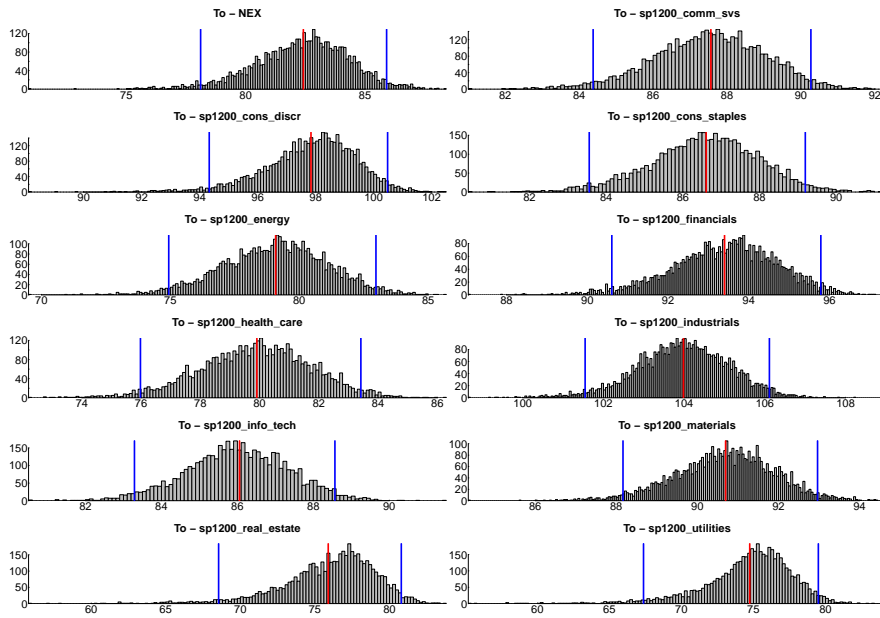
(a) Total Spillover Index



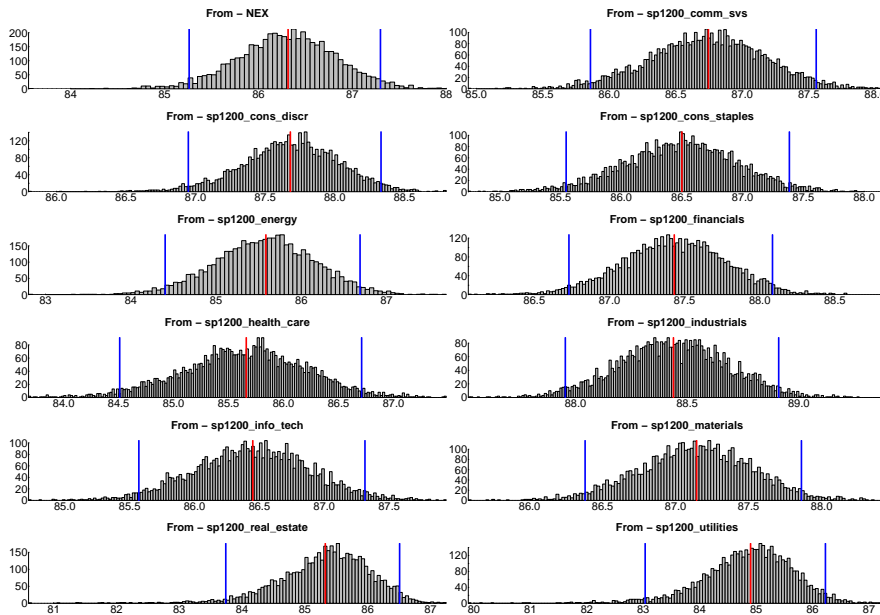
(b) Net indices

Figure 2.A.5 – TSI and Net indices’ distributions

Note : The spillover indices’ distribution is achieved with 5000 wild bootstraps. The blue bars are the Efron percentile confidence intervals – 2.5% and 97.5% distributions quantiles. The red bars are the OLS indices estimated with the VAR model.



(a) To indices



(b) From indices

Figure 2.A.6 – Directional spillover index distributions

Note : The spillover indices' distribution is achieved with 5000 wild bootstraps. The blue bars are the Efron percentile confidence intervals – 2.5% and 97.5% distributions quantiles. The red bars are the OLS indices estimated with the VAR model.

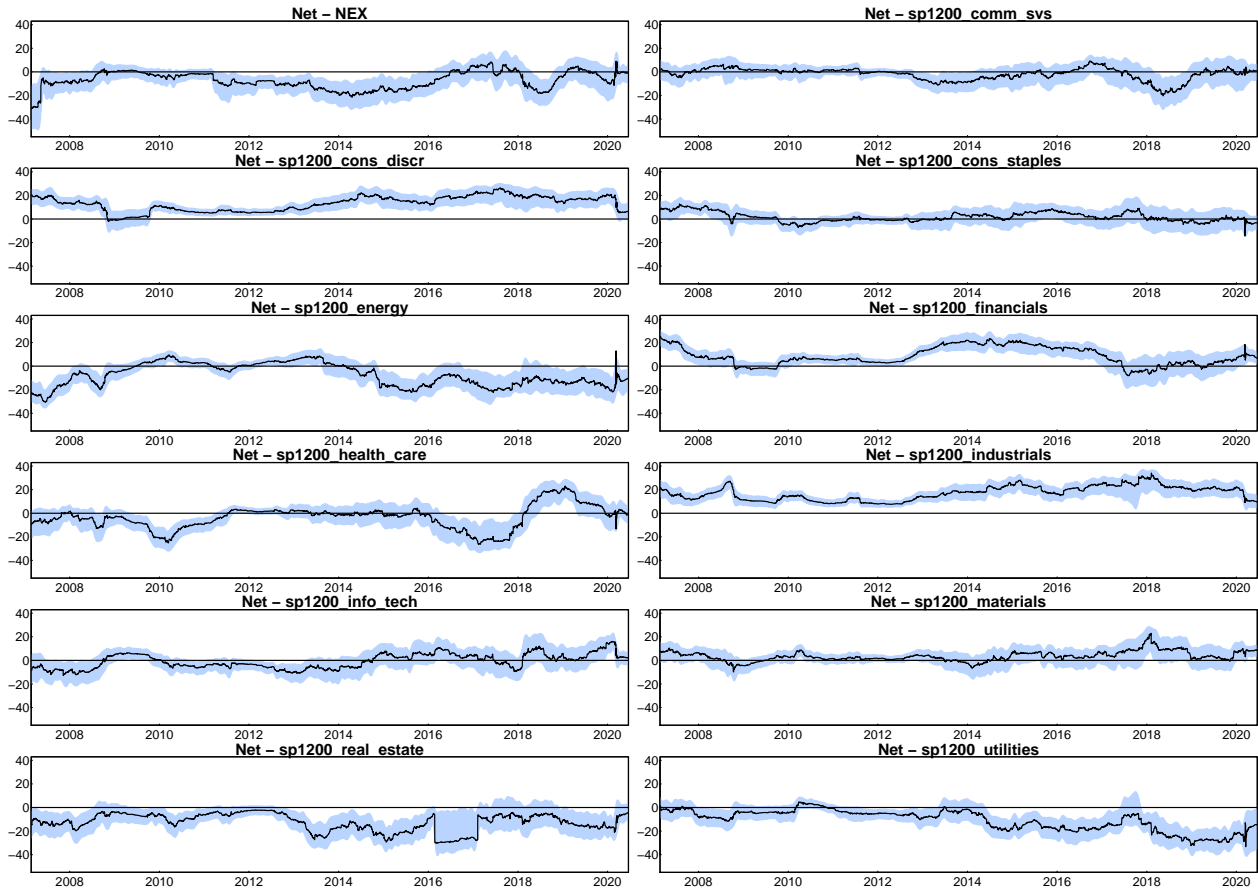
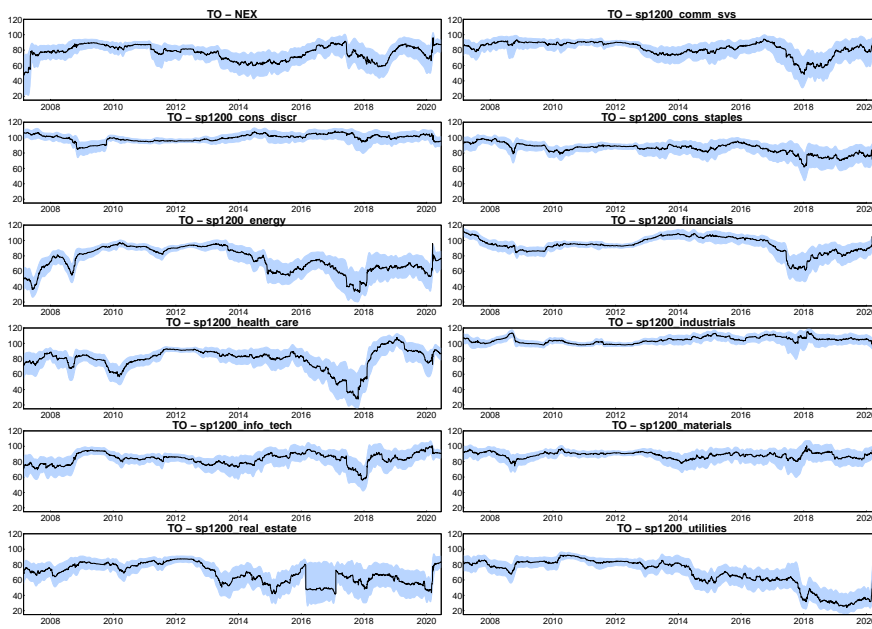
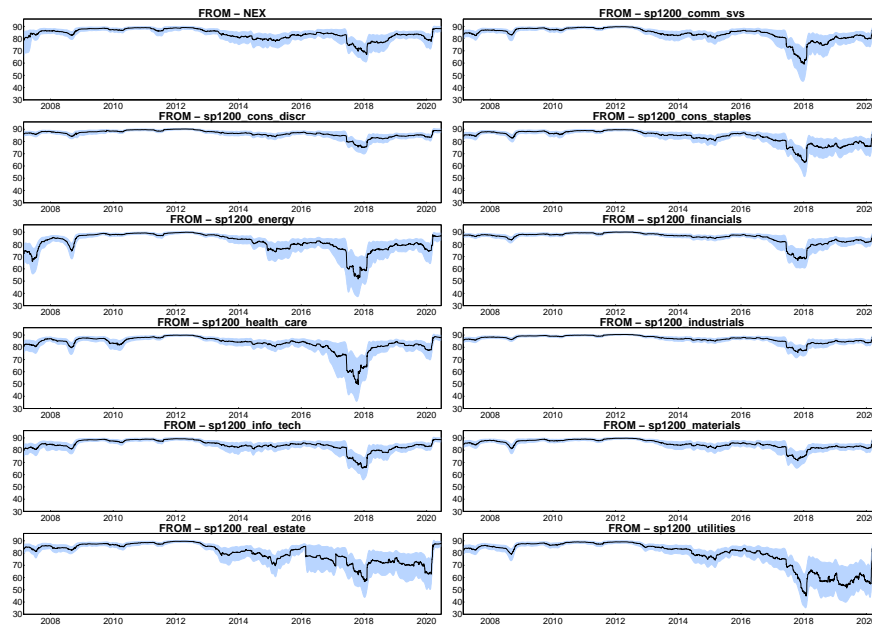


Figure 2.A.7 – NET indices over time

Note : This figure depicts the variations of the NET spillover indices, estimated with 250-day width rolling windows. On the x-axis, each point represents the ending of the rolling windows. We construct Efron percentile confidence intervals with 200 fixed-effect wild bootstraps. Smoothing splines are also applied to these intervals to improve their graphical readability. For more details on the smoothing method, see [Green and Silverman \(1993\)](#).



(a) To indices



(b) From indices

Figure 2.A.8 – Directional spillover indices over time

Note : This figure depicts the variations of the directional spillover indices, estimated with 250-day width rolling windows. On the x-axis, each point represents the ending of the rolling windows. We construct Efron percentile confidence intervals with 200 fixed-effect wild bootstraps. Smoothing splines are also applied to these intervals to improve their graphical readability. For more details on the smoothing method, see [Green and Silverman \(1993\)](#).

	NEX	Comm_svs	Cons_discr	Cons_staples	Energy	Financials	Health_care	Industrials	Info_tech	Materials	Real_estate	Utilities	from
NEX	13.68	7.52	8.86	6.5	7.84	8.80	6.24	9.78	8.13	9.69	6.9	6.05	86.32
	12.70	14.74	7.12	7.89	7.36	8.29	5.08	6.81	7.77	8.48	6.18	7.47	85.26
Comm_svs	7.21	13.25	8.84	8.73	7.12	8.35	7.72	8.84	7.73	7.96	6.38	7.87	86.75
	6.70	7.65	12.44	14.14	6.64	7.57	7.21	8.17	7.34	8.09	5.62	6.97	85.86
Cons_discr	7.64	8.05	12.32	7.89	6.59	9.02	7.41	10.27	9.33	8.10	7.60	5.77	87.68
	7.07	8.07	11.67	13.05	6.13	7.04	7.02	7.75	9.02	9.67	6.85	8.11	86.94
Cons_staples	6.25	8.82	8.74	13.50	6.47	7.54	9.26	8.78	7.39	7.19	6.92	9.13	86.5
	5.65	6.78	8.35	9.21	5.86	7.04	8.76	9.71	6.95	7.76	6.07	7.52	85.54
Energy	8.05	7.73	7.85	6.91	14.42	8.47	6.69	9.51	7.40	10.11	5.93	6.94	85.58
	7.51	8.51	7.26	8.15	13.31	15.59	6.10	7.21	6.96	7.78	5.20	6.57	84.40
Financials	8.02	7.88	9.40	7.06	7.38	12.57	6.85	10.28	7.85	8.46	8.17	6.08	87.43
	7.63	8.34	7.48	8.25	6.94	7.78	6.33	7.30	7.48	8.18	7.37	8.73	86.72
Health_care	6.38	8.30	8.72	9.84	6.65	7.78	14.34	8.82	8.40	6.85	6.23	7.68	85.66
	5.80	6.92	7.81	8.74	6.06	7.19	13.28	15.49	7.98	8.77	5.47	6.85	84.50
Industrials	8.16	7.66	9.80	7.50	7.64	9.41	7.09	11.56	8.37	9.15	7.30	6.35	88.44
	7.81	8.46	7.29	7.96	7.27	7.97	6.71	7.44	8.09	8.62	6.60	7.74	87.95
Info_tech	7.73	7.83	10.29	7.41	6.93	8.38	7.93	9.71	13.55	7.84	6.88	5.52	86.45
	7.30	8.11	7.46	8.18	6.45	7.34	7.47	8.32	12.68	14.42	6.20	7.38	85.57
Materials	8.96	7.70	8.71	6.87	9.09	8.66	6.16	10.19	7.66	12.86	6.60	6.54	87.14
	8.52	9.34	7.28	8.07	6.35	7.32	5.62	6.66	7.29	7.99	5.91	7.13	86.37
Real_estate	7.39	7.14	9.42	7.66	6.09	9.69	6.45	9.45	7.61	7.61	14.68	6.82	85.32
	6.85	7.91	8.97	9.92	5.47	6.67	5.88	6.94	7.16	8.03	13.49	16.25	83.74
Utilities	6.62	8.93	7.21	10.24	7.29	7.31	8.09	8.35	6.19	7.71	6.97	15.1	84.9
	5.87	7.23	8.43	9.40	6.53	7.91	7.44	8.70	5.60	6.71	5.88	7.80	83.03
TO	82.41	87.56	97.84	86.61	79.08	93.4	79.91	103.98	86.06	90.69	75.89	74.74	
	78.11	85.9	84.38	90.27	74.94	82.97	75.98	83.42	83.29	88.57	68.54	80.79	67.37
NET	-3.9	0.82	10.16	0.11	-6.5	5.97	-5.75	15.54	-0.39	3.55	-9.44	-10.16	86.51
	-7.45	-0.96	-1.86	3.21	-9.75	-3.52	-8.86	-2.98	-2.67	1.76	-15.34	-5.33	-15.92
													87.32

Table 2.A.4 – VAR-OLS Spillover Table

Note : The first row displays the coefficients of the generalized forecast error variance decomposition. The second row shows the Efron percentile confidence intervals for these coefficients. Pairwise connectedness ij is the estimated contribution to the forecast error variance of market i from market shocks (innovations) j , for all i and j . Therefore, the diagonal elements of the forecast error variance are the "own-asset shocks" (or "own-spillovers"). The sum of the off-diagonal columns ("to") and the sum of the off-diagonal rows ("from") are respectively the "directional spillovers to others" and the "directional spillovers from others." The difference between the "to" and the "from" depicts the net spillover indices. The Total Spillover Index (TSI) at the bottom right of the spillover table is the off-diagonal column sum (or off-diagonal row sum) divided by the column sum (or row sum).

	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	Mean
Comm_svs	5.31	5.32	5.38	5.41	5.32	5.26	5.32	5.50	5.52	5.55	5.52	5.50	5.46	5.59	5.58	5.44
Cons_discr	12.21	12.19	12.12	12.26	12.33	12.28	12.21	12.29	12.32	12.18	12.29	12.32	12.32	12.33	12.31	12.26
Cons_staples	7.83	7.70	7.75	7.75	7.63	7.63	7.59	7.56	7.48	7.56	7.61	7.66	7.69	7.64	7.63	7.65
Energy	4.75	4.77	4.83	4.87	4.88	5.00	5.14	5.07	5.01	4.96	4.93	5.00	4.96	4.93	4.92	4.94
Financials	16.12	16.41	16.32	16.32	16.50	16.32	16.30	16.07	16.23	16.13	16.05	15.99	15.88	15.86	15.83	16.16
Health_care	9.13	8.98	8.93	8.84	8.87	8.86	8.89	8.93	8.84	8.74	8.70	8.66	8.60	8.63	8.61	8.81
Industrials	16.31	16.32	16.23	16.14	16.06	16.32	16.30	16.32	16.31	16.22	16.22	16.24	16.29	16.19	16.32	16.25
Info_tech	9.32	9.35	9.39	9.47	9.58	9.47	9.50	9.45	9.60	9.75	9.70	9.66	9.84	9.78	9.76	9.58
Materials	8.39	8.52	8.48	8.39	8.43	8.42	8.37	8.25	8.16	8.32	8.28	8.33	8.35	8.55	8.53	8.38
Real_estate	4.94	4.86	4.83	4.78	4.70	4.82	4.80	4.98	5.01	5.13	5.10	5.08	5.05	5.01	5.00	4.94
Utilities	5.68	5.59	5.74	5.77	5.68	5.61	5.58	5.58	5.52	5.46	5.60	5.58	5.54	5.51	5.50	5.60

Table 2.A.5 – S&P Global 1200 composition by economic sector (in %)

Source : [Nobletz \(2022\)](#)

Note : The percentage of firms making up the S&P Global 1200 index by economic sector according to the 2018 GICS classification.

	NEX	Comm_svs	Cons_discr	Cons_staples	Energy	Financials	Health_care	Industrials	Info_tech	Materials	Real_estate	Utilities	from
NEX	13.82	7.56	8.78	6.47	7.77	8.84	6.22	9.87	7.95	9.73	6.89	6.11	86.18
Comm_svs	7.19	13.37	8.8	8.79	7.11	8.36	7.75	8.81	7.66	7.88	6.37	7.91	86.63
Cons_discr	7.58	8.07	12.31	7.88	6.63	9.07	7.38	10.3	9.31	8.06	7.67	5.73	87.69
Cons_staples	6.2	8.92	8.71	13.59	6.43	7.55	9.3	8.74	7.36	7.1	6.9	9.19	86.41
Energy	8.07	7.73	7.85	6.88	14.52	8.43	6.64	9.56	7.39	10.14	5.9	6.89	85.48
Financials	7.97	7.93	9.39	7.06	7.35	12.65	6.81	10.31	7.83	8.41	8.25	6.05	87.35
Health_care	6.35	8.39	8.68	9.91	6.6	7.76	14.48	8.79	8.37	6.76	6.2	7.71	85.52
Industrials	8.15	7.66	9.77	7.49	7.63	9.44	7.08	11.62	8.33	9.14	7.34	6.34	88.38
Info_tech	7.65	7.81	10.33	7.39	6.94	8.39	7.89	9.75	13.65	7.78	6.95	5.47	86.35
Materials	9.07	7.7	8.64	6.84	9.06	8.67	6.13	10.28	7.5	12.94	6.59	6.57	87.06
Real_estate	7.32	7.14	9.39	7.61	6.09	9.73	6.44	9.47	7.66	7.54	14.85	6.76	85.15
Utilities	6.64	9.02	7.12	10.31	7.23	7.28	8.12	8.33	6.12	7.7	6.91	15.23	84.77
to	82.2	87.92	97.46	86.63	78.85	93.51	79.77	104.21	85.48	90.24	75.96	74.73	TSI
net	-3.98	1.29	9.77	0.22	-6.63	6.16	-5.75	15.82	-0.87	3.18	-9.18	-10.05	86.41

Table 2.A.6 – VAR-LASSO Spillover table

Note : Pairwise connectedness ij is the estimated contribution to the forecast error variance of market i from market shocks (innovations) j , for all i and j . Therefore, the diagonal elements of the forecast error variance are the "own-asset shocks" (or "own-spillovers"). The sum of the off-diagonal columns ("to") and the sum of the off-diagonal rows ("from") are respectively the "directional spillovers to others" and the "directional spillovers from others." The difference between the "to" and the "from" depicts the net spillover indices. The Total Spillover Index (TSI) at the bottom right of the spillover table is the off-diagonal column sum (or off-diagonal row sum) divided by the column sum (or row sum).

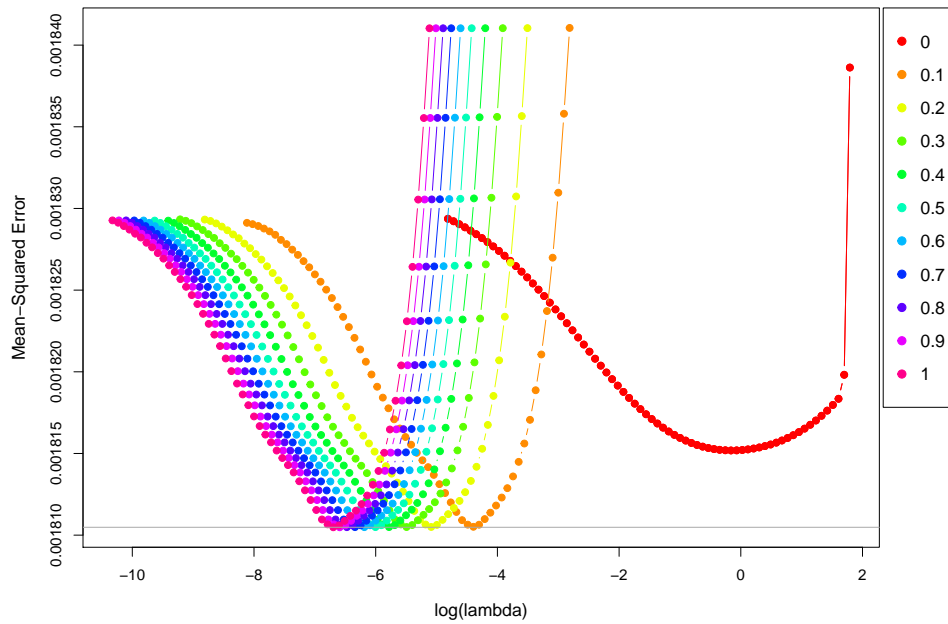
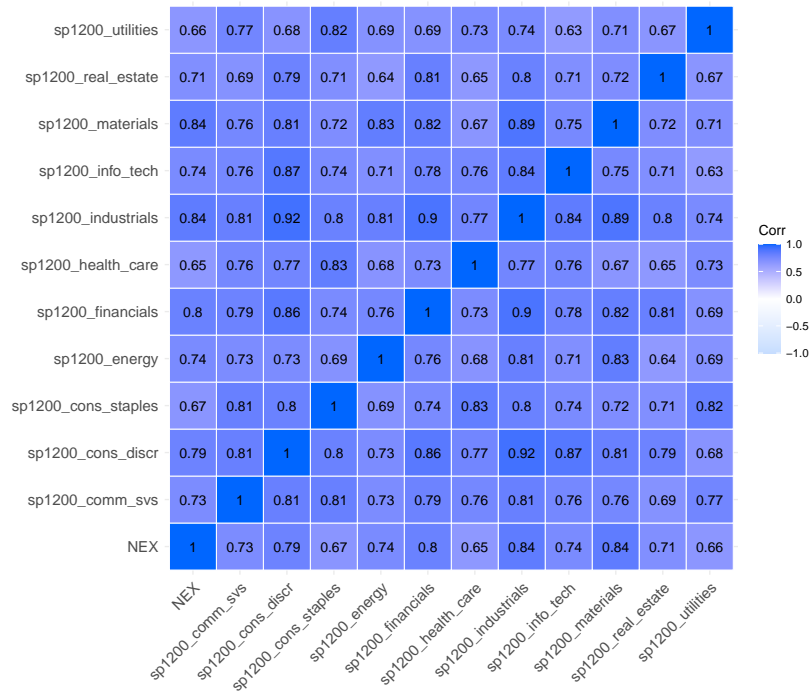
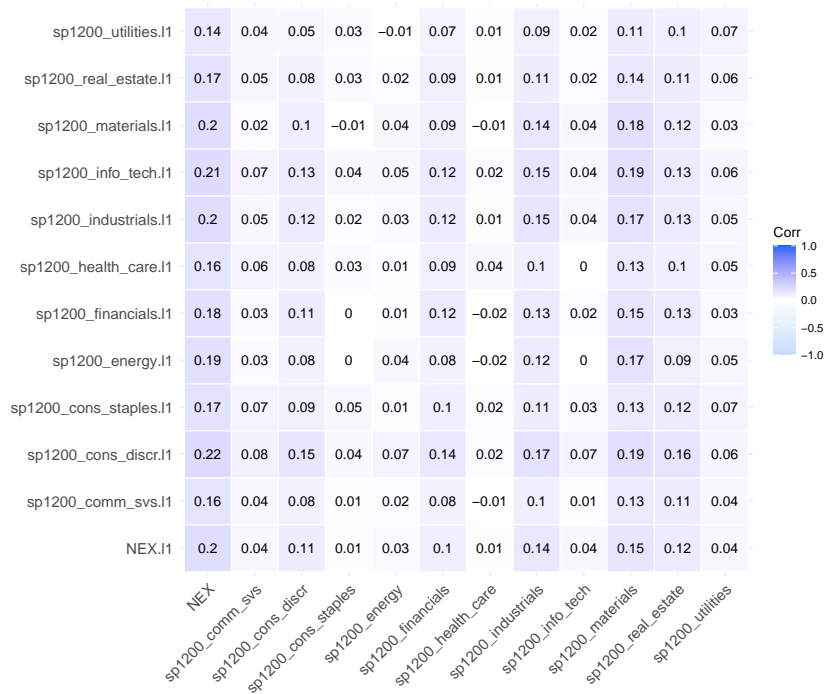


Figure 2.A.9 – Shrinking method (α) and penalty parameter (λ) selection process

Note : This graph depicts the results of the forecast error cross-validation with 10-folds. In y-axis, we have the Mean Squared Error (MSE) values, while in x-axis, we have the log values of λ . The color curves are the λ -MSE for each α specification : $\alpha = 0$, ridge ; $\alpha = 1$, LASSO ; $\alpha \in]0, 1[$ = elastic net.



(a) Instantaneous correlation coefficient matrix



(b) Correlation coefficient matrix of the VAR model variables

Figure 2.A.10 – Correlation coefficient matrix

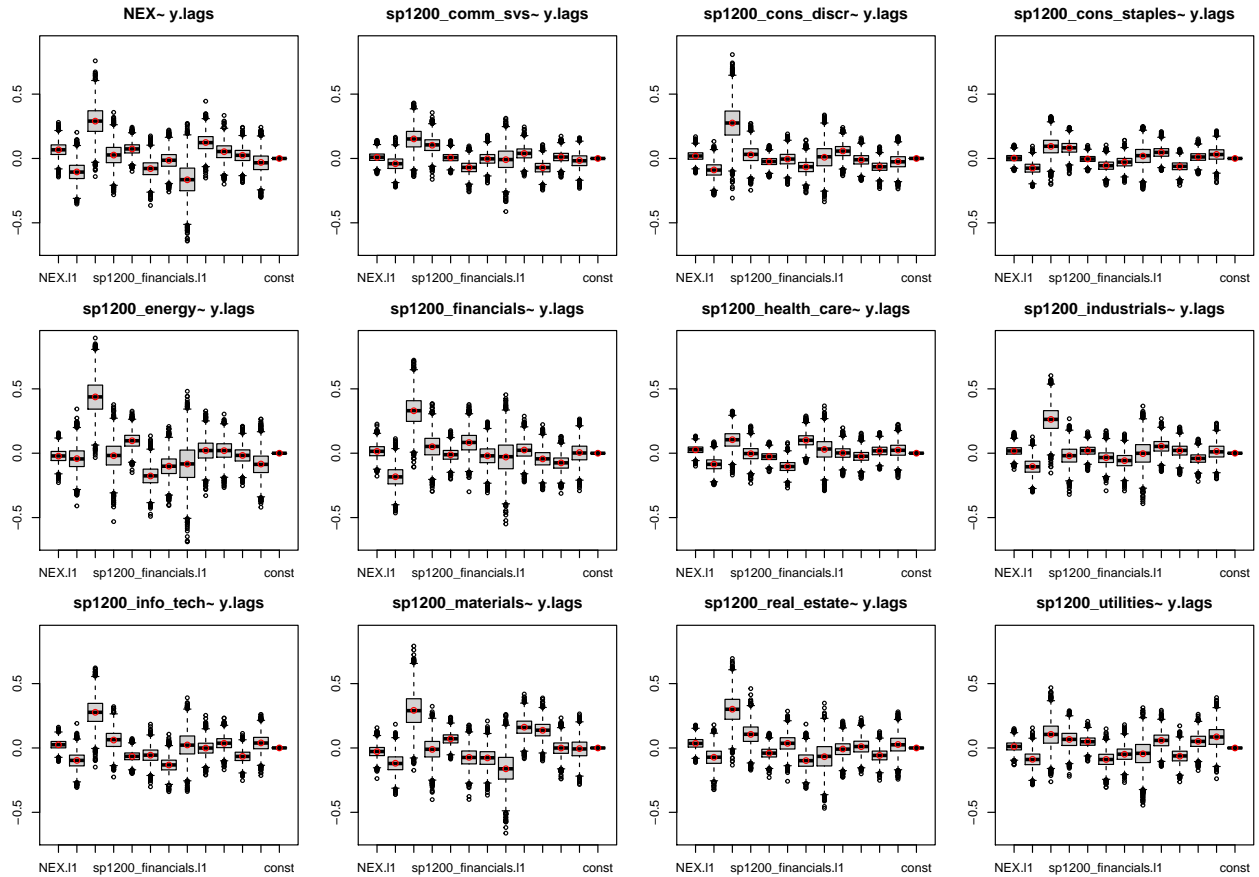


Figure 2.A.11 – Boxplots of the VAR-OLS coefficients

Note : This figure shows the boxplots of the VAR-OLS estimated parameters for all y . The red dots depict the OLS estimated parameters, while the gray bands display the Efron Percentile confidence intervals computed with 5000 wild-bootstrap. The lagged endogenous variables are in order : NEX.l1, sp1200_comm_svs.l1, sp1200_cons_discr.l1, sp1200_cons_staples.l1, sp1200_energy.l1, sp1200_financials.l1, sp1200_health_care.l1, sp1200_industrials.l1, sp1200_info_tech.l1, sp1200_materials.l1, sp1200_real_estate.l1, sp1200_utilities.l1.

3 | Large-scale natural disasters & credit market risks[†]

Abstract

We show that large natural disasters significantly raise the mortgage and corporate credit spreads in the United States, with persistent effects. Moreover, the increase in expected corporate defaults leads institutional investors to be more adverse to corporate credit risks and thus induces credit tightening. However, credit supply restrictions occur only for long-lasting natural disasters like droughts and floods, while short-lived disasters like hurricanes and severe storms are not subject to this effect. This result may be explained by the difference in media coverage and, thus, Government incentives toward investors to provide credit in the damaged area. For example, hurricanes are often more newsworthy than severe droughts, as they are more "sensational," prompting the Government and, thus, investors to extend more credit to damaged agents.

Keywords : Large natural disasters, Mortgage credit spread, Corporate credit spread, Physical climate risks.

JEL codes : G21, G23, Q54.

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Introduction

It is already well known that human-induced climate change has led to a rise in the likelihood of natural disasters since the 1950s, including an increase in heat or cold waves, more frequent heavy precipitation events, an increase in agricultural and ecological droughts, or an intensification of large tropical cyclones (IPCC, 2021). The materialization of large natural disasters can lead to significant losses in the financial system, especially if there is a gap or insufficiency in insurance coverage, causing a more detrimental macroeconomic effect (Peter et al., 2012; Scott et al., 2017); this is the physical climate risk (Carney, 2015).

For example, the Small Business Credit Survey-SBCS (2017) from the Federal Reserve Banks of Dallas, New York, Richmond, and San Francisco shows that damaging natural disasters in 2017, such as Hurricanes Harvey and Irma, induced losses for 40% of small businesses in the disaster area. Of the damaged companies, 61% suffered losses ranging from \$1 to \$25,000, and 35% endured losses greater than \$25,000. In addition, 27% of affected businesses had no insurance coverage, and only 17% were covered for business interruptions – those losses are the most significant for companies following a disaster.

Falling into this context, we analyze whether large natural disaster shocks disrupt credit market risks for US households and firms. Indeed, large natural disasters can result in significant losses due to asset destruction, and firms may also suffer losses related to business and supply chain disruption. As a result, households' and firms' balance sheets may deteriorate, leading to an increase in non-performing loans, with losses spreading to institutional investors such as banks. This point is especially true if the damaged assets are used as collateral. In response to higher credit risks, investors may tighten credit supply conditions, reinforcing the negative macroeconomic outcome of the disaster (Batten et al., 2016; Scott et al., 2017).

The literature on this issue is still scarce, even if it is rapidly growing. Our analysis may be related to several fields in the literature dealing with the effects of natural disasters (i) on household and company financial health, (ii) on credit risks, and (iii) on the banking system. Regarding the first strand, Henry et al. (2020) find that hurricanes reduce per capita consumption in Jamaica for people living in buildings with non-resistant walls. Keerthiratne and Tol (2017) highlight that households are more indebted after a natural disaster, especially the less developed countries. Also, running a meta-regression analysis, Karim and Noy (2016) show that a natural disaster negatively affects households' income and consumption. For companies, Dafermos et al. (2018), with a stock-flow ecological model, show that climate change damages negatively impact firms' capital and thus their profitability, leading to harmful effects on financial and non-financial

corporate sectors. [Keerthiratne and Tol \(2017\)](#) also find that companies get deeper in debt after a natural disaster. Moreover, natural disasters may disrupt the supply chains with "parts shortages, product design change needs, manufacturing stoppages, logistical breakdowns, and humanitarian emergencies" ([Park et al., 2013](#), page 2). Notably, [Todo et al. \(2015\)](#) show that following the Great East Japan Earthquake, supply chains outside the disaster area allowed for an earlier production recovery, while those within the disaster zone contributed to sales recovery in the medium term.

Second, the literature tends to identify a rise in US credit risks after a disaster, at least for the most vulnerable individuals. [Ratcliffe et al. \(2020\)](#) find that natural disasters reduce credit score and mortgage performance, increase the amount of debt, and worsen the access to credit cards and debt with lasting effects. These outcomes worsen for the most exposed population. Similarly, [Kousky et al. \(2020\)](#) show that households without insurance coverage after Harvey's hurricane were more likely to need a loan modification, to be 180 days or more in delinquency, or to default two years later. [Edmiston \(2017\)](#) also finds that hurricanes tend to lower credit scores with deepened effects for individuals experiencing ex-ante financial vulnerability. At last, [Roth Tran and Sheldon \(2017\)](#) highlight that only the most vulnerable individuals – individuals with the lowest credit scores, residing in a low-income area, or not receiving individual aid – are the most likely to declare bankruptcy.

Finally, US banks' responses to natural disasters are not unanimous. [Duanmu et al. \(2022\)](#) show that banks tighten their lending standards in disaster counties, notably where the likelihood of adverse natural disaster effects on the local economy is high. [Garmaise and Moskowitz \(2009\)](#) show that the 1990's California Earthquake reduced commercial real estate loans by 22%. [Cortés and Strahan \(2017\)](#) and [Ivanov et al. \(2022\)](#) find that banks respond to increased credit demand in the disaster area but tighten credit in undamaged zones. At last, [Schüwer et al. \(2019\)](#) show that after Katrina, large-cap banks did not reduce the credit supply but sold these high-risk loans in the secondary market while increasing their purchases of government securities. [Chavaz \(2016\)](#) also finds the securitization of these high-risk loans resulting from the 2005 hurricane season.

Our contributions to the existing literature are manifold. To our best knowledge, we are the first to provide a dynamic analysis of natural disaster shocks on US corporate and mortgage credit spreads. Moreover, we extend this analysis by studying how corporate default risk and credit supply respond to a disaster shock. Finally, we highlight different transmission mechanisms, regardless of whether the natural disaster is short or long-lived.

Specifically, we consider in this paper large US natural disasters over the period running from 1990 to 2019

on a monthly frequency.¹ By implementing standard VAR methodology with Impulse Response Analysis (IRF), our main results are as follows. We find that large natural disasters increase the US mortgage and corporate credit spreads with long-lasting effects. Then, focusing on the corporate market, we show that following a natural disaster, the corporate default risk increases, leading to higher investors' risk aversion and, thus, credit tightening on corporates. On this latter point, we find that only long-run disasters like drought or flooding induce credit tightening from investors, not short-lived events such as hurricanes or severe storms. Nevertheless, both disaster classes induce a rise in the expected default of companies. We may explain this result by the difference in media coverage and, thus, Government incentives for investors to grant credits toward damaged agents. For instance, we may infer that hurricanes are more "sensational" than droughts, leading to higher media coverage and Government pressures to supply credits in the disaster area.

Overall, our results indicate that large natural disasters not only impact the affected area but also generate an effect at the federal level. This point may underscore the imperfection of US insurance coverage for households and businesses. In addition, the underlying issue is that as natural disaster risk increases, insurance companies may react by no longer insuring high-risk areas or increasing their insurance prices (Angbazo and Narayanan, 1996). On the latter point, the most vulnerable populations may no longer be able to insure themselves against physical climate risks, leading to negative feedback on macroeconomic levels.

The rest of the chapter is organized as follows. Section 3.1 presents the data and provides a descriptive analysis of the natural disasters in the US territory. Our empirical strategy is described in Section 3.2. Section 3.3 displays and discusses our main results. The robustness checks are highlighted in Section 3.4, while Section 3.5 concludes the chapter.

3.1 Stylized facts and data

We first provide a descriptive analysis of large natural disaster events in the United States and the resulting economic losses. Then, we present the National Centers for Environmental Information (NCEI) database and the considered variables in more detail.

1. Large US natural disasters correspond to natural disasters that generated more than \$1 billion in losses, adjusted for inflation.

3.1.1 Descriptive statistics

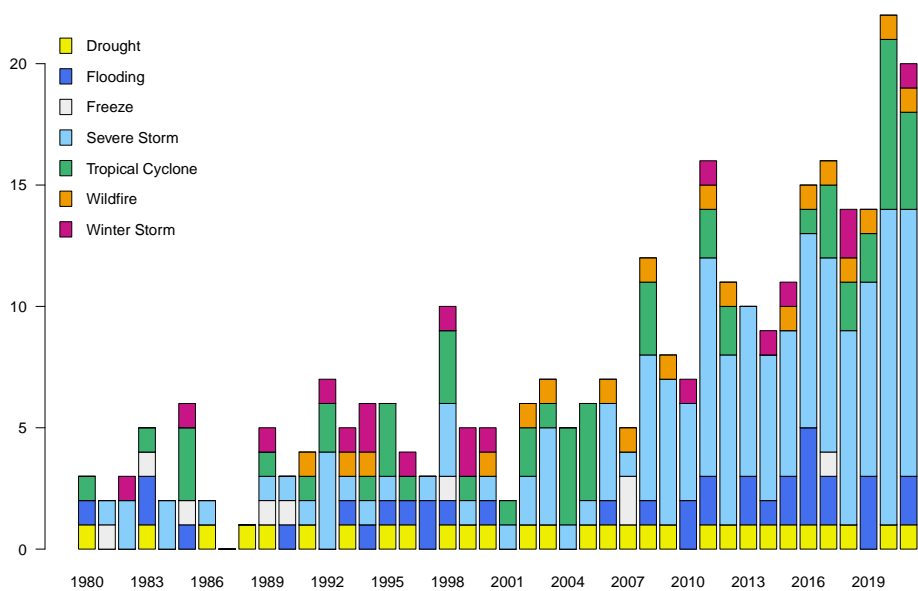


Figure 3.1.1 – US large natural disasters between 1980 and 2021 (event number)

Source : NCEI (2022).

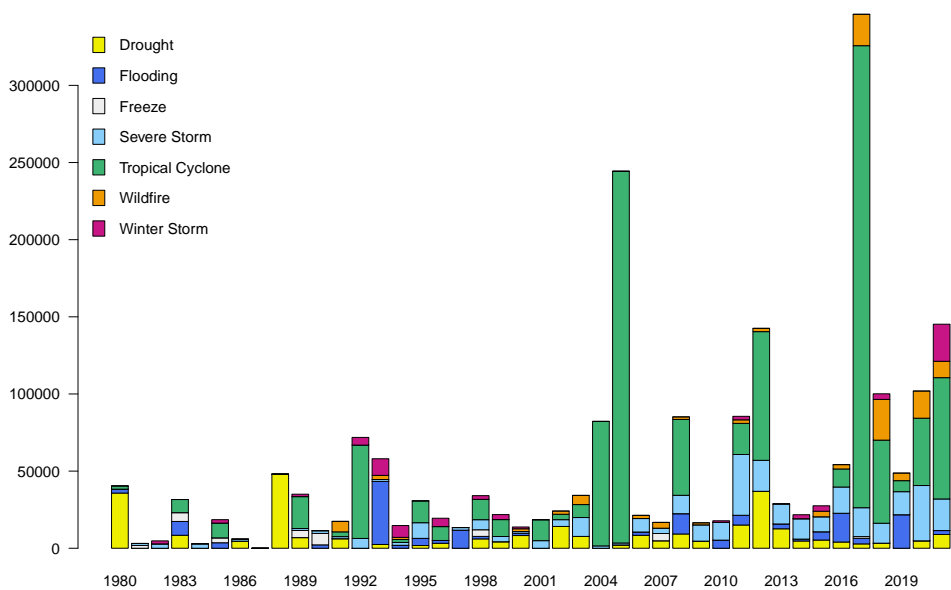


Figure 3.1.2 – US large natural disaster losses between 1980 and 2021 (\$B, 2021 CPI-adjusted)

Source : NCEI (2022).

From Figure 3.1.1, we note an increase in large natural disaster events in the United States. Indeed, we have gone from 2.9 events per year in the 1980s (1980-1989) to 5.3 and 6.3 in the 1990s (1990-1999) and 2000s (2000-2009), respectively. For the 2010s (2010-2019), the number of events per year reached 12.3, and it rose to 18.7 for the last three years (2019-2021) (Tables 3.A.1, and 3.A.2 in Appendix). In addition, Figure 3.1.2 highlights the increase in losses from natural disasters, notably driven by tropical cyclone damages, since 2004. Indeed, tropical cyclone total costs reached \$40.9 billion in the 1980s and continued to increase to \$112.8 billion, \$396.3 billion, and \$475.7 billion for the years 1990, 2000, and 2010, respectively (Table 3.A.1 in Appendix).

Moreover, Figure 3.1.2 points out two extreme points resulting from the 2005- and 2017 destructive hurricanes. For the year 2005, hurricane Dennis first struck, generating \$3.6 billion in damages and costing 15 lives. Then, the infamous Katrina hit, inducing \$180 billion of losses and 1,833 deaths, thus, becoming one of the most costly and deadly natural disasters in US history. After Katrina, Rita and Wilma occurred, costing \$26.5 and \$27.0 billion and taking 119 and 35 lives, respectively. Furthermore, 2017 is also one of the most hurricane disaster years. First, Hurricane Harvey struck, causing \$143.8 billion in damages and 89 deaths, followed by Irma, inflicting \$57.5 billion in losses and 97 deaths. Hurricane Maria was next and remained the deadliest US natural disaster, with 2,981 deaths and causing extensive damages – \$103.5 billion (NCEI, 2022).

However, we should notice that long-run disasters with droughts, floodings, and wildfires are also highly damaging and deadliest (Table 3.A.3 in Appendix). Indeed, the most damaging disasters after tropical cyclones are droughts, which have generated on average \$9.9 billion in losses per event over the entire period. For instance, the 2012 US drought has affected half of the country with moderate to extreme heat waves, leading to higher losses in the central agriculture states, i.e., widespread failures of crops like corn, sorghum, and soybean. The losses have reached \$37.5 billion, and heat waves have caused 123 deaths, while the indirect fatalities due to the rising mortality are still unknown (NCEI, 2022).

Among the reasons for the increase in natural disasters and their resulting damages, we can cite the increased exposure and vulnerability to given regions resulting from climate change. Indeed, the rise in anthropogenic greenhouse gas emissions leads to increased extreme natural disasters in frequency and magnitude (NCEI, 2022). On this last point, the IPCC (2021) shows that human-induced climate change has already led to worldwide impacts, such as the increase in heat or cold waves, the rise in heavy precipitations, the increase in tropical cyclone events, or the rise in agricultural and ecological droughts, notably due to higher evapotranspiration levels.

Nevertheless, we might assume that the upward trend in natural disasters and their underlying losses result from better natural disaster reporting. Even though we cannot exclude this risk entirely, we can assert that this trend is found regardless of the natural disaster database used, i.e., SHELDUS or EM-DAT.² In addition, a benefit of focusing on the United States is their head start in reporting natural disasters and the related costs. Indeed, the NCEI database, formerly known as NOAA (National Oceanic and Atmospheric Administration), records natural disasters since 1950, including the disaster type, the number of deaths and injuries, the insured losses, and the damages to property and agricultural sector.

3.1.2 National Centers for Environmental Information (NCEI) database

We use a natural disaster database from the NCEI to conduct our empirical analysis, the NOAA National Centers for Environmental Information (NCEI) U.S. Billion-Dollar Weather and Climate Disasters (2022).

This database focuses on the United States and discovers all-natural disasters causing economic losses above \$1 billion. The event database ranges from 1980 to 2021, with 143 Severe Storms, 56 Tropical Cyclones, 35 Floodings, 29 Droughts, 19 Wildfires, 19 Winter Storms, and 9 Freezes events (Table 3.A.3 in Appendix).³ The database provides the disaster start and end date, an event summary, the estimated CPI-adjusted (or unadjusted) losses, and the death number.

The nature of losses includes "physical damage to residential, commercial, and government/municipal buildings, material assets within a building, time element losses (i.e., business interruptions), vehicles, boats, offshore energy platforms, public infrastructures (i.e., roads, bridges, buildings), and agricultural assets (i.e., crops, livestock, timber)." (Smith and Matthews, 2015, page 1). In addition, this database relies on a variety of public and private sources, such as the National Weather Service, the Federal Emergency Management Agency (FEMA), state emergency management agencies, media reports, and insurance industry estimates (NCEI, 2022).

A limit of the NCEI database might be to focus only on natural disasters generating more than \$1 billion in losses (adjusted for CPI); still, this threshold captures most of the damages caused by natural disasters (>80%) (NCEI, 2022). In addition, focusing on large natural disasters is common in both natural disaster

2. SHELDUS is a US county-level natural disaster database covering the period from January 2016 to the present. The database provides the date of the event, the affected location, the direct losses – property and crop losses, injuries, and deaths – and the insured crop losses (SHELDUS). For the insured crop losses, the database runs from January 1989. For its part, EM-DAT is the "International Disaster Database" maintained by the "Centre for Research on the Epidemiology of Disasters" (CRED) of the "Université Catholique de Louvain (UCL)." This database reports natural and technological disasters by providing the number of total deaths, the number of total people affected, and the estimated damage (EM-DAT).

3. The number of natural disasters or losses recorded may vary slightly as this database is regularly updated.

databases and the empirical literature. For example, with the EM-DAT worldwide database, a natural disaster only enters the database if one of the following criteria is met : (i) ten or more people are killed, (ii) hundreds of people are reported affected, (iii) a state of emergency is declared, and (iv) there is a call for international assistance (EM-DAT). Therefore, only large natural disasters are eligible. Turning to the empirical literature, this is standard to apply decision rules picking the most severe natural disasters (Bourdeau-Brien and Kryzanowski, 2017; Cortés and Strahan, 2017; Dessaint and Matray, 2017). For instance, Cortés and Strahan (2017) select only natural disasters for which Governors have declared a "state of emergency" with a formal request toward the FEMA. Dessaint and Matray (2017) focus only on hurricane events that have generated total direct damages above \$5 billion (adjusted for inflation).

Finally, the main strength of the NCEI database compared to others, i.e., SHELDUS or EM-DAT, is having corrected their loss estimates for "accounting bias" and providing confidence intervals for disaster losses – the latter have been estimated by Smith and Matthews (2015) with Monte Carlo simulations. The "accounting bias" may be defined as the underestimation of total losses due to heterogeneity in data sources, methodology, and natural disaster events (Smith and Katz, 2013). For example, the underestimation of losses for the NCEI was approximately 10-15% of total losses (Smith and Katz, 2013).

In short, the NCEI database focuses on insured and uninsured losses resulting from large natural disasters, the estimated losses are based on private and public sources, and the database is purged of the "accounting bias." The following section reviews the transformation applied to our natural disaster variable and defines the credit risk variables.

3.1.3 Variables

Therefore, our natural disaster variable is the losses incurred by natural disasters (adjusted for inflation). We transform this event series into a monthly frequency, where we put zero for the economic losses in the absence of natural disasters (Figure 3.A.1 in Appendix). We focus on the period spanning from 1990 to 2019. We exclude the 1980s, as this period was marked by a substantial recession in the United States, notably triggered by the FED tightening to fight the inflation rise (Federal Reserve History). We also exclude 2021 as this year was marked by the pandemic crisis, inducing the Great Lockdown.

In addition, some natural disasters are short-lived, occurring for less than a month, like Freeze, Severe Storm, Tropical Cyclone, and Winter Storm. Conversely, some natural disasters extend over several months and thus have a longer time horizon, such as Drought, Flood, and Wildfire. For these latter disasters,

and because the underlying damages affect several months, we spread the total economic losses according to a uniform law for the hit months. We acknowledge that this data treatment is debatable; economic damages do not necessarily follow a uniform distribution, as these distributions may differ by event type or location. However, we do not have this degree of information due to too high event heterogeneity. Finally, if some natural disasters overlap in time, we sum the corresponding losses.

For the credit spreads, we use two measures : one dedicated to households and one devoted to firms (Figure 3.A.2 in Appendix). We use the mortgage spread for households as in [Gertler and Karadi \(2015\)](#); it is constructed by subtracting the 30-year Conventional Mortgage spreads with the 10-year US Treasury Securities. This index is used as an indicator of housing finance costs. The data source is the FRED (Federal Reserve Bank of St. Louis).

For companies, we consider the credit spread of [Gilchrist and Zakrajšek \(2012\)](#), numerously used in the monetary policy literature to analyze the impact of monetary policy shocks on the credit markets ([Gertler and Karadi, 2015](#); [Miranda-Agrippino and Rey, 2020](#)). The [Gilchrist and Zakrajšek \(2012\)](#) corporate bond credit spread (hereafter, the "GZ credit spread") is constructed by using "secondary market prices of senior unsecured bonds issued by a large representative sample of US non-financial firms." ([Favara et al., 2016](#)). The series is freely available on [Favara et al. \(2016\)](#)'s FEDS Notes. Hence, the GZ credit spread reflects firms' expected default and access to external finance. Finally, compared to more standard corporate credit spread measures, such as the Baa-Aaa corporate or the paper bills spreads, the GZ credit spread better predicts the future outcome of economic activity ([Gilchrist and Zakrajšek, 2012](#)).

3.2 Model

We aim to analyze the dynamic responses of the US credit spreads following a natural disaster shock. To this end, we construct a VAR(p) model and impose the disaster variable as being weakly exogenous. Suppose a K-dimensional stationary and stable VAR (p) process :

$$y_t = c + A_1 y_{t-1} + \dots + A_p y_{t-p} + B_1 x_t + u_t \quad (3.2.1)$$

Where, $y_t = (y_{1t}, \dots, y_{Kt})'$ is a K-dimensional vector of endogenous variables, and $x_t = (x_{1t}, \dots, x_{Mt})'$ is an M-dimensional vector of exogenous variables. The A_j 's with $(j = 1, \dots, p)$ are the coefficient matrices of dimension $(K * K)$, and B_1 is the exogenous coefficient matrix of dimension $(K * M)$. In addition, c is a K-dimensional vector of constants, and u_t is a K-dimensional white noise process with $u_t \sim (0, \Sigma u)$

(Lütkepohl, 2005).

In the y_t vector, we have the log +1 of the natural disaster losses, the GZ credit spread, and the mortgage spread. We apply the log +1 transformation on the natural disaster variable to deal with zero values.⁴ The GZ credit spread and the mortgage spread are taken in levels, and we include several control variables : industrial production (in log), consumer price index (in log), the 1-year Treasury bond yield, and a crisis dummy specified according to the [NBER dating recessions](#) (for the control variables, see Figure 3.A.3 in Appendix). These control variables have been selected as they are significant predictors of corporate and household credit spreads.

Moreover, restrictions are applied on the A_j 's and B_1 matrices to assume that natural disaster losses are solely explained by their lagged values and a constant. The A_j 's and B_1 matrices take the following form :

$$A_{j(j=1,\dots,p)} = \begin{bmatrix} a_{11} & 0 & 0 \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{bmatrix}_j \quad \text{and} \quad B_1 = \begin{bmatrix} 0 & 0 & 0 & 0 \\ b_{21} & b_{22} & b_{23} & b_{24} \\ b_{31} & b_{32} & b_{33} & b_{34} \end{bmatrix}$$

We express our VAR(p) model with its Wold MA representation :

$$y_t = \mu + \sum_{i=0}^{\infty} \phi_i u_{t-i} \tag{3.2.2}$$

Where, $\phi_i = \sum_{j=1}^i \phi_{i-j} A_j$, $i = 1, 2, \dots$, are the impulse responses of the system. With, $\phi_0 = I_K$, $A_j = 0$ for $j > p$, and $\mu = E(y_t)$.

Then, we apply the Cholesky decomposition of the white noise covariance matrix :

$$y_t = \mu + \sum_{i=0}^{\infty} \theta_i w_{t-i} \tag{3.2.3}$$

Where, $\theta_i = \phi_i P$, $w_t = P^{-1} u_t$ and P is the lower triangular Cholesky decomposition of $\sum u$, with $\sum u = PP'$ (Lütkepohl, 2005). The residual matrix takes the following form :

4. We are aware that Gaussian assumptions on the variables are questionable and notably that a better specification would tend toward [Brandt and Sandler \(2012\)](#)'s Bayesian Poisson vector autoregression model. However, due to the implementation complexity, we prefer first to provide analysis with "standard" econometric tools and leave this point for further extension.

$$w_t = \begin{bmatrix} p_{11} & 0 & 0 \\ p_{21} & p_{22} & 0 \\ p_{31} & p_{32} & p_{33} \end{bmatrix}^{-1} \times \begin{bmatrix} u_{nat.disasters} \\ u_{gz.spread} \\ u_{mortgage} \end{bmatrix}$$

The orthogonal residuals ordering imposes the natural disaster variable in the first position, followed by the GZ credit spread and the mortgage spread, respectively. As a result, we constrain natural disaster losses to have no contemporaneous response to shocks from the GZ credit and mortgage spreads. Instead, natural disaster shocks may have a contemporaneous impact on the others. This restriction is our central identification assumption : natural disaster shocks are unrelated to other economic variables. Additionally, we assume that GZ credit spread shocks have a contemporaneous impact on the mortgage spread, but the reverse is not true. In other words, we suppose that the corporate bond market has a contemporaneous effect on housing finance costs through household solvency, while the reverse does not hold. Note that this assumption is not central to our identification strategy as we are only interested in the responses of our credit risk variables to natural disaster shocks and no other relationships. Nevertheless, we derive all other Cholesky orders to ensure the robustness of our results.⁵

5. The corresponding results are reported in Figure 3.A.5 in Appendix and show that our findings are robust to the ordering of the variables.

3.3 Estimation results

3.3.1 Baseline VAR specification

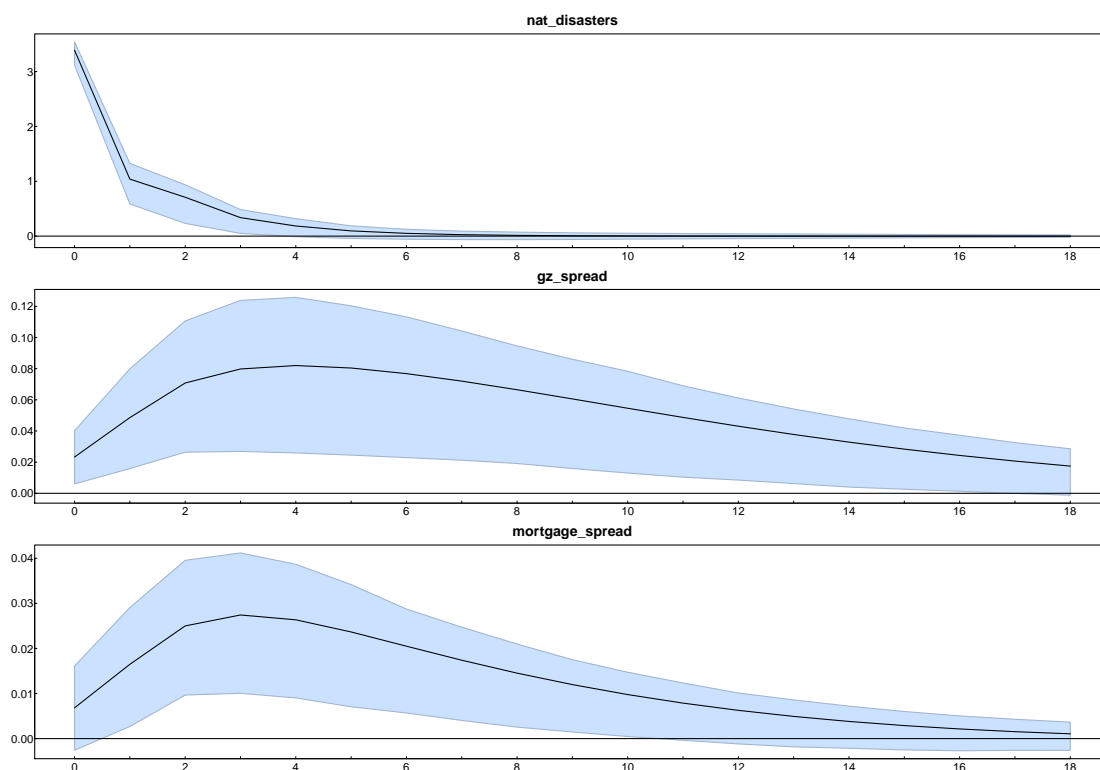


Figure 3.3.1 – Estimated orthogonalized impulse responses of a natural disaster shock

Note : The VAR is estimated with two lags, selected by the information criteria (e.g., Schwarz and Akaike), and is stable. The confidence bands are computed by standard bootstrap at 95% and are based on 1500 bootstrap replications (standard intervals).

Figure 3.3.1 depicts the Impulse Response Function (IRF) of a natural disaster shock on the corporate and mortgage credit spreads. We compute an 18-forecast horizon to project the IRFs over one year and a half. First, we observe that the natural disaster variable reacts as expected with a strong and significant increase in economic losses and not returning to its steady-state until three months following the event. Second, a natural disaster shock increases the GZ corporate credit spread up to two months, and the effects are persistent – the return to the steady-state takes more than a year. Indeed, large-scale natural disasters can significantly destroy firms’ assets, causing a decline in output, productivity, or employment levels (Batten et al., 2016; Scott et al., 2017). Natural disasters’ damages can spread to other businesses through

supply chain disruptions with "parts shortages, product design change needs, manufacturing stoppages, logistical breakdowns, and humanitarian emergencies" (Park et al., 2013, page 2). For example, according to the SBCS (2017)'s report, the 2017 highly damaging natural disasters (Section 3.1.1) resulted in losses for 40% of small businesses in the affected area. These losses were primarily due to reduced revenues rather than asset destruction – 65% of affected businesses reported losses due to power or utility loss. However, the businesses' insurance coverage did not match this result, with only 17% having business interruption insurance (9% for corporates with higher credit risk). In addition, 27% of the affected companies did not have insurance (35% for corporates with higher credit risk). As a result, firms sought financing through disaster assistance or credit applications, and firms affected by significant losses were more likely to seek funding through credit from large banks. Overall, affected firms observed higher default risk factors, leading to higher credit risks and greater financial challenges. This result is also consistent with Dafermos et al. (2018). The authors derive a stock-flow ecological model and notably show that climate change damages are expected to generate capital destruction and lower growth rates. As a result, the capital and profitability of firms are likely to be affected, leading to higher default rates and harming the financial and non-financial sectors of firms.

Third, a natural disaster shock significantly increases the US mortgage spread from the first to the third month, and the effect is persistent – we return to the steady-state ten months after the disaster, which remains less long-lasting than for the corporate credit spread. Large natural disasters induce significant asset destruction for households, negatively impacting their balance sheets and leading to higher default risk, particularly if the damaged assets are used as collateral (Batten et al., 2016; Scott et al., 2017).

The literature focusing on the United States goes in this way. For instance, Ratcliffe et al. (2020) find that natural disasters lead to a decline in credit score, mortgage performance, and debt access with a long-lasting effect. Other authors highlight more heterogeneous effects whether individuals perceive aid, have insurance, or have a stable financial situation before the event. Indeed, Edmiston (2017) shows that hurricanes tend to lower credit scores, and the effects worsen if individuals experience ex-ante financial vulnerability. Roth Tran and Sheldon (2017) add that only the most vulnerable individuals – individuals with the lowest credit scores, residing in a low-income area, or not receiving individual aid – are the most likely to declare bankruptcy. Also, Kousky et al. (2020) show that following the Harvey Hurricane, households who had not subscribed to flooding insurance experienced an increase in the likelihood of having loan modifications, having 180 days or more past due, or being in default two years after. Interestingly, Gallagher and Hartley (2017) highlight a reduction in mortgage debt for insured households following Katrina's hurricane, as individuals used the capital to pay off their mortgages.

Therefore, federal assistance or insurance is necessary to protect homeowners from climate risks. For example, the Small Business Administration (SBA) provides low-interest loans to households and businesses damaged by a natural disaster. The Federal Emergency Management Agency also offers federal assistance in the aftermath of a disaster when its impact exceeds the State's ability to respond. In particular, we have FEMA's Individuals and Households Program (IHP), which provides financial support to individuals and households in severe financial need after a disaster. Nevertheless, federal aid is insufficient to absorb all the damages of the disaster and is not intended to replace insurance. Indeed, FEMA recalls that "IHP assistance is not a substitute for insurance and cannot compensate for all losses caused by a disaster. The assistance is intended to meet your basic needs and supplement disaster recovery efforts."(2021). For example, following the events of the 2017 natural disasters, FEMA has denied two-thirds of the applications (Martín, 2019). The insurance systems are therefore crucial, but on this point, there are also mismatches between individual insurance coverage and financial need, as a large majority of households are not covered or are partially covered after a disaster. For example, three-quarters of households flooded by Hurricanes Sandy, Irma, and Harvey were uninsured (Kousky and Lingle, 2018).

Overall, a large natural disaster increases corporate and mortgage credit spreads. Large natural disasters can generate significant asset destruction leading to balance-sheet damages for households and corporates. For corporates, more than the asset damages, they can suffer from stopping activities, leading to increased unemployment, decreased productivity, and supply chain disruptions. The household and firm losses may spread to banks, especially if the damaged assets serve as collateral. Banks may respond by implementing optimization strategies to reduce risks arising from these agents, amplifying the negative effect on economic activities. In addition, the widening credit spreads may point out the inadequate US insurance coverage and the insufficiency of federal assistance. Indeed, a large share of households and corporates is not insured or adequately insured after a natural disaster, and federal aid such as FEMA's Individuals and Households Program has no vocation to cover all disaster losses.

3.3.2 Sensitivity analysis

The previous results give us a first idea of the transmission channels operating between natural disaster events and credit spreads for firms and households. Therefore, as the relationship between natural disasters and the corporate credit spread is significant, we further investigate this link by decomposing the corporate credit spread into two components : one focusing on expected corporate defaults and one on investors' credit market sentiment. In this way, we could deduce whether the increase in the corporate credit spread following a disaster is driven by firms' balance sheets deterioration or a rise in credit risk aversion. Furthermore, we investigate this relationship further by wondering whether the results differ, focusing on short- or long-run natural disasters.

3.3.2.1 Expected corporate default & investors' credit market sentiment

We are interested in whether the rise in the corporate credit spread after a disaster results from deteriorating corporate balance sheets or more investors' risk-averse behavior (or both).

Therefore, and as in [Gilchrist and Zakrajšek \(2012\)](#)'s semantic paper, we decompose the GZ corporate credit spread into two components, (1) the estimated GZ credit spread and (2) the Excess Bond Premium (EBP)(Figure 3.A.4).⁶ The estimated GZ credit spread captures the firms' expected defaults, while the EBP is a residual component capturing investors' sentiments toward corporate credit risks. Also, the EBP is an indicator apprehending economic activity's future outcomes. Hence, the authors propose two main and non-exclusive interpretations of its variation. First, the EBP increase could be due to investors over-reacting to bad news such as natural disasters. For instance, following significant losses from hurricanes, investors could anticipate higher default risks for companies, even if the corporate's fundamentals have not changed. A second possible interpretation is that the worsened credit market sentiment is causing investors to tighten their financing conditions, thereby exacerbating the negative effects of the shock. Indeed, corporate bond markets are dominated by institutional investors such as banks, insurance companies, or pension funds, which have an important role in financing large companies. Therefore, investors with less risk-bearing capacity could react by reducing their credit supply to potential borrowers.

6. $S_t^{GZ} = \hat{S}_t^{GZ} + EBP$

Where S_t^{GZ} is the GZ corporate credit spread, \hat{S}_t^{GZ} is the estimated GZ credit spread, and EBP is the Excess Bond Premium ([Favara et al., 2016](#)).

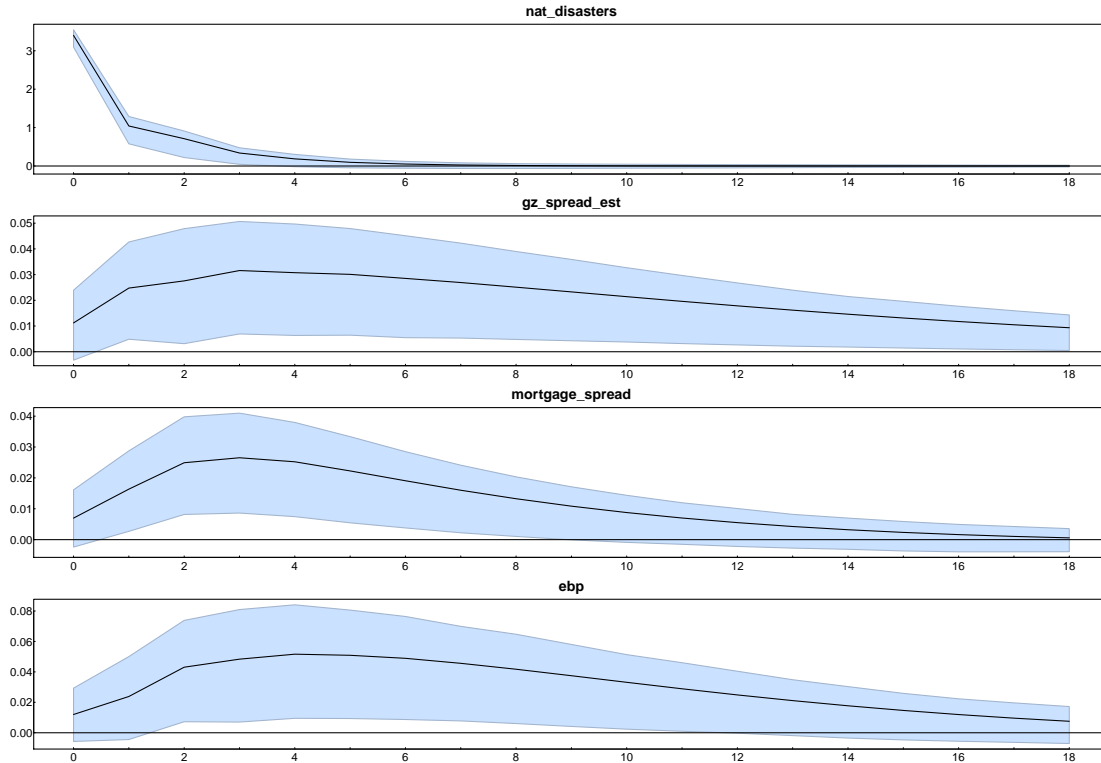


Figure 3.3.2 – Estimated orthogonalized impulse responses of a natural disaster shock

Note : The VAR is estimated with two lags selected with the Schwarz criterion and is stable. The confidence bands are computed by standard bootstrap at 95% and are based on 1500 bootstrap replications (standard intervals).

Figure 3.3.2 shows the responses of the estimated GZ credit spread, mortgage spread, and EBP to a natural disaster shock. The only difference compared to the baseline model is the Cholesky ordering. Indeed, we set the EBP variable in the last position as this series captures investors' sentiment and, therefore, is more likely to react contemporaneously to different shocks. The mortgage spread is set in the second-to-last position, assuming once again that housing finance costs may react contemporaneously to corporate balance sheets through the corporate bond market, while the reverse is not true. As previously mentioned, all Cholesky permutations have been computed to ensure the robustness of the results. As shown in Figure 3.A.6 in Appendix, the results do not change, illustrating the robustness of our findings. The responses to a natural disaster shock do not change for natural disaster losses and the mortgage spread. More interestingly, expected corporate default risk (estimated GZ credit spread) and investor credit risk aversion (EBP) increase significantly after a natural disaster shock. Corporate default risk increases for three months, while investor risk aversion rises significantly from the first to the fourth

month (roughly) after the disaster. Also, both effects are long-lasting, with a stronger persistence for firms' default risk than investors' market sentiment; after the shock, credit default risk takes more than a year to recover, while the effects on credit market sentiment persist for less than a year. In addition, as the expected corporate default and the investor risk aversion rise, we can infer that the EBP increase does not reflect a market overreaction – firms' fundamentals do change – but rather credit supply restrictions by institutional investors after a disaster.

On this point, the literature focuses primarily on banks. For example, if banks experience or anticipate large losses after a disaster, they may respond by reducing their credit supply to damaged and undamaged agents, amplifying the negative effect on the economy (Batten et al., 2016). The empirical literature is in line with credit crunch effects for developing countries but is not unanimous for developed economies such as the US. For developing countries, Brei et al. (2019) show that banks restrict their loan supply and face deposit withdrawals after Eastern Caribbean hurricanes. Also, Berg and Schrader (2012) point out that volcanic eruptions in Ecuador decreased local banks' credit supply to unknown clients. For the United States, some authors find credit tightening effects, others not. For instance, Duanmu et al. (2022) show that banks tighten lending standards in disaster-hit counties, especially when the likelihood of negative effects on the local economy is high. Garmaise and Moskowitz (2009) find that the California earthquake of the 1990s reduced commercial real estate lending in the State by 22%. For their parts, Cortés and Strahan (2017) and Ivanov et al. (2022) show that banks react to natural disasters by increasing their lending in disaster areas while reducing their credit supply in non-damaged zones. Finally, some authors point out that banks extend credit in disaster areas but protect themselves from the higher credit risk by securitizing these loans. On this point, Schüwer et al. (2019) find that highly capitalized independent banks increased their risk capital ratio after Hurricane Katrina. Those banks protected themselves from the rising credit risk not by restraining the credit access in the damaged zone but by reducing their holding in non-financial loans and increasing their ownership in government securities. Chavaz (2016), focusing on the 2005-hurricanes season, also finds that banks securitized high-risk natural disaster loans by selling them in the secondary market.

Overall, we notice a significant rise in the estimated GZ credit spread and the Excess Bond Premium. Therefore, a large-scale natural disaster leads to an increase in the probability of corporate default, which in turn leads to a deterioration of investors' credit market sentiment. Hence, institutional investors reduce their credit supply to cope with the increased risk. Nevertheless, on this last point, the literature is not consensual, although it consistently points out that banks seek to protect themselves from rising credit

risk. Some authors find credit supply restrictions in the damaged area (Garmaise and Moskowitz, 2009; Duanmu et al., 2022) or toward undamaged zones (Cortés and Strahan, 2017; Ivanov et al., 2022), while some highlight loan securitization processes (Chavaz, 2016; Schüwer et al., 2019). Therefore, we could suspect a difference in the investors' risk strategy depending on the natural disaster and the corresponding governmental pressure to grant credits. As a result, the following section analyzes whether the results differ if the natural disasters are short- or long-lived.

3.3.2.2 Short-run & long-run natural disasters

We split the natural disaster loss variable into two separate variables, a short-term and a long-term disaster variable. Recall that by short-term disasters, we infer disasters with a duration of less than one month, including Freeze, Severe Storm, Tropical Cyclone, and Winter Storm. The long-term disasters are, therefore, those of more than one-month duration, including Drought, Flooding, and Wildfire (Table C in Appendix). Figure 3.3.3 outlines the results of a short- or long-lived natural disaster shock on the mortgage and the corporate credit spreads.⁷

Figure 3.3.3 shows that the disaster classes correctly capture both short- and long-term natural disaster shocks. Indeed, with the short-term disaster model, the effects are short-lived and significant for about one month. On the contrary, a long-term natural disaster shock induces significant economic losses for up to six months. Moreover, the mortgage credit spread increases significantly whether the disaster shock is short- or long-term – housing finance costs increase instantly after short-term disasters while starting at two months for long-term disasters. Once again, we note that natural disaster shocks have lasting effects on the mortgage market, persisting for over a year for both disaster classes.

Additionally, as previously suspected, the outcomes for the business credit market vary depending on the disaster; a short-run natural disaster shock does not significantly affect the corporate credit spread, while a long-run disaster shock causes a significant rise at two months. Hence, we split the corporate credit spread again to analyze if this is the investors' credit supply conditions – the EBP – that induce this result. Figure 3.3.4 outlines the findings.⁸

7. Our results are robust to different ordering in the Cholesky decomposition, see Figure 3.A.7 in Appendix.

8. Our results are not sensitive to the ordering in the Cholesky decomposition (Figures 3.A.8 and, 3.A.9).

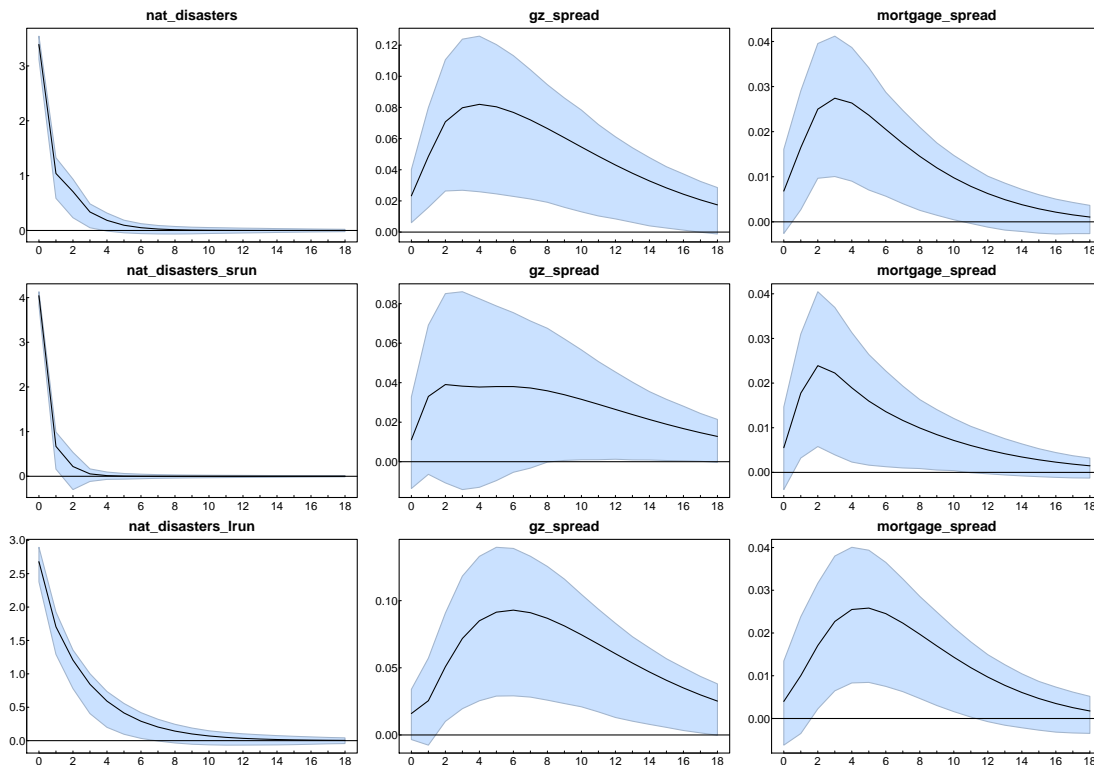


Figure 3.3.3 – Estimated orthogonalized impulse responses of a natural disaster shock

Note : The VAR models are estimated with two lags, selected with the Schwarz criterion, and are stable. The IRF reading for each model is from left to right. The confidence bands are computed by standard bootstrap at 95% and are based on 1500 bootstrap replications (standard intervals).

Following a short- or long-term natural disaster, expected corporate default increases significantly, while only a long-term disaster induces credit supply restrictions, highlighted by the significant increase in the EBP. The main takeaway is that investors react differently to short- and long-term natural disasters. Investors do not tighten credit after a short-lived natural disaster, such as hurricanes, tornadoes, or severe storms, but they do tighten credit after a long-lived disaster such as a drought, flood, or wildfire. One possible explanation is that investors' credit supply depends on Government pressure, which is related to media coverage of the disaster. On this point, [Eisensee and Stromberg \(2007\)](#) show that US relief for natural disasters depends on media coverage, while the latter depends on the disaster type. For instance, the authors find that "for every person killed in a volcano disaster, 40,000 people must die in a drought to reach the same probability of media coverage." (page 2).

In our case, we may assume that short-lived disasters – e.g., hurricanes or severe storms – benefit from higher media coverage as they are more "striking" than long-run disasters such as drought and flooding

(wildfires make the exception). Besides, long-term disasters' losses are often more difficult to estimate. For instance, the 2012 US drought has led to 123 direct deaths, while the indirect deaths due to the excess mortality are still unknown (NCEI, 2022). Therefore, the difference in media coverage may lead to different Government responses and pressure on institutional investors to provide credit to damaged agents, resulting in a credit crunch following long-lived disasters but not after short-lived disasters. Then, the credit crunch can worsen the initial effect of the natural disaster by slowing output and employment (Batten et al., 2016). Finally, the absence of a credit crunch does not necessarily mean that institutional investors are not hedging against these higher credit risks. Some authors note that banks do not restrict lending for hurricanes, i.e., short-term disasters, but sell them on the secondary market to hedge against the higher risk of default (Chavaz, 2016; Schüwer et al., 2019). These results are consistent with ours. Through securitization, the risk is spreading the climate risk outside the disaster area, increasing the probability of systemic events. On this point, Aglietta and Espagne (2016) note that "climate change impacts are systemic in nature. They affect the whole planet, in most its dimension." (page 4).

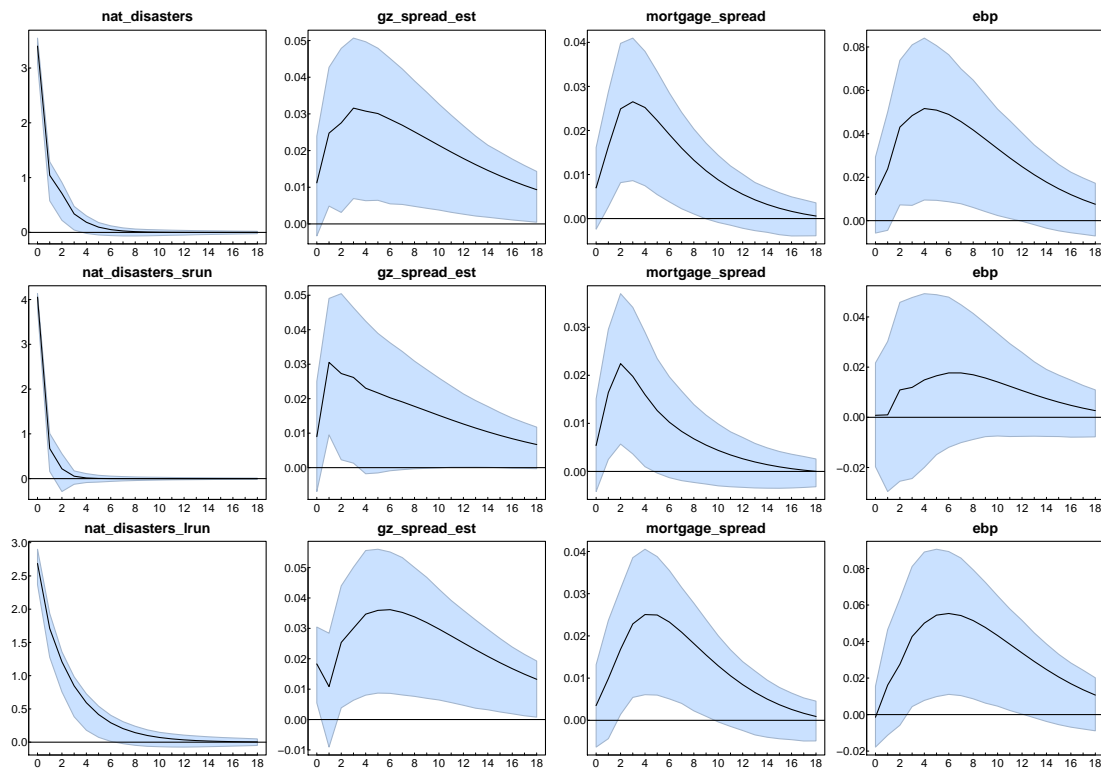


Figure 3.3.4 – Estimated orthogonalized impulse responses of a natural disaster shock

Note : The VAR models are estimated with two lags, selected with the Schwarz criterion, and are stables. The IRF reading for each model is from left to right. The confidence bands are computed by standard bootstrap at 95% and are based on 1500 bootstrap replications (standard intervals).

Overall, we show that the mortgage spread rises significantly following short- or long-run disasters, while the effects differ for corporate bond credit spreads. On this latter point, we find that for both disaster classes, the expected default of corporates increases significantly, but the credit supply conditions of investors react differently whether the disaster is short- or long-lived. Indeed, we do not find significant credit tightening after short-run disasters (e.g., hurricanes, severe storms), while this effect is significant with long-run disasters (e.g., droughts, floodings). We apprehend these findings with the difference in media coverage and, thus, federal incentives toward investors to provide credits after a disaster.

3.4 Robustness checks

First, for all our VAR specifications considered in Section 3.3, we estimate A-SVAR models to assess whether we have contemporaneous relationships between the disaster variables and the credit spreads. We show that contemporaneous natural disaster variables have no predictive power on the corporate and mortgage credit spreads (Tables 3.A.5, and 3.A.6 in Appendix). As a result, we do not retain the SVAR models as our core specifications – we do not gain information, but we lose degrees of freedom. About the SVAR models, we follow the specification of [Raddatz \(2007\)](#), [David \(2011\)](#), [Melecky and Raddatz \(2015\)](#), who investigated the effects of natural disaster shocks on economic outcomes. Hence, our A-matrices follow the same ordering of our Cholesky decompositions. For instance, for the baseline model, we specify our contemporaneous matrix with the natural disaster variable in the first position, followed by the corporate credit spread and the mortgage spread. As a result, we assume that natural disaster losses may have a contemporaneous effect on the corporate and mortgage spreads, while the reverse is not true. Also, the A-SVAR models are estimated by maximizing the negative log-likelihood. Finally, as previously mentioned, we test all Cholesky permutations to ensure our results’ robustness – the natural disaster variable is always in the first position as the variable is exogenous. The results do not change significantly (Figures 3.A.5, 3.A.6, 3.A.7, 3.A.8, and 3.A.9 in Appendix).

3.5 Conclusion

This chapter analyzes the dynamic effect of large natural disasters on the US mortgage, and corporate credit spreads over the 1990-2019 period.

Our key findings are as follows. Large natural disasters increase the US mortgage and corporate credit spreads, as they may generate significant losses for households and corporates due to asset destruction.

In addition, firms may also experience activity cessation (total or partial), a drop in demand, and, thus, a decrease in output (along with a rise in the unemployment rate). As a result, household and corporate losses may spread to the banks (or financial institutions), especially if the damaged assets are used as collateral. Hence, the banks may respond to these higher credit risks by adopting risk optimization strategies with credit tightening.

To fully apprehend this last point, we split the corporate credit spread measures into two components : the expected corporate default and the credit supply condition. We show that large natural disasters increase corporate default probability, leading to a rise in the investor's risk aversion. Thus, institutional investors react with credit tightening to cope with the higher credit risks. Nevertheless, as the literature is not clear-cut on the US banks' reactions to credit supply after a disaster – tightening or not – we suspect a difference in the investor's risk strategy depending on the natural disaster.

We investigate this issue further by splitting the natural disaster variables into two classes : the short-run (e.g., freeze, severe storm, tropical cyclone, and winter storm) and the long-run (e.g., drought, flooding, and wildfire) natural disasters. We find that the corporate credit spread reacts differently whether the natural disaster is short- or long-lived. The expected corporate default rises significantly for both disaster classes, but the credit tightening appears to occur only after long-run disasters.

A relevant explanation would come from the different media coverage depending on whether the disaster is short or long-lived. Indeed, we may assume that the media coverage is stronger toward more striking natural disasters like hurricanes, tornados, or severe storms, all belonging to the short-run disaster class. Hence, the higher media coverage may lead to higher Government pressure on institutional investors to answer the credit demand for damaged agents. The reverse mechanism holds for long-term disasters with thus fewer media coverage (except for wildfires), leading to less pressure on investors that react with credit tightening.

Finally, the credit tightening may worsen the initial disaster effect by slowing output and employment. It is worth recalling that the absence of a credit crunch for short-lived disasters does not necessarily mean that investors do not hedge themselves against the higher credit risks. For instance, they may sell the disaster loans on the secondary market, spreading the risk outside the disaster area. We leave the securitization loan process identification for further research.

Appendix 3.A

1980-1989	events	events/year	total costs	costs/year	deaths	deaths/year
Drought	5	0.5	103.69	10.37	1814	181
Flooding	4	0.4	15.05	1.51	164	16
Freeze	4	0.4	15.28	1.53	161	16
Severe Storm	7	0.7	9.6	0.96	198	20
Tropical Cyclone	6	0.6	40.93	4.09	198	20
Wildfire	0	0	0	0	0	0
Winter Storm	3	0.3	5.72	0.57	335	34
Total	29	2.9	190.26	19.03	2870	287
1990-1999	events	events/year	total costs	costs/year	deaths	deaths/year
Drought	6	0.6	23.95	2.4	1590	159
Flooding	8	0.8	64.74	6.47	194	19
Freeze	2	0.2	11.71	1.17	0	0
Severe Storm	14	1.4	34.37	3.44	337	34
Tropical Cyclone	12	1.2	112.79	11.28	299	30
Wildfire	3	0.3	10.85	1.09	29	3
Winter Storm	8	0.8	34.49	3.45	596	60
Total	53	5.3	292.91	29.29	3045	304
2000-2009	events	events/year	total costs	costs/year	deaths	deaths/year
Drought	8	0.8	59.32	5.93	190	19
Flooding	3	0.3	16.76	1.68	47	5
Freeze	2	0.2	4.72	0.47	1	0
Severe Storm	27	2.7	60.09	6.01	297	30
Tropical Cyclone	15	1.5	396.27	39.63	2443	244
Wildfire	7	0.7	18.58	1.86	109	11
Winter Storm	1	0.1	1.17	0.12	4	0
Total	63	6.3	556.9	55.69	3091	309
2010-2019	events	events/year	total costs	costs/year	deaths	deaths/year
Drought	8	0.8	84.76	8.48	271	27
Flooding	18	1.8	65.22	6.52	212	21
Freeze	1	0.1	1.14	0.11	0	0
Severe Storm	71	7.1	170.51	17.05	849	85
Tropical Cyclone	12	1.2	475.73	47.57	3567	357
Wildfire	7	0.7	62.49	6.25	209	21
Winter Storm	6	0.6	13.04	1.3	116	12
Total	123	12.3	872.89	87.29	5224	522

Table 3.A.1 – Natural disaster statistics in the United States by decade

Note : Costs are in billions of dollars adjusted for inflation (2021-CPI adjusted).

Source : [NCEI \(2022\)](#).

	events	events/years	total costs	cost/years	deaths	deaths/year
Drought	2	0.7	13.75	4.58	274	91
Flooding	5	1.7	24.26	8.09	19	6
Freeze	0	0	0.00	0.00	0	0
Severe Storm	32	10.7	71.27	23.76	213	71
Tropical Cyclone	13	4.3	129.39	43.13	205	68
Wildfire	3	1	33.11	11.04	57	19
Winter Storm	1	0.3	24.05	8.02	226	75
Total	56	18.7	295.83	98.61	994	331

Table 3.A.2 – Natural disaster statistics in the United States over the past three years (2019-2021)

Note : Costs are in billions of dollars adjusted for inflation (2021-CPI adjusted).

Source : [NCEI \(2022\)](#).

	events	events/year	total costs	costs/events	costs/year	deaths	deaths/year
Drought	29	0.7	285.46	9.84	6.80	4139	99
Flooding	35	0.8	164.32	4.70	3.91	624	15
Freeze	9	0.2	32.85	3.65	0.78	162	4
Severe Storm	143	3.4	330.88	2.31	7.88	1880	45
Tropical Cyclone	56	1.3	1147.96	20.50	27.33	6697	159
Wildfire	19	0.5	120.13	6.32	2.86	401	10
Winter Storm	19	0.5	78.47	4.13	1.87	1277	30
Total	310	7.4	2160.06	51.45	51.43	15180	362

Table 3.A.3 – Natural disaster statistics for the United States over the entire period (1980-2021)

Note : Costs are in billions of dollars adjusted for inflation (2021-CPI adjusted).

Source : [NCEI \(2022\)](#).

	Drought	Flooding	Freeze	Severe Storm	Tropical Cyclone	Wildfire	Winter Storm	Total
0	0	23	9	142	56	0	18	248
1	0	3	0	0	0	1	1	5
2	0	4	0	0	0	0	0	4
3	7	2	0	1	0	5	0	8
4	0	2	0	0	0	0	0	2
5	0	1	0	0	0	1	0	2
6	8	0	0	0	0	7	0	7
7	2	0	0	0	0	4	0	4
8	0	0	0	0	0	0	0	0
9	4	0	0	0	0	0	0	0
10	1	0	0	0	0	0	0	0
11	0	0	0	0	0	0	0	0
12	7	0	0	0	0	1	0	1
Total	29	35	9	143	56	19	19	

Table 3.A.4 – US natural disaster duration in months

Note : The row names correspond to the duration of natural disasters in months. For example, natural disasters in line '0' indicate disasters that lasted less than one month, while disasters in line '1' indicate disasters that lasted one month, and so on.

Source : [NCEI \(2022\)](#).

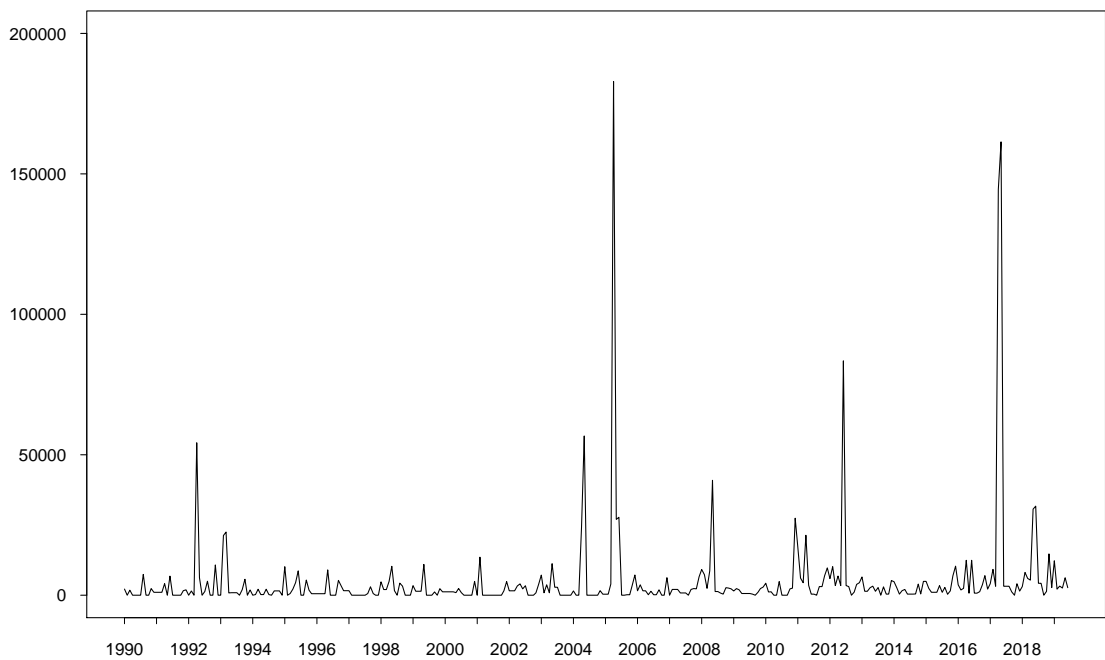


Figure 3.A.1 – US natural disaster losses between 1990 to 2019, monthly frequency (\$B, CPI-adjusted)

Sources : [NCEI \(2022\)](#), Own computation.

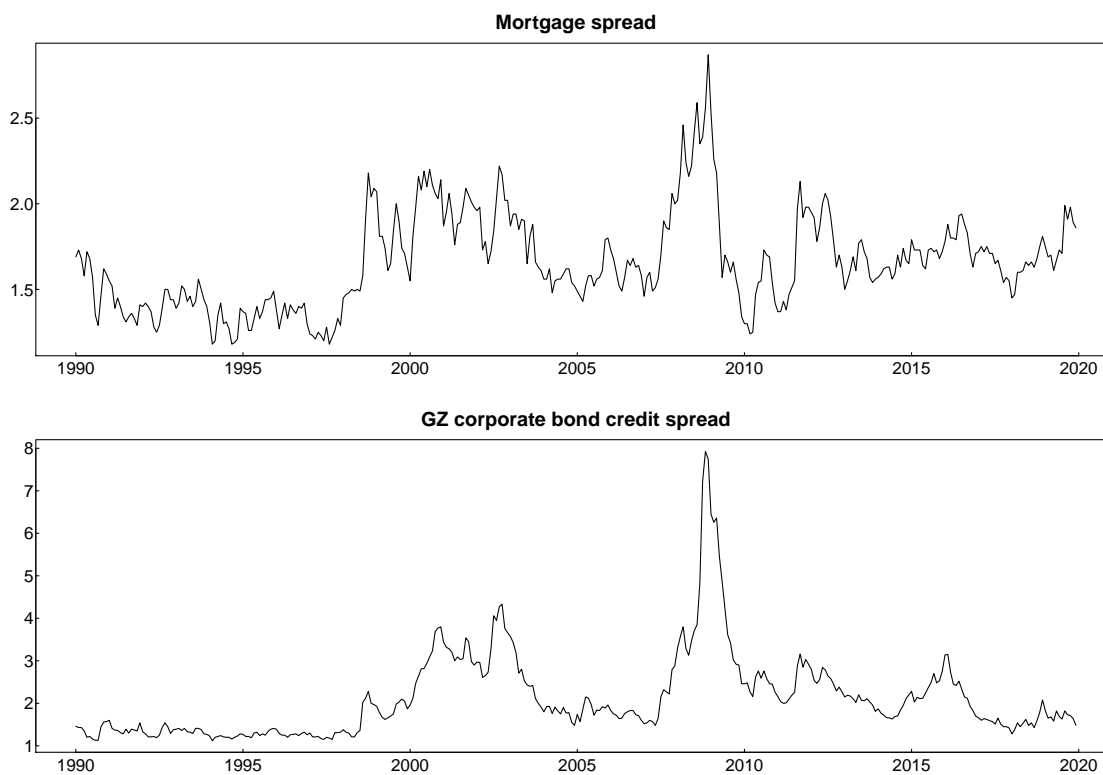


Figure 3.A.2 – Mortgage and corporate bond credit spreads

Note : The mortgage spread is constructed by subtracting the 30-year Conventional Mortgage spreads from the 10-year US Treasury Securities.

Sources :For the mortgage spread : FRED, Own computation. For the [Gilchrist and Zakrajšek \(2012\)](#) corporate bond credit spread : the index is available on [Favara et al. \(2016\)](#)'s FEDS Notes.

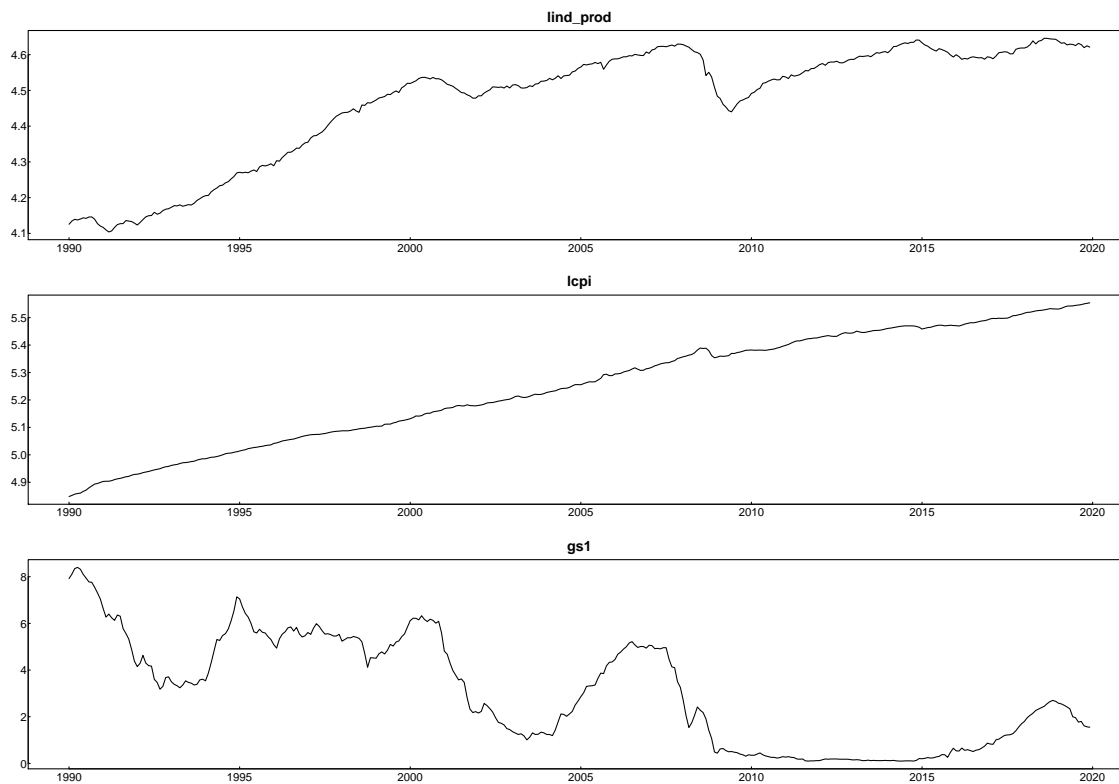


Figure 3.A.3 – Control variables

Note : the 'lind_prod,' 'lcp,' and 'gs1' are the log of industrial production, the log of the consumer price index, and the one-year Treasury bond yield, respectively.

Source : FRED.

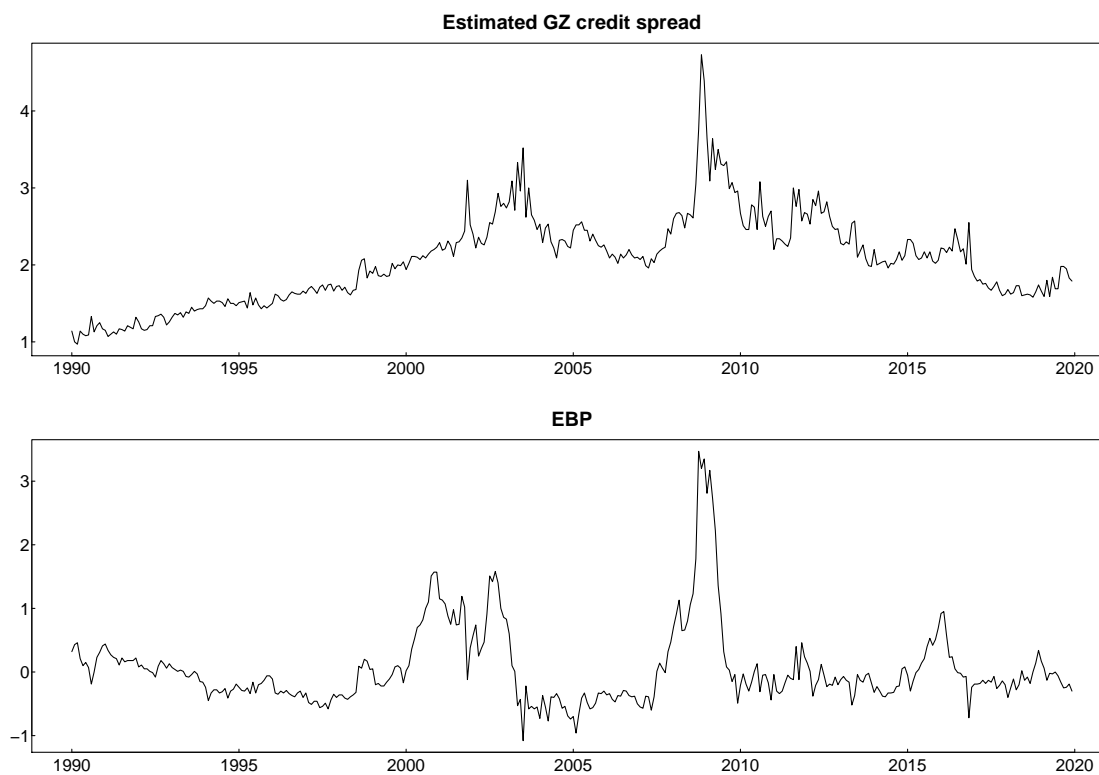


Figure 3.A.4 – Estimated GZ credit spread & Excess Bond Premium (EBP)

Note : The estimated GZ credit spread represents the expected default of firms, while the EBP is an indicator of investors' sentiment on the firms' credit risk and, therefore, on their credit supply conditions.

Sources : For the [Gilchrist and Zakrajsek \(2012\)](#) corporate credit spread components, the indices are available on [Favara et al. \(2016\)](#)'s FEDS Notes.

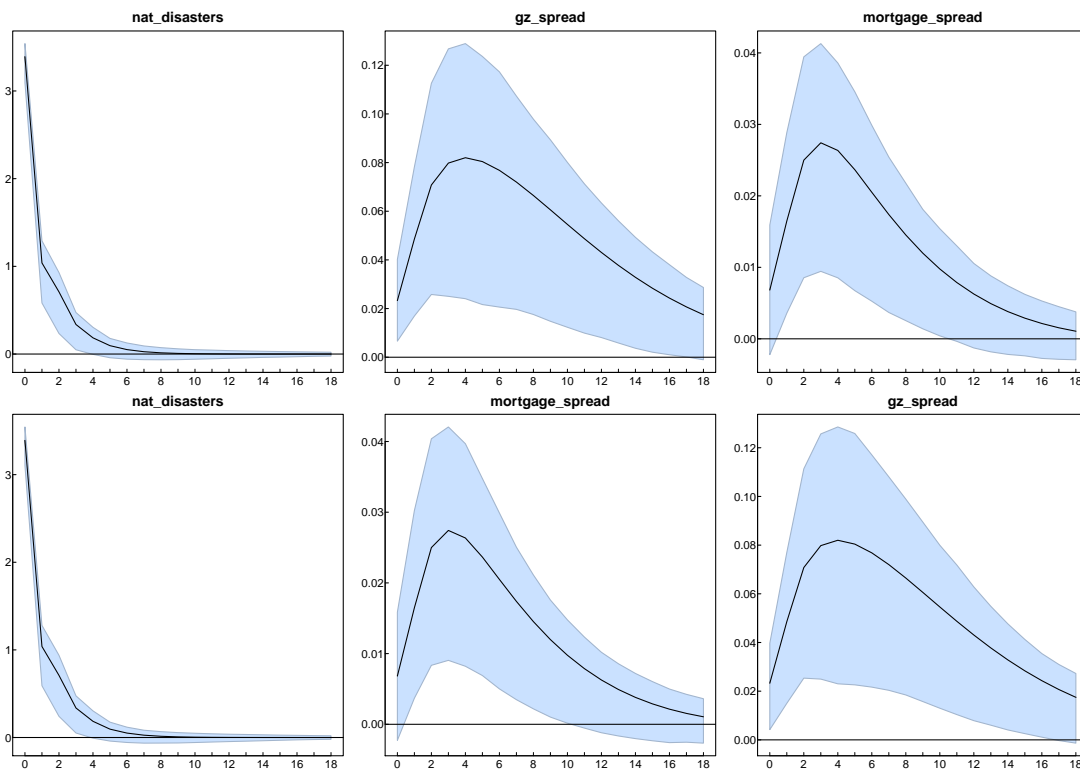


Figure 3.A.5 – Cholesky ordering robustness check – Figure 3.3.1

Note : We ensure the robustness of the baseline VAR(2) model by computing all permutations of the Cholesky order.

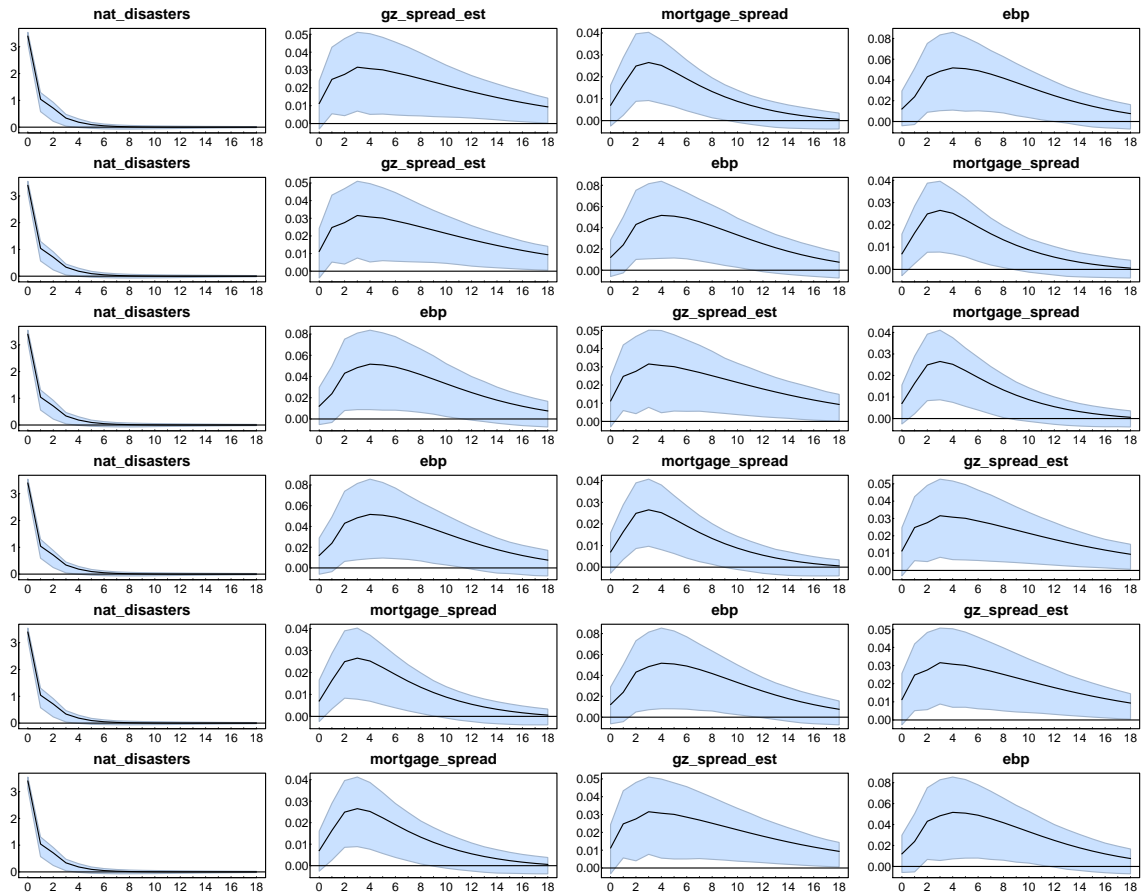


Figure 3.A.6 – Cholesky ordering robustness check – Figure 3.3.2

Note : We ensure the robustness of the VAR(2) model by computing all permutations of the Cholesky order. The 'gz_spread_est' and the 'ebp' correspond to the estimated GZ corporate bond credit spread and the Excess Bond Premium, respectively.

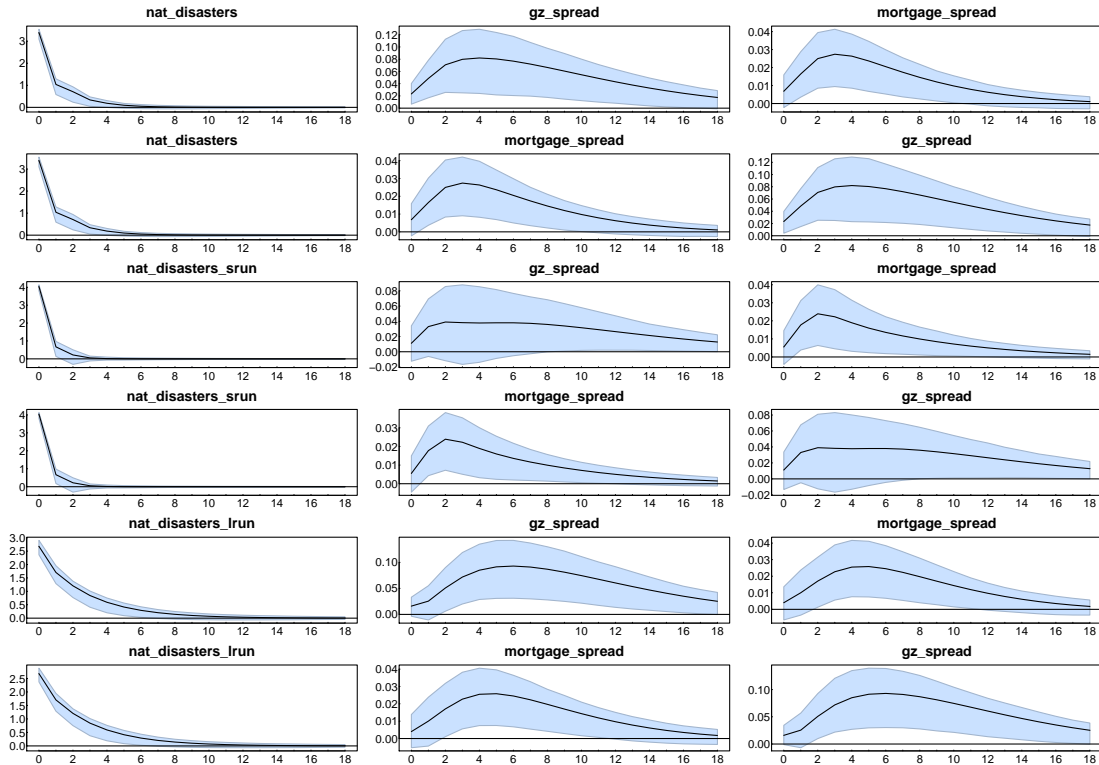


Figure 3.A.7 – Cholesky ordering robustness check – Figure 3.3.3

Note : We ensure the robustness of the VAR(2) models by computing all permutations of the Cholesky order. The 'nat_disasters,' 'nat_disasters_srun,' and 'nat_disasters_lrun' correspond to the natural disaster classes with overall, short-run, and long-run disasters. The short-run disasters include Freeze, Severe Storm, Tropical Cyclone, and Winter Storm, while the long-run disasters include Drought, Flooding, and Wildfire.

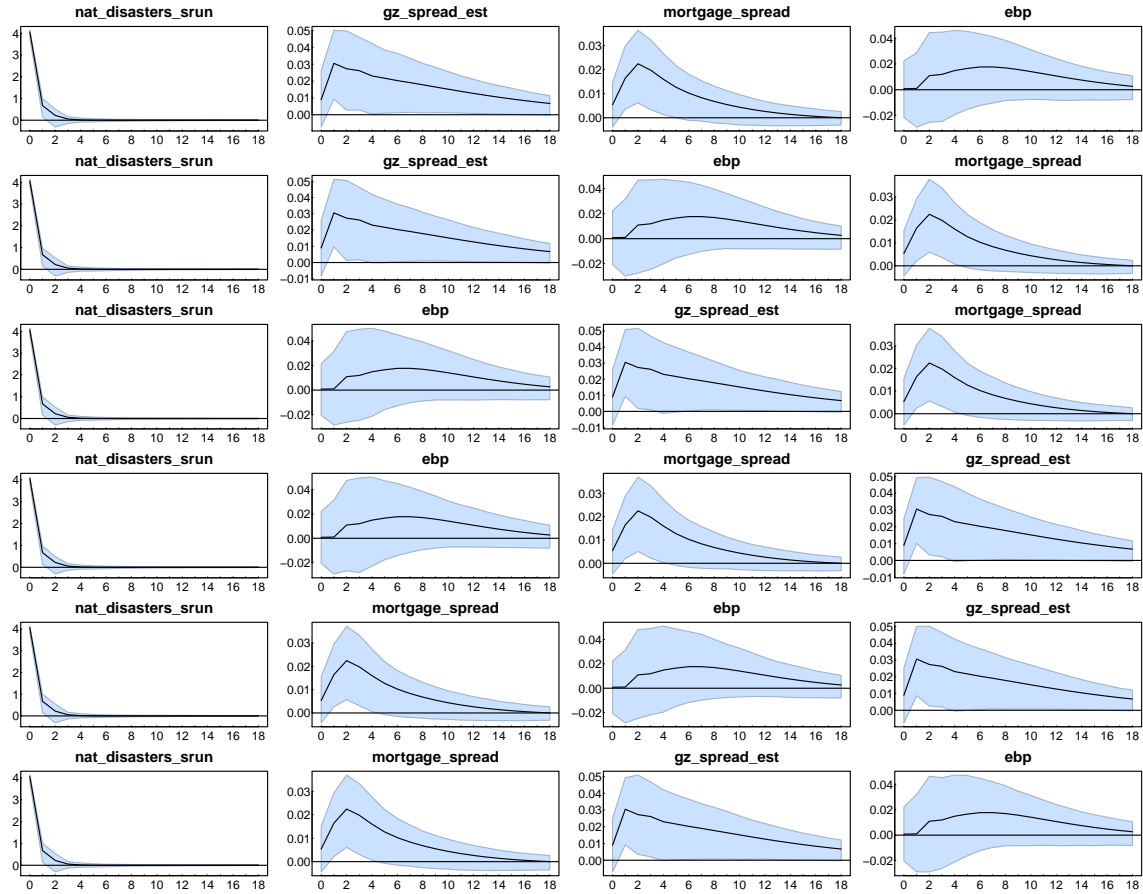


Figure 3.A.8 – Cholesky ordering robustness check – Figure 3.3.4

Note : We ensure the robustness of the VAR(2) models by computing all permutations of the Cholesky order. The 'gz_spread_est' and the 'ebp' correspond to the estimated GZ corporate bond credit spread and the Excess Bond Premium, respectively. The short-run disasters include Freeze, Severe Storm, Tropical Cyclone, and Winter Storm.

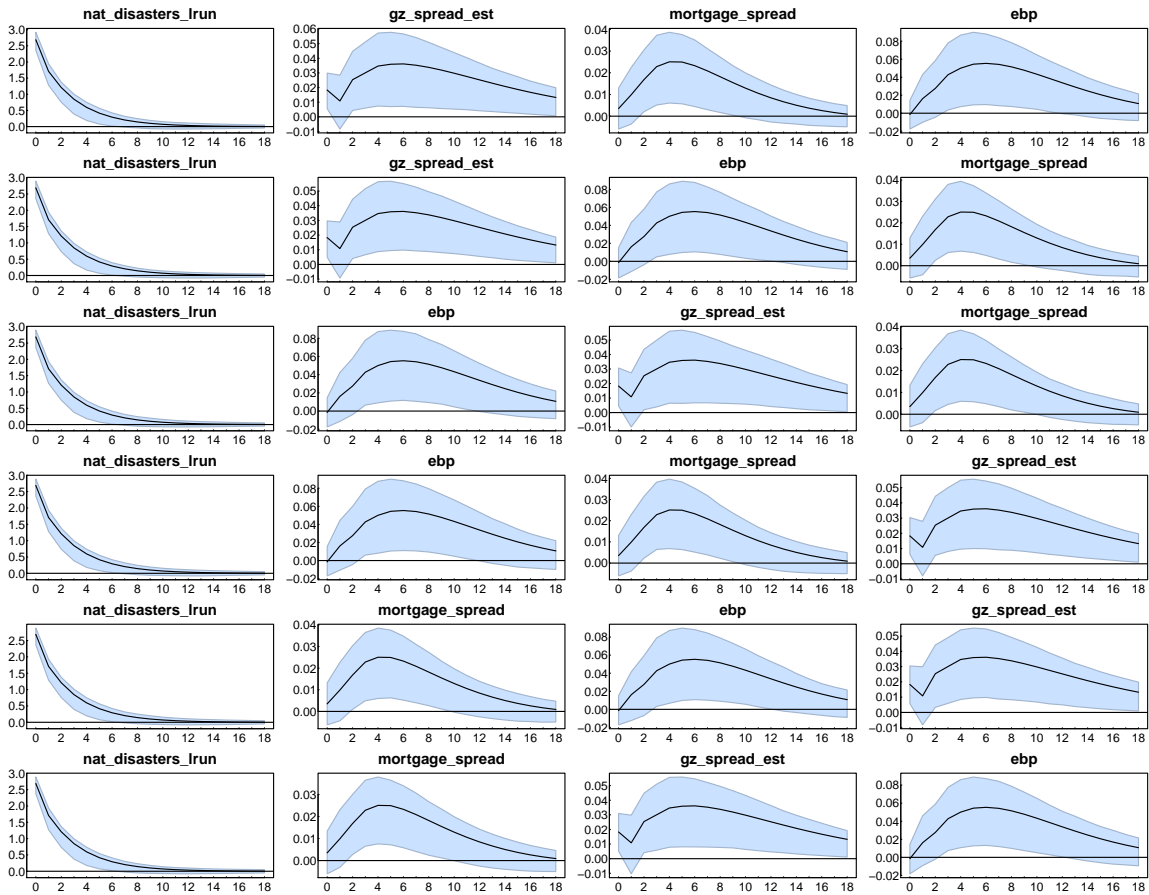


Figure 3.A.9 – Cholesky ordering robustness check – Figure 3.3.4

Note : We ensure the robustness of the VAR(2) models by computing all permutations of the Cholesky order. The 'gz_spread_est' and the 'ebp' correspond to the estimated GZ corporate bond credit spread and the Excess Bond Premium, respectively. The long-run disasters include Drought, Flooding, and Wildfire.

Natural disasters			
Estimated A-matrix			
	nat_disasters	gz_spread	mortgage_spread
nat_disasters	1.00	0.00	0.00
gz_spread	-0.01	1.00	0.00
mortgage_spread	0.00	-0.17	1.00
Standard deviation			
	nat_disasters	gz_spread	mortgage_spread
nat_disasters	0.00	0.00	0.00
gz_spread	0.30	0.00	0.00
mortgage_spread	0.30	4.81	0.00
t-student			
	nat_disasters	gz_spread	mortgage_spread
nat_disasters	NA	NA	NA
gz_spread	-0.02	NA	NA
mortgage_spread	0.00	-0.04	NA
Short-run natural disasters			
Estimated A-matrix			
	nat_disasters_srun	gz_spread	mortgage_spread
nat_disasters_srun	1.00	0.00	0.00
gz_spread	0.00	1.00	0.00
mortgage_spread	0.00	-0.17	1.00
Standard deviation			
	nat_disasters_srun	gz_spread	mortgage_spread
nat_disasters_srun	0.00	0.00	0.00
gz_spread	0.25	0.00	0.00
mortgage_spread	0.25	4.78	0.00
t-student			
	nat_disasters_srun	gz_spread	mortgage_spread
nat_disasters_srun	NA	NA	NA
gz_spread	-0.01	NA	NA
mortgage_spread	0.00	-0.04	NA
Long-run natural disasters			
Estimated A-matrix			
	nat_disasters_lrun	gz_spread	mortgage_spread
nat_disasters_lrun	1.00	0.00	0.00
gz_spread	-0.01	1.00	0.00
mortgage_spread	0.00	-0.17	1.00
Standard deviation			
	nat_disasters_lrun	gz_spread	mortgage_spread
nat_disasters_lrun	0.00	0.00	0.00
gz_spread	0.38	0.00	0.00
mortgage_spread	0.38	4.81	0.00
t-student			
	nat_disasters_lrun	gz_spread	mortgage_spread
nat_disasters_lrun	NA	NA	NA
gz_spread	-0.02	NA	NA
mortgage_spread	0.00	-0.04	NA

Table 3.A.5 – A-SVAR matrix coefficients

Note : Coefficients of the A-SVAR matrices with their standard deviation and t-student values for the models with corporate and mortgage credit spreads for all-natural disasters classes.

Natural disasters				
Estimated A-matrix				
	nat_disasters	gz_spread_est	mortgage_spread	ebp
nat_disasters	1.00	0.00	0.00	0.00
gz_spread_est	0.00	1.00	0.00	0.00
mortgage_spread	0.00	0.36	1.00	0.00
ebp	0.00	0.33	-0.48	1.00
Standard deviation				
	nat_disasters	gz_spread_est	mortgage_spread	ebp
nat_disasters	0.00	0.00	0.00	0.00
gz_spread_est	0.30	0.00	0.00	0.00
mortgage_spread	0.30	6.56	0.00	0.00
ebp	0.30	6.60	10.96	0.00
t-student				
	nat_disasters	gz_spread_est	mortgage_spread	ebp
nat_disasters	NA	NA	NA	NA
gz_spread_est	-0.01	NA	NA	NA
mortgage_spread	-0.01	0.05	NA	NA
ebp	-0.01	0.05	-0.04	NA
Short-run natural disasters				
Estimated A-matrix				
	nat_disasters_sr	gz_spread_est	mortgage_spread	ebp
nat_disasters_sr	1.00	0.00	0.00	0.00
gz_spread_est	0.01	1.00	0.00	0.00
mortgage_spread	-0.01	0.05	1.00	0.00
ebp	0.00	0.59	-0.25	1.00
Standard deviation				
	nat_disasters_sr	gz_spread_est	mortgage_spread	ebp
nat_disasters_sr	0.00	0.00	0.00	0.00
gz_spread_est	0.25	0.00	0.00	0.00
mortgage_spread	0.25	6.61	0.00	0.00
ebp	0.25	6.64	10.95	0.00
t-student				
	nat_disasters_sr	gz_spread_est	mortgage_spread	ebp
nat_disasters_sr	NA	NA	NA	NA
gz_spread_est	0.03	NA	NA	NA
mortgage_spread	-0.03	0.01	NA	NA
ebp	-0.02	0.09	-0.02	NA
Long-run natural disasters				
Estimated A-matrix				
	nat_disasters_lr	gz_spread_est	mortgage_spread	ebp
nat_disasters_lr	1.00	0.00	0.00	0.00
gz_spread_est	0.00	1.00	0.00	0.00
mortgage_spread	0.00	0.12	1.00	0.00
ebp	0.00	0.65	0.03	1.00
Standard deviation				
	nat_disasters_lr	gz_spread_est	mortgage_spread	ebp
nat_disasters_lr	0.00	0.00	0.00	0.00
gz_spread_est	0.38	0.00	0.00	0.00
mortgage_spread	0.38	6.59	0.00	0.00
ebp	0.38	6.63	10.94	0.00
t-student				
	nat_disasters_lr	gz_spread_est	mortgage_spread	ebp
nat_disasters_lr	NA	NA	NA	NA
gz_spread_est	0.00	NA	NA	NA
mortgage_spread	0.01	0.02	NA	NA
ebp	-0.01	0.10	0.00	NA

Table 3.A.6 – A-SVAR matrix coefficients

Note : Coefficients of the A-SVAR matrices with their standard deviation and t-student values for the models with GZ corporate credit spread decomposition for all-natural disaster classes.

4 | Conclusion générale

En réponse à l'urgence climatique, de profondes transformations dans le fonctionnement de nos économies sont nécessaires si nous souhaitons atteindre une neutralité carbone à l'horizon de 2050. Le système financier apparaît essentiel pour réorienter massivement les flux de capitaux vers des projets soutenant la transition énergétique et écologique. Sur ce point, le « Programme des Nations-Unies pour l'Environnement » (UNEP, 2015) définit trois grandes missions incombant à une finance responsable. Le système financier doit reconnaître les coûts et les risques associés aux secteurs fortement émetteurs en carbone. Le système financier doit soutenir massivement l'allocation des ressources vers des projets faiblement carbonés. Enfin, le système financier doit s'assurer de la résilience des institutions financières et des ménages aux chocs d'origine climatique tels que les catastrophes naturelles.

Notre thèse s'articule autour de ces trois axes. **Nous analysons le rôle de la finance dans le processus de la transition énergétique, en nous concentrant particulièrement sur l'étude de la responsabilité du secteur financier face au changement climatique.**

C'est pourquoi, dans notre premier chapitre « Green energy indices & financial markets : An in-depth look », nous construisons une nouvelle base de données sur les indices boursiers énergétiques verts. Cette question d'étude s'inscrit dans un contexte de très forte hétérogénéité des indices, notamment dans leur processus de sélection des actifs. Ainsi, ce chapitre vise à améliorer la lisibilité des indices verts au moyen d'une meilleure compréhension de leurs définitions et de leurs caractéristiques. Nous montrons que les indices boursiers verts suivent des tendances différentes de celles des indices boursiers de référence. Par exemple, nous mettons en évidence que les indices verts ont une composition hautement volatile avec beaucoup d'entrées et de sorties d'entreprises. Ce point illustre le caractère « jeune » de ces marchés avec des entreprises ayant une plus grande propension à faire défaut, à fusionner avec de plus grands groupes, ou à rencontrer des problèmes de capitalisation d'une année à l'autre. En outre, nous soulignons que peu d'entreprises composent conjointement les indices boursiers verts et les indices de référence. Ce résultat pourrait indiquer que les indices boursiers « benchmark » ne sont pas structurés pour financer

une économie à faibles émissions. C'est pourquoi, nous appelons les pouvoirs publics à la définition d'un cadre réglementaire strict encadrant les produits financiers « verts » (« taxonomie verte »), tout en se saisissant du problème de la surpondération des entreprises carbonées dans les indices de référence. Concernant ce dernier point, un moyen d'action possible consisterait à mettre en place des politiques macroprudentielles, obligeant les grands émetteurs de carbone à prendre en compte les risques financiers climatiques dans le prix de leurs actifs. Pour finir, notre nouvelle base de données ouvre la voie à de futures études académiques. Ayant identifié peu d'entreprises communes entre les indices verts et les indices de référence, il devient possible de mesurer l'interconnexion entre ces produits financiers sans craindre de créer une dépendance artificielle entre les variables. Cette question d'étude est traitée dans le deuxième chapitre de notre thèse.

Dans notre deuxième chapitre « Return spillovers between green energy indices and financial markets : a sectoral approach », nous mesurons comment les indices énergétiques verts interagissent avec les autres secteurs économiques, tels que les secteurs de l'industrie, des matériaux ou des énergies fossiles. Nous faisons le postulat que pour atteindre une neutralité en carbone, nous devons appréhender comment le secteur des énergies vertes se place face aux autres marchés. Cette analyse constitue notre apport majeur à la littérature. Nous montrons que le secteur énergétique vert a une ouverture financière significative et est particulièrement interconnecté avec les secteurs des matériaux et de l'industrie. Nous pouvons expliquer ce résultat par les similarités entre les biens produits dans ces secteurs ; par exemple, la production de turbines pour le secteur éolien ou encore de matériels photovoltaïques pour le secteur de l'énergie solaire. Ainsi, dans le cadre de politiques de réduction des émissions des secteurs polluants, nous encourageons les autorités publiques à tenir compte des effets de rétroaction potentiels sur les entreprises vertes. En outre, nous montrons que l'interdépendance entre les secteurs varie dans le temps et semble suivre les épisodes d'incertitude économique. Citons comme exemple la période de pandémie, où nous identifions une hausse de l'interdépendance entre le secteur des énergies vertes et les autres marchés, pouvant illustrer le phénomène de « fuite vers la liquidité ». En période de crise, les investisseurs rééquilibrent leurs portefeuilles financiers avec une plus faible détention d'actifs risqués, tels que des actifs verts, au profit d'actifs plus liquides, tels que des titres d'obligations souveraines. Enfin, nous observons un schéma d'interconnexion entre les secteurs des énergies vertes et des énergies fossiles, variable dans le temps. En effet, nous constatons que depuis la prise de conscience des enjeux climatiques (2014-2015), les effets de rétroaction des industries vertes sur les entreprises fossiles ont augmenté.

Dans notre troisième chapitre « Large-scale natural disasters & credit market risks », nous nous

intéressons au troisième pilier d'une finance responsable, à savoir mesurer la résilience des institutions financières et des ménages aux chocs climatiques. Ainsi, nous analysons l'impact des catastrophes naturelles de grandes ampleurs sur les risques de crédit des entreprises et des ménages aux États-Unis. Cette question d'étude, avec l'analyse des mécanismes macroéconomiques sous-jacents, constitue notre apport principal à la littérature. Nous montrons que des chocs de catastrophes naturelles induisent une hausse des risques de crédit pour les ménages et les entreprises; ces derniers pouvant subir des pertes importantes en raison d'une destruction de leurs actifs. Ces pertes peuvent se répercuter sur les banques, notamment dans le cas où les actifs détruits servaient de garantie. Nous montrons également que la hausse des probabilités de défaut des entreprises engendre une réduction de l'offre de crédit, renforçant l'effet macroéconomique négatif du choc. Pour autant, ce résultat est vrai uniquement pour les catastrophes de longue durée, telles que les sécheresses ou les inondations, et n'est pas vérifié pour les catastrophes de courte durée, telles que les ouragans ou les tempêtes sévères. Nous expliquons ce résultat par la différence de couverture médiatique entre ces événements, conduisant, alors, à des pressions gouvernementales plus au moins fortes envers les institutions à octroyer des crédits. Par exemple, les ouragans font souvent l'objet d'une couverture médiatique plus forte que les sécheresses, amenant les gouvernements à faire pression auprès des investisseurs institutionnels pour accorder des crédits dans les zones sinistrées.

Pour finir, les extensions de nos travaux peuvent être multiples. Par exemple, la base de données présentée dans notre premier chapitre souligne qu'il n'existe aucune composante commune entre les indices des secteurs des énergies vertes et des énergies fossiles. La littérature ne faisant pas consensus sur le sens des relations entre ces secteurs, il serait intéressant d'utiliser ces indices pour pousser cette analyse. En extension du deuxième chapitre, nous pourrions descendre à un niveau d'analyse plus fin en nous focalisant, non plus au niveau sectoriel, mais au niveau des groupes d'industries, des industries ou des sous-industries. Cette étude nous permettrait de comprendre plus amplement quels sont les groupes sectoriels expliquant la forte interconnexion entre le secteur des énergies vertes et les secteurs industriels. Pour ce faire, nous pourrions utiliser la méthode de [Demirer et al. \(2018\)](#) basée sur un modèle VAR-LASSO. Enfin, en extension du troisième chapitre, nous pourrions poursuivre/renforcer notre analyse à l'aide de l'économétrie bayésienne. Le recours à cette approche nous permettrait une meilleure prise en compte des dynamiques des séries. En outre, nous pourrions étendre cette étude en simulant notre modèle à l'aide des différents régimes climatiques et météorologiques estimés par l'[IEA \(2021\)](#) et ce en fonction des trajectoires carbone suivies par nos économies. Cela nous permettrait de mieux appréhender les risques climatiques futurs.

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