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Les biocarburants dans la transition énergétique : Impacts macroéconomiques et perspectives de développement

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et de M. Julien Chevallier (Université Paris 8)

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Introduction générale

Alors même qu'ils suscitent de nombreux débats aujourd'hui, le recours aux biocarburants remonte aux débuts de l'industrie automobile avec l'utilisation d'alcool pour certains moteurs à essence et d'huiles végétales pour les moteurs diesel. Durant les années 1920 et 1930, l'usage de biocarburants – purs ou mélangés à un carburant fossile – est effectivement présent dans de nombreux pays tels que l'Afrique du Sud, l'Angleterre, le Brésil, l'Italie, les États-Unis ou la Hongrie (*Kovarik*, 1998). Ce n'est qu'à partir du milieu du XX$^{\text{ème}}$ siècle que l'usage de carburants issus du pétrole et non mélangé à des biocarburants s'est réellement imposé. Diverses raisons expliquent ce fait : (i) économique, avec un prix des biocarburants élevé au États-Unis (*Kovarik*, 1998 ; *Carolan*, 2009), (ii) éthique, avec des critiques sur l'utilisation de produits alimentaires pour le transport (*Kovarik*, 1998), mais aussi (iii) en raison de choix stratégiques des industriels. En effet, la société automobile *General Motors* et la compagnie pétrolière *Standard Oil of New Jersey* se sont par exemple alliées dès 1924 pour produire du carburant fossile non mélangé (*Kovarik*, 1998).

Les biocarburants ne constituent pas un ensemble homogène et plusieurs types et générations sont à distinguer. Ceux-ci comprennent l'éthanol – pour les moteurs à essence – et le biodiesel – pouvant remplacer le diesel. L'éthanol est actuellement produit par fermentation alcoolique de sucres issus majoritairement (i) de plantes alimentaires saccharifères – canne à sucre ou betterave à sucre – et (ii) d'amidon extrait principalement du maïs. Le biodiesel est produit par estérification[1] d'huiles végétales issues de plantes oléagineuses comme le colza, le soja ou le palmier à huile. Il s'agit de la première génération (G1) de biocarburants, présente aujourd'hui dans les stations-service. La deuxième génération (G2) de biocarburants – en phase de pré-commercialisation (*IRENA*, 2016 ; *IEA*, 2017) – provient de la biomasse lignocellulosique issue de plantes spécifiquement produites pour une valorisation énergétique – triticale, switchgrass, *etc.* – ou des coproduits de plantes cultivées pour l'obtention d'un bien à plus haute valeur ajoutée comme

[1] L'estérification est la réaction chimique au cours de laquelle un acide carboxylique et un alcool sont transformés en un ester et en eau.

la paille ou les coproduits de l'industrie du bois – bois de rebut, bois mort, *etc.* Une troisième génération (G3) de biocarburants, en phase de développement, est produite à partir des graisses extraites d'algues. Enfin, une nouvelle génération de carburants de synthèse est en discussion : en réalisant l'électrolyse de l'eau – à l'aide d'électricité renouvelable – afin de produire de l'hydrogène, il est possible de l'assembler à du carbone – obtenu en dissociant du CO_2 capté dans l'atmosphère – pour produire des carburants de synthèse nommés *E-Fuels* totalement neutres en carbone. Les niveaux de maturité de ces différents carburants alternatifs sont résumés dans le tableau 1.1.

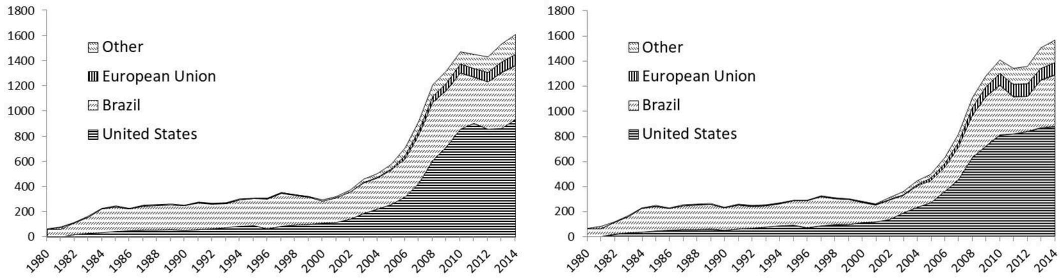
TABLE 1.1: Niveaux de maturité technologique des biocarburants

	0	1	2	3	4	5	6	7	8	9	Commer.
	Idée	Recherche			Proto.		Démonst.		Pré-com.		
1ère génération											■
2ème génération		■	■	■	■	■	■	■	■		
3ème génération		■	■	■							
E-Fuels	■										

Note : Les définitions des niveaux de maturité technologique sont disponibles dans *NASA* (2017) et proviennent à l'origine de *Mankins* (1995). La maturité de la technologie croît de 0 à 9. Proto., Démonst., Pré-com. et Commer. signifient Prototype, Démonstrateur, Pré-commercialisation et Commercialisation. Les 2ème et 3ème générations de biocarburants sont à des stades variés de maturité dus à l'existence de différentes technologies de production. Les degrés de maturité proviennent de *IRENA* (2016) et des informations sur les bioraffineries fournies dans les rapports *Global Agricultural Information Network* (GAIN) de l'*US Department of Agriculture* (USDA) *Foreign Agricultural Service.*

La production de biocarburants de première génération procure des avantages aux pays dont le secteur agricole est développé en lui offrant des débouchés supplémentaires. De plus, cette production domestique d'énergie permet de réduire la dépendance énergétique et d'améliorer le solde commercial en diminuant le volume des importations d'énergie (*Criqui et Mima*, 2012). Ces divers avantages, ajoutés à l'occurrence du premier choc pétrolier de 1973, sont les principales raisons de la mise en place du programme *ProAlcool* au Brésil dès 1975. Celui-ci consistait à accroitre la part de véhicules *Flex Fuel*, permettant l'utilisation de mélange à taux variable entre carburant pétrolier et biocarburant, et de développer la filière d'éthanol à base de canne à sucre. Cet effort politique a permis au Brésil de dominer le marché de l'éthanol durant deux décennies (voir graphique 1.1). Des politiques de développement des biocarburants ont aussi vu le jour aux États-Unis avec l'*Energy Tax Act* en 1978, réduisant les taxes sur les mélanges de carburants contenant des biocarburants, et en France avec le plan Carburol de 1981 visant à développer les recherches dans ce domaine.

FIGURE 1.1: Production (gauche) et consommation (droite) mondiale d'éthanol (milliers de barils par jour)



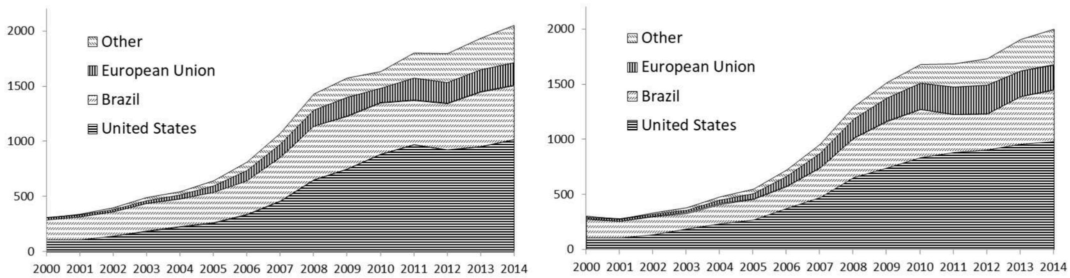
Note : Les autres pays producteurs et consommateurs sont principalement la Chine (respectivement 2,85% et 3,34% de la production et consommation mondiale), le Canada (respectivement 1,90% et 3,06%) et la Thaïlande (respectivement 1,16% et 1,25%). Source : *US Energy Information Administration* (US EIA).

D'une logique de sécurité énergétique dans les années 1970–1980, le développement rapide des biocarburants depuis le début du XXIè siècle (voir graphiques 1.1 et 1.2) s'explique désormais par leur avantage environnemental face aux carburants d'origine pétrolière. En effet, le CO_2 émis par la combustion des biocarburants est en majeure partie absorbé lors de la culture des plantes utilisées dans leur production. Ce cycle combustion-absorption du CO_2, dans le cas des plantes, opère à une échelle de temps restreinte – l'ordre de grandeur dépendant de la durée de croissance de la plante – comparée aux centaines de millions d'années nécessaires au stockage du carbone par les roches sédimentaires ou les hydrocarbures (*Kump et al.*, 2009). Ceci explique la différence de résultats des analyses de cycle de vie[2] entre ces types de carburants (voir tableau 1.2).

[2]Les analyses de cycle de vie permettent de quantifier les impacts environnementaux d'un bien sur l'ensemble de son cycle de vie, *i.e.*, sa production, le transport, sa consommation et son recyclage.

Cette caractéristique des biocarburants est désormais un des principaux arguments mis en avant pour justifier les politiques de soutien des gouvernements de nombreux pays.

FIGURE 1.2: Production (gauche) et consommation (droite) mondiale de biodiesel (milliers de barils par jour)



Note : Les autres pays producteurs et consommateurs sont principalement l'Argentine (respectivement 2,99% et 1,52% de la production et consommation mondiale), l'Indonésie (respectivement 2,90% et 1,86%), la Chine (respectivement 2,85% et 3,47%), la Thaïlande (respectivement 1,91% et 1,94%) et le Canada (respectivement 1,76% et 2,91%). Source : *US Energy Information Administration* (US EIA).

En effet, les émissions mondiales de gaz à effet de serre (GES) sont en croissance depuis 1990 (voir graphique 1.3) malgré les différentes conférences internationales sur ce sujet. Les premiers accords internationaux sur le changement climatique concentraient les efforts de réduction des émissions sur les pays développés – dont les États-Unis et les pays européens en tant que principaux contributeurs de ces émissions. Ces pays se sont engagés à réduire leurs émissions, à réaliser un inventaire annuel de celles-ci, à encourager les transferts de technologie "propre" vers les pays émergents et en développement ainsi qu'à participer au financement de leur projet permettant de limiter leurs émissions.

Au niveau mondial, le secteur des transports engendre environ 15% des émissions de GES. Or, le parc automobile mondial devrait passer de 1 milliard de véhicules particuliers en 2015 à 1,6 milliards en 2040 (*Bloomberg*, 2017), en majeure partie du fait de la croissance des parcs automobiles des pays émergents. La structure future du parc automobile impactera fortement la demande future de carburants et de biocarburants en fonction de la place prise par les véhicules électriques par rapport aux véhicules thermiques. Cependant, bien que les véhicules électriques puissent représenter plus de 30% du parc automobile en 2040 (*Bloomberg*, 2017), ce secteur de marché comprend également les véhicules hybrides participant à la poursuite de la croissance de la demande de carburants, dont celle des biocarburants.

TABLE 1.2: Réduction des émissions de GES des biocarburants

Source	Pur	Taux de mélange		
		10%	20%	85%
Betterave à sucre (G1)	53,4%	5,3%	10,7%	45,4%
Blé (G1)	20,2%	2,0%	4,0%	17,2%
Maïs (G1)	20,8%	2,1%	4,2%	17,7%
Canne à sucre (G1)	71,3%	7,1%	14,3%	60,6%
Bois (culture) (G2)	73,6%	7,4%	14,7%	62,6%
Bois (résidu) (G2)	77,5%	7,8%	15,5%	65,9%
Paille (blé) (G2)	89,3%	8,9%	17,9%	75,9%
Colza (G1)	33,8%	3,4%	6,8%	28,7%
Tournesol (G1)	47,6%	4,8%	9,5%	40,4%
Soja (G1)	31,0%	3,1%	6,2%	26,4%
Palmier à huile (G1)	29,0%	2,9%	5,8%	24,6%
Huile de cuisine usagée (G1)	84,1%	8,4%	16,8%	71,5%
Graisse animale (G1)	69,7%	7,0%	13,9%	59,2%
Bois (culture) (G2)	91,7%	9,2%	18,3%	78,0%
Bois (résidu) (G2)	96,6%	9,7%	19,3%	82,1%

Note : Ces réductions sont exprimées en fonction des carburants pétroliers. La première (seconde) partie du tableau concerne l'éthanol (le biodiesel), comparé à l'essence (au diesel). Les données "Pur" et en "Taux de mélange" représentent le pourcentage de réduction des émissions de GES pour le biocarburant pur et mélangé au carburant traditionnel dans les proportions habituelles. Le biodiesel est parfois utilisé pur. Les données proviennent de *Edwards et al.* (2014). Pour chaque source, les données concernent la technologie de production la moins efficiente en termes de réduction des émissions. Il s'agit donc ici de réductions minimum. Notons tout de même que ces données ne prennent pas en compte des changements indirects d'utilisation des sols.

D'après le scénario CPS (*Current Policy Scenario*[3]) de l'Agence Internationale de l'Energie (AIE), ce développement du parc automobile entrainerait une croissance de la demande de carburants de 40,7 millions de barils par jour en 2016 à 52,7 millions en 2040

[3] Ce scénario se base sur les politiques actuellement en place. Le scénario NPS (*New Policy Scenario*) prenant en compte les politiques futures déjà annoncées prévoit 4,1 millions de barils par jour – équivalent pétrole – de biocarburants consommés.

(*IEA*, 2017), soit une hausse de près de 30% en 24 ans. Cette demande comprendrait alors 3,2 millions de barils par jour – équivalent pétrole – de biocarburants contre 1,7 millions en 2016. Or ce scénario, prévoyant un quasi-doublement de la consommation de biocarburants, est basé sur les politiques actuelles et ne prend pas en compte les nouvelles politiques nécessaires pour répondre aux objectifs pris lors des accords de Paris (2015) suite à la COP21. Pour répondre à l'objectif d'un secteur énergétique soutenable[4], l'AIE prévoit une demande journalière de 5,6 millions de barils, équivalent pétrole, de biocarburants – soit un facteur de croissance supérieur à 3[5]. La poursuite du développement des biocarburants, en complément de l'expansion des véhicules électriques, devrait permettre de réduire les émissions de gaz à effet de serre du secteur des transports, comme ce fut le cas en France durant les années 2000 (voir graphique 1.4).

Malgré leurs avantages, en particulier en termes environnementaux, les biocarburants ne sont pas exempts de critiques en termes d'impact inflationniste sur les prix alimentaires, de changement d'affectation des sols et d'effet néfaste sur certains moteurs.

En effet, l'utilisation de matières premières agricoles dans leur production (voir graphique 1.5) entraine un détournement d'une production à caractère alimentaire vers une finalité énergétique. Avec la hausse des prix alimentaires en 2007-2008, les biocarburants ont été critiqués dans le cadre du débat "*food versus fuel*" (*OECD*, 2008). Notons que la production de biocarburants a utilisé plus de 10% de la production mondiale de maïs à partir de 2008 – avec un pic à 15% en 2015 – ainsi que 16% à 22% de la canne à sucre entre 2008 et 2016[6]. Il faut toutefois mentionner que de nombreux autres phéno-

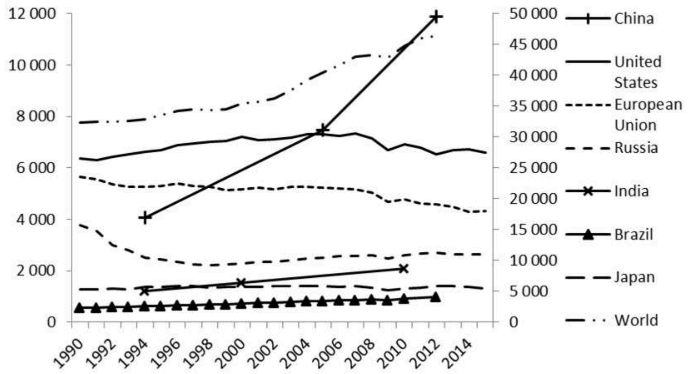
[4]La définition, selon l'AIE, d'un secteur énergétique soutenable comprend trois objectifs : (i) l'accès universel à une énergie moderne, (ii) un pic des émissions de gaz à effet de serre en 2040 suivi d'un déclin de celles-ci permettant d'atteindre la cible de 2C issue de l'accord de Paris (2015), (iii) une réduction des autres émissions permettant une forte amélioration de la qualité de l'air.

[5]Notons que ce scénario prévoit en plus un développement de l'utilisation des biocarburants dans le secteur aérien avec une consommation de 2,6 millions de barils équivalent pétrole par jour, soit une demande totale de 8,2 millions de barils équivalent pétrole par jour de biocarburants.

[6]Ces résultats proviennent des données fournies par l'USDA, concernant les intrants dans la production de biocarburants, et la *Food and Agriculture Organization* (FAO) des Nations Unies pour la production mondiale de ces produits agricoles. Les proportions d'utilisation d'intrants sont difficilement calculables pour les huiles végétales en raison des différentes techniques d'extraction d'huile existantes.

mènes ont pu entrainer cette hausse des prix alimentaires tels la forte croissance des pays émergents entrainant une plus importante demande en denrées alimentaires (*Abbott et al.*, 2011), des événements climatiques extrêmes dans certains pays producteurs (*OECD*, 2008) ainsi qu'une hausse de la spéculation sur les marchés agricoles (*Mitchell*, 2008).

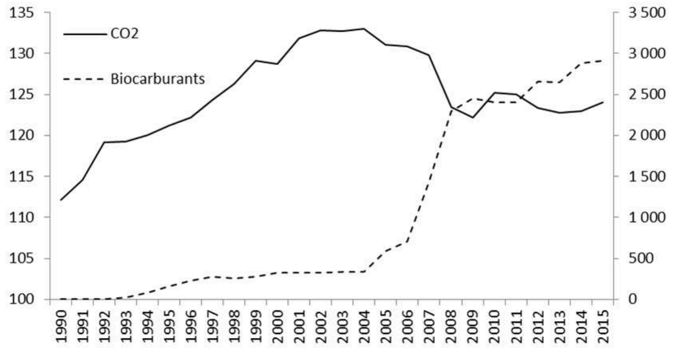
FIGURE 1.3: Emissions de gaz à effet de serre (Mt CO_2 eq.) des principaux pays émetteurs



Note : Les données par pays (échelle de gauche) proviennent de l'*United Nations Framework Convention on Climate Change* (UNFCCC). Ces pays représentent environ les deux tiers des émissions de gaz à effet de serre mondiales. Les marqueurs présents pour la Chine, l'Inde et le Brésil mentionnent les données des années pour lesquelles ces pays ont déclaré leurs émissions. Les autres pays présentés ici doivent déclarer chaque année leurs émissions. Les émissions mondiales (échelle de droite) sont issues de l'*Emission Database for Global Atmospheric Research* (EDGAR).

L'impact du développement des biocarburants de première génération sur les prix alimentaires est désormais admis au niveau des décideurs publics. Ainsi, la directive de l'Union Européenne 2015/1513 limite aujourd'hui à 7% l'incorporation de biocarburants issus de produits agricoles (première génération) dans la consommation énergétique du secteur des transports. Il n'existe cependant pas de consensus sur cette question. De nombreuses études montrent une corrélation entre les prix agricoles et les prix énergétiques – en particulier le prix du pétrole – (*Nazlioglu*, 2011 ; *Nazlioglu et Soytas*, 2012 ; *Lopez Cabrera et Schulz*, 2016), mais il n'existe pas de preuve empirique sur le rôle de la production des biocarburants dans ce phénomène. De plus, les études manquent sur l'impact du lien entre développement des biocarburants et prix alimentaires sur les pays non producteurs de ces carburants alternatifs – en majorité les pays émergents et en développement. Seuls *Chakravorty et al.* (2015) étudient l'effet du développement de l'éthanol aux États-Unis sur le taux de pauvreté en Inde. Ils prédisent une augmentation de 10% de celui-ci à long-terme.

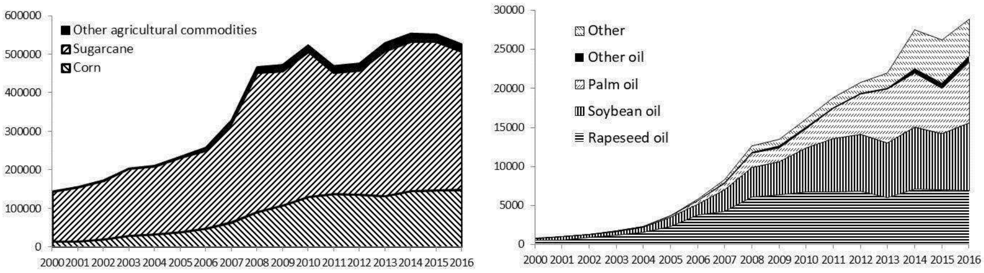
Figure 1.4: Emissions de CO_2 (kt, échelle de gauche) et consommation des biocarburants (ktep, échelle de droite) dans le secteur routier en France



Note : Le CO_2 représentait, en 2015, 99,99% des émissions de gaz à effet de serre dans le secteur du transport routier ainsi que 99,2% des émissions totales mesurées (contre 99,96% et 93,04% en 1990). Cela est dû aux différentes normes EURO mises en place depuis 1992 pour réduire les émissions de gaz localement polluants. Une norme sur les émissions de CO_2 des véhicules neufs, établie à 120g/km pour un véhicule de taille moyenne, est apparue en Europe en 2012 avec un délai de mise en conformité jusqu'en 2015. Cette norme s'établira à 95g/km en 2020 et devrait s'établir entre 68 et 78g/km en 2025. Source : Les données concernant la consommation annuelle de biocarburants proviennent d'Eurostat alors que le rapport annuel *Citepa* (2017) fournit les émissions de gaz à effet de serre par secteur d'activité.

Au-delà de ses effets sur les prix des matières premières agricoles, le développement des biocarburants peut avoir d'autres impacts. L'utilisation de matières premières agricoles dans la production énergétique peut effectivement entrainer un changement d'affectation des sols. Celui-ci peut être direct – lorsqu'une production agricole à caractère énergétique remplace une forêt – ou indirect – si une forêt est remplacée par une culture agricole à but alimentaire afin de compenser l'affectation d'une culture alimentaire vers une finalité énergétique. Ce changement d'affectation des sols peut conduire à une réduction des services écosystémiques rendus par ces terres. L'impact direct du développement des biocarburants sur la déforestation a notamment été étudié au Brésil. Durant la première décennie du XXI$^{\text{ème}}$ siècle, les nouvelles mises en culture de canne à sucre pour répondre à la demande d'éthanol auraient concerné dans une faible proportion – entre 0,6% et 3,5% – des terres forestières (*Rudorff et al.*, 2010 ; *Adami et al.*, 2012). Le changement indirect d'affectation des sols dû au développement des biocarburants, de par son caractère international, est moins aisé à quantifier mais est notamment souligné dans le cas de la production américaine d'éthanol sur les forêts de pays en développement (*Searchinger et al.*, 2008). En particulier, ce changement d'affectation des sols – direct ou indirect – impacte aussi la biodiversité en entrainant la modification ou la destruction des zones d'habitation de certaines espèces animales.

FIGURE 1.5: Consommation mondiale de matières premières (kt) dans la production d'éthanol et de biodiesel



Note : Pour la production d'éthanol (graphique de gauche), les autres matières premières comprennent le blé, le manioc, le sorgho, la betterave à sucre, le seigle, l'orge et la mélasse issue de l'industrie sucrière. Dans le cas du biodiesel (graphique de droite), les autres huiles concernent les huiles de coco, de maïs et de tournesol. Les autres matières premières comprennent les graisses animales et les huiles usagées. Source : Rapports *Global Agricultural Information Network* (GAIN) de l'*US Department of Agriculture* (USDA) *Foreign Agricultural Service*.

Enfin, une dernière critique provient des constructeurs automobiles dans le cas du biodiesel. En effet, le biodiesel est composé d'esters saturés, mono-insaturés et poly-insaturés. La présence d'une trop grande proportion d'esters saturés entraine de mauvaises propriétés à froid du biocarburant alors que des problèmes d'oxydation sont provoqués par les biodiesels contenant une forte quantité d'esters poly-insaturés. Or ces proportions sont différentes en fonction de la plante oléagineuse utilisée pour la production du biodiesel. Ainsi, l'utilisation de biodiesel – à trop grande proportion dans le carburant – à base d'huile de palme, de soja, de tournesol ou de graisses animales doit être compensée par une maintenance du véhicule plus fréquente.

Afin de répondre à ces différentes critiques, une deuxième génération de biocarburants – à base de coproduits des secteurs agricole et forestier ou de plantes énergétiques – a été développée et est en phase de pré-commercialisation. D'une part, ces biocarburants réduisent les émissions de gaz à effet de serre plus fortement que dans le cas de la première génération (voir tableau 1.2). D'autre part, l'utilisation de biocarburants, issus de coproduits possiblement non valorisés, n'entrerait pas en compétition avec une utilisation alimentaire et n'entrainerait pas de changement d'utilisation des terres. Cependant, ces avantages sont moins certains dans le cas de biocarburants issus de plantes énergétiques puisque leur culture peut entrainer des changements d'affectation des sols, notamment en remplaçant des terres agricoles en terres à caractère énergétique. Enfin, le biodiesel de deuxième génération serait d'une composition intéressante pour les constructeurs. Leur composition chimique est effectivement uniforme entre les différentes sources existantes et n'entraine pas de complication moteur lors de leur utilisation. Néanmoins, ces nouveaux biocarburants n'offrent pas les mêmes avantages au secteur agricole puisqu'ils ne concernent que leur coproduit et ne leur fournit donc plus de débouchés pour leur culture.

L'existence de ces divers avantages et inconvénients entre les première et deuxième générations de biocarburants peut entrainer des différences dans les préférences des consommateurs entre ces carburants. Notons que malgré leur rôle croissant dans le secteur du transport, les consommateurs ont une connaissance limitée de ceux-ci (*Van de Velde et al.*, 2009 ; *Pacini et Silveira*, 2011 ; *Aguilar et al.*, 2015). De plus, bien que les biocarburants soient perçus comme bénéfiques pour l'environnement (*Solomon et Johnson*, 2009 ; *Van de Velde et al.*, 2009 ; *Farrow et al.*, 2011 ; *Johnson et al.*, 2011 ; *Dragojlovic et Einsiedel*, 2015) les véhicules électriques sont parfois vus comme une meilleure solution dans la lutte contre le changement climatique (*Petrolia et al.*, 2010 ; *Aguilar et al.*, 2015). Notons toutefois qu'aucune étude n'a été réalisée sur le territoire français afin de connaitre les préférences des citoyens concernant les divers aspects des biocarburants, notamment quant aux différentes matières premières utilisables.

Ainsi dans un secteur des transports en pleine mutation – avec le développement des biocarburants de première génération, le déploiement des véhicules électriques et les nouvelles perspectives de carburants alternatifs – quelles doivent être les décisions législatives et les stratégies industrielles pour assurer le développement soutenable du secteur des biocarburants ?

Cette thèse s'inscrit précisément dans ce cadre et a pour objectif, d'une part, de mener une analyse approfondie des impacts économiques du développement des biocarburants de première génération et, d'autre part, d'étudier les préférences de la population française concernant les nouveaux biocarburants. Une telle étude permettra de contribuer à la mise en place de politiques publiques ciblées en fournissant une aide aux décideurs afin de protéger les économies les plus vulnérables des variations des prix des biocarburants, tout en tenant compte des préférences des agents en matière de choix de biocarburants. Outre cet apport en matière d'aide à la décision publique, notre thèse contribue à la littérature sous quatres angles, en mobilisant un large éventail de techniques économétriques. Notre thèse est ainsi organisée autour de quatre chapitres. Les deux premiers chapitres se focalisent sur le lien entre matières premières agricoles et énergétiques. Ce faisant, ils contribuent à la littérature portant sur le débat "*food versus fuel*". Plus spécifiquement, nous étudions les effets du développement des biocarburants sur la corrélation entre prix agricoles et prix énergétiques (chapitre 2) et, en conséquence, sur les économies émergentes et en développement productrices de matières premières utilisées dans la production de biocarburants (chapitre 3). Le chapitre 4 se concentre sur les aspects comportementaux et vise à révéler la structure des préférences des citoyens français entre les différents avantages et inconvénients des biocarburants de première et de deuxième génération. Enfin, le chapitre 5 étend l'analyse au champ de la finance et étudie l'efficience et les stratégies de couverture du risque sur le marché de l'éthanol. Revenons plus en détail sur chacun des chapitres.

S'agissant des prix, la littérature se concentre en géneral sur l'existence d'un lien entre les prix agricoles et énergétiques en étudiant parfois l'apparition d'une rupture dans cette relation (*Campiche et al.*, 2007 ; *Nazlioglu*, 2011). Même si le rôle du développement des biocarburants est parfois mentionné, les travaux existants ne prennent pas en compte la production de biocarburants dans les études économétriques. Or, ces liens entre prix agricoles et énergétiques peuvent provenir de nombreux canaux de transmission : (i) les coûts de production (*Baffes*, 2007, 2010 ; *Berument et al.*, 2014), (ii) la demande agricole à but alimentaire (*Abbott et Borot de Battisti*, 2011 ; *Abbott et al.*, 2011), (iii) les effets de richesse (*Gohin et Chantret*, 2010) et (iv) la demande agricole à finalité énergétique (*Ciaian et Kancs*, 2011). Dans le **chapitre 2**, nous intégrons la production de biocarburants dans un modèle de séries temporelles non linéaire, *i.e.*, le modèle de cointégration à transition lisse de *Saikkonen et Choi* (2004). Cela nous permet d'estimer l'effet de long terme du prix du pétrole – principal prix énergétique – sur les prix de différentes matières premières agricoles en fonction de la production de biocarburants. Nous montrons que l'effet du prix du pétrole s'est accru avec le développement des biocarburants, contribuant à la hausse des prix agricoles intervenue au début du XXI$^{\text{ème}}$ siècle. De plus, nous montrons que l'impact de l'expansion des biocarburants affecte non seulement les prix des produits agricoles entrant dans leur production, mais aussi l'ensemble des matières premières agricoles étudiées *via* les effets de substitution.

Le développement des biocarburants ayant contribué à la hausse des prix agricoles, les politiques soutenant leur expansion peuvent avoir causé des externalités sur les pays émergents et en développement dont les économies sont fortement dépendantes du secteur agricole. Le **chapitre 3** étudie ces externalités en se concentrant sur le compte courant. Nous contribuons ainsi à la littérature sur les fluctuations du compte courant –

et donc des réserves de change – en nous concentrant sur l'effet des variations des prix des matières premières agricoles à caractère énergétique. Après la construction d'un indice des prix regroupant les matières premières agricoles utilisées dans la production des biocarburants, nous analysons l'impact des variations de ce prix sur le compte courant de 16 pays émergents et en développement producteurs, exportateurs ou importateurs de ces commodités. Nous prenons en outre en compte l'effet potentiellement non linéaire exercé par le prix du pétrole sur une telle relation à l'aide d'un modèle en panel à transition lisse. Pour un pays exportateur (importateur) de produits agricoles utilisés dans la production de biocarburants mais importateur (exportateur) de pétrole brut et de produits pétroliers, un prix élevé du pétrole pourrait en effet renforcer (atténuer) l'effet des prix des biocarburants sur le solde courant *via* le lien entre le pétrole et les prix agricoles. Cependant, un prix élevé du pétrole pourrait aussi avoir une incidence négative sur l'effet du prix du biocarburant, en augmentant les dépenses d'importation en pétrole brut et produits pétroliers. Nous montrons que, sur la période 2000-2014, une hausse de 10% du prix des matières agricoles entrant dans la production de biocarburants entraine une amélioration de 2% du compte courant des pays exportateurs et producteurs. Cet effet disparait lorsque le prix du pétrole est respectivement supérieur à 45$ et 56$ pour ces deux groupes. Les pays importateurs de ces matières premières agricoles ne sont quant à eux pas impactés par les fluctuations de leurs prix, ce qui s'explique par les nombreuses politiques de protection du marché domestique mises en place pour lutter contre la hausse des prix agricoles (*Jones et Kwiecinski,* 2010).

Les première et deuxième générations de biocarburants ont des différences fondamentales en termes de soutien à la filière agricole, de réduction des émissions de GES et d'impact sur les prix alimentaires. Or, d'après les théories de la valeur de *Lancaster* (1966) et de l'utilité aléatoire de *McFadden* (1974), la disposition-à-payer d'un consommateur, ou d'un citoyen, pour un bien privé ou public, dépend des différentes caractéristiques du bien et du citoyen. Ces deux théories ont donné naissance aux expérimentations à choix discret. En appliquant cette méthode de révélation des préférences déclarées – *Dis-*

crete Choice Experiment – sur un échantillon de 972 répondants, le **chapitre 4** propose d'analyser la structure de préférence de la population française entre les principales caractéristiques des biocarburants : (i) le soutien à la filière agricole, (ii) les réductions des émissions de GES et (iii) l'impact inflationniste sur les prix alimentaires. L'estimation des poids relatifs de ces différentes caractéristiques sur l'utilité des citoyens nous permet alors de déduire le biocarburant "optimal" de leur point de vue. Les résultats soulignent que l'ensemble des citoyens préfère les biocarburants de deuxième génération par rapport à la première. En effet, les enquêtés sont prêts à payer entre 35,30 et 40,80 euros par an pour ne pas subir d'inflation des prix alimentaires liée à la production de biocarburants. Cependant, alors que près des deux tiers retireraient un gain d'utilité au développement d'une filière de biocarburants à base de résidus agricoles, un tiers des citoyens ne semble pas souhaiter l'émergence d'une nouvelle filière de biocarburants issue du secteur agricole. La majorité des répondants de l'enquête, *i.e.*, $65,1\%$, accepterait de payer $51,59$ euros par an pour financer une production de biocarburants provenant du secteur agricole. Au contraire, une minorité montre une faible disposition-à-payer pour soutenir le secteur agricole ($8,98$ euros par an). Ces derniers pourraient privilégier une production de biocarburants à base de résidus forestiers ou une réduction des émissions de GES du secteur des transports avec une technologie différente. Enfin, notons que l'ensemble des répondants seraient disposés à payer annuellement de $0,68$ euros – pour un tiers d'entre eux – à $2,64$ euros, par point de pourcentage de réduction des émissions de GES par rapport aux carburants actuels. À titre d'exemple, les répondants valorisent en moyenne à 71,81 euros par an pendant 5 ans le développement d'un carburant contenant 20% d'éthanol produit à base de paille de blé.

Enfin, le développement de la production d'éthanol aux États-Unis au début du XXI$^{\text{ème}}$ siècle a motivé l'ouverture d'un marché à terme sur cette commodité en mars 2005 par le *Chicago Board of Trade* (CBOT). Avant cela, les accords contractuels permettaient de déterminer les prix des transactions. Ils étaient généralement basés sur les contrats à terme de l'essence du *New York Mercantile Exchange* (NYMEX) (*Franken et*

Parcell, 2003). En effet, ces marchés dérivés permettent d'établir le prix sur le marché physique (*Working*, 1948). Cependant, il est nécessaire que ce marché à terme vérifie l'hypothèse d'efficience des marchés pour que le prix à terme soit un prédicteur sans biais du prix physique futur (*Chowdhury*, 1991). Cette hypothèse d'efficience de marché stipule que le prix d'un marché reflète l'ensemble des informations existantes (*Fama*, 1970). Dans la version faible de cette hypothèse, l'information considérée est consitituée de l'ensemble des prix passés[7]. De plus, cette prédiction du prix physique par le prix à terme est possible *via* le processus de découverte des prix. Celui-ci consiste en la diffusion des informations du prix à terme vers le prix physique dûe à l'intégration plus rapide des nouvelles informations sur le marché à terme (*Garbade et Silber*, 1983). La vérification de ces hypothèses sur le marché de l'ethanol est l'objectif du **chapitre 5** nous permettant aussi de discriminer entre deux modèles expliquant le lien entre ces marchés, *i.e.*, *Garbade et Silber* (1983) et *Figuerola-Ferretti et Gonzalo* (2010). Le chapitre se focalise également sur la seconde fonction des marchés à terme. Il s'agit, pour les agents du marché physique, de réduire leur exposition au risque-prix à l'aide de différents outils financiers (options, contrats à terme...) en transférant ce risque aux spéculateurs plus enclins à accepter celui-ci (*Ederington*, 1979). Ce transfert de risque s'effectue en achetant (ou en vendant) des contrats à terme lors d'une vente (ou d'un achat) sur le marché physique. Nous nous inscrivons dans un tel cadre en comparant un grand nombre de stratégies de couverture des risques *via* l'estimation de nombreux modèles économétriques, à correction d'erreur, linéaires et à changement de régimes markovien. Nos résultats vont dans le sens de la validation de l'hypothèse d'efficience faible du marché de l'ethanol, c'est à dire de l'existence d'une relation de long terme entre le prix physique et le prix à terme permettant à ce dernier d'être un predicteur non systématiquement sous- ou surestimé (*Lai et Lai*, 1991). Nous montrons en outre, *via* des simulations hors échantillon, que l'utilisation d'un modèle Garch multivarié est à priviliégier pour construire la stratégie optimale de couverture des risques.

[7] Dans sa version semi-forte, cette information est composée de l'ensemble des informations publiques. Enfin, sa version forte fait le postulat que l'ensemble de l'information privée est disponible au public.

Bibliography

Abbott, P. C. and Borot de Battisti, A. (2011). Recent global food price shocks: Causes, consequences and lessons for African governments and donors. *Journal of African Economies*, 20(Supplement 1):i12–i62.

Abbott, P. C., Hurt, C., and Tyner, W. E. (2011). What's driving food prices in 2011? *Farm Foundation Issue Report*.

Adami, M., Rudorff, B., Freitas, R., Aguiar, D., Sugawara, L., and Mello, M. (2012). Remote sensing time series to evaluate direct land use change of recent expanded sugarcane crop in Brazil. *Sustainability*, 4(4):574–585.

Aguilar, F. X., Cai, Z., Mohebalian, P., and Thompson, W. (2015). Exploring the drivers' side of the blend wall: U.S. consumer preferences for ethanol blend fuels. *Energy Economics*, 49(C):217–226.

Baffes, J. (2007). Oil spills on other commodities. *Resources Policy*, 32(3):126–134.

Baffes, J. (2010). More on the energy/nonenergy price link. *Applied Economics Letters*, 17(16):1555–1558.

Berument, M. H., Sahin, A., and Sahin, S. (2014). The relative effects of crude oil price and exchange rate on petroleum product prices: Evidence from a set of Northern Mediterranean countries. *Economic Modelling*, 42(3):243–249.

Bloomberg (2017). Electric vehicle outlook 2017. Bloomberg publishing, Bloomberg New Energy Finance.

Campiche, J. L., Bryant, H. L., Richardson, J. W., and Outlaw, J. J. (2007). Examining the evolving correspondence between petroleum prices and agricultural commodity prices. American Agricultural Economics Association Annual Meeting. Portland, OR, July 29-August 1.

Carolan, M. S. (2009). The contestation and closure of a socio-technical system in the USA. *Social Studies of Science*, 39(3):421–448.

Chakravorty, U., Hubert, M.-H., and Marchand, B. U. (2015). Food for fuel: The effect of the U.S. biofuel mandate on poverty in India. Discussion paper.

Chowdhury, A. R. (1991). Futures market efficiency: Evidence from cointegration tests. *The Journal of Futures Markets*, 11(5):577–589.

Ciaian, P. and Kancs, d. (2011). Interdependencies in the energy-bioenergy-food price systems: A cointegration analysis. *Resource and Energy Economics*, 33(1):326–348.

Citepa (2017). Rapport CCNUCC.

Criqui, P. and Mima, S. (2012). European climate-energy security nexus: A model based scenario analysis. *Modeling Transport (Energy) Demand and Policies*, 41:827–842.

Dragojlovic, N. and Einsiedel, E. (2015). What drives public acceptance of second-generation biofuels? Evidence from Canada. *Biomass and Bioenergy*, 75:201–212.

Ederington, L. H. (1979). The hedging performance of the new futures markets. *The Journal of Finance*, 34(1):157–170.

Edwards, R., Hass, H., Larive, J.-F., Lonza, L., Maas, H., and Rickeard, D. (2014). Well-to-wheels report version 4.a. Technical reports, JRC.

Fama, E. F. (1970). Efficient capital markets: A review of theory and empirical work. *The Journal of Finance*, 25(2):383–417.

Farrow, K., Teisl, M., Noblet, C., McCoy, S., and Rubin, J. (2011). *Economics effects of biofuel production*, chapter Does money grow on trees? People's willingness to pay for cellulosic wood ethanol. InTech.

Figuerola-Ferretti, I. and Gonzalo, J. (2010). Modelling and measuring price discovery in commodity markets. *Journal of Econometrics*, 158(1):95–107.

Franken, J. R. and Parcell, J. L. (2003). Cash ethanol cross-hedging opportunities. *Journal of Agricultural and Applied Economics*, 35(3):509–516.

Garbade, K. D. and Silber, W. L. (1983). Price movements and price discovery in futures and cash markets. *The Review of Economics and Statistics*, 65(2):289–297.

Gohin, A. and Chantret, F. (2010). The long-run impact of energy prices on world agricultural markets: The role of macro-economic linkages. *Energy Policy*, 38(1):333–339.

IEA (2017). World energy outlook 2017. IEA Publishing, International Energy Agency.

IRENA (2016). Innovation outlook advanced liquid biofuels. Technical report, International Renewable Energy Agency.

Johnson, D. M., Halvorsen, K. E., and Solomon, B. D. (2011). Upper Midwestern U.S. consumers and ethanol: Knowledge, beliefs and consumption. *Biomass and Bioenergy*, 35(4):1454–1464.

Jones, D. and Kwiecinski, A. (2010). Policy responses in emerging economies to international agricultural commodity price surges. OECD Food, Agriculture an Fisheries Papers 34, OECD Publishing.

Kovarik, B. (1998). Henry Ford, Charles Kettering and the fuel of the future. *Automotive History Review*, 32(Spring 1998):7–27.

Kump, L., Kasting, J., and Crane, R. (2009). *The Earth System*. Pearson, 3rd edition.

Lai, K. S. and Lai, M. (1991). A cointegration test for market efficiency. *The Journal of Futures Markets*, 11(5):567–575.

Lancaster, K. (1966). A new approach to consumer theory. *Journal of Political Economy*, 74(2):132–157.

Lopez Cabrera, B. and Schulz, F. (2016). Volatility linkages between energy and agricultural commodity prices. *Energy Economics*, 54(1):190–203.

Mankins, J. (1995). Technology readiness levels. NASA White Paper.

McFadden, D. (1974). *Frontiers of econometrics*, chapter Conditional logit analysis of qualitative choice behaviour. Academic Press, New York.

Mitchell, D. (2008). A note on rising food prices. *Policy Research Working Paper*, 4682. The World Bank.

NASA (2017). Technology readiness level definitions. Technical report. Available at: http://www.nasa.gov/pdf/458490main_TRL_Definitions.pdf (accessed 12 March 2018).

Nazlioglu, S. (2011). World oil and agricultural commodity prices: Evidence from nonlinear causality. *Energy Policy*, 39(5):2935–2943.

Nazlioglu, S. and Soytas, U. (2012). Oil price, agricultural commodity prices, and the dollar: A panel cointegration and causality analysis. *Energy Economics*, 34(4):1098–1104.

OECD (2008). Rising food prices causes and consequences. Policy brief, Organisation for Economic Co-operation and Developmen.

Pacini, H. and Silveira, S. (2011). Consumer choice between ethanol and gasoline: lessons from Brazil and Sweden. *Energy Policy*, 39(11):6936–6942.

Petrolia, D. R., Bhattacharjee, S., Hudson, D., and Herndon, C. W. (2010). Do Americans want ethanol? A comparative contingent-valuation study of willingness to pay for E10 and E85. *Energy Economics*, 32(1):121–128.

Rudorff, B., Aguiar, D., Silva, W., Sugawara, L., Adami, M., and Moreira, M. (2010). Studies on the rapid expansion of sugarcane for ethanol production in Sao Paulo state (brazil) using landsat data. *Remote Sensing*, 2(4):1057–1076.

Saikkonen, P. and Choi, I. (2004). Cointegrating smooth transition regressions. *Econometric Theory*, 20(2):301–340.

Searchinger, T., Heimlich, R., Houghton, R., Dong, F., Elobeid, A., Fabiosa, J., Tokgoz, S., Hayes, D., and Yu, T.-H. (2008). Use of U.S. croplands for biofuels increases greenhouse gases through emissions from land-use change. *Science*, 319(5867):1238–1240.

Solomon, B. D. and Johnson, N. H. (2009). Valuing climate protection through willingness to pay for biomass ethanol. *Ecological Economics*, 68(7):2137–2144.

Van de Velde, L., Verbeke, W., Popp, M., Buysse, J., and van Huylenbroeck, G. (2009). Perceived importance of fuel characteristics and its match with consumer beliefs about biofuels in Belgium. *Energy Policy*, 37(8):3183–3193.

Working, H. (1948). Theory of the inverse carrying charge in futures markets. *Journal of Farm Economics*, 30(1):1–28.

2

On the link between oil and agricultural commodity prices: Do biofuels matter?

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2.1 Introduction

Biofuel has been increasingly produced in the world to reduce greenhouse gases emissions in the transportation sector with an ethanol daily production rising from 300 to 1,615 thousand of barrels during the 2000–2014 period. The daily production of biodiesel has increased from 15 to 528 thousand barrels during that period. This biodiesel development is partly due to an increase of production in the EU and the US from 15 to 205 and from 0 to 83 thousand barrels per day, respectively.[1] Rapeseed and soybean oils are the main inputs for biodiesel production in these countries. The world ethanol market development is mainly due to the US production of corn-based ethanol increasing from 106 to 936 thousand barrels a day, leading to an increasing use of corn for energy production. The US became the first ethanol-producing country in 2006, ahead of Brazil whose sugarcane-based production multiplied by 2.3 during the 2000–2014 period. These two countries represented more than 87% of the world ethanol production in 2014.

The fast rise in biofuel production has caused a positive demand shock on agricultural markets (*OECD*, 2008), strengthening the linkages between energy and agricultural prices (*Campiche et al.*, 2007; *Ciaian and Kancs*, 2011). As illustrated by Figure 2.1, the sharp rise in crude oil prices from 2004–2006 resulted in a small increase in agricultural commodity prices.[2] This contrasts with the 2007–2008 booming episode characterized by an important rise in both price series, occurring during the acceleration phase of biofuel production development.[3] The increase in the price of agricultural raw materials during the 2000s was attributed to a combination of demand and supply shocks. Regard-

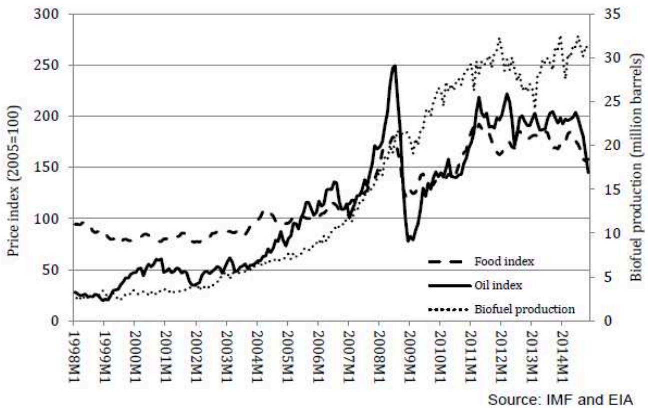
[1] They represent 55% of the world biodiesel production in 2014. Argentina, Brazil and Indonesia are the three others major producing countries with a daily production close to 50 thousand barrels a day in this year. Soybean oil is the main input used in South America while Indonesia uses palm oil.

[2] This food index includes selected commodities, such as cereals, vegetable oils, meats, and tropical products, and reflects the evolution of most agricultural commodity prices. The oil price series is the simple average of Dated Brent, West Texas Intermediate, and Dubai Fateh.

[3] Note that in both cases, the oil price has been multiplied by approximately 2.5, whereas the respective multiplication factors of commodity prices are 1.3 and 1.7.

ing the demand side, the main explanatory factors are biofuel production development (OECD, 2008) and the strong economic growth in developing countries (*Abbott et al.*, 2011; *Abbott and Borot de Battisti*, 2011). Turning to the supply side, negative shocks are attributed to higher production costs, generated by the rise in oil prices, and bad weather conditions in major producing countries. Low inventories also contributed to the price increase by preventing quantity adjustment in markets. Growing investments in agricultural derivative markets and a weak dollar have also played a role (*Mitchell*, 2008).

Figure 2.1: Evolution of oil and food price indexes and monthly biofuel production



Crude oil prices can positively influence agricultural commodity markets through the input channel. Indeed, agricultural production requires fuel and fertilizer, their price being linked to oil prices (*Baffes*, 2007; *Baffes*, 2010; *Berument et al.*, 2014). In addition, demand could lead to a negative link between oil and agricultural prices due to two main components. First, agricultural commodity demands can be affected by an income change owing to variations in economic activity and, in turn, the dynamics following oil prices (*Lardic and Mignon*, 2008). Second, the real income effect could create a negative relationship between oil and agricultural commodity prices. In their food purchasing decisions, households take into account price changes in other goods, including oil products (*Gohin and Chantret*, 2010). However, the development of biofuel production could create a positive link between agricultural and oil prices through the direct biofuel channel (*Ciaian and Kancs*, 2011). Indeed, biofuel production could increase in response to a rise in oil prices due to the substitution effect between fuel and biofuel. Therefore, a rise in biofuel input demand, and in their prices, could appear.[4] In addition, the oil price effect could be transmitted to substitutable agricultural commodities. For example, wheat and sunflower oil are substitutes for corn and rapeseed oil, respectively.[5]

Falling into this strand of the literature, the aim of this chapter is to study the effect of the price of oil on agricultural commodity prices by focusing on the long-term dynamics. We go further than the previous literature by paying particular attention to the influence of biofuel production development on this long-term relationship. To this aim, we rely on nonlinear econometrics, including cointegrating smooth transition regression. This approach is particularly appealing for our purpose since it allows the long-term relationship between oil and agricultural commodity prices to change depending on the biofuel production level. Consequently, thanks to this methodology, we are able to investigate whether the increasing link between both price series comes from the growing development of biofuel production. Our empirical analysis relies on three agricultural commodities which enter directly in biofuel production: corn and soybean for US production, and rapeseed for European production. We also consider wheat and sunflower to examine whether biofuels have affected the substitutes of previous commodities.

Our contribution to the existing literature is threefold. First, to the best of our knowledge, our study is the first to rely on the cointegrating smooth transition regression approach in order to investigate the long-term oil-price effect on agricultural commodity prices. While previous studies assume nonlinearity only in the short-run adjustment process, we investigate whether nonlinearity is present in the long-term, cointegrating

[4]Biofuel production being partially governed by governmental mandates, this relationship is however uncertain.

[5]Consumers can change their food behavior between different cereals or vegetable oils according to their price ratio. In addition, farmers can alternate their crop production between different seasons to maximize profit (*Baffes*, 2007).

relationship. This methodology allows us to distinguish the direct biofuel channel from other transmission channels. Second, we provide new evidence on the link between oil and agricultural commodity prices using a longer period than much of the literature, including the biofuel production development phase and the last economic crisis. Third, regarding our main contribution, we provide strong evidence in favor of an inflationary effect of biofuel production on agricultural commodity prices. Thus, we contribute to the "food *versus* fuel" debate according to which biofuel production accentuates food insecurity in some countries, particularly developing ones. On the whole, our results put forward that first-generation biofuel production has been one of the key causes in the recent rise in agricultural prices.

This chapter is organized as follows. Section 2.2 reviews the related literature. Section 2.3 presents the methodology and data. Section 2.4 is devoted to our empirical results. Section 2.5 introduces several robustness checks, and section 2.6 draws our main conclusions.

2.2 Literature review

2.2.1 Theoretical motivations: A brief overview

Few studies have presented a theoretical framework investigating the link between agricultural and energy markets, including the biofuel market. Considering a vertical market integration model of corn, ethanol, and byproducts, *Gardner* (2007) distinguishes corn demand between energetic and other uses. He analyzes the different impacts of subsidies on corn and ethanol. He highlights a small social cost in the short- term, increasing in the long term. Using a similar framework, *Saitone et al.* (2008) add a corn seed market and market power. The ethanol subsidy fails to increase corn output and decrease corn prices due to the market power exercised by oligopoly seed manufacturers and by oligopsony ethanol producers. However, the oil price effect on corn is not studied in these two models, neither by including production costs for corn nor by incorporating substitution elasticity between ethanol and gasoline. *de Gorter and Just* (2008, 2009, 2010) extend Gardner's model by linking corn and fuel prices with a substitution effect between ethanol and gasoline: fuel price impacts corn price but only through the direct biofuel channel. They show a decrease in the effectiveness of ethanol mandates when they are coupled with other biofuel policies such as subsidies. *Ciaian and Kancs* (2011) add oil-related production costs to the agricultural farm profit function. Furthermore, they consider two agricultural commodities, one for specific food use and one suitable for biofuel production. They show that (i) the oil price effect is stronger with than without biofuel production through the direct biofuel channel, and (ii) this finding is also valid for agricultural commodities that are not used in biofuel production via the substitution effect that exists between similar agricultural commodities.

2.2.2 Empirical literature

Since the seminal contribution of *Pindyck and Rotemberg* (1990), an increasing number of studies have analyzed comovements in commodity markets (see, e.g., *Palaskas and Varangis*, 1991; *Leybourne et al.*, 1994 or *Deb et al.*, 1996). In particular, several papers have investigated the long-term link between energy and agricultural commodity prices. Table 2.1 summarizes the literature on the oil-agricultural commodity nexus.

Various studies consider several agricultural commodities within a multivariate framework. Relying on *Johansen* (1991)'s cointegration method, *Yu et al.* (2006) analyze the long-term link between vegetable oils (soybean, sunflower, rapeseed, and palm) and crude oil prices over the period 1999–2006. The only cointegrating relationship found does not include crude oil prices, and the authors show that there is no causal relationship from crude oil to vegetable oils. With a similar methodology, *Zhang and Reed* (2008) reach the same conclusion about the lack of cointegrating and causal relationship from oil prices to various agricultural prices (corn, soybean meal, and pork) in China. Similarly, *Kaltalioglu and Soytas* (2009) do not find cointegrating relationships between crude oil, agricultural, and food price indexes over the period 1980–2008. This conclusion is also drawn by *Zhang et al.* (2010) over the 1989–2008 period using five agricultural (corn, soybean, sugar, rice, and wheat) and three energy commodities (crude oil, ethanol, and gasoline). On the whole, these papers show strong evidence against the existence of long-term relationships between agricultural commodities and crude oil.

Many papers have investigated the existence of such a long-term relationship by distinguishing each agricultural commodity. Using *Johansen* (1991)'s cointegration test, *Peri and Baldi* (2010) find evidence of a long-term link between rapeseed oil and gasoil prices. With the same approach, *Natanelov et al.* (2011) obtain cointegrating relationships with crude oil prices for wheat and cocoa prices with US data from 1989–2010. Regarding the other commodities considered, including corn and soybean, they do not find long-term relationships with crude oil prices. These results are confirmed by *Nazlioglu* (2011) with the world prices of corn and soybean from 1994–2010, and wheat from 1998–2010. The lack of a long-term relationship with crude oil for corn and soybean prices is also highlighted by *Myers et al.* (2014), *Wang et al.* (2014), and *Koirala et al.* (2015).[6] On the contrary, within a panel data framework and relying on *Pedroni* (1999)'s approach, *Nazlioglu and Soytas* (2012) emphasize the existence of a cointegrating relationship between 24 agricultural commodities and crude oil from 1980–2010. As shown, the results are less clear-cut when focusing exclusively on one particular agricultural commodity.

[6] See also the studies by *Trujillo-Barrera et al.* (2012), *Hassouneh et al.* (2012), *Abdelradi and Serra* (2015) and *Lopez Cabrera and Schulz* (2016).

In light of these conflicting findings, various methodologies have been proposed to investigate the existence of a break date in the link between crude oil and agricultural commodity prices. Several studies apply the *Johansen* (1991) methodology within a bivariate framework. *Campiche et al.* (2007) find the existence of long-term links between crude oil and (i) corn and (ii) soybean oil during 2006–2007, while it is not the case between 2003 and 2005. Similar conclusions are reached by *Nazlioglu* (2011) for corn and soybean between 2008 and 2010 and since 2004 for wheat. Other studies have also emphasized the existence of breaks in the cointegrating relationship between crude oil prices and various agricultural commodity prices, such as *Harri et al.* (2009), *Ciaian and Kancs* (2011) and *Natanelov et al.* (2011). However, no consensus emerges from these studies regarding either the existence of long-term relationships or the dates of the breaks in the cointegrating relationship, if applicable.

Turning to nonlinear cointegration studies, *Balcombe and Rapsomanikis* (2008) show that the asymmetric vector error correction (VEC) model outperforms other linear and nonlinear specifications in modeling the sugar-crude oil prices relationship in Brazil over the 2000–2006 period.[7] With a smooth transition VEC model, *Serra et al.* (2011) find evidence of cointegrating relationships between ethanol, crude oil, gasoline, and corn in the US, with the nonlinear adjustment of ethanol prices depending on the magnitude of the disequilibrium in the ethanol market.

All these studies consider nonlinearities in the adjustment process, i.e., in the short-term dynamics. To the best of our knowledge, no study has investigated the possibility of nonlinearity in the long-term, cointegrating relationship, which is the aim of the present chapter.

[7] See also *Peri and Baldi* (2010), *Natanelov et al.* (2011) and *Bakhat and Wurzburg* (2013) who rely on threshold VEC models.

Table 2.1: Summary of the literature on the long-term oil-price effect

Paper	Method	Period/Country	Existence of a long-term relationship with oil price				
			Corn	Soybean	Sunflower	Rapeseed	Wheat
Yu et al. (2006)	VECM	1999–2006 World	-	No	No	No	-
Campiche et al. (2007)	VECM	2003–2005	No	No	-	-	-
		2006–2007	Yes	Yes	-	-	-
Zhang and Reed (2008)	VECM	2000–2007 China	No	No	-	-	-
Harri et al. (2009)	VECM	2006–2008 US	Yes	Yes	-	-	No
Zhang et al. (2010)	VECM	1989–2008 US	No	No	-	-	No
Frank and Garcia (2010)	VECM	1998–2006 US	No	-	-	-	No
		2006–2009 US	No	-	-	-	No
Natanelov et al. (2011)	VECM	1989–2010 US	Yes	No	-	-	Yes
		1989–2001 US	Yes	Yes	-	-	Yes
		2002–2010 US	No	No	-	-	Yes
	TVECM	1989–2006 US	No	-	-	-	-
Serra et al. (2011)	STVECM	1990–2008 US	Yes	-	-	-	-
Ciaian and Kancs (2011)	VECM	1994–1998 World	No	No	-	-	No
		1999–2003 World	Yes	Yes	-	-	No
		2004–2008 World	Yes	Yes	-	-	Yes
Nazlioglu (2011)	VECM	1994–2010 World	No	No	-	-	-
		1994–1998 World	No	No	-	-	-
		1998–2004 World	No	No	-	-	No
		2004–2008 World	No	No	-	-	Yes
		2008–2010 World	Yes	Yes	-	-	Yes
		1998–2010 World	-	-	-	-	Yes
	Gregory and Hansen (1996)	World	04/2002	No break	-	-	07/2007
Hassouneh et al. (2012)	VECM	2006–2010 Spain	-	-	Yes	-	-
Trujillo-Barrera et al. (2012)	VECM	2006–2011 US	No	-	-	-	-
Nazlioglu and Soytas (2012)	Panel cointegration	1980–2010 World	Yes	Yes	Yes	-	Yes
Myers et al. (2014)	VECM	1990–2010 World	No	No	-	-	-
Wang et al. (2014)	VECM	1980–2012 World	No	No	-	-	No
	Gregory and Hansen (1996)	World	No break	No break	-	-	No break
Koirala et al. (2015)	*Engle and Granger* (1987)	2011–2012 US	No	No	-	-	-
Abdelradi and Serra (2015)	VECM	2008–2012 EU	-	-	-	Yes	-
Lopez Cabrera and Schulz (2016)	VECM	2003–2012 Germany	-	-	-	Yes	-

2.3 Data and methods

The choice of data frequency deserves some comment. On the one hand, monthly data do not capture causal relationships between agricultural and energy commodity prices (*Zhang and Reed*, 2008; *Nazlioglu*, 2011). On the other hand, smooth transition models require a lot of observations. Indeed, each regime should have a sufficiently large number of data, particularly the part of the sample between the two extreme regimes. Otherwise, the smooth transition function parameters would not be identifiable (*Saikkonen and Choi*, 2004). To overcome these drawbacks, we consider daily prices for oil, corn, soybean, sunflower oil, rapeseed oil, and wheat. All agricultural data are from the USDA and Thomson Reuters. The oil price series comes from Thomson Reuters, whereas US biofuel production is given by the Energy Information Administration. The oil price is the spot price for West Texas Intermediate crude oil in dollars per barrel. Concerning agricultural commodities, we use spot prices for Illinois No. 2 corn, Soft Red No. 2 wheat, and No. 1 yellow soybean. All prices are in US dollars per bushel. We also consider the European spot price for sunflower and rapeseed oils with North West Europe Ex-Tank sunflower oil in dollars per metric ton and Rotterdam Ex Mill rapeseed oil in euro per metric ton. The latter price is converted into dollars using the daily EUR/USD exchange rate from Thomson Reuters. For biofuels,[8] we use the US monthly production in thousand barrels, and we turn it into daily data by quadratic interpolation.[9] Moreover, we account for economic activity by considering the composite Standard & Poor's SP500 index. Due to a lack of data for sunflower and rapeseed oils, we investigate their relationship with oil from December 4, 2001 to November 28, 2014 (i.e., 3,389 observations). For the other commodities, the period under study begins on January 2, 1986 (i.e., 7,545 observations). All series are log-transformed, and are displayed in Figure 2.2.

[8]Unfortunately, to the best of our knowledge, neither EU nor Brazilian biofuels production data are available at a monthly frequency.

[9]The quadratic interpolation is done by considering sets of three adjacent points from the original series and fitting a quadratic curve in such a way that the sum of the high frequency data matches the observed low frequency data.

Figure 2.2: Agricultural commodities, oil prices, and biofuel production evolution in log

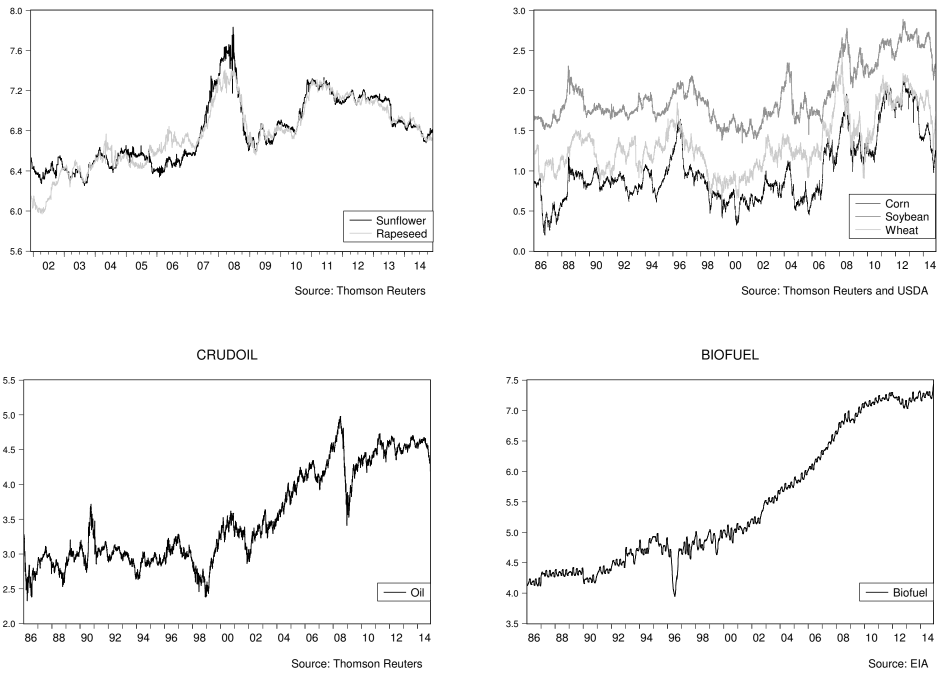


Table 2.2 presents the descriptive statistics for the growth rates of the different variables used for the entire period, and for pre- and post-2006 periods – 2006 being considered as the break date corresponding to the soaring development of biofuels (*Campiche et al.*, 2007; *Gilbert*, 2010). In the 1986–2014 period, the prices of corn, soybean, and wheat increase on average by 0.01% per day, with standard deviations of 1.91, 1.61, and 2.21, respectively. Note that this growth is lower in the first period, with a zero growth rate, than in the second, in which prices rise by 0.03% for corn and 0.02% for the other two agricultural commodities previously mentioned. In addition, the standard deviations of these growth rates are higher in the second period, reflecting the greater price volatility since 2006. The sunflower oil price evolves similarly. From 2001–2014, it increases by 0.01% per day, against -0.01% and 0.02% for the pre- and post-2006 periods, respectively. The rapeseed oil price has an inverse evolution. It increases faster in the first period than in the second, with an average rate of 0.04% and 0.01%, respectively.

Moreover, these prices have characteristics similar to financial variables with negative skewness and high kurtosis. These characteristics indicate that these prices are subject to more negative, large-scale fluctuations than the normal law would predict. The oil price increases on average by 0.01% per day over the entire period, with a higher growth rate in the pre-2006 period. Its volatility is also higher over this period. Statistics from US biofuel production reflect its development. The production growth is 0.04% per day before 2006 and 0.06% thereafter. For the SP500 index, the crisis affected its evolution. Indeed, its average daily growth rate was 0.03% before 2006 compared to 0.02% thereafter.

Table 2.2: Daily growth rate statistics

Statistics	Period	Corn	Soybean	Wheat	Oil	Biofuel	SP500	Sunflower	Rapeseed	Period
Average (percent)	1986–2014	0.01	0.01	0.01	0.01	0.04	0.03	0.01	0.02	2001–2014
	1986–2005	0.00	0.00	0.00	0.02	0.04	0.03	-0.01	0.04	2001–2005
	2006–2014	0.03	0.02	0.02	0.00	0.06	0.02	0.02	0.01	2006–2014
Standard error	1986–2014	1.91	1.61	2.21	2.47	1.03	1.15	2.55	1.90	2001–2014
	1986–2005	1.64	1.56	1.86	2.54	1.12	1.07	1.57	2.08	2001–2005
	2006–2014	2.42	1.73	2.84	2.29	0.80	1.32	2.88	1.81	2006–2014
Skewness	1986–2014	-0.34	-0.85	-0.41	-0.79	0.06	-1.31	-0.19	-0.45	2001–2014
	1986–2005	-0.42	-0.70	-0.44	-1.05	0.14	-2.09	0.50	-0.81	2001–2005
	2006–2014	-0.26	-1.09	-0.36	0.02	-0.35	-0.34	-0.24	-0.21	2006–2014
Kurtosis	1986–2014	19.39	27.73	14.20	18.87	59.48	31.91	133.64	19.70	2001–2014
	1986–2005	8.42	37.15	21.91	21.38	57.64	48.07	13.79	30.92	2001–2005
	2006–2014	20.53	13.05	7.82	9.56	38.59	13.72	117.92	10.10	2006–2014

As previously mentioned, we focus on the potential existence of a long-term cointegrating relationship between the prices of agricultural commodities and crude oil. We do not investigate the short-term dynamics since, as recalled by *Gonzalo and Pitarakis* (2006), two variables with a nonlinear cointegrating relationship do not admit an error correction model. As a first step, we determine the series' integration degree by performing various unit root tests, including tests robust to the presence of breaks. The detailed unit root test results are available in Table 2.3. All of the agricultural commodity prices series are stationary in their first difference, regardless of whether a break date is considered. The SP500 index, biofuel production and oil price series are integrated in order 1.[10]

[10]Note that for the price of oil, the conclusions of the various tests are somewhat contradictory due to the presence of a break in 2003.

Table 2.3: Unit root tests

	Variable	ADF	PP	KPSS	ZA	P
Level	Biofuel	$2.596^{(3)}$ -1.941	$2.570^{(3)}$ -1.941	$2.233^{(1)}$ 0.146	-4.541 -5.080 $12/04/1995^{(B)}$	-4.562 -5.590 $12/01/1995^{(B)}$
	Crude oil	$-3.768^{*(1)}$ -3.410	$-3.607^{*(1)}$ -3.410	$1.557^{*(1)}$ 0.146	-4.615 -5.080 $09/24/2003^{(B)}$	-4.616 -5.590 $09/23/2003^{(B)}$
	SP500	$2.352^{(3)}$ -1.941	$2.457^{(3)}$ -1.941	$1.876^{(1)}$ 0.146	-3.183 -4.930 $12/09/1994^{(I)}$	-3.153 -5.230 $12/09/1994^{(I)}$
	Corn	$-0.532^{(3)}$ -1.941	$-0.524^{(3)}$ -1.941	$1.208^{(1)}$ 0.146	-4.293 -4.930 $08/23/2006^{(I)}$	-4.334 -5.230 $08/22/2006^{(I)}$
	Soybean	$0.187^{(3)}$ -1.941	$0.155^{(3)}$ -1.941	$1.554^{(1)}$ 0.146	-4.411 -4.930 $10/02/2006^{(I)}$	-4.455 -5.230 $09/29/2006^{(I)}$
	Wheat	$-0.351^{(3)}$ -1.941	$-2.427^{(2)}$ -2.862	$1.180^{(1)}$ 0.146	-4.601 -4.930 $04/26/1996^{(I)}$	-4.505 -5.230 $04/25/1996^{(I)}$
	Sunflower	$0.287^{(3)}$ -1.941	$0.260^{(3)}$ -1.941	$0.507^{(1)}$ 0.146	-3.607 -4.930 $03/30/2007^{(I)}$	-3.475 -5.230 $03/29/2007^{(I)}$
	Rapeseed	$0.574^{(3)}$ -1.941	$0.506^{(3)}$ -1.941	$0.760^{(1)}$ 0.146	-2.349 -4.930 $09/17/2012^{(I)}$	-2.294 -5.230 $09/04/2012^{(I)}$
First-Difference	Biofuel	$-17.323^{*(2)}$ -2.862	$-73.269^{*(2)}$ -2.862	$0.132^{*(2)}$ 0.463	-	-
	Crude oil	$-88.458^{*(3)}$ -1.941	$-88.734^{*(3)*}$ -1.941	$0.066^{*(2)}$ 0.463	-	-
	SP500	$-65.552^{*(3)}$ -1.941	$-91.404^{*(3)}$ -1.941	$0.142^{*(2)}$ 0.463	-	-
	Corn	$-89.683^{*(3)}$ -1.941	$-89.637^{*(3)}$ -1.941	$0.047^{*(2)}$ 0.463	-	-
	Soybean	$-92.856^{*(3)}$ -1.941	$-92.719^{*(3)}$ -1.941	$0.041^{*(2)}$ 0.463	-	-
	Wheat	$-92.413^{*(3)*}$ -1.941	$-92.584^{*(3)}$ -1.941	$0.035^{*(2)}$ 0.463	-	-
	Sunflower	$-19.029^{*(3)}$ -1.941	$-83.923^{*(3)}$ -1.941	$0.119^{*(2)}$ 0.463	-	-
	Rapeseed	$-48.628^{*(3)}$ -1.941	$-73.300^{*(3)}$ -1.941	$0.204^{*(2)}$ 0.463	-	-

Note: ADF: Augmented Dickey-Fuller test (*Dickey and Fuller*, 1979, 1981), PP: *Phillips and Perron* (1988)'s test, KPPS: *Kwiatkowski et al.* (1992)'s test, ZA: *Zivot and Andrews* (1992)'s test, P: *Perron* (1997)'s test. For all the tests, the first and second lines present the test statistic and the critical value at the 5% significance level, respectively. The number in parenthesis mentions the variables of the selected model, (1) for trend and constant, (2) for constant, and (3) for none. The star mentions the stationarity of the variable. Concerning the ZA and P tests, the third line shows the break date, whereas the letter mentions the break type, (I) for intercept, (T) for trend and (B) for both.

The second step relies on the *Choi and Saikkonen* (2004) procedure in order to test for the presence of nonlinearity. To this end, we estimate the following two equations using ordinary least squares[11]:

$$\begin{aligned} AP_{i,t} \approx \theta_{1i} + \theta_{2i}OP_t + \theta_{3i}SP_t + \pi_{1i}OP_tB_t + \pi_{2i}SP_tB_t \\ + \sum_{k=-K}^{K} \varphi_{ki}\Delta OP_{t+k} + \sum_{k=-K}^{K} \delta_{ki}\Delta SP_{t+k} \end{aligned} \tag{2.1}$$

$$\begin{aligned} AP_{i,t} \approx \theta_{1i} + \theta_{2i}OP_t + \theta_{3i}.SP_t + \pi_{1i}OP_tB_t + \pi_{2i}SP_tB_t + \pi_{3i}B_t^3 \\ + \sum_{k=-K}^{K} \varphi_{ki}\Delta OP_{t+k} + \sum_{k=-K}^{K} \delta_{ki}\Delta SP_{t+k} \end{aligned} \tag{2.2}$$

$AP_{i,t}$ denotes the price of agricultural commodity i, OP_t is the oil price, B_t stands for the biofuel production, SP_t is the SP500 index, and π_{ji}, for $j = 1, 2, 3$, are the parameters related to the nonlinearity. This procedure consists of testing the joint significance of these parameters for the two equations via an LM-type test of a restricted model against a non-restricted model, i.e., linearity against nonlinearity.

Once the preliminary tests have been done, we can investigate the oil-price effect on agricultural commodities and the impact of biofuels on this oil-price effect. To investigate the long-term relationship between the oil price and each agricultural commodity price i, we consider the cointegrating smooth transition regression model presented by *Saikkonen and Choi* (2004).[12] Although the study of a fully functioning commodity prices system would be of interest, it is not the subject of this work, which studies the oil-price effect for each agricultural commodity chosen by distinguishing the direct biofuel channel and other channels. Specifically, we investigate the total oil-price effect by relying on the following cointegrating smooth transition regression:

$$Y_t = \mu + \nu g(X_{st}, \theta) + \sum_{j=1}^{p} \alpha_j X_{j,t} + \sum_{j=1}^{p} \delta_j X_{j,t} g(X_{st}, \theta) + u_t \tag{2.3}$$

[11] The inclusion of differentiated variables with leads and lags makes it possible to correct for correlation between the regressors and the error term. Estimations are done with K equals one to three, with and without a trend term to account for a possible trend in our data.

[12] See also *Delatte and Fouquau* (2010) or *Christopoulos and Leon-Ledesma* (2007) for application of the cointegrating smooth transition regression approach.

where Y_t denotes the endogenous variable, μ and ν are constant terms, $X_{j,t}$ is the j^{th} regressor of the I(1) vector of explanatory variables, u_t is a stationary error term with zero-mean, θ is the vector containing the threshold, c, and the transition speed, γ, parameters, and $g(X_{st}, \theta)$ is the smooth transition function depending on the transition variable X_{st}. In our case, considering biofuel development is likely to increase the link between oil and agricultural commodities, the logistic function – strictly increasing – is more appropriate than the exponential function.[13]

Using our previous notations, Equation (2.3) becomes:

$$AP_{i,t} = (\alpha_{1i} + \alpha_{2i}OP_t + \alpha_{3i}SP_t) + (\beta_{1i} + \beta_{2i}OP_t + \beta_{3i}SP_t)g(\gamma_i, c_i, B_t) + u_{i,t} \qquad (2.4)$$

To control for the economic activity effect, we include the SP500 index.[14] The first part of the equation represents the long-term oil and economic activity effects on agricultural commodity prices, whereas the second part also accounts for the same effects related to the quantity of biofuels produced. This last effect depends on the value taken by the transition function g, ranging between 0 and 1. The oil price effect without biofuel production is measured by the coefficient α_{2i}. The additional oil price effect through the direct biofuel channel is captured by $\beta_{2i} \times g(\gamma_i, c_i, B_t)$. The total oil price effect is the sum of these two parts. The model is estimated using the one-step Gauss-Newton estimator[15] with lead and lag introduced by *Saikkonen and Choi* (2004).

To test for cointegration, we perform the *Shin* (1994) and *Choi and Saikkonen* (2010) tests, hereafter S and CS. Briefly speaking, the S test corresponds to the KPSS test applied on the residuals of the relationship. By splitting the whole sample on subsamples,

[13]Note that for the sake of completeness, we have also proceeded to the estimation with the exponential specification for the transition function. However, results are not reliable due to the lack of convergence of estimates, justifying also our choice of the logistic specification.

[14]As a robustness check, we also use the Baltic Dry Index as well as the exchange rate and present results in section 2.5.

[15]The Gauss-Newton estimator reduces the bias magnitude in relation to the non linear least square estimator. In addition, the two-step Gauss-Newton estimator does not always outperform the one-step estimator.

the CS test extends the S test to improve its empirical power in the nonlinear framework.[16]

Then, we perform an LR-type exclusion test to check for the inclusion of oil in the cointegrating relationship. Finally, we apply the *Toda and Yamamoto* (1995) causality test within a bivariate framework[17] to check the causal relation between oil and agricultural commodity prices. While the Granger causality test requires us to estimate a VAR model with the optimal lag length p and to test the zero restriction for these lags, the *Toda and Yamamoto* (1995) test consists of estimating a VAR process with $p + d$ lags, where d is the integration degree of the series. We apply this test to the entire period, as well as to subsamples if nonlinearity exists.

2.4 Empirical results

The *Choi and Saikkonen* (2004) procedure allows us to verify the relevance of our modeling choice. The results, presented in Table 2.4,[18] show the presence of nonlinearity for the five equilibrium relationships. This finding confirms the existence of an effect of biofuel production on the long-term link between oil and agricultural commodity prices.

Before interpreting the estimation results, let us focus on the conclusions of the cointegration tests. Afterwards, we concentrate our analysis on three points: the price dependence of agricultural commodity with oil with and without biofuel production and the dynamic of the oil-price effect. Recall that the SP500 index allows us to account

[16]For more details on the procedure including the block size choice, see *Choi and Saikkonen* (2010). The critical values have been tabulated by *Hong and Wagner* (2008).

[17]More precisely, we apply this test with two endogenous variables and the SP500 as the exogenous variable.

[18]Note that we present results for three leads and lags. We have checked the robustness of our findings by considering various leads and lags, as well as by including a linear trend term. Results are similar and are available upon request to the author.

for the economic environment, but its effect on commodity prices is not the subject of the present study. The value of the biofuel production threshold, $\hat{c}$, indicates when the transition function takes the value of 0.5 and thus when the oil price effect through the direct biofuel channel reaches half of its maximum value. We subsequently prefer to interpret the value of the biofuel production effect on the oil-price effect and the moment when it is maximal. Finally, we discuss the long-term causality test results.

Table 2.4: Nonlinearity tests

	Test 1	Test 2	Conclusion
Corn	326.88*	327.78*	Nonlinearity
Soybean	523.27*	352.28*	Nonlinearity
Wheat	254.52*	396.12*	Nonlinearity
Sunflower	97.08*	625.22*	Nonlinearity
Rapeseed	32.20*	1151.80*	Nonlinearity

Note: For both tests, we mention the test statistics; the critical values at the 5% significance level are 5.99 and 7.81 for the first and the second test, respectively. The linearity hypothesis was rejected when the test statistic was greater than the critical value. This reject is mentioned with a star.

Table 2.5 displays the estimated coefficients of the cointegrating relationship, as well as the cointegration and exclusion tests results. The S test unambiguously confirms the presence of a cointegrating relationship between the oil price, the SP500 index, and each agricultural commodity price. Turning to the CS test, the conclusions are less clear-cut since the null hypothesis of cointegration is rejected for the corn and wheat relationships. However, this result may reflect a larger persistence of deviations from equilibrium for these two commodities, and can be due to the lack of cointegration during part of the period studied since the null hypothesis is only rejected for the first subsample. As a consequence, all relationships can be considered as cointegrating relationships. Finally, the exclusion test confirms the oil price presence in the cointegrating space for each relationship and, therefore, the existence of a long-term price link between each agricultural commodity and oil. On the whole, our findings show that there is a nonlinear long-term oil-price effect on each agricultural commodity price.

Let us now focus on the estimated coefficients of equation (2.4) presented in Table 2.5.[19] $\hat{\alpha}_2$ represents the estimated value of the long-term price link between oil and the agricultural commodity studied, whereas $\hat{\beta}_2$ corresponds to the additional price effect linked to biofuel production.

Table 2.5: Long-term estimation with exclusion and cointegration tests

	Corn	Soybean	Wheat	Sunflower	Rapeseed
$\hat{\alpha}_1$	1.216*** (0.040)	2.076*** (0.025)	1.700*** (0.032)	5.166*** (0.251)	4.633*** (0.294)
$\hat{\alpha}_2$	-0.112*** (0.013)	0.026*** (0.007)	0.094*** (0.009)	0.080*** (0.015)	0.690*** (0.022)
$\hat{\alpha}_3$	-0.011** (0.006)	-0.061*** (0.005)	-0.128*** (0.006)	0.142*** (0.041)	-0.093*** (0.043)
$\hat{\beta}_1$	-1.383*** (0.171)	-2.338*** (0.124)	-3.603*** (0.152)	1.017*** (0.271)	1.502*** (0.307)
$\hat{\beta}_2$	0.929*** (0.035)	0.394*** (0.025)	0.400*** (0.028)	0.856*** (0.024)	0.263*** (0.025)
$\hat{\beta}_3$	-0.248*** (0.033)	0.184*** (0.024)	0.335*** (0.029)	-0.605*** (0.045)	-0.380*** (0.046)
$\hat{\gamma}$	5.539*** (0.362)	10.147*** (0.685)	15.638*** (2.201)	64.018** (34.625)	333.219 (230.968)
$\hat{c}$	6.348*** (0.015)	6.476*** (0.008)	6.246*** (0.011)	6.358*** (0.009)	5.807*** (0.003)
Exclusion test	821.74 16.919	350.03 16.919	438.91 16.919	1931.87 16.919	1968.99 16.919
Shin test	0.268* 0.895	0.188* 0.895	0.224* 0.895	0.349* 0.895	0.204* 0.895
Choi and Saikkonen test	2.826 (3) 2.421	1.326*(4) 2.627	2.619 (3) 2.421	2.000*(3) 2.421	2.135*(3) 2.421

Note: For the coefficients rows, the first line is the estimated coefficient. The second line indicates the standard error. The number of stars indicates the significance level, one for 10%, two for 5%, three for 1% and none in case of non-significance. For the Exclusion test row, the first line indicates the test statistic, and the second line mentions the critical value at the 5% significance level from the chi2 distribution for nine degrees of freedom. The oil exclusion hypothesis of the cointegrating vector was rejected when the test statistic exceeded the critical value. For the cointegration rows, the first line indicates the test statistics and the second line mentions the critical value at the 5% significance level. The star mentions the non-reject of the null hypothesis of cointegration. For the *Choi and Saikkonen* (2004)'s test, the number in parenthesis is the number of subsamples.

In the absence of biofuel production, the parameters associated with soybean, sunflower, rapeseed, and wheat are positive: an increase in the price of oil leads to an increase in these four prices. Conversely, the oil price has an opposite effect on corn with a pa-

[19] Results are presented for three leads and lags, but remain robust no matter the number of leads and lags used.

rameter of -0.112. The difference in the long-term oil-price effect between commodities can have two main causes relying on the two transmission channels. Considering first the input channel, it depends positively upon oil-related production cost share in total costs. Therefore, we calculate these shares with USDA data[20] for the three US agricultural commodities[21] and present results in Appendix 1. The greater dependency of wheat on oil prices compared to soybean is explained by the more intensive use of oil-related inputs for the former than the latter. With regard to our estimation results for rapeseed and sunflower, it appears that the rapeseed crop would require the highest amount of oil-based inputs.[22] However, this input channel does not explain the negative parameter for corn.

Considering the demand channel, the long-term oil-price effect is inversely proportional to the agricultural commodity income elasticity. However, this elasticity is low for agricultural food. Thus, meat income elasticity[23] needs to be considered in parallel with the ratio of feed use for each commodity. Appendix 2 presents the ratio of "feed and residual use" to total domestic use.[24] As expected given its associated estimated negative value, the share of feed used overall is the highest for corn, especially before biofuel production expansion. To sum up, we provide new evidence of the existence of a long-term positive effect of oil prices on commodity prices for four agricultural products through the input channel, and a negative price effect for corn, highlighting the importance of the demand channel.

We now focus on the additional oil-price effect linked to biofuel production. As expected, the three agricultural commodities significantly used for biofuel production (corn,

[20] Data are available in the table "Commodity Costs and Returns" for each agricultural commodity.

[21] To our knowledge, European farm data for sunflower and rapeseed are not available.

[22] To explain this difference, we note that rapeseed requires a large amount of nitrogen during its culture and is a major consumer of fertilizer.

[23] The income elasticity is higher for meat than for cereals or vegetable oils. For example, *Gallet* (2010) lists 3,357 income elasticities for several meats estimated in 393 studies and shows that the average income elasticities for beef, poultry, pork, and lamb are approximately 1, 0.82, 0.8, and 0.74, respectively.

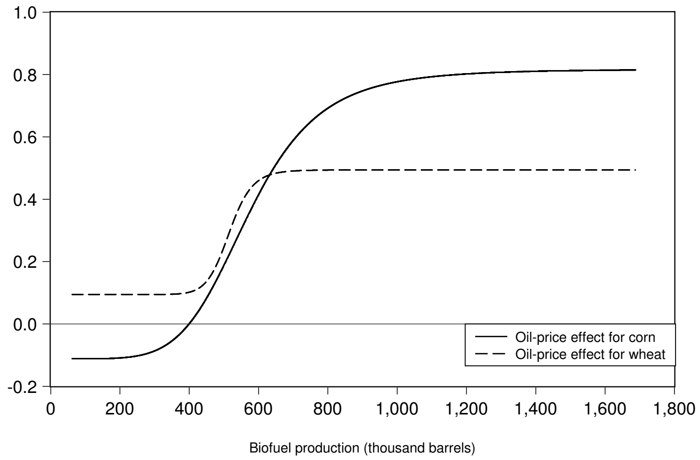
[24] These data are available in the table "Supply and disappearance" in the USDA database.

soybean and rapeseed) display positive $\hat{\beta}_2$ parameters, meaning that the oil-price effect through the direct biofuel channel exists for those commodities. Corn is the main input used in US biofuel production, as confirmed by the high value of its associated estimated coefficient. In addition, the negative oil-price effect for corn operating through the demand channel must have decreased with the significant decline in its use in feed.

The additional long-term oil-price effect also exists for wheat and sunflower. The transmission of this effect from biofuel feedstocks to those two commodities operates through the substitution channel. Calculating the total oil-price effect for sunflower and rapeseed, we get 0.936 and 0.953, respectively. For corn and wheat, the total effect is estimated at 0.817 and 0.494. Thus, as expected, the substitution effect is higher between vegetable oils compared to cereals. On the whole, our results highlight a positive impact of biofuel production on the long-term effect from oil to agricultural commodity prices. Consequently, growing biofuel production has contributed to the agricultural price increase.

Let us now investigate the dynamics of the long-term oil-price effect displayed in figures 2.3 and 2.4. Concerning corn, the long-term oil-price effect increase begins to occur at a biofuel production of 200,000 barrels a day , i.e., approximately in 2002. This result is consistent with Nazlioglu (2011)'s findings using Gregory and Hansen (1996)'s test. The share of corn used in US ethanol production crossed the 10% threshold at that time. The oil-price effect reaches its maximum at a daily 1.4 million-barrel production, i.e., in 2011. This threshold corresponds to a share of 45% used in biofuel production. Regarding wheat, this increase occurs for a daily biofuel production close to 400,000 barrels, i.e., in 2006. The biofuel impact for wheat begins when the oil-price effect for corn switches to positive values. In addition, there is a relative parallelism between the two slopes. These findings are consistent with both the existence of a substitution effect between these two cereals and the oil-price effect transmission from corn to wheat prices.

Figure 2.3: Oil-price effect for corn and wheat based on daily biofuel production



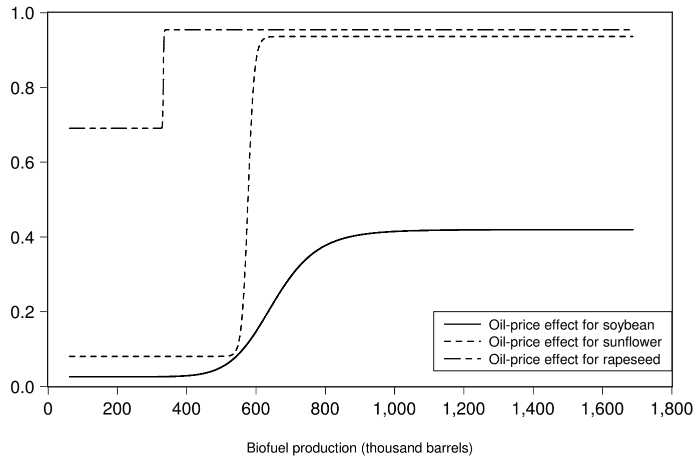
The additional oil-price effect for soybean appears in 2006 – as for wheat – when the share of soybean used in US biodiesel production exceeds 10%, as for corn. However, the long-term oil-price effect reaches its maximum as early as 2008; the share of soybean used in biofuel production then attained only 15%. Concerning rapeseed oil, the related transition speed parameter is high but is not significant, a characteristic that is likely due to the use of US biofuel production data instead of European data. Nevertheless, there are breaks in the long-term oil-price effect in 2005 and 2006 for rapeseed and sunflower, respectively.

To investigate whether causality exists from oil to agricultural commodity prices, we apply Toda and Yamamoto (1995)'s test on both the overall period and subsamples deduced from previous results.[25] Results presented in Table 2.6 suggest a causal effect from oil to agricultural commodities over the entire period, with the exception of soybean. In addition, there is weak evidence of a causal effect from rapeseed and corn to the oil price. The most interesting finding is the stronger causal effect from oil to agricultural prices for corn, soybean, sunflower, and rapeseed after the first break date, i.e., after the

[25]Thus, we use three break dates for corn, soybean, and wheat, i.e., 12/31/2001 and 12/31/2010, 12/31/2005 and 12/31/2007, 12/31/2006 and 12/31/2007, respectively. For sunflower and rapeseed, the subsamples are 2001–2005 and 2006–2014, 2001–2004 and 2005–2014, respectively.

additional long-term oil-price effect appearance related to biofuel production development. It is worth mentioning that only wheat and oil prices are not characterized by a causal relationship during the last period. The long-term oil-price effect for wheat could therefore be linked to this substitution effect with corn.

Figure 2.4: Oil-price effect for vegetable oils based on daily biofuel production



2.5 Robustness checks

To check the robustness of our findings, we now consider new control variables. The corresponding results for the estimations and causality tests are available on request.

Consider first the robustness of our results to the proxy used for the economic activity. To this end, we replace the SP500 index by the Baltic Dry Index.[26] The biofuel impact on the long-term oil-price effect is confirmed for all commodities. While the oil-price effect without accounting for biofuel production is lower (or more negative)

[26]Data come from the Baltic Exchange. The Baltic Dry Index represents shipping costs by sea for the main commodities. As a useful gauge of global trade, it is frequently used as a physical proxy for economic activity (see e.g. *Sengupta and Tam*, 2009).

than the previous results for all commodities, the additional effect is higher, except for sunflower. Cointegration test results are close to the previous results; the only changes concerning corn and wheat for which the CS test detects a cointegrating relationship with the price of oil and sunflower for which no cointegration is found. Concerning the causality analysis, our main results remain valid. The only change is the appearance of a causal relationship from rapeseed to oil prices, but its intensity is weaker than the reverse causal effect.

Table 2.6: Long-term causality test

	Entire period	1986–2001	2002–2010	2011–2014
Oil to corn	0.009***	0.965	0.021**	0.032**
Corn to oil	0.051*	0.770	0.049**	0.458
	Entire period	1986–2005	2006–2007	2008–2014
Oil to Soybean	0.215	0.201	0.007***	0.080*
Soybean to Oil	0.770	0.804	0.060*	0.552
	Entire period	1986–2006	2006–2007	2008–2014
Oil to Wheat	0.013**	0.006***	0.090*	0.204
Wheat to Oil	0.590	0.104	0.907	0.935
	Entire period	2001–2005	2006–2014	
Oil to Sunflower	0.000***	0.052*	0.000***	
Sunflower to Oil	0.754	0.698	0.476	
	Entire period	2001–2004	2005–2014	
Oil to Rapeseed	0.000***	0.736	0.000***	
Rapeseed to Oil	0.066*	0.693	0.243	

Note: We mention the p-value of the causality test. One, two and three stars indicate the reject of the non-causality hypothesis at the 10%, 5% and 1% significance levels, respectively.

Second, since agricultural commodity prices are affected by exchange rate variations (*Frank and Garcia*, 2010), we consider the US dollar exchange rate as an additional control variable.[27] On the whole, our previous findings remain valid since the biofuel impact on the long-term oil-price effect is confirmed for all commodities but wheat. In addition, this specification leads to the same result about the causal relationship between rapeseed and oil prices compared to the model with the Baltic Dry Index.

[27] We use the Trade Weighted US Dollar Index with major currencies from the FED.

2.6 Conclusion

This study investigates the long-term link between the price of oil and several agricultural commodity prices, by paying particular attention to the impact of biofuel production on this relationship. To this end, we rely on the nonlinear framework of cointegrating smooth transition regression models.

Our key findings can be summarized as follows. First, we provide clear evidence that the growing biofuel production has contributed to agricultural price increases in recent years. Indeed, we find evidence of a rising long-term oil-price effect on the agricultural commodity prices used in biofuel production. Second, we show that this impact is transmitted to other agricultural commodity markets through the substitution effect existing between raw materials. Third, in the absence of biofuel production, only rapeseed prices are strongly affected by oil prices in the long term.

Our results have two important implications. First, they suggest that agricultural commodities could be seen as energy commodities at the expense of their food purpose. The production of biofuel based on agricultural commodities could be limited to levels avoiding the direct biofuel channel appearance. Thus, the development of biofuel production should focus on second-generation biofuels based on agricultural plant residuals and non-food plants. Second, changes in agricultural price dynamics, partly due to the development of biofuels, could have some impact in hedging strategies in agricultural markets, with the possibility of using the oil market for a cross-hedging strategy, or in the economy of countries whose activity is dependent on agricultural commodities used in biofuel production, as studied in *Gomes et al.* (2017).

Bibliography

Abbott, P. C. and Borot de Battisti, A. (2011). Recent global food price shocks: Causes, consequences and lessons for African governments and donors. *Journal of African Economies*, 20(Supplement 1):i12–i62.

Abbott, P. C., Hurt, C., and Tyner, W. E. (2011). What's driving food prices in 2011? *Farm Foundation Issue Report*.

Abdelradi, F. and Serra, T. (2015). Food-energy nexus in Europe: Price volatility approach. *Energy Economics*, 48:157–167.

Baffes, J. (2007). Oil spills on other commodities. *Resources Policy*, 32(3):126–134.

Baffes, J. (2010). More on the energy/nonenergy price link. *Applied Economics Letters*, 17(16):1555–1558.

Bakhat, M. and Wurzburg, K. (2013). Price relationships of crude oil and food commodities. *Economics for Energy Working Papers*, WP FA06/2013.

Balcombe, K. and Rapsomanikis, G. (2008). Bayesian estimation and selection of nonlinear vector error correction models: The case of the sugar-ethanol-oil nexus in Brazil. *American Journal of Agricultural Economics*, 90(3):658–668.

Berument, M. H., Sahin, A., and Sahin, S. (2014). The relative effects of crude oil price and exchange rate on petroleum product prices: Evidence from a set of Northern Mediterranean countries. *Economic Modelling*, 42(3):243–249.

Campiche, J. L., Bryant, H. L., Richardson, J. W., and Outlaw, J. J. (2007). Examining the evolving correspondence between petroleum prices and agricultural commodity prices. American Agricultural Economics Association Annual Meeting. Portland, OR, July 29-August 1.

Choi, I. and Saikkonen, P. (2004). Testing linearity in cointegrating smooth transition regressions. *Econometrics Journal*, 7(2):341–365.

Choi, I. and Saikkonen, P. (2010). Tests for nonlinear cointegration. *Econometric Theory*, 26(3):682–709.

Christopoulos, D. K. and Leon-Ledesma, M. A. (2007). A long-run non-linear approach to the Fisher effect. *Journal of Money, Credit and Banking*, 39(2-3):543–559.

Ciaian, P. and Kancs, d. (2011). Interdependencies in the energy-bioenergy-food price systems: A cointegration analysis. *Resource and Energy Economics*, 33(1):326–348.

de Gorter, H. and Just, D. R. (2008). Water in the U.S. ethanol tax credit and mandate: Implications for rectangular deadweight costs and the corn-oil price relationship. *Review of Agricultural Economics*, 30(3):397–410.

de Gorter, H. and Just, D. R. (2009). The welfare economics of a biofuel tax credit and the interaction effects with price contingent farm subsidies. *American Journal of Agricultural Economics*, 91(2):477–488.

de Gorter, H. and Just, D. R. (2010). The social costs and benefits of biofuels: The intersection of environmental, energy and agricultural policy. *Applied Economic Perspectives and Policy*, 32(1):4–32.

Deb, P., Trivedi, P. K., and Varangis, P. (1996). The excess co-movement of commodity prices reconsidered. *Journal of Applied Econometrics*, 11(3):275–291.

Delatte, A. L. and Fouquau, J. (2010). Smooth transition in China new evidence in the cointegrating money demand relationship. *Economics Bulletin*, 30(1):265–273.

Dickey, D. and Fuller, W. (1979). Distribution of the estimators for autoregressive time series with a unit root. *Journal of the American Statistical Association*, 74(366):427–431.

Dickey, D. A. and Fuller, W. A. (1981). Likelihood ratio statistics for autoregressive time series with a unit root. *Econometrica*, 49(4):1057–1072.

Engle, R. F. and Granger, C. (1987). Co-integration and error correction: Representation, estimation, and testing. *Econometrica*, 55(2):251–276.

Frank, J. and Garcia, P. (2010). How strong are the linkages among agricultural, oil, and exchange rate markets? GBATA Eleventh International Conference. Prague, Czech Republic, July 7-11.

Gallet, C. A. (2010). The income elasticity of meat: A meta-analysis. *Australian Journal of Agricultural and Resource Economics*, 54(4):477–490.

Gardner (2007). Fuel ethanol subsidies and farm price support. *Journal of Agricultural and Food Industrial Organization*, 5(2).

Gilbert, C. L. (2010). How to understand high food prices. *Journal of Agricultural Economics*, 61(2):398–425.

Gohin, A. and Chantret, F. (2010). The long-run impact of energy prices on world agricultural markets: The role of macro-economic linkages. *Energy Policy*, 38(1):333–339.

Gomes, G., Hache, E., Mignon, V., and Paris, A. (2017). On the current account - biofuels link in emerging and developing countries: Do oil price fluctuations matter? *Working Papers*, 2017-07. CEPII research center.

Gonzalo, J. and Pitarakis, J.-Y., editors (2006). *Threshold Effects in Multivariate Error Correction Models*, volume Volume 1: Econometric Theory of *Palgrave Handbook of Econometrics*. Palgrave MacMillam, New-York.

Gregory, A. W. and Hansen, B. E. (1996). Residual-based tests for cointegration in models with regime shifts. *Journal of Econometrics*, 70(1):99–126.

Harri, A., Nalley, L., and Hudson, D. (2009). The relationship between oil, exchange rates, and commodity prices. *Journal of Agricultural and Applied Economics*, 41(2):501–510.

Hassouneh, I., Serra, T., Goodwin, B. K., and Gil, J. M. (2012). Non-parametric and parametric modeling of biodiesel, sunflower oil, and crude oil price relationships. *Energy Economics*, 34(5):1507–1513.

Hong, S. H. and Wagner, M. (2008). Nonlinear cointegration analysis and the environmental kuznets curve. *Economics Series*, 224. Institute for Advanced Studies.

Johansen, S. (1991). Estimation and hypothesis testing of cointegration vectors in gaussian vector autoregressive models. *Econometrica*, 59(6):1551–1580.

Kaltalioglu, M. and Soytas, U. (2009). Price transmission between world food agricultural raw material and oil prices. GBATA Eleventh International Conference. Prague, Czech Republic, July 7-11.

Koirala, K. H., Mishra, A. K., D'Antoni, J. M., and Mehlhorn, J. E. (2015). Energy prices and agricultural commodity prices: Testing correlation using copulas method. *Energy*, 81(3):430–436.

Kwiatkowski, D., Phillips, P. C., Schmidt, P., and Shin, Y. (1992). Testing the null hypothesis of stationarity against the alternative of a unit root. *Journal of Econometrics*, 54(1-3):159–178.

Lardic, S. and Mignon, V. (2008). Oil prices and economic activity: An asymmetric cointegration approach. *Energy Economics*, 30(3):847–855.

Leybourne, S. J., Lloyd, T. A., and Reed, G. V. (1994). The excess comovement of commodity prices revisited. *World Development*, 22(11):1747–1758.

Lopez Cabrera, B. and Schulz, F. (2016). Volatility linkages between energy and agricultural commodity prices. *Energy Economics*, 54(1):190–203.

Mitchell, D. (2008). A note on rising food prices. *Policy Research Working Paper*, 4682. The World Bank.

Myers, R. J., Johnson, S. R., Helmar, M., and Baumes, H. (2014). Long-run and short-run co-movements in energy prices and the prices of agricultural feedstocks for biofuel. *American Journal of Agricultural Economics*, 96(4):991–1008.

Natanelov, V., Alam, M. J., McKenzie, A. M., and van Huylenbroeck, G. (2011). Is there co-movement of agricultural commodities futures prices and crude oil? *Energy Policy*, 39(9):4971–4984.

Nazlioglu, S. (2011). World oil and agricultural commodity prices: Evidence from non-linear causality. *Energy Policy*, 39(5):2935–2943.

Nazlioglu, S. and Soytas, U. (2012). Oil price, agricultural commodity prices, and the dollar: A panel cointegration and causality analysis. *Energy Economics*, 34(4):1098–1104.

OECD (2008). Rising food prices causes and consequences. Policy brief, Organisation for Economic Co-operation and Developmen.

Palaskas, T. B. and Varangis, P. N. (1991). Is there excess co-movement of primary commodity prices? A co-integration test. *Policy, Research, and External Affairs Working Papers*, (WPS 758). The World Bank.

Pedroni, P. (1999). Critical values for cointegration tests in heterogeneous. *Oxford Bulletin of Economics and Statistics*, 61(4):653–669.

Peri, M. and Baldi, L. (2010). Vegetable oil market and biofuel policy: An asymmetric cointegration approach. *Energy Economics*, 32(3):687–693.

Perron, P. (1997). Further evidence on beaking trend functions in macroeconomic variables. *Journal of Econometrics*, 80(2):355–385.

Phillips, P. C. and Perron, P. (1988). Testing for a unit root in time series regression. *Biometrika*, 75(2):335–346.

Pindyck, R. S. and Rotemberg, J. J. (1990). The excess co-movement of commodity prices. *The Economic Journal*, 100(403):1173–1189.

Saikkonen, P. and Choi, I. (2004). Cointegrating smooth transition regressions. *Econometric Theory*, 20(2):301–340.

Saitone, T. L., Sexton, R. J., and Sexton, S. E. (2008). Market power in the corn sector: How does it affect the impacts of the ethanol subsidy. *Journal of Agricultural and Resource Economics*, 33(2):169–194.

Sengupta, R. and Tam, Y. M. (2009). Recent movements in the Baltic Dry Index. *Economic Synopses*, 12. Federal Reserve Bank of Saint Louis.

Serra, T., Zilberman, D., Gil, J. M., and Goodwin, B. K. (2011). Nonlinearities in the U.S. corn-ethanol-oil-gasoline price system. *Agricultural Economics*, 42(1):35–45.

Shin, Y. (1994). A residual based test of the null of cointegration against the alternative of no cointegration. *Econometric Theory*, 10(1):91–115.

Toda, H. Y. and Yamamoto, T. (1995). Statistical inference in vector autoregressions with possibly integrated processes. *Journal of Econometrics*, 66(1-2):225–250.

Trujillo-Barrera, A., Mallory, M., and Garcia, P. (2012). Volatility spillovers in U.S. crude oil, ethanol, and corn futures markets. *Journal of Agricultural and Resource Economics*, 37(2):247–262.

Wang, Y., Wu, C., and Yang, L. (2014). Oil price shocks and agricultural commodity prices. *Energy Economics*, 44(1):22–35.

Yu, T.-H. E., Bessler, D. A., and Fuller, S. (2006). Cointegration and causality analysis of world vegetable oil and crude oil prices. American Agricultural Economics Association Annual Meeting. Long Beach, CA, July 23-26.

Zhang, Q. and Reed, M. (2008). Examining the impact of the world crude oil price on China's agricultural commodity prices: The case of corn, soybean, and pork. Southern Agricultural Economics Association Annual Meeting. Dallas, TX, February 2-5.

Zhang, Z., Lohr, L., Escalante, C., and Wetzstein, M. (2010). Food versus fuel: What do prices tell us? *Energy Policy*, 38(1):445–451.

Zivot, E. and Andrews, D. W. K. (1992). Further evidence on the great crash, the oil-price shock, and the unit-root hypothesis. *Journal of Business and Economic Statistics*, 10(3):251–270.

2.A Production costs for corn, soybean, and wheat

	Corn			Soybean			Wheat		
	Fertilizer	Energy	Oil Cost	Fertilizer	Energy	Oil Cost	Fertilizer	Energy	Oil Cost
1986	36.23%	8.01%	44.23%	11.49%	15.88%	27.37%	33.69%	15.63%	49.32%
1987	24.23%	9.68%	43.90%	10.99%	18.63%	29.62%	31.34%	18.13%	49.46%
1988	29.56%	9.27%	48.83%	12.88%	17.77%	30.64%	35.09%	16.86%	51.94%
1989	37.73%	9.49%	47.22%	16.26%	12.61%	28.87%	34.75%	16.56%	51.31%
1990	33.90%	19.11%	53.01%	15.00%	14.20%	29.20%	30.57%	18.27%	48.85%
1991	34.17%	14.50%	48.66%	13.97%	14.20%	29.20%	30.57%	17.27%	48.85%
1992	32.75%	13.88%	46.63%	13.99%	12.61%	26.60%	30.28%	18.45%	48.73%
1993	32.92%	13.71%	46.64%	13.18%	12.42%	25.60%	29.59%	18.33%	47.92%
1994	33.02%	13.59%	46.60%	13.26%	11.37%	24.63%	29.74%	15.23%	44.97%
1995	37.21%	11.94%	49.15%	13.96%	10.93%	24.89%	34.06%	13.81%	47.87%
1996	32.60%	15.55%	48.15%	14.20%	12.84%	27.04%	32.32%	14.87%	47.18%
1997	31.82%	15.51%	47.33%	11.56%	9.21%	20.78%	30.31%	15.57%	45.88%
1998	29.53%	14.90%	44.43%	11.49%	7.71%	19.20%	33.19%	10.95%	44.14%
1999	27.92%	15.02%	42.94%	11.87%	7.91%	19.78%	31.65%	12.19%	43.84%
2000	26.90%	18.15%	45.05%	11.78%	11.45%	23.23%	30.45%	16.09%	46.55%
2001	34.51%	13.07%	47.59%	11.83%	10.80%	22.63%	37.43%	14.39%	51.82%
2002	29.46%	13.12%	42.58%	10.02%	9.58%	19.59%	31.30%	15.32%	46.62%
2003	31.58%	14.38%	45.96%	10.32%	11.30%	21.62%	34.33%	16.27%	50.59%
2004	31.28%	16.77%	48.05%	10.72%	11.64%	22.36%	32.50%	17.40%	49.91%
2005	44.24%	16.91%	61.15%	12.16%	15.35%	27.52%	33.49%	20.76%	54.25%
2006	46.48%	16.66%	63.13%	14.30%	14.81%	29.11%	34.26%	21.46%	55.72%
2007	48.39%	16.41%	64.79%	14.68%	14.60%	29.28%	35.93%	21.73%	57.65%
2008	55.48%	17.00%	72.47%	20.10%	16.16%	36.26%	42.13%	20.26%	62.38%
2009	49.39%	10.97%	60.37%	18.15%	10.35%	28.50%	38.45%	10.84%	49.29%
2010	39.15%	9.02%	48.17%	13.56%	12.76%	26.32%	31.71%	14.96%	46.67%
2011	44.36%	9.76%	54.12%	16.70%	15.34%	32.03%	36.38%	16.18%	52.56%
2012	44.80%	8.77%	53.57%	21.80%	12.34%	34.14%	36.39%	15.33%	51.72%
2013	43.14%	9.08%	52.22%	21.21%	11.98%	33.19%	36.03%	15.13%	51.16%
2014	41.82%	9.19%	51.02%	20.82%	11.99%	32.80%	34.53%	15.17%	49.70%

Note: The fertilizer costs include commercial fertilizer, soil conditioner, and manure. The energy columns consist of fuel, lubrication, and electricity costs. The oil cost is the sum of the two previous columns. All of these costs are expressed as a percentage of operating costs, including seed, fertilizer, chemicals, custom operations, energy, repairs, baling, and irrigation.

2.B Feed, food and biofuel utilization for corn, soybean oil, and wheat

	Corn		Soybean		Wheat	
	Feed	Biofuel	Feed	Biofuel	Feed	Food
1986-1987	79.07%	4.92%	8.28%	0.00%	33.50%	59.48%
1987-1988	79.28%	4.62%	7.46%	0.00%	26.48%	15.93%
1988-1989	75.19%	5.49%	7.70%	0.00%	15.36%	74.12%
1989-1990	76.18%	5.59%	8.10%	0.00%	14.02%	75.47%
1990-1991	76.38%	5.79%	7.45%	0.00%	35.34%	57.86%
1991-1992	75.78%	6.29%	7.56%	0.00%	21.60%	69.76%
1992-1993	77.15%	6.25%	9.13%	0.00%	17.17%	74.04%
1993-1994	74.37%	7.28%	6.95%	0.00%	21.92%	70.31%
1994-1995	76.09%	7.43%	9.63%	0.00%	26.78%	66.30%
1995-1996	74.24%	6.26%	7.50%	0.00%	13.48%	77.44%
1996-1997	75.48%	6.13%	7.64%	0.00%	23.65%	68.48%
1997-1998	74.80%	6.69%	8.84%	0.00%	19.93%	72.71%
1998-1999	74.55%	7.08%	11.22%	0.00%	28.29%	65.89%
1999-2000	74.46%	7.47%	9.48%	0.00%	21.49%	71.46%
2000-2001	74.65%	8.08%	9.31%	0.00%	22.60%	71.42%
2001-2002	73.93%	8.94%	9.06%	0.00%	15.27%	77.73%
2002-2003	70.21%	12.60%	7.52%	0.00%	10.35%	82.11%
2003-2004	69.40%	14.02%	6.66%	0.81%	16.96%	76.37%
2004-2005	69.39%	14.97%	10.21%	2.55%	15.47%	77.89%
2005-2006	66.95%	17.55%	10.29%	8.66%	13.61%	79.69%
2006-2007	61.01%	23.34%	7.99%	14.86%	10.30%	82.50%
2007-2008	56.87%	29.60%	4.93%	17.70%	1.52%	90.15%
2008-2009	50.53%	36.51%	5.99%	12.72%	21.08%	72.82%
2009-2010	46.11%	41.50%	6.01%	10.62%	12.59%	81.39%
2010-2011	42.64%	44.80%	7.24%	16.30%	7.85%	85.62%
2011-2012	41.31%	45.70%	5.06%	26.62%	13.40%	80.16%
2012-2013	41.68%	44.83%	5.87%	25.09%	26.21%	68.52%
2013-2014	43.65%	44.50%	5.33%	26.43%	17.75%	76.11%

Note: The fertilizer costs include commercial fertilizer, soil conditioner, and manure. The energy columns consist of fuel, lubrication, and electricity costs. The oil cost is the sum of the two previous columns. All of these costs are expressed as a percentage of operating costs, including seed, fertilizer, chemicals, custom operations, energy, repairs, baling, and irrigation.

3

On the current account - biofuels link in emerging and developing countries: Do oil price fluctuations matter?

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3.1 Introduction

For the past two decades, a strong interest has emerged in favor of the integration of renewable energies in the electricity mix and in the transportation sector. This constitutes a major concern for developed economies as well as for developing and emerging countries in order to ensure energy transition policies, to fight against climate change and reduce Greenhouse Gas Emissions. Implementing renewable energies is all the more relevant because they allow the country to earn double dividends, as their diffusion *de facto* reduces the volume of imported fossil fuels in parallel of environmental objectives (*Criqui and Mima*, 2012). Along these lines, the use of biofuels is encouraged in developed countries and in emerging economies such as Brazil,[1] China and India for environmental concerns, as well as for promoting energy security, agricultural opportunities and economic growth. For instance, the European Union introduced a blending target of biofuels in petroleum products in 2003, and the Renewable Fuel Standard program (2005) combined with the Energy Independence and Security act of 2007 (36 billion gallons of biofuels by 2020) allowed the establishment of mandatory target of biofuels utilization in the United States' transportation sector. However, such environmental policies may cause externalities or adverse effects on the economy of emerging and developing countries whose activity is highly dependent on agricultural commodities used in biofuel production. Aiming at investigating those topical issues, this chapter analyzes the price impact of biofuels on the economy of such countries, focusing on the current account.

By concentrating on the current account, we fall into the spirit of the oil - macroeconomy literature. Indeed, it is well known that oil-exporting countries experiment large current account improvements following a sharp rise in oil prices (see *Allegret et al.* (2014) and the references therein). In other words, for such countries, oil windfalls constitute a

[1] Brazil launched the Proalcool program in 1975 just after the first oil shock. This program triggered an acceleration in the use of ethanol for the transportation sector and innovations on flex-fuel engines for the car industry.

key source of foreign exchange and income. The price of oil is also a key element behind agricultural commodity prices (see *Paris* (2018) and the references therein, and Section 3.2). Shocks in the price of oil spill over agricultural production costs which comprise fertilizer and fuel (*Baffes*, 2007, 2010; *Berument et al.*, 2014), thus decreasing supply. On the consumer side, the impact can be either negative or positive. On the one hand, positive shocks in the price of oil have a negative impact on demand if in their food purchasing decisions, households account for price changes in other goods among those oil products (*Gohin and Chantret*, 2010). In this case, oil and agricultural commodity prices would have a negative relationship. On the other hand, a positive link between agricultural commodity demand and oil prices is likely to occur through the development of biofuels: due to the substitution effect between fuel and biofuel, a rise in the price of oil could lead to an increase in the demand for biofuel (*Ciaian and Kancs*, 2011). In this context, oil and agricultural commodity prices would be positively related.

The preceding arguments show that important links exist between the price of agricultural raw materials used in biofuel production, the price of oil and the current account of emerging and developing countries exporting or importing agricultural commodities.[2] While the impacts caused by biofuel production development are likely to be highly significant on the economy of such countries, the literature on this topic is very scarce.[3] This chapter aims at filling this gap by examining the price impact of biofuels, through the price of its agricultural inputs, on the current account for a panel of 16 countries – 9 developing and 7 emerging economies – which are either exporters, producers or importers of agricultural commodities used in biofuel production. As stressed above, due

[2]The rise in the price of agricultural commodities may exert important effects on the current account of emerging and developing countries. Regarding countries exporting agricultural commodities, the effect may be not clear cut at a first sight. Indeed, the direct effect may be positive on the current account if the price increase is sufficient to compensate the potential decrease in the quantity of exported agricultural commodities. However, the commodity price increase is detrimental for domestic consumption which, in turn, negatively affects economic activity and the current account.

[3]Indeed, most of the studies dealing with developing and emerging countries have been concerned with the impact of current and targeted domestic biofuel production on land or agricultural commodities' availability, on water resources required for cultivation and on food prices (see, e.g., *Khanna et al.*, 2008; *Yang et al.*, 2011; and *Khanna and Crago*, 2012). The main exception is *Chakravorty et al.* (2015) who have addressed the impact of US biofuel mandate on poverty in India.

to the links existing between the price of agricultural commodities, the price of oil and the current account, the biofuels-current account nexus is likely to depend on the dynamics in the oil market. Indeed, for a country exporting (resp. importing) agricultural commodities used in biofuel production but importing (resp. exporting) crude oil, a high price of oil could strengthen (resp. weaken) the effect of biofuel prices on the current account *via* the link between oil and agricultural prices. However, this high oil price could affect negatively this biofuel price effect with an increase in the country's import spending for crude oil.

Acknowledging this major role played by the price of oil, we account for such nonlinearities by estimating a panel smooth transition regression (PSTR) model. In this type of modeling, the price impact of biofuels on the current account varies, depending on the value of another observable variable, i.e., the price of oil. Specifically, the observations in the panel are divided into two homogeneous groups or "regimes" – high oil price and low oil price regimes –, with different coefficients depending on the regimes. Regression coefficients are allowed to change gradually when moving from one group to another: PSTR is a regime-switching model where the transition from one state to the other is smooth rather than discrete. To our best knowledge, this chapter is the first paper to address the price impact of biofuels on the current account for such countries by accounting for nonlinearities exerted by the price of oil.

Estimating PSTR models over the 2000–2014 period for emerging and developing countries classified into three groups – exporters, producers, importers of agricultural commodities used for biofuel production – our results can be summarized as follows. We show that, overall, a rise in the biofuel price tends to improve the current-account position for exporting and producing countries. However, this biofuel price impact is nonlinear, depending on the level reached by the price of oil. For low values of the price of oil, a 10% increase in the price of biofuels significantly improves the current account by around 2%. When the price of oil exceeds the threshold of 56 US dollars per barrel for producers and 45 US dollars for exporters, changes in the price of biofuels on the current account tend to weaken until becoming negligible. For agricultural commodity exporters which are also oil importers, these findings indicate that, in the case of an oil price increase, the current account is pulled by two opposite forces, making its overall reaction moderate or even nil.

The rest of the chapter is organized as follows. Section 3.2 provides some stylized facts regarding the links between agricultural commodity and oil prices, and their evolution. Section 3.3 describes the data and methodology. Section 3.4 presents our findings and Section 3.5 concludes the chapter.

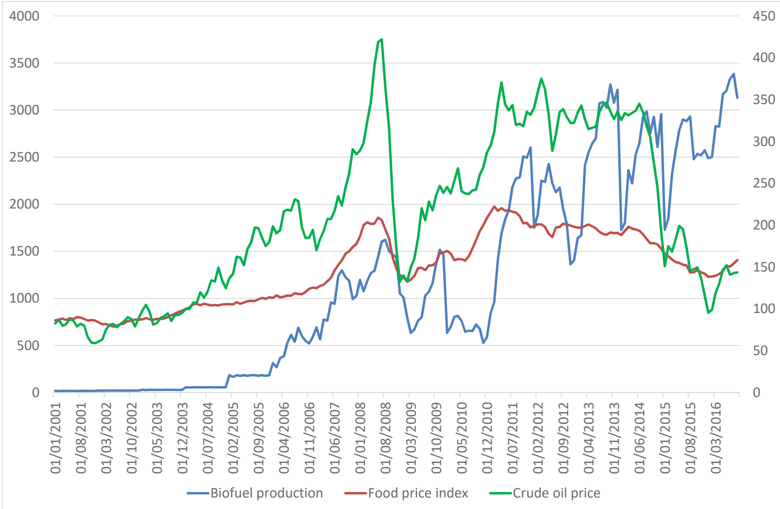
3.2 Some stylized facts

The various concerns previously mentioned in Section 3.1 – regarding environmental issues, energy security, agricultural opportunities and economic growth – have lead to a sharp rise in biofuel production since the mid-2000s. As shown in Figure 3.1, while biofuel production was on average around 30 thousand barrels from 2001 to 2005, it started to take off in 2006 with a production that has increased more than ten-fold compared to the beginning of the first half of the 2000s. First-generation biofuels being produced with agricultural commodities (animal fats, starch, sugar and vegetable oil),[4] this dynamics has been accompanied by an increase in the price of those raw materials (see Figure 3.1).[5]

[4]Typical first-generation biofuels are sugarcane ethanol, starch-based or 'corn' ethanol, biodiesel and Pure Plant Oil (PPO). The feedstock for producing first-generation biofuels either consists of sugar, starch and oil bearing crops or animal fats that, in most cases, can also be used as food and feed or consists of food residues (*IEA*, 2010).

[5]In particular, the "food *versus* fuel" debate that followed the large increase in commodity prices in 2007-2008 triggered several articles about co-movements between commodity prices, subsidies policy in the agricultural sector and economic development based on biofuels production policy (see, e.g., *Thompson* (2012) and the references therein). Moreover, in addition to biofuels, the upward dynamics of agricultural commodity prices during the 2000s comes from a combination of demand and supply shocks. On the demand side, strong economic growth in developing and emerging countries (especially China) has played a positive impact on the global call for commodities (*Abbott and Borot de Battisti*,

Figure 3.1: Biofuel production, crude oil price and food price index



Note: This figure reports the evolution of biofuel production (left-hand scale; source: US Energy Information Administration), crude oil price (simple average of Dated Brent, West Texas Intermediate, and the Dubai Fateh spot prices; right-hand scale; source: IMF) and food price index (right-hand scale; source: FAO) over the January 2001 - September 2016 period at monthly frequency.

Specifically, let us now provide a first insight regarding the links between agricultural commodity prices and the price of oil, and their evolution along with the development of biofuel production. To this end, we consider monthly price series ranging from January 1980 to June 2016. All agricultural commodity and oil price series are taken from IMF.[6] Table 3.1 reports the correlations of some agricultural commodity price series with the price of oil, all series being expressed in first-logarithmic difference.

As shown, correlations are quite low over the whole period, the highest value being equal to 16% for palm oil. These results indicate that the links between agricultural

2011; *Abbott et al.*, 2011). On the supply side, adverse local agro-climatic conditions (temperature and precipitation) in major producing countries (*OECD*, 2008) negatively affected the volume of commodities available in the market.

[6] The crude oil price index is the simple average of Dated Brent, West Texas Intermediate, and the Dubai Fateh spot prices.

commodity and oil prices are not very strong on the full sample. As stressed above, the development of biofuel production has been particularly important since the mid-2000s and not accounting for this dynamics may mask important evolutions in the link between our series of interest. Indeed, the rise in biofuel production may have intensified the relation between agricultural commodity and oil prices.

Table 3.1: Correlations between agricultural commodity and oil price series

	Corn	Wheat	Soybean oil	Palm oil	Sugar cane
1980.02-2016.06	0.0443	0.0820	0.1331	0.1601	0.0167
1980.02-2005.12	-0.1146	-0.0380	-0.0502	0.0277	0.0031
2006.01-2016.06	0.3112	0.2437	0.5383	0.4504	0.0829
	Sorghum	Sugar beet	Rapeseed oil	Sunflower oil	
1980.02-2016.06	0.0291	0.0404	0.0758	0.0968	
1980.02-2005.12	-0.0886	0.0115	-0.0458	-0.0360	
2006.01-2016.06	0.2260	0.1237	0.5059	0.2819	

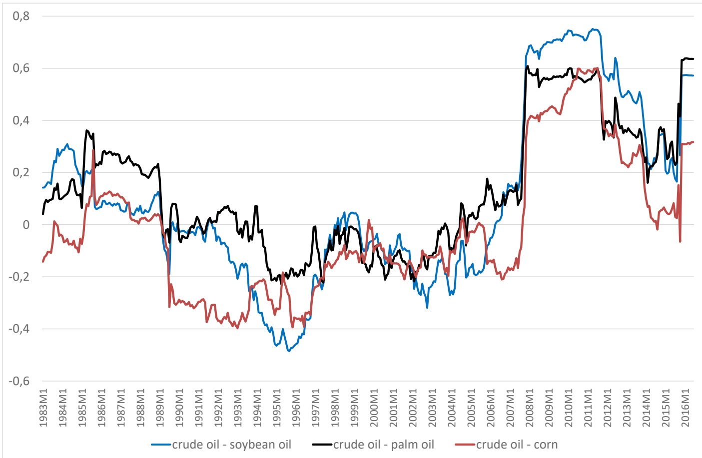
Note: This table reports correlations between agricultural commodity and oil price series expressed in first-logarithmic difference. Source: authors' calculations based on IMF data.

To simply illustrate the hypothesis of a stronger link between agricultural commodities and oil prices since the development of biofuel production, we also calculate the previous correlations over two subperiods, i.e., before and after 2006 as this year corresponds to the date of the major take-off in biofuel production worldwide. As shown in Table 3.1, correlations over the first subperiod are very weak, and even slightly negative for some commodities. Clearly, the links between agricultural commodities and oil were very tiny. These findings are in sharp contrast with those obtained after 2006. All correlations have strongly increased, the most impressive rises being observed for palm oil, rapeseed oil, and soybean oil.

This preliminary analysis based on correlation coefficients reveals that the links between agricultural commodity prices and the price of oil have sharply increased with the development of biofuel production. To complement this first investigation, Figure

3.2 reports rolling correlations (calculated for a three-year window) between the price of oil and three agricultural commodity prices, namely soybean oil, palm oil and corn prices (price series being expressed in their first-logarithmic difference).[7] While these correlations followed a declining trend during the first mid-2000s, the dynamics evolves in the opposite sense after, with values reaching very high levels—this pattern being thus observed for commodities used both for biodiesel and ethanol.

Figure 3.2: Rolling correlations



This figure displays three-year rolling correlations between the price of oil and (i) soybean oil price, (ii) palm oil price, and (iii) corn price (expressed in their first-logarithmic difference). Source: authors' calculations based on price data extracted from IMF.

3.3 Data and methodology

For our estimations, we rely on annual data over the 2000–2014 period. The choice of the starting date, 2000, is guided by data availability considerations. Indeed, our biofuel price index is based on information provided by the reports of the US Department of

[7]The figures for the other commodities considered display similar patterns.

Agriculture (see Section 3.3.1), which date back only from 2000. The dependent variable is the current account to GDP ratio, extracted from WDI (World Development Indicators, World Bank). Turning to the explanatory and control variables, we consider usual current-account determinants (see below, subsection 3.3.2) in addition to our biofuel feedstock price index whose calculation is described below.[8] As stressed above, we acknowledge that this current account - biofuel price relationship may vary depending on the price of oil. The latter is defined as the simple average (in logarithm) of Dated Brent, West Texas Intermediate and the Dubai Fateh spot prices, and is extracted from IMF (International Financial Statistics, IFS).

3.3.1 Aggregated biofuel price and panel of countries

As first-generation biofuels are produced from agricultural commodities, the first step consists in selecting those raw materials. In a second step, we have to identify for each retained commodity which emerging and developing countries are producers, exporters and/or importers. This leads us to select the following 10 commodities used in biofuel production: sugar cane, sugar beet, corn, soybean oil, palm oil, wheat, sorghum, cassava, rapeseed oil, and sunflower oil.[9] Turning to the panel of countries (see Table 3.2), we consider as producer (resp. exporter, importer) a country which produces (resp. exports, imports) at least one of the commodities listed above. As previously mentioned, the choice of the retained countries has been guided by the selected raw materials. Specifically, we relied on data provided by the Observatory of Economic Complexity (OEC) and the Food and Agriculture Organization of the United Nations (FAO) concerning production, exports and imports of our 10 commodities for all emerging and developing

[8] As (i) the biofuel feedstock price index can be calculated only at the yearly frequency, and (ii) data on the current-account position for our panel of countries are available only at the same frequency, this explains why we use annual data in our empirical analysis.

[9] While emerging and developing countries are not major actors on rapeseed oil and sunflower oil markets, we include those commodities in our analysis as they enter significantly in the biofuel production process.

countries. Among the various countries, we selected those for which those amounts of production, exports and imports reach the highest levels. Following this procedure, we selected 16 countries.

Table 3.2: Panel of countries

Producer	Exporter	Importer
Congo	Argentina	*Algeria*
Nigeria	Brazil	*Bangladesh*
Pakistan	China	*Egypt*
Sudan	India	*Ethiopia*
Argentina	Indonesia	*Iran*
Brazil	Mexico	*Pakistan*
China	Thailand	*Sudan*
India		China
Indonesia		India
Mexico		Indonesia
Thailand		Mexico
		Thailand

Note: In italics: developing country; otherwise: emerging country. Emerging: G20 countries or countries in the upper-middle income group classification from the World Bank (GNI per capita between \$4,036 and \$12,475); Developing: otherwise.

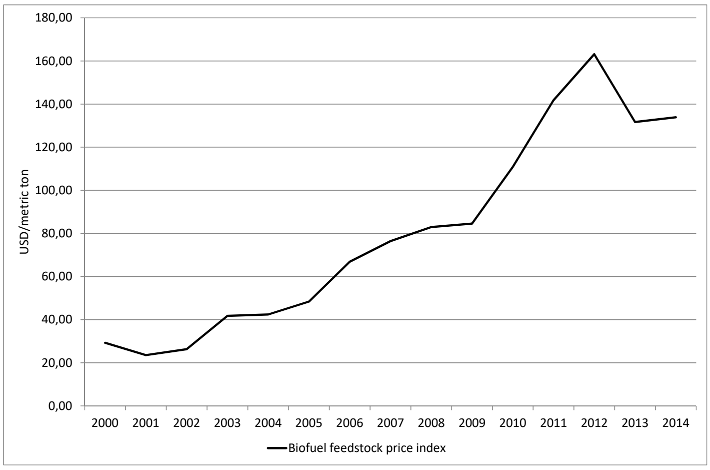
From the selected 10 commodities, we construct an aggregate biofuel price index based on the weight of each commodity in the volume of biofuel production. Let us now briefly describe the construction of the biofuel price index.

First, we have to identify the countries which are major players in biofuel production. Based on data from the US Energy Information Administration, we select a sample of 14 countries and regions, representing between 97% and 100% of the world ethanol and biodiesel production depending on the considered year.[10] Second, we rely on annual reports of the US Department of Agriculture (USDA) to specify the quantity of each commodity used in the production of biofuels in each selected country for each year. Third, we aggregate these data to determine the total quantity of each agricultural com-

[10]These countries are the following: Argentina, Australia, Brazil, Canada, China, Colombia, Guatemala, Indonesia, Malaysia, Peru, Philippines, Thailand, United States, and the EU28.

modity used in the annual production of biofuels at a world level and, in turn, their corresponding share. Fourth, based on these weights, we construct a price index for one ton of agricultural input in the biofuel production.[11] Finally, we calculate our aggregate price index from these data and the world price of each agricultural commodity – the latter being computed on the basis of the prices of the three main producers of each commodity.[12] The evolution of this biofuel feedstock price index is displayed on Figure 3.3.

Figure 3.3: Biofuel feedstock price index evolution



Source: authors' calculations.

3.3.2 Current-account determinants

Based on the previous literature,[13] we rely on the usual current-account determi-

[11] As an illustration, one ton of input in 2010 was composed of sugar cane for 69.95%, corn for 24.18%, sugar beet for 1.70%, rapeseed oil for 1.25%, wheat for 1.13%, soybean oil for 1.04%, palm oil for 0.46%, cassava for 0.25%, sunflower oil for 0.026%, and sorghum for 0.024%.

[12] In doing so, we account for disparities in agricultural prices that may be caused by protection of some domestic markets or high transportation costs.

[13] See *Calderon et al.* (2002), *Chinn and Prasad* (2003), *Gruber and Kamin* (2007), *Calderon et al.* (2007), *Chinn and Ito* (2007), *Chinn and Ito* (2008), *Brissimis et al.* (2012), *Cheung et al.* (2013) and *Allegret et al.* (2014) among others.

nants: the net foreign asset (NFA) position expressed as percentage of GDP, the ratio of exports plus imports of goods and nonfactor services to GDP as a proxy of openness, dependency ratio expressed as the ratio of dependent population (below 15 and above 65) to the working age population (between 15 and 64), terms of trade (in logarithm) defined as the ratio of export prices to import prices, GDP per capita, adjusted by PPP exchange rates, relative to the United States, the ratio of M2 to GDP used as an indicator of financial depth, and the population growth rate. All these variables are taken from WDI.

3.3.3 PSTR specification

To assess the potential nonlinear effect exerted by the price of oil on the biofuel price - current account relationship, we rely on the PSTR methodology proposed by *Gonzales et al.* (2005). According to the PSTR specification, current-account regression coefficients are allowed to change across countries and with time, depending on the price of oil. The observations are divided in – say – two regimes delimited by a threshold reached by the oil price, with estimated coefficients that vary depending on the considered regime. The change in the estimated value of coefficients is smooth and gradual, as PSTR models are regime-switching models in which the transition from one state to the other is smooth rather than discrete. Thanks to these specificities, PSTR models allow us to account for sufficient heterogeneity in view of the diversity of our sample of countries.

Let $CA_{i,t}$ denote the current account in percent of GDP in country i at time t. The PSTR specification is given by:

$$CA_{i,t} = \alpha_i + \beta_0 \Delta B_t + \beta_1 \Delta B_t \times F(P_t; \gamma, c) + \phi' X_{i,t} + \epsilon_{i,t} \tag{3.1}$$

for $i = 1, ..., N$, N being the number of countries, and $t = 1, ..., T$. α_i stands for country fixed effects, ΔB_t denotes the biofuel price index expressed in first logarithmic difference, P_t is the price of oil expressed in logarithm that acts as a transition variable, F is a transition function, $X_{i,t}$ is a vector of control variables, and $\epsilon_{i,t}$ is an independent and identically distributed error term. To assess the impact of the price of oil on the biofuel price - current account relationship, we consider that only the biofuel price varies according to the level reached by the price of oil.

The transition function F is bounded between 0 and 1, and is expressed as:

$$F\left(P_t;\gamma,c\right)=\left[1+\exp\left(-\gamma\prod_{l=1}^{m}\left(P_t-c_l\right)\right)\right]^{-1} \tag{3.2}$$

γ ($\gamma>0$) denotes the slope parameter and $c_l, l=1,...,m$ ($c_1\leq c_2\leq ...\leq c_m$), are the threshold parameters. From an empirical point of view and as mentioned by *Gonzales et al.* (2005), it is sufficient to consider only the cases of $m=1$ (logistic) or $m=2$ (quadratic logistic) to capture the nonlinearities due to regime switching.[14]

Depending on the value reached by the price of oil, the link between the current-account position and the biofuel price is given by a continuum of parameters, namely β_0 in the first regime (when $F(.)=0$) and $\beta_0+\beta_1$ in the second regime (when $F(.)=1$). In other words, depending on the level of the price of oil, a biofuel price change has a different effect—that varies across countries and over time—on the current account dynamics.

Put it differently and as stressed above, the existence of this continuum of parameters allows us to deal with both heterogeneity and stability issues. This advantage of the PSTR specification however requires some caution when interpreting the slope coefficients in the two extreme regimes. Indeed, the coefficients are not directly interpretable in the sense that marginal effects have to be calculated, namely:

[14]Note that the PSTR model can be extended to r regimes, with $r>2$ (see *Gonzales et al.*, 2005).

$$\frac{\partial \Delta CA_{i,t}}{\partial \mathrm{B}_t} = \beta_0 + \beta_1 \times F(P_t; \gamma, c) \tag{3.3}$$

It is also worth mentioning that our PSTR specification is not dynamic, in the sense that it does not include an autoregressive structure – a characteristic that led *Fok et al.* (2005) to introduce the PSTAR model. While the latter specification has the advantage of being dynamic by including lagged values of the dependent variable as regressors, this benefit is counterbalanced by the well known complications related to the estimation of dynamic panel data models when the time dimension T is fixed and finite. As we are precisely in the case where T is quite weak, this justifies our choice to not introduce an autoregressive structure in our specification.

Following the methodology used in the time series context, *Gonzales et al.* (2005) suggest a three step strategy to apply PSTR models: (i) specification, (ii) estimation, (iii) evaluation and choice of the number r of regimes. The identification step aims at testing for homogeneity against the PSTR alternative and at selecting (i) between the logistic and logistic quadratic specification of the transition function—i.e., the appropriate order of m—and (ii) the transition variable as the one that minimizes the associated p-value. Then, if the nonlinearity hypothesis is retained, nonlinear least squares are used in the estimation step to obtain the parameter estimates once the data have been demeaned (see *Hansen*, 1999; and *Gonzales et al.*, 2005). Finally, various misspecification tests are applied in the third step to check the validity of the estimated PSTR model and determine the number of regimes r.

3.4 Results

We start by testing the linearity hypothesis in Equation (3.1) using the *Gonzales et al.* (2005) test with the price of oil (in logarithm) as the transition variable. Results are reported in Table 3.3 for the following panels of countries whose composition is given in Table 3.2: the whole panel including our 16 considered countries, the panel of 11 producing countries, the sample of 7 exporting countries, and the panel of 12 importing countries.

Table 3.3: Linearity tests (p-values)

	LM	F	LR
Whole sample	0.02**	0.03**	0.02**
Producing countries	0.05*	0.08*	0.05*
Exporting countries	0.04**	0.06*	0.04**
Importing countries	0.26	0.30	0.26

Note: This table reports the results of Lagrange multiplier (LM), F-type (F) and likelihood ratio (LR) tests for linearity. Null hypothesis: linear model. Alternative hypothesis: PSTR model with two regimes (r=1). *** (resp. **, *): rejection of the null hypothesis at the 1% (resp. 5%, 10%) significance level.

Results in Table 3.3 indicate that the null of linearity is rejected in favor of the alternative of logistic PSTR specification for all panels except importing countries. The latter result regarding importers may be related to the policies implemented in some of those importing economies.

In Asia (China, India, and Indonesia for example), governments introduced specific measures after the 2007-2008 peak in commodity prices in order to protect domestic markets from inflation pressures. In China, a mix of temporary economic tools regarding import tariffs or the cancellation of VAT rebate on exports for specific agricultural products was implemented until 2007 to stabilize the domestic market (*Jones and Kwiecinski*, 2010). As an illustration, soybeans' import tariff was divided by 3 and the 13% rebate on ethanol, soybeans and grains exports was eliminated. In India, import tariffs for maize (resp. vegetable oil) reduced from 50% to zero (resp. 80% to zero) till 2007. Indonesia applied the same kind of fiscal tools regarding soybeans (reduction of import tariffs from

10% to zero) and palm oil (restriction of exports). All those measures could have limited the current-account deterioration with the reduction of international price pressures in the domestic market, thus explaining the absence of nonlinearities on the biofuel price impact on the current account in importing countries.[15]

Table 3.4: Transmission of world commodity prices to the domestic market: Elasticity of price transmission (2003–2006 and 2003–2009)

	2003-2006	2003-2009
China, soybean	0.95	0.38
India, soybean	1.40	0.56
Indonesia, wheat	3.05	0.46

Source: *Jones and Kwiecinski* (2010).

Turning to the three other panels, in the whole sample as well as in commodity-producing and -exporting countries, fluctuations in the price of biofuels impact the current account differently, depending on the level reached by the price of oil. Let us now proceed to the estimation of the PSTR models to investigate this property more deeply.

Table 3.5 reports the estimation of our PSTR model (Equation (3.1)) using the price of oil as the transition variable for the three panels of countries for which the null hypothesis of linearity has been rejected.[16]

Let us first briefly comment the results concerning the control variables. For the whole sample, the effect of (lagged) NFA to GDP ratio ($NFA(-1)$) on the current account is negative. This result may be seen as quite surprising at a first sight. Indeed, countries experiencing large net foreign asset positions also have large current account

[15] As illustrated in Table 3.4, elasticities of international price transmission have indeed strongly decreased across the two considered periods reaching values less than unity.

[16] To save space, results of the corresponding misspecification tests are not reported, but are available upon request to the authors. All the estimated models displayed in Table 3.5 have successfully passed the tests (parameter constancy, no remaining heterogeneity).

surpluses. An increase in the net foreign asset position tends to augment income issued from foreign direct investments, improving the current account. However, a second, contradictory effect has to be accounted for: countries displaying large net foreign asset positions are able to undergo long-lasting trade deficits while remaining solvent. In our case, this effect tends to dominate the previous one, explaining the negative link between net foreign asset and current-account positions (*Allegret et al.*, 2014). An additional interpretation is provided by *Chinn and Prasad* (2003). According to the authors, from an intertemporal perspective, a country that experiences a significant stock of net foreign liabilities relative to its GDP has to run trade balance surpluses to pay off its liabilities or, at least, to run smaller current account deficits to stabilize its net foreign liabilities to GDP ratio. As a consequence, the expected relationship between the net foreign asset position and the current account is negative. Population (POP) positively affects the current account, while the dependency ratio has a negative impact. As recalled by *Allegret et al.* (2014), this result could be related to the life-cycle hypothesis: a rise in the dependency ratio tends to exert a negative effect on aggregate domestic saving, affecting in turn negatively the current-account position.

Consistent with the Harberger-Laursen-Metzler effect (see *Bouakez and Kano*, 2008), we find that terms of trade (TOT) and current account are positively linked: if income increases more than spending following an improvement in terms of trade, the current account will automatically improve. Openness has a negative influence on the current account for exporting countries. Given that our sample of exporters mainly contains emerging countries, this result is in line with those generally obtained in the literature for such economies (*Chinn and Prasad*, 2003; *Cheung et al.*, 2013; and *Allegret et al.*, 2014). The underlying idea is that openness lifts trade barriers favoring flows of goods and services and foreign direct investments, making those countries more attractive to foreign capital and increasing investment opportunities. Consequently, the relationship between openness and the current account is negatively signed.

Table 3.5: PSTR estimation results

	Whole sample		Producing countries		Exporting countries	
	Regime 1	Regime 2	Regime 1	Regime 2	Regime 1	Regime 2
ΔB	0.19***	-0.18**	0.21**	-0.20*	0.24***	-0.22**
$NFA(-1)$	-0.12***		-0.01		-0.01	
Openness	0.01		0		-0.11*	
Dependency	-0.17*		0.05		0	
TOT	0.11***		0.09*		0	
$GDP\ PPP$	-0.02		0.02		-0.05	
$M2$	0.09		0.10		-0.05	
POP	0.15***		0.13**		0.05	
c	4.09 (60\$)		4.03 (56\$)		3.81 (45\$)	
γ	5.92		7.70		3.36	
Hausman test stat.	33.35		22.94		18.73	
(Hausman p-value)	(0.00)		(0.00)		(0.00)	

Note: This table reports the estimation of PSTR models (Equation (3.1)). *** (resp. **, *) denotes significance at the 1% (resp. 5% and 10%) level based on robust standard errors (i.e., corrected for heteroskedasticity and autocorrelation). Hausman's specification test: (i) null hypothesis: difference in coefficients not systematic (random effects model); (ii) alternative hypothesis: difference in coefficients systematic (fixed effects model).

It is worth mentioning that GDP per capita, adjusted by PPP exchange rates, relative to the United States ($GDP\ PPP$) is never significant. This finding is in accordance with *Chinn and Prasad* (2003), *Cheung et al.* (2013) and *Allegret et al.* (2014), and can be explained through the stage of economic development of our countries relative to the United States. Indeed, some countries are at early stages of development with a corresponding negative effect on the current account, while others have reached higher levels of development with an associated positive impact on the current-account position. On the whole, the coefficient of the variable is found to be non-significant due to the compensation of negative and positive effects. Finally, our findings show that financial depth, proxied by the ratio $M2/GDP$ ($M2$), has no significant effect on the current-account position. This result is not surprising given our panel of countries, which are economies characterized by a weak developed financial system.

Let us now turn to our main variable of interest, namely the price of biofuels. Our PSTR estimations show that, overall, the current-account position is positively affected by the price of biofuels.[17] The intensity of such impact is nonlinear, depending on the level reached by the price of oil. For the three samples of countries, when the price of oil is low (Regime 1), the biofuel price impact is positive with a coefficient amounting to about 0.20. In other words, a 10% increase in the price of biofuels leads to a current-account improvement of 2%. As expected, this effect is higher and more significant for exporting countries than for producing economies. Indeed, exporters' current account is directly affected by our biofuel price index *via* the price of agricultural commodities exported. Given the construction of our producers' panel—which mainly includes exporters—we obtain a similar, but weaker effect for this group of countries. The biofuel impact on the current account differs in the second regime. Indeed, in this regime characterized by a price of oil higher than 60 US dollars per barrel for the whole sample, fluctuations in the price of biofuels no longer affect the current-account position when $F(.) = 1$. The threshold c after which the price of biofuels has no significant effect at this value of the transition function varies across groups, being equal to 56 US dollars per barrel for producers and 45 US dollars per barrel for exporters.

A possible explanation for these results is the following. For the group of exporting countries, when the price of oil is low, positive variations in the price of commodities used in biofuel production translate into an improvement in terms of trade which, in turn, positively impact the current account. When the price of oil tends to increase, it exerts a negative impact on the trade balance of exporters which are crude oil importers due to the rise in the corresponding country's import spending for crude oil (see Table 3.6 for an illustration). On the whole, the current account, under these conditions, is pulled by two opposite forces making its overall reaction to biofuel price changes moderate or even negligible.

Turning to the group of producing countries, which comprises oil exporters (such

[17] It is worth mentioning that we have also estimated our model lagging the price of biofuels. The results (available upon request to the authors) were very similar, highlighting the robustness of our findings to endogeneity issues.

as Mexico, Nigeria, Sudan to name a few), positive variations in the price of biofuels increase the trade-off between biofuel and oil when the price of oil is low. Higher prices of biofuels increase the demand for oil, thus benefiting oil exporters. As a result, the impact on the current account is positive.

Table 3.6: Oil and petroleum products' balances, in million barrels per day (2004-2014)

	Oil	Petroleum products
Argentina	-0.1121	-0.0393
Brazil	0.1473	0.2272
China	4.5562	0.4541
India	2.3620	-0.6389
Indonesia	0.4613	0.4094
Mexico	-1.1697	0.4091
Thailand	0.6653	-0.1329

Note: This table reports the mean oil balance and the mean petroleum products' balance over the 2004-2014 period. A positive (resp. negative) sign indicates that the concerned country is importer (resp. exporter) over the considered period. Source: ENERDATA.

Considering finally the whole sample, as it includes both mechanisms, the biofuel price impact on the current account is weakened, and the threshold oil price value is higher.

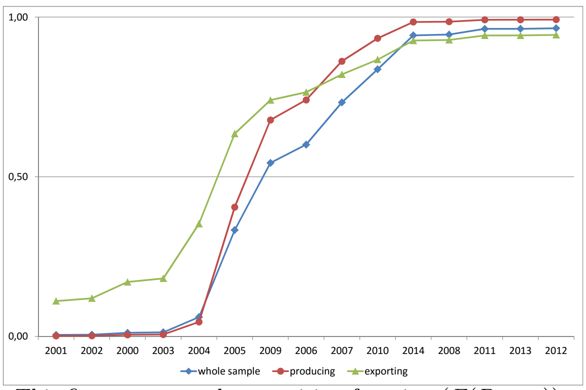
For the sake of completeness, Figure 3.4 displays the transition functions.[18] As shown, Regime 2 occurred more often during the covered period, especially for exporting countries. It is worth noticing that, for our three estimated models, Regime 1 corresponds to the 2001-2005 period when biofuel commodities had a low correlation with the price of oil.

Finally, it should be emphasized that our analysis relies on the conventional, i.e., structural approach of the current account, in the spirit of *Debelle and Faruqee* (1996) and *Chinn and Prasad* (2003) among others. As previously described, this approach

[18] It should be mentioned that when representing these functions, the x axis generally reports the values of the transition variable. Here, the x axis refers to the year of the corresponding values.

is based on a saving-investment perspective to motivate the choice of current-account structural determinants which are included in our empirical specification. Razin (1993) and Obstfeld and Rogoff (1996) have proposed an alternative framework, known as the intertemporal approach to the current account. Such setting extends dynamic optimizing models to the open economy context, and allows to derive some implications in an intertemporal perspective, i.e., in a more dynamic way than ours. Specifically, from a theoretical viewpoint, the underlying model assumes that a representative consumer maximizes a time-separable utility function. Then, changes in the current account position reflect the impacts of shocks hitting consumers' income. In other words, the current account is viewed as a means to smooth consumption when temporary shocks affect consumers' income. As an example, a country facing a negative shock – such as a natural disaster affecting the commodities used in biofuel production – which compromises its production capacity may smooth its effects over time through running current account deficits instead of absorbing its consequences immediately. While our methodology provides interesting findings by accounting for nonlinearity, the intertemporal approach – based on explicit microeconomic foundations – would constitute a promising extension of our structural analysis by complementing it in a dynamic perspective.

Figure 3.4: Transition functions



Note: This figure reports the transition function ($F(P_t; \gamma, c)$) associated with each estimated PSTR model for the three groups of countries. Source: authors' calculations.

3.5 Conclusions and policy implications

Assessing the impact of fluctuations in the price of biofuels on the economy of emerging and developing countries is worthy of investigation. Indeed, many developed economies promote the use of biofuels for environmental concerns and to ensure energy security, leading a to sharp rise in their production or imports since the mid-2000s. First-generation biofuels being produced from agricultural commodities, this huge increase in biofuel production has been accompanied by an acute rise in the price of those raw materials. As a result, such development of biofuels is likely to generate externalities and adverse effects on the economy of emerging and developing countries whose activity strongly depends on agricultural commodities involved in the biofuel production process.

The present chapter tackles this issue by considering a panel of 16 developing and emerging countries which either produce, export or import agricultural commodities used in biofuel production. Following the oil-macroeconomy literature, we focus on the current-account position of the considered countries as the latter is likely to be affected by the sharp rise in the price of the involved agricultural commodities.

Acknowledging that oil is a key input in agricultural production processes, changes in its price obviously affect agricultural commodities prices. We specifically account for this characteristic by investigating whether the biofuel price-current account relationship depends on the value reached by the price of oil. To this end, we rely on the estimation of a panel smooth-transition regression model in which the biofuel price-current account nexus is allowed to vary depending on whether the price of oil is low or high.

Considering the 2000–2014 period, our findings show that a rise in the biofuel price tends to improve the current-account position for agricultural commodity-producing and -exporting countries. However, this impact is nonlinear, depending on the level reached by the price of oil. Specifically, we find that for low values of the price of oil – i.e., below 60 US dollars per barrel for our whole panel of countries –, a 10% increase in the price of biofuels leads to a significant current-account improvement of about 2%. When the price of oil increases to exceed 56 US dollars per barrel for producers and 45 US dollars for exporters, the effect of fluctuations in the price of biofuels on the current account tends to decrease until becoming non significant. For commodity exporters which are also oil importers, these findings illustrate that, when the price of oil increases, the current account is pulled by two opposite forces, making its overall reaction moderate or even nil.

On the whole, our findings put forward the importance of accounting for the effect of the price of oil in designing policies to promote the use of biofuels. In particular, while an increase in the biofuel price is benefit for commodity-exporting countries in a low oil price regime, it is no more the case in high oil price states. With regard to the "food *versus* fuel" debate, sharp increase in the price of biofuels coupled with strong rise in the price of oil are likely to exert important detrimental effects on the economy of agricultural commodity-exporting countries.

The results presented in this chapter provide useful implications in a medium-run perspective, as guided by our structural approach. A promising extension would be to enlarge this analysis in a more dynamic way, by adopting an intertemporal perspective. Indeed, relying on the intertemporal approach to the current account would allow us to have a better understanding of the dynamic effects on the current account position of various shocks – with different degrees of persistence – and to derive relevant policy implications.

Bibliography

Abbott, P. C. and Borot de Battisti, A. (2011). Recent global food price shocks: Causes, consequences and lessons for African governments and donors. *Journal of African Economies*, 20(Supplement 1):i12–i62.

Abbott, P. C., Hurt, C., and Tyner, W. E. (2011). What's driving food prices in 2011? *Farm Foundation Issue Report*.

Allegret, J.-P., Couharde, C., Coulibaly, D., and Mignon, V. (2014). Current accounts and oil price fluctuations in oil-exporting countries: The role of financial development. *Journal of International Money and Finance*, 47(C):185–201.

Baffes, J. (2007). Oil spills on other commodities. *Resources Policy*, 32(3):126–134.

Baffes, J. (2010). More on the energy/nonenergy price link. *Applied Economics Letters*, 17(16):1555–1558.

Berument, M. H., Sahin, A., and Sahin, S. (2014). The relative effects of crude oil price and exchange rate on petroleum product prices: Evidence from a set of Northern Mediterranean countries. *Economic Modelling*, 42(3):243–249.

Bouakez, H. and Kano, T. (2008). Terms of trade and current account fluctuation: The Harberger-Laursen-Metzler effect revisited. *Journal of Macroeconomics*, 30(1):260–281.

Brissimis, S., Hondroyiannis, G., Papazoglou, C., Tsaveas, N., and Vasardini, M. (2012).

Current account determinants and external sustainability in periods of structural change. *Economic Change and Restructuring*, 45(1):71–95.

Calderon, C., Chong, A., and Loayza, N. (2002). Determinants of current account deficits in developing countries. *The B.E. Journal of Macroeconomics*, 2(1):1–22.

Calderon, C., Chong, A., and Zanforlin, L. (2007). Current account deficits in Africa: Stylized facts and basic determinants. *Economic Development and Cultural Change*, 56:191–221.

Chakravorty, U., Hubert, M.-H., and Marchand, B. U. (2015). Food for fuel: The effect of the U.S. biofuel mandate on poverty in India. Discussion paper.

Cheung, C., Furceri, D., and Rusticelli, E. (2013). Structural and cyclical factors behind current account balances. *Review of International Economics*, 21(5):923–944.

Chinn, M. D. and Ito, H. (2007). Current account balances, financial development and institutions: Assaying the world "saving glut". *Journal of International Money and Finance*, 26(4):546–569.

Chinn, M. D. and Ito, H. (2008). Global current account imbalances: American fiscal policy versus East Asian savings. *Review of International Economics*, 16(3):479–498.

Chinn, M. D. and Prasad, E. S. (2003). Medium-term determinants of current accounts in industrial and developing countries: An empirical exploration. *Journal of International Economics*, 59(1):47–76.

Ciaian, P. and Kancs, d. (2011). Interdependencies in the energy-bioenergy-food price systems: A cointegration analysis. *Resource and Energy Economics*, 33(1):326–348.

Criqui, P. and Mima, S. (2012). European climate-energy security nexus: A model based scenario analysis. *Modeling Transport (Energy) Demand and Policies*, 41:827–842.

Debelle, G. and Faruqee, H. (1996). What determines the current account? A cross-sectional and panel approach. IMF Working Papers 96/58, International Monetary Fund.

Fok, D., van Dijk, D., and Franses, H. P. (2005). A multi-level panel STAR model for US manufacturing sectors. *Journal of Applied Econometrics*, 20(6):811–827.

Gohin, A. and Chantret, F. (2010). The long-run impact of energy prices on world agricultural markets: The role of macro-economic linkages. *Energy Policy*, 38(1):333–339.

Gonzales, A., Terasvirta, T., and van Dijk, D. (2005). Panel smooth transition regression models. Research Paper Series 165, Quantitative Finance Research Centre, University of Technology, Sidney.

Gruber, J. W. and Kamin, S. B. (2007). Explaining the global pattern of current account imbalances. *Journal of International Money and Finance*, 26(4):500–522.

Hansen, B. E. (1999). Threshold effects in non-dynamic panels: Estimation, testing, and inference. *Journal of Econometrics*, 93(2):345–368.

IEA (2010). Sustainable production of second generation biofuels. Technical report.

Jones, D. and Kwiecinski, A. (2010). Policy responses in emerging economies to international agricultural commodity price surges. OECD Food, Agriculture an Fisheries Papers 34, OECD Publishing.

Khanna, M. and Crago, C. L. (2012). Measuring indirect land use change with biofuels: Implications for policy. *Annual Review of Resource Economics*, 4(1):161–184.

Khanna, M., Onal, H., Chen, X., and Huang, H. (2008). Meeting biofuels targets: Implications for land use, greenhouse gas emissions and nitrogen in Illinois. Environmental and Rural Development Impacts Conference, October 15-16, 2008, St. Louis, Missouri 53491, Farm Foundation, Transition to a Bio Economy Conferences.

Obstfeld, M. and Rogoff, K. (1996). *Foundations of International Macroeconomics*, volume 1. The MIT Press, 1 edition.

OECD (2008). Rising food prices causes and consequences. Policy brief, Organisation for Economic Co-operation and Developmen.

Paris, A. (2018). On the link between oil and agricultural commodity prices: Do biofuels matter? *International Economics*. (forthcoming).

Razin, A. (1993). The dynamic-optimizing approach to the current account: Theory and evidence. NBER Working Papers 4334, National Bureau of Economic Research, Inc.

Thompson, P. B. (2012). The agricultural ethics of biofuels: The food vs. fuel debate. *Agriculture*, 2(4):339–358.

Yang, J., Xu, M., Zhang, X., Hu, Q., Sommerfeld, M., and Chen, Y. (2011). Life-cycle analysis on biodiesel production from microalgae: Water footprint and nutrients balance. *Bioresource Technology*, 102(1):159–165.

4

Citizens in energy transition: Analyzing the case of biofuels acceptance in France

[This chapter is co written with Benoît Chèze, Pascal Gastineau and Pierre-Alexandre Mahieu]

4.1 Introduction

The French transportation sector is currently facing several major challenges: (i) increasing its energy efficiency, (ii) reducing its environmental footprint, in particular by lowering its dependence on fossil fuels, and (iii) integrating the notion of sustainable development.

The transportation sector accounts for 34% of the final energy consumed in France, 92% of which comes from petroleum products in 2015.[1] Oil is a non-renewable resource, and France imports all the oil it consumes. To that extent, policy makers attempt to diversify the transportation sector energy supplies in order to ensure its long-term independence from oil. Turning to environmental concerns, 26.4% of national greenhouse gas (GHG) emissions in 2015 were due to the transportation sector (excluding land use changes), making it the biggest emitter of GHGs at the French level. Road transport of goods or passengers represents more than 95% of these emissions. The implementation of renewable energies in the transportation sector is therefore all the more relevant as their expansion allows France to earn a double dividend by reducing the volume of fossil fuels imported in parallel with environmental objectives (*Criqui and Mima*, 2012). In addition to GHGs, the transportation sector is also one of the main contributor to the emissions of particulate matter (both $PM_{2.5}$ and PM_{10}), Polycyclic aromatic hydrocarbons ($PAHs$), copper, lead, or nitrous oxides.

Renewable fuels are one of the energy transition technologies considered by policy makers to decarbonize the transportation sector. Since 2006, their consumption has been multiplied by five in France. However, biofuels actually used are first-generation biofuels coming from agricultural crops as rapeseed or sugarbeet. The use of agricultural raw materials for their production has largely called into question their sustainability. In-

[1]All these data come from Odyssee concerning energy and UNFCCC GHG profiles for emissions.

deed, these biofuels induce an additional demand for agricultural raw materials initially devoted to food, inducing at the same time a competition on the uses with the food (and thus potentially a rise of the corresponding prices) leading to the "food *versus* fuel" debate,[2] but also a competition on the uses of arable land and uses of water for irrigation. Several pathways exist to limit the environmental consequences of the transportation sector without using agricultural raw materials. One is the development of new types of biofuels, also called second-generation biofuels, mainly relying on lignocellulosic biomass[3] or agricultural residues. In this regard, the “food *versus* fuel" debate leads to the adoption of the EU directive 2015/1513 to limit the use of first-generation biofuels to 7% of the final consumption of energy in the transportation sector by 2020.[4]

This support for second-generation biofuels is motivated by better score in GHG emissions reduction from Life Cycle Analysis (LCA) (*Edwards et al.*, 2014) and a lower impact on agricultural prices. While second-generation biofuels have these advantages compared to the first generation, they provide less opportunities for the agricultural sector and have higher production costs. Note that effect of the second-generation biofuels on agricultural prices and agricultural activities could vary among feedstock used. Agricultural residuals-based biofuels can provide agricultural opportunities by valuing co-products without any impact on food prices. Energy crop-based biofuels can also provide agricultural opportunities by using “marginal” land for energy crop production (*McElroy and Dawson*, 1986). But they may yield to a rise in food prices, especially if energy crops used are in competition with food crops.[5] On the contrary, wood residuals-based biofuels do not lead agricultural support and risk in food prices. The citizens' biofuels acceptance and the purchasing behavior of consumers could thereby depend on

[2]In particular, it deals with the role of biofuels in the large increase in agricultural commodity prices during the 2000's, see, e.g., *OECD* (2008), *Nazlioglu* (2011), *Nazlioglu and Soytas* (2012) and *Paris* (2018).

[3]Biomass-based biofuels can be produced from wood residuals or energy crops as switchgrass or jatropha.

[4]Note that this limit will also concern biofuels produced from energy crop grown on agricultural land, except under specified conditions.

[5]The interaction between the dedicated energy crop and food prices would depend on the definition of “marginal” land, for example in terms of economic output or reduced crop yield potential, unsuitability for food crop production among others (*Wilson et al.*, 2014).

their preferences between the different characteristics of these two generations of biofuels, i.e., their respective advantages and disadvantages.

Despite their increasing role in the transportation sector, the general public has low knowledge about biofuels (*Van de Velde et al.*, 2009; *Pacini and Silveira*, 2011; *Aguilar et al.*, 2015) and fuel-cell vehicles are seen as a better technology to replace fossil-fuel vehicles (*Petrolia et al.*, 2010; *Aguilar et al.*, 2015). However, according to various studies (e.g., *Solomon and Johnson*, 2009; *Van de Velde et al.*, 2009; *Farrow et al.*, 2011; *Johnson et al.*, 2011; *Dragojlovic and Einsiedel*, 2015) citizens have a rather positive opinion about biofuels in term of environmental benefits but prefer biofuels from non-edible feedstock (*Jensen et al.*, 2010; *Farrow et al.*, 2011; *Delshad and Raymond*, 2013; *Aguilar et al.*, 2015; *Dragojlovic and Einsiedel*, 2015). Note that wood residuals-based biofuels are not always considered as environmentally friendly due to the problem of deforestation (*Jensen et al.*, 2010) but it does not in *Farrow et al.* (2011). Finally, people see the decrease of energy dependency as one of the main advantages of biofuels (*Ulmer et al.*, 2004; *Jensen et al.*, 2010; *Farrow et al.*, 2011; *Jensen et al.*, 2012).

Aiming at investigating these topical issues, this chapter uses a Discrete Choice Experiment (DCE) to analyze the preference structure of French citizens about biofuels depending on their main characteristics: (i) the opportunities for the agricultural sector of the domestic economy, (ii) the ability to reduce GHG emissions of the transportation sector and (iii) the impact on the food prices. While Contingent Valuation methods (CV) allow to estimate a global willingness to pay (WTP), the DCE approach is able to disentangle WTPs by biofuels characteristics, named attributes. A payment vehicle is necessary to estimate these WTP. We choose to introduce a new tax paid by all French citizen and reused specifically to develop new biofuels. By this, we allow each citizen to finance the development of new biofuels and finally to fight against climate change. We also provide marginal rates of substitution (MRS) between the impacts on citizens' utility of the "agricultural support" and "the food prices increase" attributes. These MRS are proposed to investigate the citizens trade-off between these two attributes in the "food *versus* fuel" debate.

To our knowledge, this study is the first to apply a stated preference method to the case of biofuels in France. Contrary to the bulk of the literature in the field, we are not interested in the extra fuel-price that consumers are willing to pay for the development of biofuels. The DCE presented here rather proposes to investigate citizens' preferences for supporting, or not, the financing of a biofuel deployment policy to sustain the decarbonization of the transportation sector. This seems relevant given the objectives that France has to achieve in terms of GHG reduction on the one hand, and in terms of biofuels consumption on the other hand. In 2016, France is the fifth largest producer of biofuels in the world (2nd in Europe after Germany) according to data coming from US Energy Information Administration. Moreover, we go further than previous literature by highlighting spatial preference heterogeneity in biofuels acceptance. Our main results can be summarized as follows. A new tax to encourage the development of biofuels could be accepted by almost two-thirds of the French population. In addition, a potential risk of food prices increase is homogeneously seen as a disadvantage; revealing a strong preference for second-generation biofuels. However, regarding the "agricultural support" and the "reduction in GHG emissions" attributes, the French population preferences appear to be heterogeneous: two-thirds of respondents have higher WTP for both attributes than the other third. Combined with other results presented in this chapter, finding tends to highlight a strong preference for second-generation biofuels based on agricultural residuals in the French population.

The rest of the chapter is organized as follows. Section 4.2 reviews the literature regarding WTP estimations about biofuels. Section 4.3 describes our methodology. Results are presented in Section 4.4, and Section 4.5 provides some discussion. Section 4.6 concludes the chapter.

4.2 Literature review

Let us start by reviewing the literature based on CV methodology. *Savvanidou et al.* (2010) analyze WTP for biofuels compared to fossil fuels in Greece with a CV survey and conclude to a mean premium of 0.079€ per liter. *Petrolia et al.* (2010) find a premium in the US between 0.06$ and 0.12$ per gallon for a 10% ethanol blend (E10) compared to gasoline. In addition, they estimate a premium in the range 0.13-0.15 per gallon for a 85% ethanol blend (E85). On the contrary, *Liao and Pouliot* (2016) highlight that consumers in Arkansas, Colorado, Iowa and Oklahoma accept to purchase E85 only if a discount exists in the price compared to E10. Only Californian consumers accept to pay a premium for E85. The lack of willingness-to-pay for biodiesel is also found by *Kallas and Gil* (2015) in Barcelona province.

With a CV survey in Boston, Minneapolis and Portland, *Li and McCluskey* (2017) find a premium of 11% for second-generation biofuels compared to gasoline with a higher WTP for Portland followed by Minneapolis, and then Boston. *Solomon and Johnson* (2009) use the CV analysis in US Midwestern states to estimate the premium attributed to second-generation biofuels from different feedstocks – agricultural residues, municipal solid wastes as well as wood and paper mill residues – compared to gasoline. They find an annual WTP between 252$ and 556$ depending on the treatment of non-respondents. In addition, no difference exists between the three feedstocks proposed.

Turning now to the DCE approach, Table 4.9 in Appendix 4.A presents a summary of the literature about WTP for biofuels using this methodology. *Giraldo et al.* (2010) and *Gracia et al.* (2011) evaluate WTP in Zaragoza (Spain) for biodiesel. They find a WTP of 0.05€ and 0.07€ per liter for biodiesel compared to conventional diesel, respectively. *Jensen et al.* (2010, 2012) estimate preferences in the US between E10 and E85 from different sources. Biofuels from grass provide the higher WTP following by wood and then corn. In addition, WTP is positively correlated with GHG emissions reduction and negatively with the distance of the station (as in *Gracia et al.* (2011) in Zaragoza) and the quantity of biofuels imported. This last result is also found by *Farrow et al.* (2011) in the New England states and *Bae* (2014) in South Korea. The positive impact of GHG emissions reduction is also highlighted by *Susaeta et al.* (2010) for E10. In their studies in Arkansas, Florida and Virginia, they fail to find an impact on preferences of the enhancing biodiversity that can come from wood-based biofuels. Finally, *Aguilar et al.* (2015) find a positive effect of the blend rate in the US – despite some conflicting results according to the econometric model used – and of the energy contents, i.e., the number of miles per gallon. According to their results, consumers prefer corn- and cellulosic-based ethanol compared to ethanol without information about feedstock used. Note that in Barcelona, an increase in bread price accentuates the non-acceptance of biodiesel (*Kallas and Gil*, 2015). Finally, spatial heterogeneity in preferences is found in terms of reduction in GHG emissions (*Susaeta et al.*, 2010) and feedstock used in biofuel production (*Jensen et al.*, 2010, 2012, *Aguilar et al.*, 2015).

4.3 Methodology

4.3.1 Theoretical framework

The choice experiment modeling framework relies on the characteristics theory of value (*Lancaster*, 1966) and the random utility theory (*McFadden*, 1974). According to *Lancaster* (1966), the value of a good is defined by the sum of values of each own characteristics. In a DCE approach, each attribute k provides a utility level for each respondent n and for each alternative i which the respondent is facing. The (indirect) utility $V_{n,i}$ of an alternative $i \in \{1, \dots, I\}$ for respondent $n \in \{1, \dots, N\}$, where I and

N are given, possibly large, finite integers, is derived from the K observable attributes of the alternative, denoted as $X_i = (x_{i1}, \ldots, x_{ik}, \ldots, x_{iK})$, as well as of a set of A social, economic and attitudinal characteristics (socio-economic variables) characterizing the respondent, denoted as $Z_n = (z_{n1}, \ldots, z_{na}, \ldots, z_{nA})$:

$$V_{n,i} = V(X_i, Z_n) \quad \text{for } n = 1, \ldots, N \text{ and } i = 1, \ldots, I \, . \tag{4.1}$$

McFadden (1974) proposes to consider individual choices as a deterministic component and some degree of randomness. Combining these two approaches, the random utility of the i-th alternative for each individual n, $U_{i,n}$, can be divided into a deterministic part, $V_{n,i} = V(X_i, Z_n)$, and a stochastic element, $\epsilon_{n,i}$, capturing the unsystematic and unobserved random element of individual n's choice (*Louviere et al.*, 2000; *Holmes and Adamowicz*, 2003; *Hanley et al.*, 2005):

$$U_{n,i} = V(X_i, Z_n) + \epsilon_{n,i} \tag{4.2}$$

Assuming the rationality of individuals, respondents choose the alternative i from a finite set of alternatives S, also called scenarios in the DCE context, if its utility, $U_{n,i}$, is greater than the utility derived from any other alternatives j, $U_{n,j}$:

$$U_{n,i} > U_{n,j} \Rightarrow V_{n,i} + \epsilon_{n,i} > V_{n,j} + \epsilon_{n,j} \quad \forall\, j \neq i \; ; \; i, j \in S \tag{4.3}$$

The probability to choose the alternative i is thus the same as the probability that the utility of alternative i is greater than the utility of any other alternative (*Adamowicz et al.*, 1998). Following *Train* (2009), the probability that the respondent n chooses the alternative i is:

$$P_{n,i} = P\left\{U_{n,i} > U_{n,j} \quad \forall\, j \neq i; \;\; i, j \in S\right\} \tag{4.4}$$

$$\Leftrightarrow P_{n,i} = P\left\{V_{n,i} + \epsilon_{n,i} > V_{n,j} + \epsilon_{n,j} \quad \forall\, j \neq i; \;\; i, j \in S\right\} \tag{4.5}$$

$$\Leftrightarrow P_{n,i} = P\left\{\epsilon_{n,j} < V_{n,i} - V_{n,j} + \epsilon_{n,i} \quad \forall\, j \neq i; \;\; i, j \in S\right\} \tag{4.6}$$

4.3.2 Survey design and data

The DCE approach allows us to estimate the trade-off between different characteristics, called attributes, under hypothetical scenarios. After discussions with biofuels and fuels experts as well as with fuels consumers having knowledge of biofuels or not, we selected four main attributes: (i) the monetary vehicle, i.e., an annual fiscal contribution during five years, (ii) the support for agricultural sector, (iii) the variation in GHG emissions and (iv) the impact on food prices. We emphasize here our deliberate choice of using an annual fiscal contribution instead of a purchasing fuel-price as "monetary vehicle" attribute. It allows no-vehicle users to also express their preferences to participate, or not, to the development of biofuels and to finally finance an energy transition technology aiming at fighting climate change.[6] GHG emissions reduction is a traditional attribute in DCEs addressing biofuels issues (*Jensen et al.*, 2010; *Susaeta et al.*, 2010; *Farrow et al.*, 2011; *Jensen et al.*, 2012).[7] The two other attributes allow us to distinguish biofuels according to their type (i.e., first- or second-generation) and their underlying feedstock without providing too many information to respondents. Over-solicitation with unnecessary details are discouraged in DCEs (*Bateman et al.*, 2002; *Champ et al.*, 2017; *Johnston et al.*, 2017), in order to avoid (i) investigations of information understanding and (ii) taking into account subjective perceptions (*Johnston et al.*, 2017).

Three usual attributes in DCE analysis about biofuels are omitted in our work to limit the number of attributes. First, we do not include availability of biofuels in gas station. However, we mention to respondents that new biofuels will be available in all gas stations. Second, we do not mention the blend rate of biofuels in fuel to avoid problem of

[6]Note that a similar fiscal contribution exists in France to finance public audiovisual group, French households are thus familiar with this kind of public contribution.

[7]Note that Table 4.9 in the Appendix 4.A provides attributes and levels used by previous DCE on biofuels.

motor compatibility. We provide information to respondents about the compatibility of biofuels in development with all vehicles. Third, we do not incorporate the biofuel price in the experiment as already explained.

Levels for each attribute (see Table 4.1) were selected after discussions with biofuels and fuels experts. These focus groups lead us to specify the “Support for agricultural sector" and the “Impact on food prices" attributes as dichotomous choices – “Yes" or “No" – instead of continuous variables with different quantified levels. Indeed, imprecise or qualitative terms for levels need to be explained in a clearly and comprehensive manner (*Johnston et al.*, 2012), which is difficult to achieve in the case of biofuels. After these discussions, the chosen attributes and levels are:

1. The monetary contribution paid by each household in Euros per year during five years: this attribute is the monetary attribute or cost attribute. The amount varies due to several factors including the biofuels generation, the feedstock used, the blend rate in the traditional fuel, etc. The maximal amount is based on the rounded amount of the audiovisual contribution paid by French citizens. The minimal level of this attributes is low – corresponding to 1.25€ per month – to allow low-income households to contribute without an high impact on their budgetary constraint. This attribute takes the following values: 0€ (only for the status quo), 15€, 50€, 100€, 150€.

2. The support for the agricultural sector: the increase of first-generation biofuels production yields to an additional demand for agricultural commodities used in their production rising agricultural activity. The development of agricultural residuals- or energy crop-based biofuels (second-generation) could also lead to a support for the agricultural sector. On the contrary, development of wood residuals-based biofuels (second-generation) should not have impact on agricultural activity. This attribute is qualitative and is expressed as the existence, or not, of an increase in agricultural activities compared to the situation without new biofuels development

as: "No" (status quo), "Yes".

3. The variation in GHG emissions: the reduction in GHG emissions can vary based on the generation of biofuels developed, the feedstock used, and the blend rate of biofuels in the traditional fuel. Second-generation biofuels provide higher reduction in GHG emissions compared to first-generation biofuels. Levels are based on LCA analysis (*Edwards et al.*, 2014) and depend on various factors mentioned previously. This attribute is expressed in percentage of variation compared to the status quo: 0% (only for the status quo), -5%, -20%, -30%, -50%.

4. The impact on food prices: this attribute indicates how food prices could be impacted by the development of biofuels. Development of first-generation biofuels will lead to an increase in food prices by using additional agricultural commodity in its production. Researches in second-generation biofuels have been encouraged to avoid a food prices increase based on an energetic use of food crops. This attribute is qualitative and is expressed as the existence, or not, of an increase in food prices compared to the situation without new biofuels development as: "No" (status quo), "Yes".

Table 4.1: Attributes and levels used for survey

Attributes	Levels
Monetary contribution	0€ (only SQ); 15€; 50€; 100€; 150€
Support for agricultural sector	Yes; No (SQ)
Emissions variation	0% (only SQ); -5%; -20%; -30%; -50%
Impact on food prices	Yes; No (SQ)

Note: "SQ" refers to levels in the status quo (but also possible in the other options) and "only SQ" concerns levels only possible in the status quo option.

To select the optimal combinations of attributes' levels[8] in choices cards presented to respondents, we use the D-optimality criterion providing ten choices cards.[9] These were randomly blocked to two different blocks containing five choices cards. This first

[8]The total number of scenarios is $4^2 \times 2^2 = 64$. Therefore, we cannot submit all choices to respondents.
[9]The design is done with *dcreate* package for STATA created by Arne Risa Hole.

design has been administrated to a test sample comprising 42 respondents, i.e., 630 observations, to estimate[10] priors used in a second efficient design.

This DCE has been administered in March 2018 thanks to an on-line survey addressed to 997 French people aged 18 years or older. The survey begins with some information about biofuels in terms of actual use, political determination to develop them, their advantages and disadvantages. In addition, we mention the potential impact of responses on political choices to improve consequentiality[11] and incentive-compatible[12] value elicitation (*Herriges et al.*, 2010; *Johnston et al.*, 2017). We also warn respondents about the negative impact of a new tax – with the monetary contribution – on their disposable income. This allows us to reduce the hypothetical bias.[13] We mention that various successive choices will be proposed between two scenarios – A and B – and a status quo option, and used an example of choices card to explain each attributes (see Figure 4.1 for an example of choices card). We also give the number of successive choices tasks to respondents to reduce implications for sequencing (*Bateman et al.*, 2004). We then randomly attribute to each respondent a block of choices set, whose five choices card are given in a randomize order to avoid having a potential declining concentration (last choices) always affecting the same choice set. In addition, we follow the advice of *Börger* (2016) by forcing respondents to stay on each choice task a minimum amount of time before being able to continue the survey. By this, we avoid negative effects of speedy responses. In order to detect protest answers, respondents choosing the status quo in all choice sets were asked the reasons of their choices. Respondents finish survey by responding to social and economic questions allowing us to analyze the impact of these citizens' characteristics on their preferences structure.

[10] These estimations were done with the Conditional Logit model presented in Appendix 4.B.

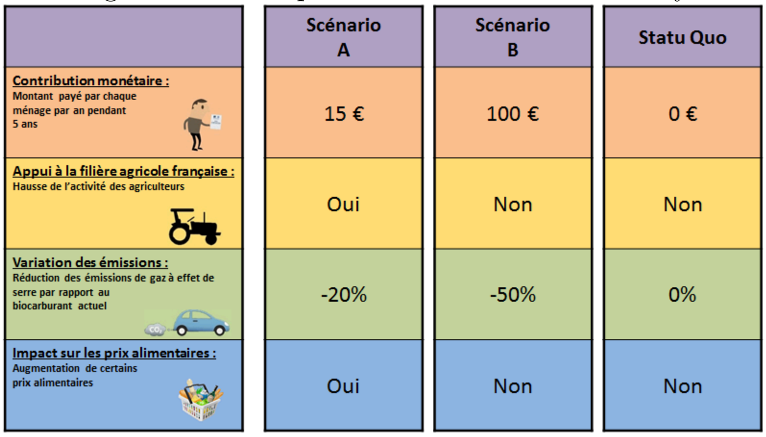
[11] Consequentiality concerns a situation in which a respondent faces or perceives a nonzero probability that her response will influence decisions and that she will have to pay for these decisions if these have a cost. Consequentiality is one necessary but not sufficient condition for incentive-compatibility of value elicitation (*Herriges et al.*, 2010; **?**; *Carson et al.*, 2014).

[12] A mechanism is incentive-compatible when the respondent theoretically has the incentive to truthfully reveal private information asked for by the mechanism (*Carson et al.*, 2014).

[13] The hypothetical bias refers to the possible overestimation of WTP due to the hypothetic characteristic of scenarios.

We identified and removed 23 protest answers among 166 respondents choosing the status quo in all choice sets. The final sample size is thus 972. Its characteristics are presented in Table 4.2 and compared with the results of the last population survey in France provided by the national statistical institute (INSEE). According to Table 4.2, our sample is rather representative of the French population. Note however an under-representation of retired in the sample. This is especially due to a high quantity of retired among the 23 protest respondents removed from the sample. This leads to a highest quantity of workers in our sample than in the French population and potential overestimated WTPs.

Figure 4.1: Example of a choices card for survey



4.3.3 Econometric models

According to equation (4.2), the random utility $U_{n,i}$ is composed of a deterministic component, $V_{n,i} = V(X_i, Z_n)$, and a stochastic element, $\epsilon_{n,i}$. Before estimating an econometric model, one needs to specify the deterministic part of the utility function, $V_{n,i} = V(X_i, Z_n)$. The linear specification is often chosen in the literature as it is the simplest to work with. We thus introduce the column vector of parameters $\beta_n = (\beta_{n1}, \ldots, \beta_{nK})'$, which are the coefficients quantifying the (linear) influence of the

Table 4.2: Selected characteristics of our study sample and the 2014 National Survey

Characteristics	Our sample	2014 Survey
Size	972	-
Gender (% female)	51.0%	51%
Age		
Young (18 to 29)	20.7%	20.6%
Young adult (30 to 44)	28.3%	27.9%
Adult (45 to 59)*	26.1%	28.6%
Old (60 and older)	24.9%	22.9%
Professional activity		
Top socio-professional category**	16.2%	13.7%
Middle socio-professional category**	16.2%	13.7%
Low socio-professional category***	32.2%	27.5%
Retired***	23.1%	32.6%
Inactive	12.2%	12.5%

T-tests test shows significant differences * at 10% significance level; ** at 5% significance level, and *** at 1% significance level.

$K = 4$ attributes on utility, and may be specific to each respondent n.

We also introduce an Alternative Specific Constant (ASC) term to capture the effect of unobserved influences (omitted variables) on the utility function, which is a dummy variable taking the value 1 if none of the hypothetical alternatives is chosen (i.e., the status quo alternative is chosen), and 0 otherwise. Thus, the ASC defines a situation with no creation of a new monetary contribution, no additional support for agricultural sector, no reduction in GHG emissions in the transportation sector and no increase in food prices. A negative and statistically significant coefficient η would indicate strong preferences for moving from the current situation, i.e., to accept a new monetary contribution to finance biofuels development in our case.

Hence, the model is specified so that the probability of selecting a particular biofuels development scenario i is a function of attributes X_i of that alternative, of the alternative specific constant ASC, and of the socio-economic characteristics Z_n of the respondent n.

As the utility $V_{n,i}$ is assumed to be an additive function, equation (4.2) becomes:

$$U_{n,i} = \eta ASC + X_i(\beta_n + \alpha Z'_n) + \epsilon_{n,i} \tag{4.7}$$

where $Z'_n = (z_{1n}, .., z_{An})$ represents the vector of the A socio-demographic characteristics of the n-th respondent. X_i comprises all x_{ik} corresponding to the different level taken by the four attributes "Monetary contribution", "Emissions variation", "Support for agricultural sector" and "Impact on food prices". Note that in our case, "Monetary contribution" is the monetary vehicles allowing us to estimate WTP for each attributes. Thus specified, $\beta' = (\beta_{n1}, \beta_{n2}, \beta_{n3}, \beta_{n4})$ coefficients quantify the influence which the various levels of these attributes have on the utility that citizens associate with the different alternatives available, relative to the utility of the status quo option. The matrix α of size (K, A) is composed of coefficients $\alpha_{i,a}$ capturing the cross-effect of socio-economic characteristic a on attribute i.

The Conditional Logit (CL) model, also called the multinomial logit model, is the workhorse model for analyzing discrete choice data and is widely used in DCEs. Its mathematical specifications are presented in Appendix 4.B. This model has several well-known limitations. An important drawback is that it assumes homogeneous preferences across respondents, meaning that the probability that an agent n chooses alternative i in a choice set S, is considered fixed across all individuals ($\beta_n = \beta$ for all n), while we can expect the preferences to vary among the respondents. Two other important drawbacks are the hypothesis of the independence of irrelevant alternatives (IIA) and uncorrelated unobserved components. IIA implies that the relative probabilities of two options being chosen are unaffected by the introduction or removal of other alternatives (details are provided in Appendix 4.B). If the IIA property is violated then the CL model does not fit the data. Results will be biased, leading to unrealistic predictions, and hence a discrete choice model that does not require the IIA property should be used.

Compared to the CL model, the Random Parameter Logit (RPL) model (*McFadden and Train*, 2000; *Train*, 2009), also called the mixed logit model, releases the IIA hypothesis and is more valuable to take into account the heterogeneity of preferences. Indeed, the preferences parameters β are allowed to vary randomly across respondents allowing for the fact that different decision makers may have different preferences: $\beta_n \neq \beta_m \quad \forall\ n \neq m;\ n,\ m \ \in 1, \ldots, N$. As such, conditional on the individual-specific parameters and error components, we can define the logit[14] probability that respondent n chooses a specific alternative i for a given β:

$$P_{n,i}|\beta = L_{n,i}(\beta) = \frac{e^{V_{n,i}(\beta)}}{\sum_j e^{V_{n,j}(\beta)}} \tag{4.8}$$

Following this, the unconditional choice probability of choosing alternative i is the logit formula in equation (4.8) integrated over all values of β weighted by the density of β:

$$P_{n,i} = \int L_{n,i}(\beta) f(\beta|\Omega) d\beta \tag{4.9}$$

where $f(\beta)$ is the density function for β, describing the distribution of preferences over individuals, and Ω is the fixed parameters of the distribution.[15]

The choice probability in equation (4.9) cannot be calculated exactly because the integral does not have a closed form in general. This integral is approximated through simulations. For a given value of the parameters Ω, a value of β is drawn from its distribution. Using this draw, the logit formula in (4.8) is calculated. This process is repeated for many draws, and the mean of the resulting $L_{n,i}(\beta)$ is taken as the approximate choice

[14] As the error term is assumed to be IID Type I Extreme Value. Note that Appendix 4.B details calculation to obtain its probability.

[15] β is usually assumed to take on a multivariate normal distribution, with mean b and covariance ω where the off-diagonal elements of the covariance matrix are zero. Random parameters are generally supposed to be normally distributed in the RPL model because it is the most easily applied distribution allowing for both negative and positive preferences.

probability yielding equation (4.10):

$$SP_{n,i} = \frac{1}{R}\sum_{r=1}^{R} L_{n,i}(\beta_r) \tag{4.10}$$

where R is the number of draws of β, and SP is the simulated probability that an individual n chooses alternative i.

Another way to relax the IIA hypothesis and to account for heterogeneity in respondents' preferences is to analyze the sample with a Latent Class (LC) model. In the latter, each respondent is sorted into a number of classes C in which preferences are assumed to be homogeneous with respect to attributes. In contrast, preferences are allowed to be heterogeneous between each latent class segment c ($c \in C$).

Compared to equation (4.8), the logit probability that respondent n prefers a specific alternative i over alternatives j is no more defined for a given β but becomes conditional on class c. Indeed, the βs are now assumed to follow a discrete distribution and belong to one class c of C classes. Thus, the conditional probability that respondents who are members of class c choose alternative i is:

$$P_{n,i}|\beta_c = \frac{e^{V_{n,i}(\beta_c)}}{\sum_j e^{V_{n,j}(\beta_c)}}; \quad \forall\ c \in \{1,\ldots,C\} \tag{4.11}$$

where β_c is the vector of preferences parameters specific to each class c, representing the average importance of each attribute for respondents belonging to c.

The unconditional probability of individual n selecting choice option i can be expressed as:

$$P_{n,i} = \sum_{c=1}^{C}(\Pi_{n,c}P_{n,i}|\beta_c) = \sum_{c=1}^{C}\left(\Pi_{n,c}\frac{e^{\beta_c' X_i}}{\sum_j e^{\beta_c' X_j}}\right) \tag{4.12}$$

where $\Pi_{n,c}$ is the probability of membership of respondent n in class c:

$$\Pi_{n,c} = \frac{e^{Z_n'\theta_c}}{\sum_{h=1}^{C} e^{Z_n'\theta_h}} \tag{4.13}$$

where Z_n is the vector of psychometric constructs and socioeconomic characteristics, and θ is the vector of parameters associated to Z_n (*Boxall and Adamowicz*, 2002).

According to equation (4.13), the probability of belonging to a class c with specific preferences is probabilistic, and depends on the social, economic and attitudinal characteristics of the respondents. Combining equation (4.12) and equation (4.13), it comes that the LC model assumes that respondent characteristics affect choice indirectly through their impact on segment membership. Note that θ_c includes $C-1$ class membership parameters with θ_C being normalized to zero for identification. All other coefficients θ_c are thus interpreted relative to this normalized class.

4.4 Results and interpretation

Recall that we aim at analyzing citizen's motivation to reduce GHG emissions in the transportation sector by developing new biofuels. We estimate WTP associated with various biofuel characteristics. The DCE presented in Section 4.3.2 has been conducted among 972 respondents. Therefore, we obtained 4,860 elicited choices (thus corresponding to 14,580 observations).[16]

Table 4.3 presents results for the CL and RPL models. As expected, the RPL model is preferred to the CL specification due to its highest value of the log-likelihood function. Note that applications of the RPL model have shown its superiority in terms of overall fit and welfare estimates (*Lusk et al.*, 2003). Moreover, it is a flexible model able to

[16]As we have 972 respondents with 5 choices cards between 3 alternatives, i.e., $972 * 5 * 3$.

approximate any discrete choice model (*McFadden and Train*, 2000) and relaxes the IIA assumption (*Greene*, 2008). We thus only comment results for the RPL models.[17] Here, ASC coefficient as well as the parameters of "Agricultural support", "Emissions variation" and "Food prices increase" are specified to be normally distributed. Their mean and standard deviation are then estimated by simulations based on 1000 Halton draws. The normal distribution is symmetric and unbounded leading few *a priori* assumptions on respondents' preferences: positive as well as negative parameter values may be taken, in order to capture heterogeneity in the population. The parameter of monetary vehicles is assumed to be constant as usual in the literature (*Hensher and Green*, 2003). For each model, socio-economic variables is used in interaction with "Agricultural support" and "Emissions variation" attributes. They give information on preferences heterogeneity in these attributes.

Let us first comment results from RPL models without socio-economic characteristics. The sign of the ASC coefficient is negative and significant at the 1% level, indicating that respondents value negatively the fact of staying in the status quo situation: respondents thus value positively a tax for biofuels development. As expected, the utility of the biofuel development for the French citizens decreases with the monetary contribution as their disposable income decreases. In addition, each percentage point of reduction in GHG emissions increases the respondents' utility as the associated coefficient is positive. In terms of agricultural support and food prices increase, respondents' utility increases with biofuel production based on agricultural sector but decrease with production leading to an increase in food prices. These findings highlight preferences for second-generation biofuels compared to the first one and are consistent with results in *Jensen et al.* (2010, 2012) and *Farrow et al.* (2011). In addition, there is support for second-generation biofuels coming from agricultural input as agricultural residues and maybe energetic crops. Note that all coefficients' standard deviations are significant, indicating that the RPL model provides a better representation of the choices than a CL model as there is het-

[17] The CL models results are however kept for robustness checks.

erogeneity among respondents around the mean.

Table 4.3: Results of the CL and RPL models

Attributes	CL model	CL model with interact.	RPL model Coefficient	RPL model Std. Deviat.	RPL model with interact. Coefficient	RPL model with interact. Std. Deviat.
Alter. Spec. Constant	-0.189*** (0.053)	-0.191*** (0.053)	-0.891*** (0.120)	2.690*** (0.144)	-0.858*** (0.118)	2.694*** (0.143)
Monetary contribution	-0.011*** (0.000)	-0.011*** (0.000)	-0.016*** (0.001)	- -	-0.016*** (0.001)	- -
Agricultural support	0.451*** (0.042)	0.500*** (0.050)	0.640*** (0.055)	0.472*** (0.132)	0.720*** (0.066)	0.210 (0.290)
In high density area	- -	-0.120* (0.069)	- -	- -	-0.173* (0.104)	0.638*** (0.160)
Emissions variation	0.022*** (0.002)	0.020*** (0.002)	0.028*** (0.003)	0.043*** (0.003)	0.027*** (0.003)	0.045*** (0.003)
In high density area	- -	0.007*** (0.002)	- -	- -	0.012*** (0.004)	- -
For young adult	- -	-0.005** (0.002)	- -	- -	-0.009* (0.005)	- -
Food prices increase	-0.451*** (0.041)	-0.451*** (0.041)	-0.582*** (0.057)	0.634*** (0.112)	-0.600*** (0.059)	0.735*** (0.099)
N (Ind.)	972	972	972		972	
N (Obs.)	14,580	14,580	14,580		14,580	
McFadden R^2	0.065	0.067	-		-	
Log Likelihood	-4,990.93	-4,979.18	-4,187.74		-4,170.27	

Note: Alternative Specific Constant refers to the dummy variable equals to 1 if the status quo is chosen and 0 otherwise. For each variable, the first line concerns the estimated coefficient and the second line (in brackets) displays the standard error. The number of stars, i.e., one, two and three, refers to the 10%, 5% and 1% significance level, respectively. "High density area" concerns city with more than 1,500 population per square kilometers and "Young adult" refers to respondents from 30 to 44 years old.

In the extended RPL model (Table 4.3, two last columns), the negative coefficient of the "young adult" variable indicates that people aged from 30 to 44 are less sensitive than other age classes to the reduction of GHG emissions attributes. This coefficient remains, in absolute value, inferior to the coefficient of the "Emissions variation" attribute (-0.009 and 0.027, respectively). Even for this age class, these results indicate that the reduction of GHG keeps a positive impact on their utility. Regarding now respondents living in a densely populated city ($\geq 1500/km^2$), they are more positively impacted than others by a reduction of GHG emissions. On the contrary, this population of urban citizens appears to be a bit less sensitive than others to the question of supporting the agricultural sector in their preferences. These findings are similar – but not perfectly – with results in *Jensen et al.* (2010, 2012) and *Aguilar et al.* (2015). Compared to these articles, no spatial heterogeneity in preferences is effectively found in terms of French regions. Heterogeneity in preferences is here captured by the localization context, i.e., the city densities. As density of the cities is negatively correlated with the share of agricultural land in the department, this result confirms the idea that local environment in terms of agricultural activity do have an impact on French's preferences for supporting the agricultural sector through biofuels production. Note that this spatial heterogeneity explains all the heterogeneity in preferences as the standard deviation of the "Agricultural support" becomes not statistically significant when including this localization variable. However, some heterogeneity remains among preferences in the "Agricultural support" attribute in high density areas as the standard deviation of this interaction variable is significant.

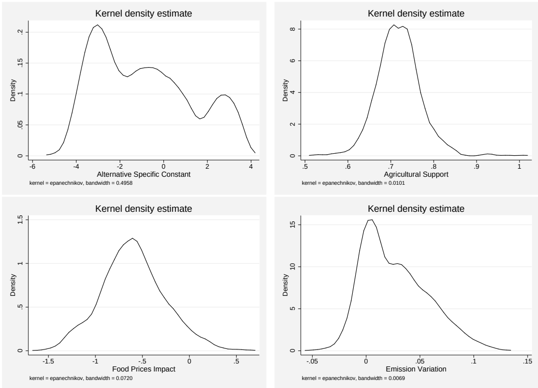
As explained in Section 4.3.3, another way to take into account heterogeneity in respondents' preferences is to analyze the sample with a Latent Class (LC) model. In order to better understand citizen's preferences for the various attributes we thus now try to determine various classes of citizens whom have similar preferences.

Using a kernel density function, Figure 4.2 provides the distribution of the individual coefficients estimated by the RPL model with socio-economic variables.[18] Regarding the "Support for agricultural sector" and the "Impact on food prices" attributes, the distribution of these coefficients appears to be concentrated around a single value. On the contrary, the "Emissions variation" attribute coefficient seems to be distributed around two local maximum, both positive. Finally, there are at least three groups of preferences for the ASC coefficient. This latter point is of great interest with three distinct local maximums: (i) negative, (ii) positive and (iii) null. It tends to indicate that our sample of

[18] The distributions based on the RPL model without socio-economic variables are similar and available upon request to authors.

respondents can be split, at worst, in three distinct groups. A first group of respondents values negatively the fact of staying in the status quo situation (i.e., no development of new biofuels) while the second group values positively this situation. The last group seems to be indifferent among staying in or moving away from the status quo.

Figure 4.2: Kernel density of coefficients with RPL model



Though very useful and often revealing, comments based on graphs are always vulnerable to subjective interpretation and more objective statistical analysis is needed. Another way to choose the number of classes in the LC model is the use of information criterion as Consistent Akaike Information Criterion (CAIC) and Bayesian Information Criterion (BIC) presented in Table 4.4. Despite the three modes in the ASC coefficient distribution, we finally choose two classes due to the higher decrease in information criteria from models with one (CL model) to two classes compared to others.

Table 4.4: Criteria for determining the optimal number of segments

Nb. of classes	Parameters	Log Likelihood	CAIC	BIC
1	8	-4,979	10,043	10,035
2	10	-4,205	8,513	8,500
3	15	-4,027	8,219	8,198
4	20	-3,975	8,178	8,149
5	25	-3,957	8,206	8,169

Results from LC models – with[19] and without socio-economic variables as Segment function – are presented in Table 4.5. The extended model displays utility parameters into two classes: (i) the Class 1 with 65.1% of the respondents and (ii) the Class 2 comprising 34.9% of them. As expected, these two classes differ widely in their preferences: while the first one has a strong utility to move from the status quo, with a negative and significant coefficient of the ASC, the second one has an utility to stay in the current situation. An interesting result from this model is the relative equality in the parameter linked to the GHG emissions reduction. Reduction in GHG emissions affected all respondents' utility in a similar way with preferences parameter of 0.028 and 0.022. Therefore, heterogeneity in respondents' behavior is linked to biofuel development and not to the fight against climate change through reduction in GHG emissions. In addition, a difference between these two classes concerns the "food *versus* fuel" debate. Compared to the Class 1, the second class has a stronger disutility to see an increase in food prices (-1.288, compared to -0.378) and a lower utility for an agricultural support due to a new biofuel development (0.284, compared to 0.552). On the contrary, the negative impact of the food prices on utility seems to be lower than the positive effect of agricultural support on utility for the first Class. Finally, note that respondents living in city with high density are more likely to be in the first class as well as young populations.

4.5 Willingness to pay and marginal rate of substitution

Tables 4.6 and 4.7 present WTP estimates coming from respectively (i) the CL and RPL models results and (ii) the LC models results. As mentioned in the introduction, welfare measures can be determined in the form of marginal WTP by estimating the marginal rate of substitution (MRS) between the considered attribute and income. The marginal utility of income is represented by the cost attribute's coefficient, β_{cost}, which is

[19] Here, age of respondents and density are included as continuous variables.

assumed constant as mentioned before. Here it corresponds to the monetary contribution. As WTP are expressed in the monetary unit, those presented below are thus expressed in Euros by years during five years. Estimates of the WTP values are obtained for each of the non-monetary attributes using the Wald procedure (Delta method).[20] Since utilities are modeled as linear functions of the attributes, the marginal rate of substitution between two attributes is the ratio between the coefficients:[21]

$$WTP_k = -\frac{dx_{cost}}{dx_k} = -\frac{dU/dx_k}{dU/dx_{cost}} = -\frac{\partial V/\partial x_k}{\partial V/\partial x_{cost}} = -\frac{\beta_k}{\beta_{cost}} \tag{4.14}$$

Eq. (4.14) corresponds to the WTP for the attribute k with levels x.

For a LC model, the WTP for the individual n for a variation of the attribute k can be computed per class as

$$WTP_k^c = \Pi_{n,c}^* \left(-\frac{\beta_k^c}{\beta_{cost}^c} \right) \tag{4.15}$$

where c are the latent classes, β_k^c the parameter associated to attribute k for each latent class c, β_{cost}^c the parameter associated to the monetary attributes for each latent class c, and $\Pi_{n,c}^*$ the posterior estimate of the individual-specific class probability of membership of respondents n in class c. For each model, the estimated standard deviations and confidence intervals around the mean of the WTP estimates are obtained using the Krinsky and Robb parametric bootstrapping method (*Krinsky and Robb*, 1986).

To gain more insights into the extent to which respondents take place in the "food *versus* fuel" debate, we provide the MRS between "Impact on food prices" and "Support for agricultural sector" attributes. This MRS allows us to analyze the willingness to offset food price increasing with agricultural supporting and is calculated as:

[20]The Delta method stipulates that the WTP for a unit change of a given attribute can be computed as the marginal rate of substitution between the quantity expressed by the considered attribute and the cost attribute (*Louviere et al.*, 2000).

[21]It should be noted that the derivative of the unobserved part of the utility function is supposed to be zero with respect to both attributes.

$$MRS_{a,f} = -\frac{\beta_a}{\beta_f} \tag{4.16}$$

where β_a and β_f are parameters associated to "Agricultural support" and "Food prices increase" attributes, respectively. A $MRS_{a,f}$ significantly lower (resp. greater) than one indicates a stronger (resp. smaller) preference for the use of non-agricultural (resp. agricultural) commodities in biofuels production.

Table 4.5: Results of the LC model with 2 classes

Attributes	without socio-eco. varia.		with socio-eco. varia.	
	Class 1	Class 2	Class 1	Class 2
ASC	-1.467***	0.512***	-1.464***	0.495***
	(0.091)	(0.162)	(0.090)	(0.162)
Monetary contribution	-0.011***	-0.031***	-0.011***	-0.032***
	(0.001)	(0.002)	(0.001)	(0.002)
Agricultural support	0.554***	0.279**	0.552***	0.284**
	(0.049)	(0.136)	(0.049)	(0.136)
Emissions variation	0.028***	0.022***	0.028***	0.022***
	(0.002)	(0.005)	(0.002)	(0.005)
Food prices increase	-0.377***	-1.302***	-0.378***	-1.288***
	(0.044)	(0.174)	(0.044)	(0.173)
Segment function				
Pop. density	-	-	-	-0.00003**
	-	-	-	(0.00001)
Age	-	-	-	0.0159***
	-	-	-	(0.0048)
Constant	-	-	-	-1.2707***
	-	-	-	(0.2518)
N (Ind.)	633	339	633	339
N (Obs.)	9,495	5,085	9,495	5,085
Class share (%)	65.1	34.9	65.1	34.9
Log Likelihood	-4,214		-4,205	

Note: ASC mentions the Alternative Specific Constant and refers to the dummy variable equals to 1 if the status quo is chosen and 0 otherwise. For each attribute, the first line concerns the estimated coefficient and the second line (in brackets) displays the standard errors. The number of stars, i.e., one, two and three, refers to the 10%, 5% and 1% significance level, respectively. Age of respondents and population density are included as continuous variables.

If we focus on the LC model with socio-economic variables in the Segment function (Table 4.7), results can be interpreted in the following way. French citizens in the first class (resp. second class) of our sample accept to pay 51.59 Euros (resp. 8.98 Euros) per year to finance the development of a new biofuel allowing a support for the agricultural sector. On the contrary, they need to receive in average 35.30 Euros and 40.80 Euros per year to accept an increase in the food prices for the first and the second group, respectively. This result confirms a strong preference for second-generation biofuels, whatever the class under consideration. In addition, French citizens accept to pay in average 2.64 Euros or 0.68 Euro – for the Class 1 and 2, respectively – per year per percentage point of reduction in GHG emissions allowed by the new biofuels. Globally, we note that the risk in food prices increase seems to be a disadvantage in biofuels development for the respondents in the Class 2 with a MRS much lower than one. They are against biofuels produced from agricultural product and would appear to prefer wood residuals-based biofuels. On the contrary, majority of our sample accept to use agricultural products in biofuels production. However, they prefer agricultural residuals-based biofuels in line with its strong and negative WTP concerning the food prices increase.

Table 4.6: WTP estimates with CL and RPL models

Attributes	CL model	CL model with socio-eco. varia.	RPL model	RPL model with socio-eco. varia.
Agricultural support	41.13 [34.75 ; 47.52]	45.57 [37.91 ; 53.24]	40.07 [34.51 ; 45.64]	44.40 [37.69 ; 51.11]
In high density area	- -	-10.94 [-21.34 ; -0.54]	- -	-10.65 [-21.22 ; -0.76]
Emissions variation	1.99 [1.79 ; 2.20]	1.85 [1.60 ; 2.09]	1.77 [1.53 ; 2.01]	1.65 [1.32 ; 1.97]
In high density area	- -	0.67 [0.39 ; 0.95]	- -	0.77 [0.33 ; 1.21]
For young adult	- -	-0.44 [-0.74 ; -0.15]	- -	-0.57 [-1.05 ; -0.08]
Food prices increase	-41.15 [-47.29 ; -35.02]	-41.05 [-47.18 ; -34.92]	-36.42 [-42.20 ; -30.63]	-37.01 [-42.95 ; -31.09]
$MRS_{a,f}$	1.00 [0.82 ; 1.18]	1.11 [0.89 ; 1.33]	1.10 [0.90 ; 1.30]	1.20 [0.97 ; 1.43]

Note: The first line mentions the willingness to pay in Euros per years or the MRS between "Agricultural support" and "Food prices increase". The second line refers to the confidence interval at 90% level.

Table 4.7: WTP estimates with Latent Class models

Attributes	without socio-eco. varia. Class 1	without socio-eco. varia. Class 2	with socio-eco. varia. Class 1	with socio-eco. varia. Class 2
Agricultural support	51.67 [44.12 ; 59.22]	8.93 [1.61 ; 16.24]	51.59 [44.04 ; 59.15]	8.98 [1.75 ; 16.22]
Emissions variation	2.64 [2.38 ; 2.90]	0.71 [0.44 ; 0.98]	2.64 [2.38 ; 2.91]	0.68 [0.42 ; 0.95]
Food prices increase	-35.13 [-41.87 ; -28.39]	-41.63 [-51.83 ; -31.42]	-35.30 [-42.06 ; -28.55]	-40.80 [-50.81 ; -30.79]
$MRS_{a,f}$	1.47 [1.16 ; 1.78]	0.21 [0.05 ; 0.38]	1.46 [1.16 ; 1.76]	0.22 [0.06 ; 0.38]

Note: The first line mentions the willingness to pay in Euros per years or the MRS between "Agricultural support" and "Food prices increase". The second line refers to the confidence interval at 90% level.

Table 4.8: Mean WTP for various biofuels

Biofuels	Agricultural Support	Emission Variation	Food Prices Impact	WTP with RPL model	WTP with LC model
E20 sugar beet	Yes	-10.7%	Yes	22.36	20.48
E85 sugar beet	Yes	-45.4%	Yes	84.56	88.47
E10 wood residuals	No	-7.8%	No	13.98	15.28
E20 wood residuals	No	-15.5%	No	27.78	30.37
E85 wood residuals	No	-65.9%	No	118.13	129.12
E10 wheat straw	Yes	-8.9%	No	56.16	54.18
E20 wheat straw	Yes	-17.9%	No	72.29	71.81
E85 wheat straw	Yes	-75.9%	No	176.26	185.45
B20 rapeseed oil	Yes	-6.8%	Yes	15.37	12.84
B100 rapeseed oil	Yes	-33.8%	Yes	63.77	65.74
B10 wood residuals	No	-9.7%	No	17.39	19.01
B20 wood residuals	No	-19.3%	No	34.60	37.82
B100 wood residuals	No	-96.6%	No	173.16	189.27

Note: WTP come from model with socio-economic variables and are expressed in Euros per year during five years. Reductions in GHG emissions derive from *Edwards et al.* (2014).

Last but not least, WTP estimates presented here allow us to deduce over the French population, the mean WTPs for the development of biofuels from various feedstocks and incorporated in fuels with various blend rates. Table 4.8 presents these results with information about effects on attributes for each biofuel. WTP for high blended biofuels are obviously greater than low blend rates as they provide higher reduction in GHG emissions. However, high blended biofuels – as E85 or B100 – are not suitable as long as existing vehicles cannot accept these kinds of fuels. In addition, biofuels from wheat straw maximizes the WTP of French population by allowing agricultural support without any impact on food prices. This feedstock is followed by wood residuals and then food crops.

4.6 Conclusion

This chapter investigates French population motivations and obstacles to finance new biofuels development in the transportation sector. It uses a quantitative approach based on a Discrete Choice Experiment to measure the relative weight of various biofuels' characteristics in citizens' utility based on a sample of 972 respondents. We value respondents' willingness to pay for several components of their decision such as the agricultural support of a biofuel development, the reduction in greenhouse gas emissions from the transportation sector and the existence of an impact of biofuels development on food prices. Regarding the latter, French behavior towards risk in food prices increase is a potential major component explaining their willingness to accept a tax to finance a new biofuel production.

Using three econometric models, namely the Conditional Logit, the Random Parameter Logit and the Latent Class models, we find that the risk in food prices increase is a prominent obstacle for respondents' fundings of biofuels development. All else being equal, approximatively two-thirds of respondents need to receive in average 35.30 Euros by year to accept an increase in food prices. Other part of French citizens need to receive 40.80 Euros. These two amounts are very close, highlighting a rather clear preference for the development of second-generation biofuels.

Furthermore, the reduction in greenhouse gas emissions that may come along with new biofuels incorporation in the transportation sector is seen by respondents as an important reason to support its development. In particular, two-thirds accept to pay in average 2.64 Euros by year for each percentage point of greenhouse gas emissions reduction, all else being equal. On the contrary, one-third has a lower annual willingness to pay of 0.68 Euros. This difference depends, in part, the age of respondents and on whether or not they are living in high density cities.

Last, the impact of biofuels development on the agricultural sector is a decisive factor for two-thirds of respondents accepting to pay 51.59 Euros to support agricultural sector with biofuels. The second part of French citizens has a weak willingness to pay of 8.98 Euros per year. An heterogeneity in agricultural preferences exists thus among French population and can be explained by population density and thus by local agricultural environment of respondents.

Our results highlight the preference for second-generation biofuels produced by non-food commodities as in *Jensen et al.* (2010, 2012) and *Farrow et al.* (2011). Mores specifically, 65.1% of our sample appears to accept the production of agricultural residuals-based biofuels, whereas a minority, i.e., 34.9%, has a low acceptance for agricultural-based biofuels. These latter could prefer wood residuals-based biofuels or other technologies to reduce greenhouse gas emissions in the transportation sector. Agricultural residuals-based biofuels can thus maximize French population preferences as the wheat straw-based biofuels.

These findings are of great interest for policy makers. Indeed, renewable fuels deployment is an integral part of the public policies mix adopted, both at the national and European level, to decarbonize the transportation sector. But widespread deployment of energy transition technologies will largely depend on the attitudes and preferences of consumers and citizens for these technologies. Regarding biofuels, the “food *versus* fuel" debate clearly dominates the issue of their acceptance by the civil society. In this regard, the EU directive 2015/1513 to limit the use of first-generation biofuels to 7% of the final consumption of energy in the transport sector by 2020 is heading in the right direction.

Based on French citizens' preferences, this chapter comes to the conclusion that it is first the agricultural residuals-based biofuels and then the wood residuals-based biofuels which should be encouraged by policy makers.

Bibliography

Adamowicz, W., Boxall, P., Williams, M., and Louviere, J. (1998). Stated preference approaches for measuring passive use values: Choice experiments and contingent valuation. *American Journal of Agricultural Economics*, 80(1):64–75.

Aguilar, F. X., Cai, Z., Mohebalian, P., and Thompson, W. (2015). Exploring the drivers' side of the blend wall: U.S. consumer preferences for ethanol blend fuels. *Energy Economics*, 49(C):217–226.

Bae, J. (2014). Non-linear preferences on bioethanol in South Korea. *Environmental and Resource Economics Review*, 23(3):515–551.

Bateman, I. J., Carson, R. T., Day, B. H., Hanemann, W. M., Hanley, N., Hett, T., Jones-Lee, M., Loomes, G., Mourato, S., Ozdemiroglu, E., and Pearce, D. W. (2002). *Economic valuation with stated preference techniques: A manual*. Cheltenham: Edward Elgar.

Bateman, I. J., Cole, M., Cooper, P., Georgiou, S., Hadley, D., and Poe, G. L. (2004). On visible choice sets and scope sensitivity. *Journal of Environmental Economics and Management*, 47(1):71–93.

Börger, T. (2016). Are fast responses more random? Testing the effect of response time on scale in an online choice experiment. *Environmental and Resource Economics*, 65(2):389–413.

Boxall, P. C. and Adamowicz, W. L. (2002). Understanding heterogeneous preferences in random utility models: A latent class approach. *Environmental and Resource Economics*, 23(4):421–446.

Carson, R. T., Groves, T., and List, J. A. (2014). Consequentiality: A theoretical and experimental exploration of a single binary choice. *Journal of the Association of Environmental and Resource Economists*, 1(1):171–207.

Champ, P. A., Boyle, K. C., and Brown, T. C. (2017). *A primer on nonmarket valuation.* Amsterdam: Springer Science & Business Media.

Criqui, P. and Mima, S. (2012). European climate-energy security nexus: A model based scenario analysis. *Modeling Transport (Energy) Demand and Policies*, 41:827–842.

Delshad, A. and Raymond, L. (2013). Media framing and public attitudes toward biofuels. *Review of Policy Research*, 30(2):190–210.

Dragojlovic, N. and Einsiedel, E. (2015). What drives public acceptance of second-generation biofuels? Evidence from Canada. *Biomass and Bioenergy*, 75:201–212.

Edwards, R., Hass, H., Larive, J.-F., Lonza, L., Maas, H., and Rickeard, D. (2014). Well-to-wheels report version 4.a. Technical reports, JRC.

Farrow, K., Teisl, M., Noblet, C., McCoy, S., and Rubin, J. (2011). *Economics effects of biofuel production*, chapter Does money grow on trees? People's willingness to pay for cellulosic wood ethanol. InTech.

Giraldo, L., Gracia, A., and Do Amaral, E. (2010). Willingness to pay for biodiesel in Spain: A pilot study for diesel consumers. *Spanish Journal of Agricultural Research*, 8(4):887–894.

Gracia, A., Barreiro-Hurl., and Perez y Perez, L. (2011). Consumers willingness to pay for biodiesel in Spain. 2011 International Congress, 8/30-9/2, 2011, Zurich, Switzerland, European Association of Agricultural Economists.

Greene, W. (2008). *Econometric Analysis.* Prentice-Hall, New Jersey, 6th edition.

Hanley, N., Adamowicz, W., and Wright, R. E. (2005). Price vector effects in choice experiments: an empirical test. *Resource and Energy Economics*, 27(3):227–234.

Hensher, D. and Green, W. (2003). The mixed logit model: The state of practice. *Transportation*, 30(2):133–176.

Herriges, J., Kling, C., Liu, C.-C., and Tobias, J. (2010). What are the consequences of consequentiality? *Journal of Environmental Economics and Management*, 59(1):67–81.

Holmes, T. and Adamowicz, W. (2003). *A primer on nonmarket valuation*, chapter Feature based methods. Kluwer Academic Publishers.

Jensen, K., Clark, C., English, B., and Toliver, D. (2012). Effects of demographics and attitudes on willingness-to-pay for fuel import reductions through ethanol purchases. *Agriculture*, 2(4):165–181.

Jensen, K. L., Clark, C. D., English, B. C., Menard, R. J., Skahan, D. K., and Marra, A. C. (2010). Willingness to pay for E85 from corn, switchgrass, and wood residues. *Energy Economics*, 32(6):1253–1262.

Johnson, D. M., Halvorsen, K. E., and Solomon, B. D. (2011). Upper Midwestern U.S. consumers and ethanol: Knowledge, beliefs and consumption. *Biomass and Bioenergy*, 35(4):1454–1464.

Johnston, R. J., Boyle, K. J., Adamowicz, W., Bennett, J., Brouwer, R., Cameron, T. A., Hanemann, W. M., Hanley, N., Ryan, M., Scarpa, R., Tourangeau, R., and Vossler, C. A. (2017). Contemporary guidance for stated preference studies. *Journal of the Association of Environmental and Resource Economists*, 4(2):319–405.

Johnston, R. J., Schultz, E. T., Segerson, K., Besedin, E. Y., and Ramachandran, M. (2012). Enhancing the content validity of stated preference valuation: The structure and function of ecological indicators. *Land Economics*, 88(1):102–120.

Kallas, Z. and Gil, J. (2015). Do the spanish want biodiesel? A case study in the Catalan transport sector. *Renewable Energy*, 83:398–406.

Krinsky, I. and Robb, A. L. (1986). On approximating the statistical properties of elasticities. *The Review of Economics and Statistics*, 68(4):715–719.

Lancaster, K. (1966). A new approach to consumer theory. *Journal of Political Economy*, 74(2):132–157.

Li, T. and McCluskey, J. J. (2017). Consumer preferences for second-generation bioethanol. *Energy Economics*, 61:1–7.

Liao, K. and Pouliot, S. (2016). Estimates of the demand for E85 using stated-preference data off revealed-preference choices. Agricultural & Applied Economics Association Annual Meeting, Boston, MA, 7/31-8/02.

Louviere, J., Hensher, D., and Swait, J. (2000). *Stated choice methods: analysis and applications*. Cambridge University Press.

Lusk, J., Roosen, J., and Fox, J. (2003). Demand for beef from cattle administered growth hormones or fed genetically modified corn: a comparison of consumers in France, Germany, the United Kingdom and the United States. *American Journal of Agricultural Economics*, 85(1):16–29.

McElroy, G. and Dawson, M. (1986). Biomass from short-rotation coppice willow on marginal land. *Biomass*, 10:225–240.

McFadden, D. (1974). *Frontiers of econometrics*, chapter Conditional logit analysis of qualitative choice behaviour. Academic Press, New York.

McFadden, D. and Train, K. E. (2000). Mixed MNL models for discrete response. *Journal of applied Econometrics*, 15(5):447–470.

Nazlioglu, S. (2011). World oil and agricultural commodity prices: Evidence from non-linear causality. *Energy Policy*, 39(5):2935–2943.

Nazlioglu, S. and Soytas, U. (2012). Oil price, agricultural commodity prices, and the dollar: A panel cointegration and causality analysis. *Energy Economics*, 34(4):1098–1104.

OECD (2008). Rising food prices causes and consequences. Policy brief, Organisation for Economic Co-operation and Developmen.

Pacini, H. and Silveira, S. (2011). Consumer choice between ethanol and gasoline: lessons from Brazil and Sweden. *Energy Policy*, 39(11):6936–6942.

Paris, A. (2018). On the link between oil and agricultural commodity prices: Do biofuels matter? *International Economics*. (forthcoming).

Petrolia, D. R., Bhattacharjee, S., Hudson, D., and Herndon, C. W. (2010). Do Americans want ethanol? A comparative contingent-valuation study of willingness to pay for E10 and E85. *Energy Economics*, 32(1):121–128.

Savvanidou, E., Zervas, E., and Tsagarakis, K. P. (2010). Public acceptance of biofuels. *Energy Policy*, 38(7):3482–3488.

Solomon, B. D. and Johnson, N. H. (2009). Valuing climate protection through willingness to pay for biomass ethanol. *Ecological Economics*, 68(7):2137–2144.

Susaeta, A., Alavalapati, J., Lal, P., Matta, J. R., and Mercer, E. (2010). Assessing public preferences for forest biomass based energy in the southern United States. *Environmental management*, 45(4):1432–1009.

Train, K. E. (2009). *Discrete choice methods with simulation*. Cambridge University Press, Cambridge, 2nd edition.

Ulmer, J. D., Huhnke, R. L., Bellmer, D. D., and Cartmell, D. D. (2004). Acceptance of ethanol-blended gasoline in Oklahoma. *Biomass and Bioenergy*, 27(5):437–444.

Van de Velde, L., Verbeke, W., Popp, M., Buysse, J., and van Huylenbroeck, G. (2009). Perceived importance of fuel characteristics and its match with consumer beliefs about biofuels in Belgium. *Energy Policy*, 37(8):3183–3193.

Wilson, P., Glithero, N., and Ramsden, S. (2014). Prospects for dedicated energy crop production and attitudes towards agricultural straw use: The case of livestock farmers. *Energy Policy*, 74:101–110.

4.A Literature summary

Table 4.9: List of DCE about biofuels with details about attributes and levels

Authors	Country	Attributes	Levels
Susaeta et al. (2010)	US	Percentage reduction of CO_2 emissions (per mile traveled)	E10: 1-3% (low), 4-7% (medium), 8-10% (high) E85: 1-60% (low), 61-70% (medium), 71-90% (high)
		Percentage improvement of biodiversity by reducing wildfire risk and improving forest health	E10: 1-20% (low), 21-40% (medium), 41-60% (high) E85: 1-25% (low), 26-50% (medium), 51-75% (high)
		Increase of the fuel price of fuel at the pump per gallon	E10: \$0.2, \$0.5, \$0.75, \$1 E85: \$0.3, \$0.6, \$1, \$1.5
Giraldo et al. (2010)	Spain	Biodiesel	Biodiesel, conventional diesel
		Price	€0.99, €1.10, €1.21
		Brand	Big brand petrol stations, small or local petrol stations
		Proximity	Petrol station is close to everyday route (Yes), otherwise (No)
Jensen et al. (2010, 2012)	US	Fuel price (price per gallon)	E85: \$1.34, \$1.42, \$1.50, \$1.58, \$1.66 (E10: \$2.00)
		Feedstock for the ethanol	E85: corn, switchgrass, wood wastes (E10: corn)
		Percent of fuel from imported sources	E85: 10%, 33%, 50% (E10: 60%)
		Level of GHG emissions reductions compared with E10	E85: 10%, 50%, 73%
		Availability of the fuel nearby	E85: 'on your way', 2 min 'out of your way', 5 min 'out of your way' (E10: 2 min out of the way)
Gracia et al. (2011)	Spain	Price (€ per litre)	1.05, 1.1, 1.15, 1.20
		Type of diesel	Biodiesel, Biodiesel with a sustainable label, Conventional Diesel (SQ)
		Availability in a petrol station close to the everyday router	Yes, No
		Place of production	Europe, Outside Europe
Farrow et al. (2011)	US	Price (price per gallon)	Usual fuel: range of \$1.50 to \$4.50 with a mean of \$2.50 Ethanol: range of \$1.30 to \$4.65 with a mean close to \$2.50
		Feedstock for the ethanol	Corn, wood
		GHG emissions (pounds per gallon)	Usual fuel: range of 15 to 25 with a mean of 20 Corn based ethanol: reduction range of 5% to 60% with a mean of 23% Wood based ethanol: reduction range of 40% to 80% with a mean of 65%
		Import rate	Random
Bae (2014)	South Korea	Price changes of gasoline	+20 KRW, +80 KRW, +120 KRW
		Method of providing bioethanol	Use of domestic feedstock for domestic bioethanol: Domestic barley is used for producing domestic bioethanol Use of imported feedstock bioethanol: Tapioca is imported for producing domestic bioethanol Import of bioethanol: Bioethanol is imported
		Blending ratios of bioethanol to gasoline	3%, 5%, 10%
Aguilar et al. (2015)	US	Price/gallon	\$2.75, \$3.25, \$3.75 (second round: \$3.10, \$3.45, \$3.80)
		Miles per gallon	20 mpg, 25 mpg, 30 mpg
		Ethanol content	0%, 10%, 20%, 85%
		Ethanol source	corn-ethanol, cellulosic-ethanol, undisclosed feedstock
Kallas and Gil (2015)	Spain	Type of diesel	conventional diesel, B10, B20, B30
		Location of the petrol station	'usual route', 'outside the usual route'
		Type of the petrol station	'local petrol stations','multinational operator'
		Price of the bread	unchanged, +5%, +10%, +20%

4.B Mathematical details of the econometric models

Different discrete choice models are obtained from different assumptions about the distribution of the random terms.

Assuming $\epsilon_{n,i}$ being Independent and Identically Distributed (IID) and following a type I extreme-value distribution, i.e., a standard Gumbel distribution, the cumulative distribution function F and the density function f of each $\epsilon_{n,i}$ are given by:

$$F(\epsilon_{n,i}) = e^{-e^{-\epsilon_{n,i}}} \tag{4.17}$$

$$f(\epsilon_{n,i}) = e^{-\epsilon_{n,i}} e^{-e^{-\epsilon_{n,i}}} \tag{4.18}$$

Equation (4.6) becomes therefore:

$$P_{n,i}|\epsilon_{n,i} = \prod_{j \neq i} e^{-e^{-(V_{n,i}-V_{n,j}+\epsilon_{n,i})}} \tag{4.19}$$

The non conditional probability for an agent n to choose the alternative i is therefore the integration of $P_{n,i}|\epsilon_{n,i}$ over the distribution of $\epsilon_{n,i}$:

$$P_{n,i} = \int \left(\prod_{j \neq i} e^{-e^{-(V_{n,i}-V_{n,j}+\epsilon_{n,i})}} \right) e^{-\epsilon_{n,i}} e^{-e^{-\epsilon_{n,i}}} d\epsilon_{n,i} \tag{4.20}$$

By replacing $\epsilon_{n,j}$ with s, equation (4.20) becomes:

$$P_{n,i} = \int_{s=-\infty}^{+\infty} \left(\prod_{j \neq i} e^{-e^{-(V_{n,i}-V_{n,j}+s)}} \right) e^{-s} e^{-e^{-s}} ds \tag{4.21}$$

As $V_{n,i} - V_{n,i} = 0$, we have:

$$P_{n,i} = \int_{s=-\infty}^{+\infty} \left(\prod_{j \neq i} e^{-e^{-(V_{n,i}-V_{n,j}+s)}} \right) e^{-s} e^{-e^{-(V_{n,i}-V_{n,i}+s)}} ds \tag{4.22}$$

and the last term can be introduced into the product,

$$P_{n,i} = \int_{s=-\infty}^{+\infty} \left(\prod_j e^{-e^{-(V_{n,i}-V_{n,j}+s)}} \right) e^{-s} ds \tag{4.23}$$

By removing the first exponential from the product, we obtain:

$$P_{n,i} = \int_{s=-\infty}^{+\infty} exp\Big(- \sum_j e^{-(V_{n,i}-V_{n,j}+s)} \Big) e^{-s} ds \tag{4.24}$$

$$P_{n,i} = \int_{s=-\infty}^{+\infty} exp\Big(- e^{-s} \sum_j e^{-(V_{n,i}-V_{n,j})} \Big) e^{-s} ds \tag{4.25}$$

We now define $t = e^{-s}$. The expression $-e^{-s}ds$ therefore gives dt and note that t approaches zero (resp. positive infinity) if s tends to infinity (resp. negative infinity) as:

$$P_{n,i} = \int_{t=+\infty}^{0} exp\Big(- t \sum_j e^{-(V_{n,i}-V_{n,j})} \Big) (-dt) \tag{4.26}$$

that is to say:

$$P_{n,i} = \int_{t=0}^{+\infty} exp\Big(- t \sum_j e^{-(V_{n,i}-V_{n,j})} \Big) dt \tag{4.27}$$

This expression is now easy to integrate and allows us to obtain expression in equation (4.8).

$$P_{n,i} = \frac{exp\big(- t \sum_j e^{-(V_{n,i}-V_{n,j})} \big)}{- \sum_j e^{-(V_{n,i}-V_{n,j})}} \Bigg]_0^{+\infty} \tag{4.28}$$

$$P_{n,i} = 0 - \frac{1}{- \sum_j e^{-(V_{n,i}-V_{n,j})}} \tag{4.29}$$

$$P_{n,i} = \frac{1}{\sum_j e^{-(V_{n,i}-V_{n,j})}} = \frac{e^{V_{n,i}}}{\sum_j e^{V_{n,j}}} \tag{4.30}$$

The CL model is estimated using maximum likelihood procedures. The probability that a respondent n chooses a particular alternative is $\prod_i (P_{n,i})^{y_{n,i}}$ with $y_{n,i} = 1$ if the alternative i is chosen and zero otherwise. Assuming the independence in choices of each respondent, the likelihood and log-likelihood functions are given by:

$$L(\beta) = \prod_{n=1}^{N} \prod_{i} (P_{n,i})^{y_{n,i}} \tag{4.31}$$

$$LL(\beta) = \sum_{n=1}^{N} \sum_{i} y_{n,i} ln(P_{n,i}) \tag{4.32}$$

with:

$$P_{n,i} = \frac{e^{V_{n,i}}}{\sum_j e^{V_{n,j}}} \tag{4.33}$$

where $P_{n,i}$ only depends on observable components. Here the β' vector contains the β_{ik} parameters from equation (4.1), and vector X_i holds the attribute content of alternative i.

This model also requires the hypothesis of independence of irrelevant alternatives (IIA), which implies that the relative probabilities of two options being chosen are unaffected by the introduction or removal of other alternatives. Indeed, according to equation (4.33), we have:

$$\frac{P_{n,i}}{P_{n,k}} = \frac{\frac{e^{V_{n,i}}}{\sum_j e^{V_{n,j}}}}{\frac{e^{V_{n,k}}}{\sum_j e^{V_{n,j}}}} = \frac{e^{V_{n,i}}}{e^{V_{n,k}}} \tag{4.34}$$

4.C Results for Latent Class model with 3 classes

Table 4.10: Results of the LC model with 3 classes

Attributes	without socio-eco. variable			with socio-eco. variables		
	Class 1	Class 2	Class 3	Class 1	Class 2	Class 3
ASC	1.244***	-2.004***	-1.477***	1.303***	-1.985***	-1.473***
	(0.260)	(0.184)	(0.169)	(0.276)	(0.182)	(0.167)
Monetary	-0.022***	-0.035***	-0.003**	-0.022***	-0.034***	-0.003***
contribution	(0.004)	(0.002)	(0.001)	(0.004)	(0.003)	(0.001)
Agricultural	0.193	0.403***	0.665***	0.200	0.398***	0.662***
support	(0.211)	(0.130)	(0.065)	(0.219)	(0.130)	(0.065)
Emissions	0.013	0.036***	0.031***	0.014	0.034***	0.031***
variation	(0.009)	(0.004)	(0.003)	(0.009)	(0.004)	(0.003)
Food prices	-1.393***	-0.992***	-0.389***	-1.404***	-0.993***	-1.142***
increase	(0.271)	(0.131)	(0.060)	(0.285)	(0.130)	(0.060)
Segment function						
Pop. density	-	-	-	-0.00003**	-0.00004***	-
	-	-	-	(0.00001)	(0.00001)	-
Age	-	-	-	0.0183***	-0.0005	-
	-	-	-	(0.0058)	(0.0062)	-
Constant	-	-	-	-1.1417***	0.0488	-
	-	-	-	(0.3296)	(0.3244)	-
N (Ind.)	258	337	377	254	337	381
N (Obs.)	3,870	5,055	5,655	3,810	5,055	5,715
Class share (%)	26.6%	34.7%	38.7%	26.1%	34.7%	39.2%
Log Likelihood		-4,039			4,027	

Note: ASC mentions the Alternative Specific Constant and refers to the dummy variable equals to 1 if the status quo is chosen and 0 otherwise. For each attribute, the first line concerns the estimated coefficient and the second line (in brackets) mentions the standard errors. The number of stars, i.e., one, two and three, refers to the 10%, 5% and 1% significance level, respectively. Age of respondents and population density are included as continuous variables.

5

Efficiency market hypothesis and optimal hedge ratio of the ethanol market

[This chapter is co-written with E. Hache and is in revision process in *The Energy Journal*]

5.1 Introduction

Ethanol is derived from various agricultural products (cassava, corn, hemp, sugar beet or sugarcane) and has been increasingly added to gasoline blends for several reasons: (i) it helps to reduce greenhouse gases emissions (GHG) in the transportation sector, (ii) if produced with agricultural feedstock, ethanol can be seen as a renewable energy, and (iii) from a technical point of view, the use of ethanol helps to boost octane numbers and leads to an improvement in thermal engine efficiency. All these factors have contributed to the development of ethanol's use worldwide. Such recent evolution calls for a detailed investigation of the ethanol market to fully understand its dynamics. Specifically, the aim of this chapter is to study the ethanol price dynamics and determine the optimal hedging strategy on the US market.

Ethanol policy is a story that has many chapters in the past 40 years in the US. Ethanol inclusion in US gasoline blends began in 1908 when the Model-T Ford could be customized to run on gasoline or alcohol. It was not until the late Seventies, however, that the meaningful inclusion of ethanol came about. The first government involvement for ethanol was the Energy Tax Act of 1978 (a tax exemption for adding ethanol to the gasoline blend) in the wake of geopolitical concerns in the oil market with the 2^{nd} world oil shock. The Surface Transportation Assistance Act of 1982 and the Tax Reform Act of 1984 gave an impetus for ethanol inclusion despite a decrease of the tax exemption during the 1992–2000 period with the Omnibus Budget Recollection Act. The Renewable Fuel Standard (RFS) program, created by the Energy Policy Act of 2005 and extended by the Energy Independence and Security Act of 2007, has led to a new expansion of the US ethanol market. Ethanol production and consumption have since been multiplied by four between 2005 and 2016, increasing approximately from 300 to 1,200 million gallons.

Since 2009 the US has become a net exporter in the ethanol market. According to the US Census Bureau, the Department of Commerce, and the Department of Agriculture, the US exported 836 million gallons of ethanol in 2015 (5.7% of total US ethanol production) and imported 93 million gallons of fuel ethanol (less than 1% of US ethanol consumption). Canada (30% of US exports), Brazil (14%), Philippines (9%), China (8%), and India (6%) are the top destinations of US ethanol in 2015. Brazil also remains the main supplier for the US with 73% of the imported ethanol volume in 2015. This export-import structure within the ethanol market with Brazil can be easily explained by the RFS and California Low Carbon Fuel Standard (LCFS) targets put in place for the reduction of GHG emissions that impose more stringent requirements. As mentioned by the Energy Information Administration,[1] life cycle analysis (LCA) studies demonstrate that ethanol from sugarcane has a better scoring in terms of GHG emissions than products based on corn feedstock. It contributes to the substitution of corn-ethanol production from the countryside with imported sugarcane-ethanol from Brazil. The ethanol market structure is already driven by (i) the inclusion policy of different countries, (ii) energy prices and especially the evolution of the crude oil price, and (iii) the regulatory framework. But recent changes prove that the production process (ethanol is derived from different agricultural products) could also impact the international market structure and ethanol price dynamics. Ethanol prices registered several ups and downs since 2008, with prices ranging from $1.47 per gallon to more than $4 per gallon following the volatility observed in energy and agricultural prices.

Due to the increase of ethanol production and consumption in the US in the first part of the last decade, futures contracts on corn-based ethanol were launched on March 2005 on the Chicago Board of Trade (CBOT).[2] Derivatives markets allow commercial players to reduce their price risk exposure with various hedging strategies and different tools (futures contracts, options, etc.). These tools protect against adverse price movements

[1] https://www.eia.gov/todayinenergy/detail.php?id=25312

[2] CME Group is the world's leading and most diverse derivatives marketplace, made up of four markets, CME, CBOT, NYMEX, and COMEX. Each market offers a wide range of global benchmarks across major asset classes.

in order to reduce the risk of loss in the business. In this context, the optimal hedging strategy is to minimize the variance of the hedge portfolio containing spot and futures contracts. A variety of questions has been asked regarding the derivatives strategy, which is related to traders' behavior, speculation, price volatility, etc.

The motivations of this chapter are threefold. Firstly, considering the role of the ethanol market could play in the transportation sector for its own energy transition, we study the long-term relationship between ethanol spot prices and the prices of futures contracts on the CBOT; allowing us to investigate the weak form of the efficient market hypothesis.[3] To the best of our knowledge, this is the first study focusing on ethanol in this research field. Secondly, we have a methodological motivation and contribution. Indeed, we compute a wide range of time-varying hedge ratios[4] with different econometric models to look for the optimal hedging strategy for ethanol commercial players. We consider adjustments to long-term equilibrium and regime shifts governed by a Markov chain (as *Alizadeh et al.* (2008)) and short-run dynamics between spot and futures price changes (as in *Salvador and Arago* (2014)). In addition, we extend the work of *Salvador and Arago* (2014) by allowing short-run dynamics between prices to be state-dependent on price volatility. *Hamilton* (1989) proposes the Markov-switching model while *Krolzig* (1999) extends this specification to the vector autoregressive (VAR) model. By including structural breaks in the variance equation, we take into account the high volatility persistence (*Lamoureux and Lastrapes*, 1990). With structural breaks in the short-run dynamics, we allow for time-varying behavior in the adjustment to the equilibrium and the short-run dynamic processes. We then include an informational link between mean and volatility processes across each market state (*Alizadeh et al.*, 2008). Finally, rely-

[3] An efficient market is characterized by prices that reflect all available information. The weak form of market efficiency considers only historical price or return series in the information set (*Fama*, 1970).

[4] One of them is the hedge ratio which is initially defined as the estimated coefficient between spot and futures price changes based on Ordinary Least Squares (OLS) estimation (*Ederington*, 1979) i.e., the ratio of the unconditional spot and futures price changes covariance over the unconditional variance of the futures price changes. It provides the number of futures contracts to buy or sell for one unit of the underlying asset (in the case of this chapter: ethanol) to minimize the variance of the hedged portfolio returns.

ing on the Gjr framework (*Glosten et al.*, 1993), we introduce asymmetric behavior to the variance process (see also *Brooks et al.* (2002)) to take into account different responses to new information according to the past shocks sign. Therefore, we estimate a Markov-switching vector error correction model with a Gjr-MGarch error structure (Ms-VECM-Gjr-MGarch). To overcome *Johansen* (1988)'s approach drawbacks,[5] we use *Nielsen* (2010)'s nonparametric cointegration approach to analyze its ability to improve hedging strategy. As *Nielsen* (2010)'s nonparametric cointegration procedure does not require model specification, we assume non-linear dynamics in short-run and variance equations. Thirdly, we check the performance of a cross-hedging strategy[6] with the gasoline futures market. Indeed, *Franken and Parcell* (2003) highlight its efficiency while *Dahlgran* (2009) concludes there is a lower performance with this market compared to the ethanol futures market.

The rest of the chapter is organized as follows. Section 5.2 briefly reviews the literature on storable commodity market efficiency and hedging-ratio estimation. In section 5.3 we present data and the Markov-switching vector error correction model (Ms-VECM-Gjr-MGarch). Section 5.4 presents empirical results on the efficient market hypothesis and the optimal hedging strategy. The main conclusions are summarized in the section 5.5.

5.2 A brief overview of literature

Following the works of *Kaldor* (1939), *Working* (1948), *Brennan* (1958) and *Telser* (1958), spot and futures prices of a storable commodity should be equal. The difference

[5] In particular, Johansen's procedure could lead to an estimation bias due to the restrictions imposed on the short-run dynamics which are supposed to be linear.

[6] Cross-hedging occurs when the asset underlying the contract is different than the asset whose price is being hedged (*Hull*, 2005).

between these prices is explained by the cost of storage and the interest rate as,

$$F_t^T = S_t exp[(r_t + \bar{s})(T - t)] \tag{5.1}$$

and with a log-transformation,

$$f_t^T = s_t + (r_t + \bar{s})(T - t) \tag{5.2}$$

Here, F_t^T (resp. f_t^T) is the price (resp. log-price) of futures contract at the time t for a maturity T. S_t (resp. s_t) is the spot price (resp. log-price) at the same date. r_t and $\bar{s}$ refer, respectively, to the risk-free interest rate and the cost of carry, this latter is supposed to be constant. According to the aforementioned works, the difference between spot and futures prices is instantaneously compensated by arbitrageurs.

This hypothesis has been relaxed by *Garbade and Silber* (1983). They mention that arbitrageurs operate in the markets if the spread between these prices is large enough to enlarge their profits according to the transaction and information costs. Therefore, the unit relationship between spot and futures prices is only valid in the long term.The spot and futures markets are thus efficient if prices are cointegrated as in *Chowdhury* (1991) or *Lai and Lai* (1991). In addition, Garbade and Silber (1983) show that futures markets integrate new information faster than in the underlying spot market, leading to a causality from futures to spot prices. It helps the price discovery process registered in commodities markets which leads to informational efficiency for physical and financial markets.

Figuerola-Ferretti and Gonzalo (2010) extent this model by integrating the convenience yield, i.e., the premium attributed by agents for physically holding the commodity instead of holding a futures contract. It depends on various market characteristics in the spot market (weather conditions, geopolitical unrest, transaction costs, etc.).[7] With a

[7] See *Routledge et al.* (2000) or *Heaney* (2002) for more details on the convenience yield.

constant free-risk interest rate, one-period futures contract and the approximation of the convenience yield, y_t, used by these authors, as:

$$y_t = \gamma_1 s_t - \gamma_2 f_t \tag{5.3}$$

equation (5.2) becomes

$$f_t = \frac{1-\gamma_1}{1-\gamma_2} s_t + \frac{\bar{r}+\bar{s}}{1-\gamma_2} \tag{5.4}$$

Their theoretical framework allows a long-term relationship, i.e., a cointegrating relationship, with a non-unit coefficient between spot and futures prices. In addition, they mention that the coefficient value depends on the spot market condition. The parameter is greater (resp. smaller) than unity if the spot market is in contango (resp. backwardation).

Literature about the estimation of an optimal hedge ratio has been developed since the seminal work of *Ederington* (1979) who proposes using the estimated coefficient between changes in spot and futures prices with an ordinary least square estimator (OLS). However, this hedge ratio is unsatisfactory for many markets (*Cecchetti et al.*, 1988; *Myers and Thompson*, 1989). *Baillie and Myers* (1991) and *Kroner and Sultan* (1993) state that the hedge ratio should be time-varying based on the time-varying distribution of many asset prices. They propose computing this dynamic optimal hedge ratio (δ_t) for each period by taking into account all past information (Ω_{t-1}) such as:

$$\delta_t|\Omega_{t-1} = \frac{\sigma_{t-1}(\Delta F_{t-1}, \Delta S_{t-1})}{\sigma^2_{t-1}(\Delta F_{t-1})} \tag{5.5}$$

Many studies estimate those conditional covariance (σ_{t-1}) and variance (σ^2_{t-1}) with the multivariate Garch model proposed by *Engle and Kroner* (1995) as, for instance, *Kroner and Sultan* (1993), *Garcia et al.* (1995) or *Kavussanos and Nomikos* (2000) and conclude there has been an improvement of the hedging strategy with the dynamic hedge ratio compared to the constant formulation. The improvement degree depends on the market and the futures maturity studied (*Lien and Tse*, 2002).

The estimation of the dynamic hedge ratio should integrate the possible existence of a cointegrating relationship between spot and futures prices. *Kroner and Sultan* (1993), *Ghosh* (1993), *Chou et al.* (1996) or *Lien* (1996) highlighted an underestimated hedge ratio if this characteristic is not accounted for. In addition, *Brooks et al.* (2002) show the improvements of the hedge ratio effectiveness with the integration of the asymmetric volatility response against positive and negative shocks, i.e., the leverage effect. Furthermore, the conditional mean (*Sarno and Valente*, 2000) and variance (*Lamoureux and Lastrapes*, 1990) estimations can be biased if regime shifts exist. Thus, the hedge ratio effectiveness can be improved by integrating regime shifts in the estimation. *Lee and Yoder* (2007a,b) include regime shifts in the variance process and show an improvement – but not always significant – of the hedge ratio effectiveness. *Alizadeh et al.* (2008) extent this model by integrating regime shifts in variance and conditional mean processes and highlight a significant effectiveness improvement for most of the markets studied. Finally, *Salvador and Arago* (2014) propose incorporating (i) the regime shifts, the cointegrating relationship and the leverage effect in the same model in order to estimate an optimal dynamic hedge ratio, as well as (ii) the short-run dynamics between spot and futures price changes.

The literature concerning hedging strategies on energy markets is well developed with, for instance, *Lien and Yang* (2008) for heating and crude oil markets, *Alizadeh et al.* (2008) on crude oil, unleaded gasoline and heating oil markets, *Hanly* (2017) with WTI and Brent crude oils, natural gas, unleaded gasoline, heating oil and gasoil. However, the literature on hedging strategies on ethanol market is very scarce. *Franken and Parcell* (2003) highlight the cross-hedging efficiency between ethanol spot price and unleaded gasoline futures markets. However, while they correct the estimation for autocorrelation and heteroscedasticity, they do not incorporate the error correction term, regime switching and time-varying variance process. Finally, *Dahlgran* (2009) compares direct hedging for ethanol commercial agents with cross-hedging strategy with unleaded and Reformulated Gasoline Blendstock for Oxygen Blending (RBOB gasoline) futures markets. He demonstrates that the direct hedging strategy outperforms cross-hedging for a four-week, and more, hedge horizon.

5.3 Data and methodology

As stressed above, our chapter deals with the relationship between the spot prices and the futures prices of ethanol. As transaction volumes have risen, in particular for the shortest maturities, we focus on the relationship between the spot prices and the prices for the two-month futures contracts. The data studied are relative to the ethanol in the North American market: the spot price for ethanol (Argus Ethanol USGC barge/rail fob Houston), the futures prices of ethanol on the CBOT, and the transaction volumes and open interest for the same market, (weekly market business reports of the Commodity Futures Trading Commission [CFTC]). Apart from the spot price of ethanol, these pieces of information are all in the public domain. The data cover the period from July 2008 to December 2016, corresponding to 468 weekly observations. The prices are expressed in US dollars per gallon and are log-transformed.

Table 5.1 presents some descriptive statistics and tests results. Unit root tests confirm the stationarity of spot and futures prices series in their first-difference.[8] In addition, the *Ljung and Box* (1978) and ARCH tests confirm the presence of autocorrelation in most cases and heteroscedasticity, respectively. These characteristics justify the choice of a specification with autoregressive terms and heteroscedastic errors.

[8]In view of the conflicting results for the spot log-price series, we apply the *Perron* (1990)'s unit root test which confirms its non-stationarity with a break in mean on March 12 2014. We choose this test in view of series characteristics, i.e., the absence of trend and a potential break in the mean. We present results with innovational-outlier model for break date determination. Results with additional-outlier model are similar.

Table 5.1: Summary statistics and unit root tests

Variables	Log		First-log differences	
	Spot	Futures	Spot	Futures
Mean	/	/	0.000	0.000
Std. errors	/	/	0.050	0.040
Skewness	/	/	0.047	-0.283
Kurtosis	/	/	6.039	4.288
ADF	0.047*	0.297	0.001*	0.001*
PP	0.099*	0.306	0.001*	0.001*
KPSS	0.010	0.010	0.100*	0.100*
Perron	-1.148	-1.229	/	/
	-3.8	-3.8	/	/
Q(6)	0.001	0.001	0.001	0.681
$Q^2(6)$	0.001	0.001	0.001	0.001

Note: This table reports descriptive statistics and the p-value of the unit root tests applied, i.e., Augmented *Dickey and Fuller* (1979, 1981)'s test (ADF), *Phillips and Perron* (1988)'s test (PP) and *Kwiatkowski et al.* (1992)'s test (KPSS). The Perron's line refers to the *Perron* (1990) test with the test's statistic and the critical value at a 5% significance level in the first and second line, respectively. The critical value comes from *Perron and Vogelsang* (1992). The null hypothesis of unit root with break is rejected if the test statistics is greater than the critical value. The star mentions the stationarity of the variable at a 10% significance level. Q(6) and $Q^2(6)$ are the p-value of the *Ljung and Box* (1978)'s test and ARCH test (*Engle*, 1982) for 6^{th} order autocorrelation, respectively.

We apply the *Johansen* (1988)'s test to check the existence of a long-term relationship with unit cointegrating vectors and to estimate the conditional mean with a Markov switching vector error correction model (Ms-VECM) within a bivariate framework. The inclusion of a multivariate generalized autoregressive conditional heteroscedasticity (MGarch) error structure allows us to compute the dynamic hedge ratio. By including a long-term equilibrium, we eliminate the bias in the hedge ratio estimation mentioned by *Kroner and Sultan* (1993) and *Ghosh* (1993). In addition, the nonlinear specification avoids estimation bias due to the existence of multiple regimes in the mean (*Sarno and Valente*, 2000) and variance (*Lamoureux and Lastrapes*, 1990) equations. Furthermore, the dynamic hedge ratio computed with this specification outperforms OLS hedge ratio in many energy markets (*Alizadeh et al.*, 2008). Finally, we take into account the leverage effect within the Gjr framework.

It should be emphasized that the *Johansen* (1988) cointegration test requires assumptions regarding the short-run dynamics that must follow a linear process. Using *Johansen* (1988)'s procedure with a non-linear short-run specification may lead to bias in both cointegration test results and long-term estimations, generating in turn a bias on the short-run and conditional variance estimations. To overcome these major drawbacks, we rely on *Nielsen* (2010)'s nonparametric variance ratio testing approach as this methodology does not require assumptions in the short-run specification.[9] The nonparametric variance ratio trace statistic is defined by:

$$\Lambda_{n,r}(d_1) = T^{2d_1} \sum_{j=1}^{n-r} \lambda_j \tag{5.6}$$

where λ_j, $j = 1, ..., n$, are the eigenvalues, listed by increasing order, of the observed $(n \times T)$ time series matrix, r is the cointegration rank tested and d_1 is a summation parameter fixed to 0.1.[10] The eigenvalues of the price series matrix are given by the solutions of:

$$|\lambda B_T - A_T| = 0 \tag{5.7}$$

with

$$\begin{aligned} A_T &= \sum_{t=1}^{T} Z_t Z_t' \\ B_T &= \sum_{t=1}^{T} \tilde{Z}_t \tilde{Z}_t' \end{aligned} \tag{5.8}$$

where $\tilde{Z}_t$ is the fractional difference of Z_t truncated by d_1. Z_t is our time series matrix after demeaning. The null hypothesis is the presence of $r-1$ cointegration relationships. A test statistic that is greater than the critical value leads to the rejection of the null hypothesis in favor of the alternative, i.e., the existence of r cointegration relationships. In addition, the estimated cointegration coefficients are provided by the eigenvectors

[9]For more details on the testing procedure, see *Nielsen* (2010).
[10]As mentioned by *Nielsen* (2010), the choice of $d_1 = 0.1$ maximizes the power of the test.

associated with eigenvalues and converge to their real values. Therefore, by using both *Johansen* (1988) and *Nielsen* (2010) cointegration approach, we can analyze the effect of the long-term estimation bias on the hedge ratio efficiency.

The Ms-VECM with Gjr-MGarch[11] error structure can be expressed by:

$$\begin{aligned} \Delta X_t &= c + \Gamma_{st}\Delta X_{t-1} + \Pi_{st} X_{t-1} + \epsilon_{t,st} \\ \epsilon_{t,st} &= \begin{pmatrix} \epsilon_{s,t,st} \\ \epsilon_{f,t,st} \end{pmatrix} |\Omega_{t-1} \backsim IN(0, H_{t,st}) \end{aligned} \tag{5.9}$$

where $\Delta X_t = (\Delta s_t, \Delta f_t)'$ (resp. $X_{t-1} = (s_{t-1}, f_{t-1})'$) is the vector of log-returns (resp. log-price) and c is a vector of constant. Γ_{st} and Π_{st} are coefficient matrices related to short- and long-term dynamics, respectively.[12] These (2×2) matrices depend on the regime st, $st = 1, 2$. $\epsilon_{t,st}$ is a regime-dependent Gaussian white noise vector. With our multivariate Garch error structure, the error covariance matrix, $H_{t,st}$, is time- and regime-dependent.

As mentioned by *Alizadeh et al.* (2008), two steps are necessary to estimate this model. Firstly, we check the existence of a cointegrating relationship between spot and futures prices. Considering a linear process, we apply the *Johansen* (1988)'s test. The λ_{max} and λ_{trace} statistics allow us to check the rank of the matrix Π. Under the alternative hypothesis, there is at least one cointegrating relationship. If the rank of the long-term adjustment is non-null, Π can be decomposed such as $\Pi = \alpha\beta'$. The vectors α and β are (2×1) coefficient vectors referring to the error correction coefficients, i.e., characterizing the adjustment process to the long-term equilibrium, and the long-term coefficients, describing the long-term equilibrium, respectively. In addition, we apply the likelihood ratio test from *Johansen* (1995) to check the existence of unitary long-term

[11] We estimate a wide range of specifications but only detail the more complex model.

[12] We integrate only one lag in the short-run dynamics according to the information criterion BIC from *Schwarz* (1978) during the *Johansen* (1988) cointegration procedure.

coefficients between spot and futures prices. The non-reject of the null hypothesis of unit coefficient will favor the *Garbade and Silber* (1983) model against that proposed by *Figuerola-Ferretti and Gonzalo* (2010).

Secondly, we introduce regime shifts depending on an unobserved state variable st. The latter can takes two values, $st = 1, 2$, corresponding to two different regimes. This variable follows a first order Markov process with the transition probability matrix:

$$P = \begin{pmatrix} P_{11} & P_{21} \\ P_{12} & P_{22} \end{pmatrix} = \begin{pmatrix} 1 - P_{12} & P_{21} \\ P_{12} & 1 - P_{21} \end{pmatrix} \tag{5.10}$$

where P_{12} (resp. P_{21}) is the probability that the system will shift from state 1 (resp. 2) to state 2 (resp. 1). P_{11} (resp. P_{22}) is the probability that the system will stay in regime 1 (resp. regime 2). We obviously have $P_{11} + P_{12} = 1$ and $P_{21} + P_{22} = 1$.

All the coefficients depend on the regime st except for the long-term coefficients, β. Indeed, variables with a nonlinear cointegrating relationship do not admit an error correction model (*Gonzalo and Pitarakis*, 2006). In the presence of a cointegrating relationship, the Π_{st} matrix is decomposed as $\Pi_{st} = \alpha_{st}\beta'$.

The conditional covariance matrix of error terms, $H_{t,st}$, is regime-dependent, time-varying, and follows a multivariate Garch specification with a *Baba et al.* (1987) framework, i.e., BEKK, as:

$$H_{t,st} = C'_{st}C_{st} + A'_{st}\epsilon_{t-1}\epsilon'_{t-1}A_{st} + B'_{st}H_{t-1}B_{st} + D'_{st}\eta_{t-1}\eta'_{t-1}D_{st} \tag{5.11}$$

with ϵ_{t-1} and H_{t-1} being the vector of mean equation residuals and the global covariance matrix for the past period, respectively. η_{t-1} is negative past shocks, i.e., $\eta_{t-1} = min(\epsilon_{t-1}, 0)$. C_{st} is a (2×2) lower triangular matrix containing regime-dependent coefficients. A_{st}, B_{st} and D_{st} are (2×2) diagonal matrices of coefficients measuring the past shock effects on the conditional covariance matrix, their persistence and the additional effect of a past negative shock, respectively. However, the conditional covariance matrix depends on the sequence of all previous regimes through H_{t-1}. With this path-dependence problem, the estimation by the maximum likelihood method is numerically infeasible. To overcome this problem, we follow the formulations of *Gray* (1996) and *Lee and Yoder* (2007b) concerning the conditional variances, h_{ss} and h_{ff}, and the conditional covariance, h_{sf}, respectively, as:

$$h_{ss,t} = \pi_{1,t}(r^2_{s,1,t} + h_{ss,1,t}) + (1 - \pi_{1,t})(r^2_{s,2,t} + h_{ss,2,t}) - [\pi_{1,t} r_{s,1,t} + (1 - \pi_{1,t}) r_{s,2,t}]^2 \quad (5.12)$$

$$h_{ff,t} = \pi_{1,t}(r^2_{f,1,t} + h_{ff,1,t}) + (1 - \pi_{1,t})(r^2_{f,2,t} + h_{ff,2,t}) - [\pi_{1,t} r_{f,1,t} + (1 - \pi_{1,t}) r_{f,2,t}]^2 \quad (5.13)$$

$$\begin{aligned} h_{sf,t} = {} & \pi_{1,t}(r_{s,1,t} r_{f,1,t} + h_{sf,1,t}) + (1 - \pi_{1,t})(r_{s,2,t} r_{f,2,t} + h_{sf,2,t}) \\ & -[\pi_{1,t} r_{s,1,t} + (1 - \pi_{1,t}) r_{s,2,t}][\pi_{1,t} r_{f,1,t} + (1 - \pi_{1,t}) r_{f,2,t}] \end{aligned} \quad (5.14)$$

In equations (5.12), (5.13) and (5.14), $\pi_{st,t}$ is the probability of being in the state st at the time t. $h_{ss,st,t}$ (resp. $h_{ff,st,t}$) is the regime-dependent variance concerning the spot (resp. futures) price at the time t and is contained in $H_{t,st}$. Similarly, $h_{sf,st,t}$ is the state-dependent covariance at the time t and is an element of the same matrix. $r_{s,st,t}$ (resp. $r_{f,st,t}$) is the regime-dependent conditional mean of the spot (resp. futures) price equation at the time t. These latter are calculated from the following equations:

$$\epsilon_{s,t} = \Delta s_t - [\pi_{1,t} r_{s,1,t} + (1 - \pi_{1,t}) r_{s,2,t}] \quad (5.15)$$

$$\epsilon_{f,t} = \Delta f_t - [\pi_{1,t} r_{f,1,t} + (1 - \pi_{1,t}) r_{f,2,t}] \quad (5.16)$$

This Ms-VEC model is estimated by maximizing of the likelihood function. Each state-dependent error follows a N-dimensional normal distribution with zero mean and $H_{t,st}$ covariance matrix. The global density function is a mixture of these distributions weighted by the probability of being in each regime:

$$f(X_t,\theta) = \frac{\pi_{1,t}}{2\pi}|H_{t,1}|^{-\frac{1}{2}}exp(-\frac{1}{2}\epsilon'_{t,1}H_{t,1}^{-1}\epsilon_{t,1}) + \frac{\pi_{2,t}}{2\pi}|H_{t,2}|^{-\frac{1}{2}}exp(-\frac{1}{2}\epsilon'_{t,2}H_{t,2}^{-1}\epsilon_{t,2}) \tag{5.17}$$

$$L(\theta) = \sum_{t=1}^{T} log f(X_t,\theta) \tag{5.18}$$

with θ denoting the parameter vector. The log-likelihood function (equation (5.18)) is maximized using the expectation-maximisation algorithm proposed by *Dempser et al.* (1977) under constraints like $\pi_{1,t} + \pi_{2,t} = 1$, $\pi_{1,t} \geqslant 0$ and $\pi_{2,t} \leqslant 1$.

With our specification, we can compute the dynamic hedge ratio as:

$$\delta_t|\Omega_{t-1} = \frac{h_{sf,t-1}}{h_{ff,t-1}} \tag{5.19}$$

where $h_{sf,t-1}$ et $h_{ff,t-1}$ are defined in equations (5.14) and (5.13), respectively.

In order to analyze the hedging strategies' performance of each specification[13] we compute hedged portfolios each week and their returns variance over the samples chosen as:

$$VAR(\Delta s_t - \delta_t \Delta f_t) \tag{5.20}$$

In addition, as in *Kroner and Sultan* (1993) or *Alizadeh et al.* (2008) among others, we compute the hedger's utility function as

$$E_{t-1}U(\Delta s_t - \delta_t\Delta f_t) = E_{t-1}(\Delta s_t - \delta_t\Delta f_t) - k \times VAR_{t-1}(\Delta s_t - \delta_t\Delta f_t) \tag{5.21}$$

where k is the degree of risk aversion. This utility function represents economic benefits

[13]We estimate 22 specifications including 8 linear and 14 nonlinear models. Specifications vary about inclusion, or not, of error correction and autoregressive terms in mean equation, asymmetry in variance equation, as well as parameters allowed to switch. In addition, we use an OLS model and a naive model, i.e., with a unit hedging ratio.

from the hedging strategy. Another way to consider this benefit is the value-at-risk (VaR) exposure and is computed as

$$VaR = W_0[E(\Delta s_t - \delta_t \Delta f_t) + Z_\alpha \sqrt{VAR(\Delta s_t - \delta_t \Delta f_t)}] \tag{5.22}$$

where W_0 is the initial value of the portfolio and Z_α is the normal distribution quantile.

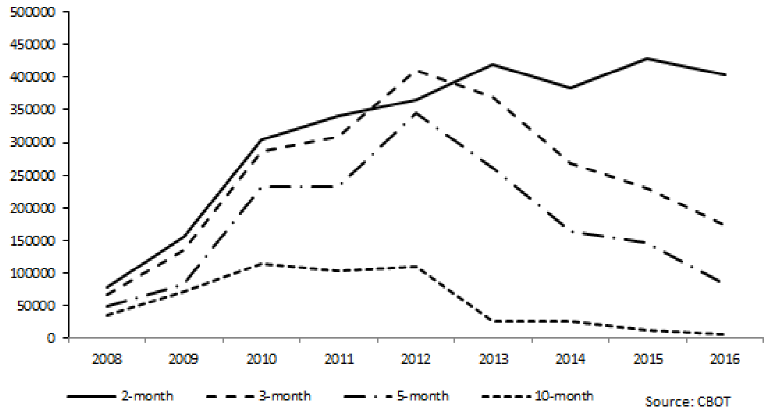
5.4 Empirical results

Futures contracts on corn-based ethanol were launched on floor-based trading in March 2005. The CBOT launched the ethanol contract on the electronic platform in 2006 contributing to an increase in liquidity within the market. In 2007 options contracts were also launched in the market. For the first time, the volume reached 1,000 contracts in July 2006 and it really took off after 2009 with a sharp increase in the spot prices. During previous decades, and especially in the initial phase of construction of the ethanol futures market, the main objective was to attract and concentrate the liquidity required for commercial traders to achieve hedging activities. Nevertheless, the rise in transaction volumes has been accompanied by a concentration of traders' liquidity on the shortest maturity contracts exchanged on commodity markets. This factor has been observed and studied, for example on the WTI market in the US (*Hache and Lantz*, 2013).[14] For ethanol futures prices, we observed a decrease in transaction volumes between 2008 and 2016 as contract terms grew longer (Figure 5.1), and a virtual absence of liquidity for long-term contracts (compared to short-term maturity). In fact, the inadequate information available at any given moment t on contracts whose maturity period is greater than one year does not give traders the incentives to trade in the market. As a consequence, the liquidity for distant contracts at a maturity greater than five months decreases sharply. Moreover the maturity greater than two months registered a sharp

[14] See also the literature review in *Lautier* (2005).

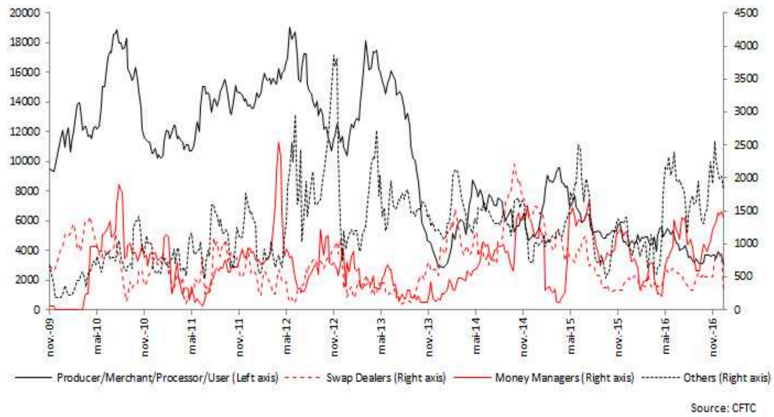
decline in transaction volumes after 2012.

Figure 5.1: Open interest by contracts maturity



On the one hand, by studying available data from 2008 to 2016, we observed a marked rise in transaction volumes for each maturity. Measured in batches of 29,000 gallons (a standard financial contract for ethanol on the CBOT), these transactions have risen, for two-month term contracts, from around 78,864 in 2008 to 404,133 in 2016, i.e., multiplied by a factor of 5 (Figure 5.2). On the other hand, the share of non-commercial players increased from around 15% before 2008 to over 35% on average since 2014 (Figure 5.3). However, both the increase in the volume of transactions on financial trading floors and the growing share of non-commercial players should be kept in perspective. As mentioned previously, during the previous three decades and especially in the initial phase of construction of the commodities markets, the main objective of the different derivatives marketplaces was to attract and concentrate the liquidity required for commercial traders to achieve hedging activities. In October 1974, the NYMEX launched the first energy contracts for industrial fuel oil. *Simon* (1984) explains the failure of this first attempt by the under-development of the financial markets and because of the very specific contract specifications (the delivery point of the futures contracts was Rotterdam which held no appeal for the American commercial players). A contract for heating oil in the NYMEX was also launched in 1978 and was abandoned because of inadequate liquidity's volume. During the 1980s in the context of deregulation put in place by the Reagan administration, the NYMEX decided a simultaneous launch of energy contracts: gasoline (1981), crude oil (1983), and heating oil (1990). In Europe the International Petroleum Exchange (IPE) launched its first fuel oil contract in 1981. Since then, financial markets have registered an increase in transactions volume and in the share of non-commercial players in the exchange markets. In the petroleum sector, competition between the two main exchanges (i.e., the NYMEX in New York and the Intercontinental exchange [ICE] in London) led to a strong deregulation process. In the US, for example, the introduction at the end of December 2000 of the law modernizing commodities markets, the Commodity Futures Modernization Act (CFMA), triggered market instability in the crude oil market (*Medlock and Jaffe*, 2009; *Hache and Lantz*, 2013).

Figure 5.2: Position (number of contracts) by actors



In order to analyze the ability of *Garbade and Silber* (1983) and *Figuerola-Ferretti and Gonzalo* (2010) to explain the ethanol market, we apply Johansen(1988)'s cointegration tests. The results in Table 5.2 confirm the presence of a long-term relationship between spot and futures ethanol prices regardless of the cointegration test used. The Likelihood Ratio test does not reject the null hypothesis of unit coefficient at a 10% significant level. Thus, the *Garbade and Silber* (1983)'s theory is a valid explanation of the long-term relationship between spot and futures prices in the ethanol market. Finally, the long-term causality tests conclude in favor of a price discovery process from futures to spot prices, at a 10% significant level. These findings are in line with the informational efficiency of the US ethanol market.

Figure 5.3: Commercial positions

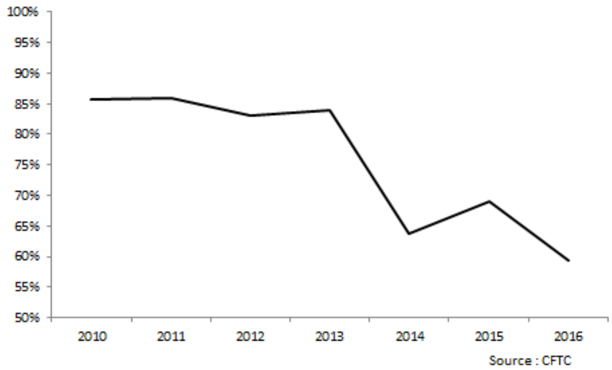


Table 5.2: Cointegration and causality tests

$$\beta_s s_t + f_t + \beta_0 = u_t$$

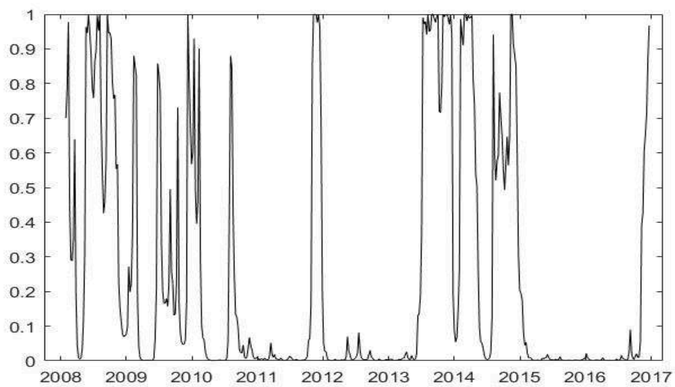
Lags	H_0	P-value λ_{max} test	P-value λ_{trace} test	Cointegration vector (β_s 1 β_0)	LR test $H_0 : \beta_s$=-1	LR test $H_0 : \beta_0$=0
1	r=0	0.001	0.001	(-1.044 1 0.109)	0.078	0.001
-	H_0	Test stat	Critical Value	Cointegration vector	-	-
-	r=0	3.78	3.57	(-1.010 1 -)	-	-
		Causality test			P-value	
		Spot to futures prices			0.867	
		Futures to spot prices			0.087	

Note: The two first lines present the *Johansen* (1988)'s test results. The lags column mentions the number of lags in the VEC Model. Lag length choice is based on *Schwarz* (1978)'s Information Criterion. The two P-value columns refer to the P-value of two tests mentioned. P-value inferior to 0.05 leads to the null hypothesis reject of zero cointegrating relationship against one. Cointegration vector column mentions coefficients estimated with $\hat{\beta}_s$ normalized to unity. The LR test checks the existence of a one-to-one relationship between spot and futures prices. We mention the P-value of the test. The next two lines present the *Nielsen* (2010) test results with the test statistic and the critical value associated at a 5% significance level. The chosen specification is constant and without trend. The null hypothesis is rejected when the test statistic is superior to the critical value. Note that constant is not estimated with this procedure. The causality test refers to the *Toda and Yamamoto* (1995) test whose null hypothesis is the absence of long-term causality.

We estimate the Ms-VEC model with two states applied to both the mean and the variance equations. These two states refer to low and high volatility regimes. Table 5.3

presents results with the Nielsen's cointegration specification.[15] In each state, only futures prices adjusts to equilibrium ($\alpha_{f,st}$). This result highlights the minor role of futures prices in the discovery process in the short term. Note that the adjustment process is faster during the low volatility regime ($st = 2$), compared to the high volatility regime ($st = 1$). Concerning the short-run dynamics ($\gamma_{ij,st}$), these two markets (spot and futures) seem to be disconnected during normal periods and only past changes of futures prices have a significant impact on spot prices for the high volatility state ($\gamma_{sf,1}$). This last result highlights the fact that futures market can help in understanding the ethanol price dynamics during periods of instability. Furthermore, the relationship is regime-dependent, confirming the ability of our Markov-switching specification to describe it. Figure 5.4 presents the probability of being in the regime of high volatility.[16] Two main periods of high volatility are observed in 2008–2009 and 2013–2014. Market volatility during these two periods could be explained by the low liquidity during the first one (Figure 5.1) and by few positions taken by commercial agents for the second period (Figure 5.2).

Figure 5.4: Smoothed probabilities of being in a high volatility state



[15]Table 5.3 presents results for the best models in terms of explanatory power and hedging strategy. We interpret results only for the more explanatory model. Results concerning the 22 specifications are available upon request.

[16]We represent the smoothed probability which provides the best estimation of the states at each time using full-sample information. See *Krolzig* (1997) for further details on its calculation as well as on other existing probabilities. This figure concerns the Ms-VECM^N-Gjr-MGarch. The figure for the VECM^J-Ms-MGarch is similar and available upon request to the authors.

Turning to the conditional variance equation, as expected, we note a high persistence degree ($a_{ii,st}^2 + b_{ii,st}^2$ for $st = 1, 2$) during volatile periods. This feature is common to oil and gasoline markets (*Fong and See*, 2002; *Alizadeh et al.*, 2008). In addition, our specification captures well the leverage effect especially during volatile periods with high and significant coefficients $d_{ii,st}$. Losses in players' portfolio, i.e., negative shocks, have a greater impact on future volatilities than gains, i.e., positive shocks. Finally, the probability of switching from high to low variance states (P_{12}) is greater compared to the probability of switching from low to high variance regimes (P_{21}). This result indicates a shorter duration for high volatility regimes and is confirmed by the average expected state duration calculation proposed by *Hamilton* (1989).[17] This latter result is interesting as it supports the idea of a certain efficiency of the financial market in the short run through the arbitrage process realized by the different players. These durations are nine and twenty weeks for high and low volatility regimes, respectively.

Our different model specifications allow us to compute the dynamic hedge ratios. We also compute the naive ($\delta = 1$) and OLS hedge ratios of *Ederington* (1979). We provide information about a non-hedged strategy for comparison purpose. In addition, we compute cross-hedge ratios with gasoline futures markets estimating from our different specifications. These latter will allow us to compare hedging with the ethanol futures market and cross-hedging with the gasoline futures market.[18] The gasoline market could be used by ethanol commercial agents for risk hedging (*Franken and Parcell*, 2003). Table 5.4 provides variance, utility and value-at-risk for main specifications and each market,[19] as well as the variance improvement of the best strategy compared to each other. During the final period of our sample, i.e., Panel A, the optimal specification is a VAR-Gjr-MGarch. The lack of high volatility (Figure 5.4) during this period explains this result, as well as a possible lack of a cointegration relationship. In addition, all

[17]The average expected duration of state 1 (resp. 2) can be calculated by $(P_{12})^{-1}$ (resp. $(P_{21})^{-1}$).

[18]New York Harbor Reformulated RBOB Regular Gasoline Contract. More details on http://www.cmegroup.com/trading/energy/refined-products/rbob-gasoline.html

[19]A table with all the specifications is available upon request to the authors.

cross-hedging strategies underperform both direct hedging strategies and the situation without a hedging strategy.

Table 5.3: Estimation results

	Ms-VECM^N-Gjr-MGarch				VECM^J-Ms-MGarch			
β_s	-1.011	(-)			-1.044	(-)		
β_f	1	(-)			1	(-)		
β_0	-	(-)			0.109	(-)		
	$st=1$		$st=2$					
$c_{s,st}$	-0.005	(0.417)	0.002	(0.429)	0.001	(0.791)		
$c_{f,st}$	-0.011	(0.049)	0.006	(0.017)	0.003	(0.203)		
$\alpha_{s,st}$	-0.001	(0.960)	-0.001	(0.977)	-0.001	(0.923)		
$\alpha_{f,st}$	-0.083	(0.048)	-0.119	(0.001)	-0.076	(0.001)		
$\gamma_{ss,st}$	0.037	(0.801)	-0.145	(0.390)	-0.114	(0.140)		
$\gamma_{sf,st}$	0.317	(0.029)	0.230	(0.214)	0.260	(0.002)		
$\gamma_{fs,st}$	0.065	(0.552)	0.072	(0.651)	0.051	(0.445)		
$\gamma_{ff,st}$	0.025	(0.822)	-0.071	(0.686)	-0.027	(0.733)		
	$st=1$		$st=2$		$st=1$		$st=2$	
$c_{11,st}$	0.034	(0.001)	0.011	(0.016)	0.030	(0.001)	0.013	(0.001)
$c_{21,st}$	0.037	(0.001)	0.029	(0.001)	0.034	(0.001)	0.029	(0.001)
$c_{22,st}$	0.043	(0.001)	0.029	(0.001)	0.049	(0.001)	0.030	(0.001)
$a_{11,st}$	0.626	(0.001)	0.292	(0.037)	0.815	(0.001)	0.376	(0.001)
$a_{22,st}$	0.309	(0.060)	0.189	(0.144)	0.536	(0.001)	0.256	(0.027)
$b_{11,st}$	0.001	(0.971)	0.214	(0.266)	0.001	(0.887)	0.149	(0.458)
$b_{22,st}$	0.427	(0.021)	0.001	(0.945)	0.391	(0.006)	0.001	(0.869)
$d_{11,st}$	0.657	(0.025)	0.320	(0.053)	-	-	-	-
$d_{22,st}$	0.571	(0.014)	0.442	(0.005)	-	-	-	-
P_{11}	0.890	(0.001)			0.880	(0.001)		
P_{12}	0.110	(0.009)			0.120	(0.001)		
P_{21}	0.050	(0.001)			0.056	(0.001)		
P_{22}	0.950	(0.001)			0.944	(0.001)		
LogL	1.951×10^3				1.936×10^3			
	Spot	Futures			Spot	Futures		
JB	0.001	0.001			0.001	0.001		
Q(6)	0.160	0.665			0.004	0.834		
$Q^2(6)$	0.001	0.001			0.001	0.001		

Note: J and N refer to *Johansen* (1988) and *Nielsen* (2010)'s cointegration estimation, respectively. For each parameter, we mention the estimated coefficients and the P-value of the Student test in bracket. The coefficient is significant at the 10%, 5% or 1% if P-value is less than 0.10, 0.05 or 0.01, respectively. LogL, JB, Q(6) and $Q^2(6)$ are the log-likelihood, the *Jarque and Bera* (1980) test for normality, the *Ljung and Box* (1978) test for autocorrelation and the ARCH test (*Engle*, 1982) for heterosckedasticity, respectively.

Table 5.5 displays results of the main hedging strategies for two other panels,[20] i.e., the first half of 2010 and 2012. The VECM-Ms-MGarch with Johansen's cointegration provides the best strategy for both periods. This result confirms the suitability of Markov-switching and Johansen's cointegration specifications for the hedging strategy on the ethanol market. Note that coefficients of this model are consistent with the previous specification presented (Table 5.3). Hedgers can decrease \$1,268 and \$2,453 of their average weekly value-at-risk with an initial portfolio value of \$1,000,000 compared to

[20]A table with all the specifications is available upon request to the authors.

the simple OLS specification. These weekly decreases correspond to \$9,144 and \$17,689 annualized decreases, that is to say, only 0.09% and 1.77% of the initial portfolio value. Finally, cross-hedging strategies outperform the non-hedged situation for each period with the OLS and Ms-VECM^N-Gjr-MGarch for panels B and C, respectively. This last result highlights the ability of the Nielsen procedure to provide a good hedging strategy.

Table 5.4: In-sample hedging simulation

	Ethanol spot and futures				Ethanol spot and gasoline futures			
	Var.	V. Impr.	Util.	VaR	Var.	V. Impr.	Util.	VaR
Panel A								
No Hedged	12.82	56.5%	-5.127	59,073	**12.82**	**56.5%**	**-5.127**	**59,073**
Naive	5.650	1.44%	-2.260	39,219	36.67	84.8%	-14.67	99,912
OLS	6.053	8.02%	-2.423	40,596	18.16	69.3%	-7.266	70,322
MGarch	5.640	1.28%	-2.256	39,187	18.96	70.6%	-7.583	71,841
VAR-Gjr-MGarch	**5.568**	**-**	**-2.227**	**38,933**	18.18	69.3%	-7.271	70,348
VECM^J-MGarch	5.592	0.43%	-2.237	39,019	18.92	70.5%	-7.569	71,774
VECM^N-Gjr-MGarch	5.611	0.76%	-2.244	39,084	18.24	69.4%	-7.295	70,465
Ms-MGarch	6.054	8.03%	-2.422	40,599	18.13	69.2%	-7.250	70,247
VAR-Ms-Gjr-MGarch	6.467	13.9%	-2.587	41,960	18.36	69.6%	-7.346	70,708
VECM^J-Ms-Gjr-MGarch	6.596	15.5%	-2.638	42,376	18.17	69.3%	-7.267	70,327
VECM^N-Ms-MGarch	6.620	15.8%	-2.648	42,453	18.00	69.0%	-7.201	70,007
Ms-VAR-MGarch	5.626	1.02%	-2.250	39,135	18.06	69.2%	-7.222	70,112
Ms-VECM^J-Gjr-MGarch	5.598	0.53%	-2.239	39,038	18.37	69.7%	-7.347	70,712
Ms-VECM^N-MGarch	5.855	4.91%	-2.342	39,927	18.36	69.7%	-7.345	70,705

Note: Panel A refers to 5/25/16-12/21/16. Variance (Var.) and Utility (Util.) are presented in 10^{-4} and 10^{-3}, respectively. Variance improvement (V. Impr.) measures the incremental variance reduction of the best strategy versus the other strategies with the formula: $[Var(Strategy_i) - Var(Best)]/Var(Strategy_i)$. VaR is in US dollars for an initial investment of \$1 million and $k = 4$. J and N refer to *Johansen* (1988) and *Nielsen* (2010)'s cointegration estimation, respectively.

Table 5.6 present results for the out-of-sample simulation concerning the period from December 28, 2016, to June 21, 2017, i.e., 25 observations. Concerning nonlinear specifications, we estimate the model at each point of time to forecast states' probabilities as well as state-dependent conditional mean and variance-covariance matrix. We then compute the prediction of the hedge ratio after recomposition of the global variance-covariance matrix coming from equations (5.13) and (5.14). The optimal hedging strategy is the linear multivariate Garch specification with a variance improvement of 80.5% and 22.9% compared to a no-hedged situation and the OLS-based hedge ratio, respectively. However, this strategy does not significantly outperform most of the specifications studied especially the naive strategy consisting of a unit hedge ratio. In addition, cross-hedging with the gasoline market is not efficient compared to the direct hedging strategy. This result is also valid compared to the no-hedged situation for most of the strategies. Furthermore, nonlinear specifications do not seem efficient for hedging in the ethanol market. This result could be explained by the difficulty in well-forecasting the states' probability or by the absence of high volatility periods. Finally, the *Johansen* (1988) cointegration procedure outperforms the nonparametric approach of *Nielsen* (2010) for 10 strategies against eight with ethanol markets but out-performs for eight against 10 strategies with cross-hedging in gasoline futures market.[21]

5.5 Conclusion

In this chapter, we analyze the ethanol prices dynamics in the US from 2008 to 2016. For this purpose, we use a Markov-switching vector error correction model with an asymmetric Garch error structure. This specification allows us to study the short-term, long-term and variance dynamics across different volatility regimes. From the cointegration test we could not reject the hypothesis of a long-term equilibrium relationship between spot and futures prices. Two distinct states (low and high volatility) should be distinguished for the short-term dynamics. We provide several dynamic hedge ratios and we examine their performance through in-sample and out-sample simulations.

The ethanol market is characterized by its efficiency and a price-discovery process from futures to spot prices in the long term. The cost-of-carry model from *Garbade and Silber* (1983) is able to well-explain the long-term relationship. In addition, the ethanol futures market can well-explain the spot prices dynamics during the periods of high volatility. Furthermore, hedging strategies based on ethanol futures contracts always

[21] These results come from the comparison between *Johansen* (1988) and *Nielsen* (2010)'s approach for each specification including those not presented in Table 5.4, 5.5 and 5.6.

outperform the cross-hedging strategy based on the use of gasoline futures contracts. Markov-switching specification and *Johansen* (1988)'s cointegration procedure are able to provide an efficient hedging strategy for two-third of the periods analyzed. Then, a simple multivariate Garch model is the best hedging strategy during the first half of 2017 according to the out-of-sample simulation. Finally, while *Nielsen* (2010)'s nonparametric tool provides a clear explanation power for the price dynamics, it cannot be used as a hedging strategy in the ethanol market.

Table 5.5: In-sample hedging simulation with panel B and C

	Ethanol spot and futures				Ethanol spot and gasoline futures			
	Var.	V. Impr.	Util.	VaR	Var.	V. Impr.	Util.	VaR
Panel B								
No Hedged	9.774	48.3%	-3.910	51,584	9.774	48.3%	-3.910	51,584
Naive	5.797	12.9%	-2.319	39,728	17.87	71.7%	-7.148	69,751
OLS	5.395	6.50%	-2.158	38,325	**7.752**	**34.9%**	**-3.101**	**45,939**
Gjr-MGarch	5.606	10.0%	-2.242	39,065	7.917	36.2%	-3.167	46,426
VAR-MGarch	5.612	10.1%	-2.245	39,088	8.072	37.5%	-3.229	46,879
VECM^J-MGarch	5.617	10.2%	-2.247	39,105	8.033	37.2%	-3.213	46,764
VECM^N-Gjr-MGarch	5.645	10.6%	-2.258	39,201	8.069	37.4%	-3.228	46,869
Ms-MGarch	5.104	1.17%	-2.042	37,278	7.916	36.2%	-3.167	46,425
VAR-Ms-MGarch	5.129	1.65%	-2.052	37,369	7.848	35.7%	-3.139	46,224
VECM^J-Ms-MGarch	**5.044**	**-**	**-2.018**	**37,057**	7.883	36.0%	-3.153	46,327
VECM^N-Ms-MGarch	5.160	2.24%	-2.064	37,480	7.818	35.4%	-3.127	46,134
Ms-VAR-Gjr-MGarch	5.153	2.11%	-2.061	37,454	7.973	36.7%	-3.189	46,590
Ms-VECM^J-MGarch	5.251	3.94%	-2.100	37,808	7.822	35.5%	-3.129	46,148
Ms-VECM^N-Gjr-MGarch	5.105	1.19%	-2.042	37,280	8.232	38.7%	-3.293	47,339
Panel C								
No Hedged	10.95	75.9%	-4.380	54,600	10.95	75.9%	-4.380	54,600
Naive	3.133	16.0%	-1.253	29,207	14.19	81.4%	-5.676	62,152
OLS	2.850	7.75%	-1.140	27,853	11.11	76.3%	-4.444	54,996
Gjr-MGarch	3.414	22.9%	-1.366	30,486	11.02	76.1%	-4.406	54,763
VAR-Gjr-MGarch	3.309	20.5%	-1.324	30,016	11.09	76.2%	-4.438	54,957
VECM^J-MGarch	3.288	20.0%	-1.315	29,919	10.96	76.0%	-4.385	54,633
VECM^N-MGarch	2.800	6.10%	-1.120	27,608	10.95	75.9%	-4.379	54,594
Ms-MGarch	2.676	1.75%	-1.071	26,994	10.98	76.0%	-4.391	54,668
VAR-Ms-MGarch	2.742	4.12%	-1.097	27,324	10.78	75.6%	-4.314	54,186
VECM^J-Ms-MGarch	**2.629**	**-**	**-1.052**	**26,754**	10.52	75.0%	-4.209	53,523
VECM^N-Ms-Gjr-MGarch	2.645	0.60%	-1.058	26,835	10.57	75.1%	-4.228	53,642
Ms-VAR-Gjr-MGarch	2.762	4.81%	-1.105	27,421	11.53	77.2%	-4.461	55,104
Ms-VECM^J-MGarch	2.848	7.68%	-1.139	27,844	10.80	75.7%	-4.321	54,231
Ms-VECM^N-Gjr-MGarch	2.704	2.77%	-1.082	27,133	**9.811**	**73.2%**	**-3.924**	**51,681**

Note: Panel B and C refer to 1/06/10-8/04/10 and 1/09/12-8/01/12, respectively. Variance (Var.) and Utility (Util.) are presented in 10^{-4} and 10^{-3}, respectively. Variance improvement (V. Impr.) measures the incremental variance reduction of the best strategy versus the other strategies with the formula: $[Var(Strategy_i) - Var(Best)]/Var(Strategy_i)$. VaR is in US dollars for an initial investment of $1 million and $k = 4$. Figures in bold denote the best-performing model for each market. J and N refer to *Johansen* (1988) and *Nielsen* (2010)'s cointegration estimation, respectively.

Table 5.6: Out-sample hedging simulation

	Ethanol spot and futures				Ethanol spot and gasoline futures			
	Var.	V. Impr.	Util.	VaR	Var.	V. Impr.	Util.	VaR
No Hedged	13.18	80.5%***	-5.271	59,895	13.18	80.5%***	-5.271	59,895
Naive	2.803	8.35%	-1.120	27,622	24.35	89.5%***	-9.742	81,428
OLS	3.331	22.9%**	-1.332	30,116	13.32	80.7%***	-5.328	60.221
MGarch	**2.569**	**-**	**-1.027**	**26,445**	13.54	81.0%***	-5.416	60,715
VAR-Gjr-MGarch	2.647	2.95%	-1.059	26,847	13.45	80.9%***	-5.381	60,519
VECM^J-MGarch	2.679	4.11%	-1.072	27,009	13.56	81.1%***	-5.422	60,750
VECM^N-Gjr-MGarch	2.706	5.06%	-1.082	27,140	13.58	81.1%***	-5.431	60,797
Ms-Gjr-MGarch	3.040	15.5%	-1.216	28,768	13.46	80.9%***	-5.384	60,533
VAR-Ms-Gjr-MGarch	3.077	16.5%	-1.231	28,942	13.92	81.5%***	-5.570	61,569
VECM^J-Ms-Gjr-MGarch	3.080	16.6%	-1.232	28,957	13.48	80.9%***	-5.393	60,588
VECM^N-Ms-Gjr-MGarch	3.098	17.1%	-1.239	29,042	13.58	81.1%***	-5.432	60,805
Ms-VAR-MGarch	3.021	15.0%	-1.208	28,678	13.65	81.2%***	-5.458	60,952
Ms-VECM^J-MGarch	3.083	16.7%	-1.233	28,973	**13.11**	**80.4%*****	**-5.243**	**59,738**
Ms-VECM^N-Gjr-MGarch	3.098	17.1%	-1.239	29,042	13.21	80.6%***	-5.286	59,981

Note: Variance (Var.) and Utility (Util.) are presented in 10^{-4} and 10^{-3}, respectively. Variance improvement (V. Impr.) measures the incremental variance reduction of the best strategy versus the other strategies with the formula: $[Var(Strategy_i) - Var(Best)]/Var(Strategy_i)$. Stars (*, **, ***) indicate that the best strategy outperforms the competing model at a 10%, 5% and 1% significance level, respectively. The P-values are provided from *White* (2000)'s reality check using the stationary bootstrap of *Politis and Romano* (1994). VaR is in US dollars for an initial investment of $1 million and $k = 4$. J and N refer to *Johansen* (1988) and *Nielsen* (2010)'s cointegration estimation, respectively.

In order to get a full understanding of the different hedging strategies in the financial ethanol market, this chapter could be extended in various ways. The methodology used with RBOB gasoline market could be applied to other commodities futures markets such as crude oil, corn or sugar. More globally compared to mature futures market (crude oil, sugar, etc.), the ethanol market was launched in 2005 and the traders' behaviour could have been influenced by many factors such as a lack of information regarding the physical production, commercial strategy (anti-dumping), fiscal policy in producing countries (taxes in Brazil, in the US, etc. and more global uncertainties regarding energy and environmental policies all around the world, etc.). It could explain the fact that the ethanol futures market has not appealed to the traders since the beginning of the last decade but it could become a key market in the near future with the environmental and regulatory constraints of a 2C scenario.

Bibliography

Alizadeh, A. H., Nomikos, N. K., and Pouliasis, P. K. (2008). A markov regime switching approach for hedging energy commodities. *Journal of Banking and Finance*, 32(9):1970–1983.

Baba, Y., Engle, R. F., Kraft, N. K., and Kroner, K. F. (1987). Multivariate simultaneous generalized arch. University of California, San Diego, unpublished manuscript.

Baillie, R. T. and Myers, R. J. (1991). Bivariate garch estimation of the optimal commodity futures hedge. *Journal of Applied Econometrics*, 6(2):109–124.

Brennan, M. J. (1958). The supply of storage. *American Economic Review*, 48(1):50–72.

Brooks, C., Henry, O. T., and Persand, G. (2002). The effect of asymmetries on optimal hedge ratios. *Journal of Business*, 75(2):333–352.

Cecchetti, S. G., Cumby, R. E., and Figlewski, S. (1988). Estimation of the optimal futures hedge. *The Review of Economics and Statistics*, 70(4):623–630.

Chou, W. L., Fan, D. K. K., and Lee, C. F. (1996). Hedging with the Nikkei index futures: The conventional model versus the error correction model. *The Quarterly Review of Economics and Finance*, 36(4):495–505.

Chowdhury, A. R. (1991). Futures market efficiency: Evidence from cointegration tests. *The Journal of Futures Markets*, 11(5):577–589.

Dahlgran, R. A. (2009). Inventory and transformation hedging effectiveness in corn crushing. *Journal of Agricultural and Resource Economics*, 34(1):154–171.

Dempser, A., Laird, N., and Rubin, D. B. (1977). Maximum likelihood from incomplete data via the EM algorithm. *Journal of the Royal Statistical Society. Series B (Methodological)*, 39(1):1–38.

Dickey, D. and Fuller, W. (1979). Distribution of the estimators for autoregressive time series with a unit root. *Journal of the American Statistical Association*, 74(366):427–431.

Dickey, D. A. and Fuller, W. A. (1981). Likelihood ratio statistics for autoregressive time series with a unit root. *Econometrica*, 49(4):1057–1072.

Ederington, L. H. (1979). The hedging performance of the new futures markets. *The Journal of Finance*, 34(1):157–170.

Engle, R. F. (1982). Autoregressive conditional heteroscedasticity with estimates of the variances of the United Kingdom inflation. *Econometrica*, 50(4):987–1008.

Engle, R. F. and Kroner, K. F. (1995). Multivariate simultaneous generalized arch. *Econometric Theory*, 11(1):122–150.

Fama, E. F. (1970). Efficient capital markets: A review of theory and empirical work. *The Journal of Finance*, 25(2):383–417.

Figuerola-Ferretti, I. and Gonzalo, J. (2010). Modelling and measuring price discovery in commodity markets. *Journal of Econometrics*, 158(1):95–107.

Fong, W. and See, K. (2002). A markov switching model of the conditional volatility of crude oil prices. *Energy Economics*, 24(1):71–95.

Franken, J. R. and Parcell, J. L. (2003). Cash ethanol cross-hedging opportunities. *Journal of Agricultural and Applied Economics*, 35(3):509–516.

Garbade, K. D. and Silber, W. L. (1983). Price movements and price discovery in futures and cash markets. *The Review of Economics and Statistics*, 65(2):289–297.

Garcia, P., Roh, J.-S., and Leuthold, R. M. (1995). Simultaneously determined, time-varying hedge ratios in the soybean complex. *Applied Economics*, 27(12):1127–1134.

Ghosh, A. (1993). Cointegration and error correction models: Intertemporal causality between index and futures prices. *The Journal of Futures Markets*, 13(2):193–198.

Glosten, L. R., Jagannathan, R., and Runke, D. E. (1993). On the relation between the expected value and the volatility of the nominal excess return on stocks. *The Journal of Finance*, 48(5):1779–1801.

Gonzalo, J. and Pitarakis, J.-Y., editors (2006). *Threshold Effects in Multivariate Error Correction Models*, volume Volume 1: Econometric Theory of *Palgrave Handbook of Econometrics*. Palgrave MacMillam, New-York.

Gray, S. F. (1996). Modeling the conditional distribution of interest rates as a regime-switching process. *Journal of Financial Economics*, 42(1):27–62.

Hache, E. and Lantz, F. (2013). Speculative trading and oil price dynamic: A study of the WTI market. *Energy Economics*, 36:334–340.

Hamilton, J. D. (1989). A new approach to the economic analysis of nonstationary time series and the business cycle. *Econometrica*, 57(2):357–384.

Hanly, J. (2017). Managing energy price risk using futures contracts: A comparative analysis. *The Energy Journal*, 38(3):93–112.

Heaney, R. (2002). Approximation for convenience yield in commodity futures pricing. *Journal of Futures Markets*, 22(10):1005–1017.

Hull, J. (2005). *Options, Futures, and Other Derivatives*. Prentice Hall, 6 edition.

Jarque, C. M. and Bera, A. K. (1980). Efficient tests for normality, homoscedasticity and serial independence of regression residuals. *Economics Letters*, 6(3):255–259.

Johansen, S. (1988). Statistical analysis of cointegration vectors. *Journal of Economic Dynamics and Control*, 12(2-3):231–254.

Johansen, S. (1995). *Likelihood-Based Inference in Cointegrated Vector Autoregressive Models*. Oxford, Oxford university press edition.

Kaldor, N. (1939). Speculation and economic stability. *The Review of Economic Stability*, 7(1):1–27.

Kavussanos, M. G. and Nomikos, N. K. (2000). Hedging in the futures market. *The Journal of Derivatives*, 8(1):41–58.

Krolzig, H.-M. (1997). *Markov-Switching Vector Autoregressions: Modelling, Statistical Inference, and Application to Business Cycle Analysis*. Lecture Notes in Economics and Mathematical Systems. Springer,, Berlin.

Krolzig, H.-M. (1999). Statistical analysis of cointegrated VAR process with markovian regime shifts. Department of Economics, University of Oxford, unpublished manuscript.

Kroner, K. F. and Sultan, J. (1993). Time-varying distributions and dynamic hedging with foreign currency futures. *Journal of Financial and Quantitative Analysis*, 28(4):535–551.

Kwiatkowski, D., Phillips, P. C., Schmidt, P., and Shin, Y. (1992). Testing the null hypothesis of stationarity against the alternative of a unit root. *Journal of Econometrics*, 54(1-3):159–178.

Lai, K. S. and Lai, M. (1991). A cointegration test for market efficiency. *The Journal of Futures Markets*, 11(5):567–575.

Lamoureux, C. G. and Lastrapes, W. D. (1990). Persistence in variance, structural change, and the garch model. *Journal of Business and Economic Statistics*, 8(2):225–234.

Lautier, D. (2005). Term structure models of commodity prices: a review. *Journal of Alternative Investments*, 8(1):42–64.

Lee, H.-T. and Yoder, J. (2007a). Optimal hedging with a regime-switching time-varying correlation GARCH model. *The Journal of Futures Markets*, 27(5):495–516.

Lee, H.-T. and Yoder, J. K. (2007b). A bivariate Markov regime switching GARCH approach to estimate time varying minimum variance hedge ratios. *Applied Economics*, 39(10):1253–1265.

Lien, D. (1996). The effect of the cointegration relationship on futures hedging: A note. *The Journal of Futures Markets*, 16(7):773–780.

Lien, D. and Tse, Y. K. (2002). Some recent developments in futures hedging. *Journal of Economic Survey*, 16(3):357–396.

Lien, D. and Yang, L. (2008). Asymmetric effect of basis on dynamic futures hedging: Empirical evidence from commodity markets. *Journal of Banking & Finance*, 32(2):187–198.

Ljung, G. M. and Box, G. (1978). On a measure of lack of fit in time series models. *Biometrika*, 65(2):297–303.

Medlock, K. B. and Jaffe, A. M. (2009). Who is in the oil futures market and how has it changed. James A. Baker III Institute For Public Policy, Rice University, unpublished manuscript.

Myers, R. J. and Thompson, S. R. (1989). Generalized optimal hedge ratio estimation. *American Journal of Agricultural Economics*, 71(4):858–868.

Nielsen, M. O. (2010). Nonparametric cointegration analysis of fractional systems with unknown integration orders. *Journal of Econometrics*, 155(2):170–187.

Perron, P. (1990). Testing for a unit root in a time series with a changing mean. *Journal of Business and Economic Statistics*, 8(2):153–162.

Perron, P. and Vogelsang, T. J. (1992). Testing for a unit root in a time series with a changing mean: Corrections and extensions. *Journal of Business and Economic Statistics*, 10(4):467–470.

Phillips, P. C. and Perron, P. (1988). Testing for a unit root in time series regression. *Biometrika*, 75(2):335–346.

Politis, D. N. and Romano, J. P. (1994). The stationary bootstrap. *Journal of the American Statistical Association*, 89(4):1303–1313.

Routledge, B. R., Seppi, D. J., and Spatt, C. S. (2000). Equilibrium forward curves for commodities. *The Journal of Finance*, 55(3):1297–1337.

Salvador, E. and Arago, V. (2014). Measuring hedging effectiveness of index futures contracts: Do dynamic models outperform static models? A regime-switching approach. *The Journal of Futures Markets*, 34(4):374–398.

Sarno, L. and Valente, G. (2000). The cost of carry model and regime shifts in stock index futures markets: An empirical investigation. *The Journal of Futures Markets*, 20(7):603–624.

Schwarz, G. (1978). Estimating the dimension of a model. *The Annals of Statistics*, 6(2):461–464.

Simon, Y. (1984). Les marchés à terme de produits pétroliers. *L'Actualité Economique*, 60(3):375–406.

Telser, L. G. (1958). Futures trading and the storage of cotton and wheat. *Journal of Political Economy*, 66(3):233–255.

Toda, H. Y. and Yamamoto, T. (1995). Statistical inference in vector autoregressions with possibly integrated processes. *Journal of Econometrics*, 66(1-2):225–250.

White, H. (2000). A reality check for data snooping. *Econometrica*, 68(6):1097–1126.

Working, H. (1948). Theory of the inverse carrying charge in futures markets. *Journal of Farm Economics*, 30(1):1–28.

6

Conclusion générale

Cette thèse a proposé une analyse approfondie (i) des impacts économiques des biocarburants en lien avec le développement de leur production, (ii) des préférences des Français entre les différents biocarburants existants et (iii) des caractéristiques spécifiques aux marchés financiers liés aux biocarburants. Outre ces contributions, notre thèse fournit une aide aux décideurs publics quant à la poursuite du développement des biocarburants – notamment de deuxième génération – et une stratégie pour les industriels de ce secteur pour se protéger de la volatilité des prix. À cette fin, nous avons étudié le lien entre les biocarburants de première génération et les prix agricoles, puis les conséquences de l'existence d'une telle relation sur des pays émergents et en développement. Nous avons ensuite analysé les préférences de la population française concernant les différentes caractéristiques des biocarburants. Enfin, nous avons étudié les propriétés du marché financier de l'éthanol aux États-Unis en termes d'efficience, ainsi que sa capacité à être utilisé par les industriels pour réduire leur risque-prix.

La première génération de biocarburants étant produite à partir de matières premières agricoles, le chapitre 1 a traité de l'impact de leur développement sur le niveau des prix de produits agricoles. L'expansion de la production de biocarburants a engendré une controverse politique et économique sur la moralité d'utiliser des biens à finalité alimentaire pour un but énergétique : le débat "*food versus fuel*", dont l'un des axes est la contribution de la production de ces biocarburants à la forte hausse des prix agricoles intervenue durant les années 2000. Afin de contribuer à ce débat, nous avons estimé l'impact de la production de biocarburants de première génération sur le lien entre les prix du pétrole et agricoles. Prendre en compte les prix de l'énergie, en particulier du pétrole est en effet crucial car ce dernier intervient en tant qu'intrant dans les cultures agricoles et peut être vu comme un substitut aux biocarburants *via* les carburants pétroliers. Nous avons alors mis en évidence le rôle de la production des biocarburants dans la hausse des prix des produits agricoles par le renforcement du lien entre les prix du pétrole et des produits agricoles entrant dans la production des biocarburants. La forte hausse du prix des biens agricoles est donc liée à la fois au développement de ces biocarburants de première génération et aux prix élevés du pétrole durant les années 2000. De plus, les autres produits agricoles (non utilisés dans la production de biocarburants) sont aussi impactés du fait des phénomènes de substitution qui s'opèrent.

Or, de nombreux pays développés – dont l'Allemagne, les États-Unis ou la France – ont encouragé l'utilisation des biocarburants de première génération, contribuant à l'inflation des prix agricoles au milieu des années 2000. En conséquence, un tel développement de ces biocarburants est susceptible de générer des effets sur les pays émergents et en développement dont l'économie dépend des produits agricoles utilisés dans leur processus de production. Nous avons donc étudié l'impact des variations des prix des matières premières agricoles – entrant dans la production des biocarburants – sur le solde courant de 16 économies émergentes et en développement en prenant en compte les fluctuations du prix du pétrole – ce dernier étant un déterminant des prix agricoles et du compte courant de ces économies. Nous montrons qu'une augmentation de 10% du prix des produits agricoles tend à améliorer d'environ 2% la position du compte courant de ces pays producteurs et exportateurs de produits agricoles. Cet effet tend à diminuer – puis disparaître – lorsque le prix du pétrole dépasse 45 dollars américains par baril pour les économies exportatrices de ces matières premières agricoles et 56 dollars concernant les pays producteurs. Les fluctuations des prix agricoles n'ont pas affecté la balance courante des économies importatrices grâce à la mise en place de politiques de protection de leurs marchés domestiques. Ainsi, le développement des biocarburants à base de produits agricoles peut profiter aux pays émergents et en développement exportateurs et producteurs de ces biens agricoles, sous réserve que l'économie mondiale enregistre une période de bas prix du pétrole.

Afin de pallier les problèmes de la première génération de biocarburants – dont ceux étudiés précédemment –, une deuxième génération est en phase de pré-commercialisation. Celle-ci permet d'accroître les réductions d'émission de GES et les intrants de cette nouvelle génération n'entrent pas en compétition avec la consommation alimentaire. Cependant, les biocarburants de deuxième génération ne sont pas homogènes et se distinguent entre eux en termes d'impact agricole. En effet, ces biocarburants peuvent être produits à partir de résidus agricoles ou de plantes énergétiques profitant au secteur agricole, mais aussi de résidus de bois. Le choix de l'intrant à utiliser pour leur production peut alors dépendre des préférences de la population en termes d'impacts sur l'environnement et les prix alimentaires – permettant de distinguer entre première et deuxième générations – et de soutien à la filière agricole – permettant de discriminer ces préférences entre les différents intrants de la deuxième génération. Pour révéler ces préférence, nous avons mis en place une enquête à choix discrets – de type *Discrete Choice Experiment* – auprès de 972 Français nous permettant de mettre en évidence une préférence de l'ensemble des répondants pour les biocarburants de deuxième génération en raison d'une aversion à l'égard des hausses de prix des biens alimentaires. Celle-ci est évaluée monétairement par une disposition à payer comprise entre 35,30 euros et 40,80 euros par an pour éviter ces hausses de prix. De plus, une majorité des répondants, *i.e.*, 65,1%, valorise fortement le soutien à la filière agricole avec une disposition à payer de 51,59 euros par an, contre 8,98 euros pour la minorité. La population française est donc partagée sur la question de l'intrant à utiliser pour la production de biocarburants de deuxième génération. La majorité préfère une production à partir de résidus agricoles, alors que la minorité semble favoriser l'usage de résidus de bois ou d'une autre technologie pour réduire les émissions de GES du secteur des transports. Notons aussi que la population française est partagée quant à la valorisation de ces réductions. La majorité est prête à payer 2,64 euros par an par point de pourcentage de réduction des émissions du secteur des transports contre une valorisation à 0,68 euro par la minorité.

Au vu de la poursuite probable de l'expansion du marché des biocarburants, en particulier de deuxième génération, le recours aux marchés financiers dérivés correspondant doit permettre aux industriels d'anticiper les prix futurs et de se protéger de la volatilité des prix. Nous avons alors étudié la capacité du marché à terme de l'éthanol du *Chicago Board of Trade* (CBOT) à assurer ces deux fonctions. D'après nos résultats, l'hypothèse d'efficience des marchés financiers ne peut pas être réfutée pour le marché à terme de l'éthanol. En conséquence, le prix à terme est un prédicteur sans biais du prix physique et peut donc être utilisé pour fixer les prix des échanges sur le marché physique. Nous avons aussi établi que le recours au marché dérivé permet de réduire de plus de 80% – concernant le premier semestre 2017 – l'exposition au risque-prix des industriels comparée à une situation sans stratégie de couverture du risque ou en utilisant le marché à terme de l'essence. Nous avons montré, à l'aide de simulations, que la stratégie optimale pour le calcul du ratio de couverture consistait à modéliser (*via* un modèle GARCH multivarié) les moments d'ordre 2 du système constitué des prix à terme et physique.

Au total, plusieurs résultats clés peuvent être déduits des analyses menées dans notre thèse. Le premier chapitre a montré l'existence d'un impact négatif des biocarburants de première génération sur les prix agricoles *via* un effet inflationniste. Bien qu'une quantité non négligeable de produits agricoles puisse être utilisée dans la production de biocarburants sans impact sur les prix agricoles – 10% de la production de maïs dans le cas de la production d'éthanol aux États-Unis –, il s'avère impératif de développer une production de biocarburants ne nécessitant pas de matières premières à visée alimentaire. Le deuxième chapitre a mis en évidence un effet positif du développement des biocarburants de première génération sur les économies des pays émergents et en développement lorsque le prix du pétrole n'excède pas 50 dollars le baril. Cependant, il est important de noter que celui-ci fut majoritairement dans un régime de prix supérieur à 50 dollars – en dehors de 2015–2016 – depuis l'expansion des biocarburants. Cette dynamique a donc peu profité à ces économies tout en contraignant les pays importateurs de ces produits agricoles à mettre en place des politiques de protection de leurs marchés domestiques face aux hausses des prix internationaux sur ces matières premières. Les résultats de nos deux premiers chapitres permettent ainsi de comprendre les raisons de la mise en place de la directive européenne 2015/1513 limitant l'usage des biocarburants de première génération et encourageant par là même le développement à grande échelle de la deuxième génération.

Cependant, un investissement important est nécessaire afin de développer cette nouvelle filière. En France, celui-ci pourrait être partiellement financé par une contribution exceptionnelle au vu de la disposition de la population française à financer les biocarburants de deuxième génération. En particulier, les résultats de notre troisième chapitre mettent en évidence une disposition à payer moyenne d'environ 71 euros par an pendant 5 ans dans le cas du développement d'un carburant contenant 20% de biocarburant issu de la paille de blé. De plus, ce montant pourrait varier en fonction de l'hétérogénéité des préférences de la population française afin d'accroître l'acceptabilité de cette contribution. Cette hétérogénéité s'explique en partie par l'âge du répondant – la valorisation des réductions d'émission diminuant avec l'âge – et par son environnement local. En effet, nous montrons que les répondants vivant dans des zones densément peuplées – et donc peu agricoles – valorisent plus ces réductions mais moins l'appui à la filière agricole comparativement à la population située dans des zones faiblement peuplées. Un second axe d'appui à la filière des biocarburants serait de permettre aux industriels de se protéger efficacement face à la volatilité des prix des biocarburants par l'instauration de marchés dérivés sur l'éthanol et le biodiesel en Europe.

Cette thèse peut être étendue dans plusieurs directions. Une première piste consisterait à étendre l'étude du chapitre 1 à un cadre multivarié afin de pouvoir mettre en évidence l'ensemble des relations entre les prix du pétrole et des principales matières agricoles en fonction de la production de biocarburants. Une telle modélisation permettrait une analyse plus fine des effets de substitution entre produits agricoles. Le chapitre 3 pourrait être enrichi en intégrant dans l'enquête une réduction du prix des carburants contenant des biocarburants. Une telle redistribution de la contribution prélevée vers les consommateurs pourrait accroître l'acceptabilité de celle-ci. De plus, cette enquête pourrait être réalisée dans d'autres pays européens, notamment ceux caractérisés par un secteur agricole peu développé. Une telle extension permettrait d'étudier les préférences concernant les biocarburants dans un pays où la production ne proviendrait pas de produits agricoles domestiques. Enfin, le chapitre 4 peut être étendu en analysant des stratégies de couverture croisée du risque en utilisant des marchés à terme du maïs – en tant qu'intrant principal de l'éthanol américain – ou du pétrole. Il serait aussi pertinent d'intégrer les coûts de transaction afférant à la gestion du portefeuille de couverture.

Résumé

Après avoir montré l'existence d'un impact inflationniste des biocarburants de première génération sur les prix agricoles *via* un renforcement du lien entre les prix agricoles et du pétrole, nous soulignons l'absence d'un réel effet positif de leur expansion sur les économies émergentes et en développement. De plus, la hausse des prix agricoles a contraint certains pays importateurs de ces produits agricoles à mettre en place des politiques de protection de leurs marchés domestiques. Ces résultats prouve qu'il s'avère impératif de développer une production de biocarburants ne nécessitant pas de matières premières à visée alimentaire. Or, nous mettons en évidence la préférence de la population française pour ces biocarburants de deuxième génération, d'autant plus pour une production issue de résidus agricoles. Enfin, nous établissons – en prenant l'exemple d'un marché américain – que la mise en place de marchés dérivés des biocarburants en Europe pourrait permettre aux industriels de se protéger efficacement face à la volatilité des prix.

Abstract

Having shown the existence of an inflationary impact of first-generation biofuels on agricultural prices through a stronger link between agricultural and oil prices, we highlight the lack of a real positive effect of their expansion on the emerging and developing economies. In addition, the rise in agricultural prices has required some importing countries of these agricultural products to implement policy measures to protect their domestic markets. These results prove that it is imperative to develop a production of biofuels that do not use food crops. However, we highlight the preference of the French population for these second-generation biofuels, especially for a production based on agricultural residuals. Finally, we establish – using the example of the US market of ethanol – that the establishment of biofuel derivatives markets in Europe could enable industrials to protect themselves efficiently against price volatility.