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Faculty of Social Sciences
Institute of Economic Studies

MASTER'S THESIS

Impacts of Ethanol Policy on Corn Prices: A Meta-Analysis

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Declaration of Authorship

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Prague, May 19, 2017

Signature

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Abstract

Deflecting a significant portion of corn production to ethanol for fuelling purposes increases the prices of corn. Although many studies examined the relationship between biofuels and agricultural commodity prices in the last decade, their estimates vary broadly (from nil to 85%). Without knowing the precise estimates of these impacts, policymakers can hardly set the biofuel policies optimally. I conduct a meta-analysis of over 150 estimates of the effect of corn ethanol production on corn prices to bring more clarity to the issue. Furthermore, I detect substantial selective reporting bias in the literature. After controlling for this bias with the use of various methods including the mixed-effects multilevel model, the results show that the true effect of a one billion gallon expansion in corn ethanol on corn prices is about 2-3%, which is less than commonly thought.

JEL Classification	C52, C81, C83, Q16, Q18
Keywords	ethanol, biofuels, corn price, meta-analysis, selective reporting, publication bias

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Abstrakt

Studie provedené během poslední dekády na téma souvislostí mezi biopalivy a cenou zemědělských komodit potvrzují všeobecně přijímanou teorii o pozitivním vztahu mezi těmito dvěma veličinami. Avšak odhady závažnosti dopadů rozšířování produkce etanolu na ceny zemědělských komodit (například kukuřice) se značně rozcházejí - v literatuře najdeme hodnoty pohybující se v rozmezí 0-85%. Zákonodárci mohou jen obtížně vytvářet nové či měnit stávající politiky týkající se biopaliv bez znalosti jejich konkrétních dopadů na ceny potravin. V této práci využívám meta-analytické metody k přesnějšímu určení míry závislosti mezi těmito dvěma veličinami. Kromě toho nacházím v literatuře věnované odhádům této korelace přítomnost značné publikační selektivity. S pomocí několika metod, mezi kterými je i víceúrovňový model smíšených efektů a které si dokáží poradit s publikační selektivitou, docházím k výsledkům očištěným o způsobené vychýlení. Skutečný efekt zvýšení produkce etanolu o 1% na zvýšení ceny kukuřice se tak pohybuje v rozmezí 0.05-0.11%, což je méně než se doposud předpokládalo.

Klasifikace JEL	C52, C81, C83, Q16, Q18
Klíčová slova	ethanol, biopaliva, cena kukuřice, meta-analýza, publikační selektivita

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Master's Thesis Proposal

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Topic characteristics Understanding the precise impacts of biofuels on agricultural commodity prices is of principal importance when it comes to Ethanol Policies. However, the literature on this topic is characterized by contradictory findings. Studies published between 2007 and 2014 that estimate the effects of U.S. corn ethanol policy on corn prices present estimates that vary broadly (from 0 to 80%). Such divergent results make it difficult to assess the merits of alternative biofuel policies. During the last decade, there has been more than a fivefold increase in global liquid biofuel production and it is projected that the share of biofuels in global transportation fuel will increase from 2% in 2010 to 27% by 2050. That is another reason why it is of major importance to pay attention to this topic and examine it properly.

In the last 8 years, more than 30 studies bringing over 150 medium-to-long run estimates of the effect of corn ethanol production on corn prices have been published. A systematic method how to make use of all this work is to collect these numerous estimates and summarize them quantitatively. One of the most suitable methods for this purpose is the so-called meta-analysis (Stanley, 2001), which we would like to use to obtain the best possible estimates.

This thesis should build upon the recently conducted meta-analysis Condon *et al.* (2015) and should try to further deepen the understanding of the precise impacts of biofuels on agricultural commodity prices. The main objective of this thesis will be the search of publication bias that is very probable to have significant effect on the so far published literature. According to Stanley (2008) publication selection bias has been found in many areas of empirical economics. Considering how often publication bias occurs, Stanley (2005) recommends that we should include the assumption of the presence of publication bias into every meta-analytical study. However, this has not been done in the previous meta-analyses on this topic. If we find out that the literature is significantly influenced by publication selection bias, we will also estimate its size, which will allow us to obtain the "true" impact of biofuels on agricultural commodity prices.

Outline

1. Introduction
2. Literature review
3. Data
4. Methods
5. Results
6. Conclusion

Core bibliography

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Author

Supervisor

Chapter 1

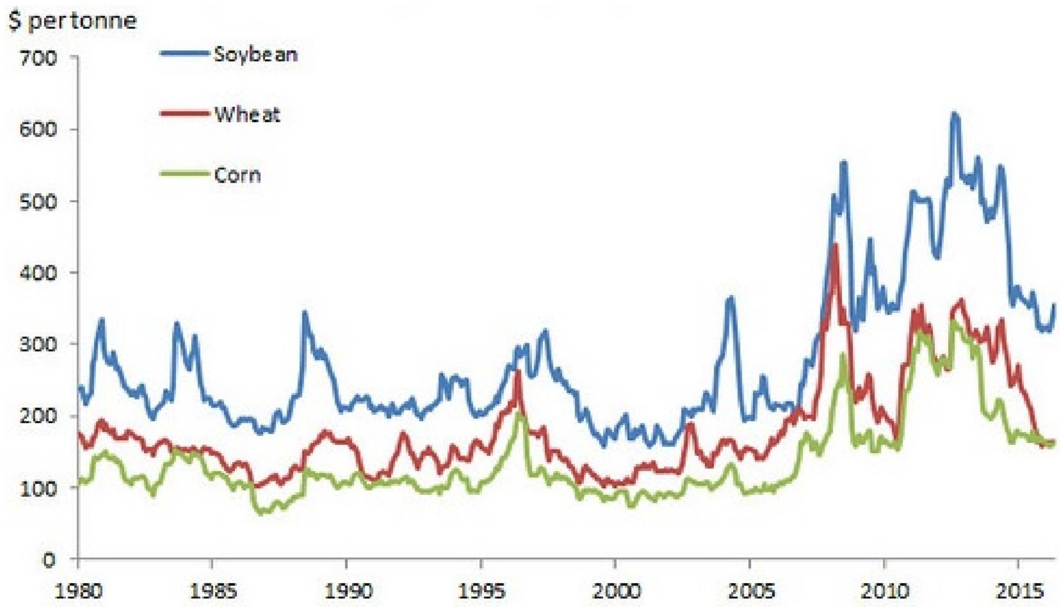
Introduction

Understanding the precise impacts of ethanol expansions on agricultural commodity prices is of principal importance when it comes to biofuel policies. If policymakers knew the exact impacts of biofuel policies they are proposing, they could account for it and set the mandates, tax credits or any other policy tool or measure optimally. Unfortunately, the literature on this topic is characterized by contradictory findings. Studies published between 2007 and 2017 that estimate the effects of biofuel policies related to corn ethanol expansions on corn prices present estimates that vary broadly (from 0 to 85%). Such divergent results make it difficult to assess the merits of any biofuel policy.

During the last decade, there has been more than a fivefold increase in global liquid biofuel production (Condon *et al.* 2015). This rapid growth can be largely credited to the three biggest biofuel producers in the world, which are the United States, Brazil, and the European Union. At the same time, these three regions also consume the largest shares of biofuels and, according to Enciso *et al.* (2016), the situation will most probably not change significantly in the next few years as their projections show in Figure 2.2. These regions and especially their policymakers influence the agricultural and biofuel markets substantially when deciding about trade policies, mandates, or tax credits.

Historically, agricultural commodity prices were decreasing in the 1970-2000 period. This trend changed in 2005 when the crop prices began to rise mirroring the expanding production of biofuels (FAO 2013). The sudden increase in corn production is clearly visible in the Figure 1.1. Since then, agricultural prices reached two major peaks - in 2008 and 2010. In addition to showing these two peaks, Figure 1.1 also depicts the correlation between corn, wheat, and soybean prices. When estimating the impacts of biofuel policies on corn prices, we should keep in mind that corn is also commonly used for feeding purposes for livestock. Therefore, an increase in corn prices will be probably associated with an increase in animal source food prices.

Figure 1.1: Relationship between corn, wheat, and soybean prices

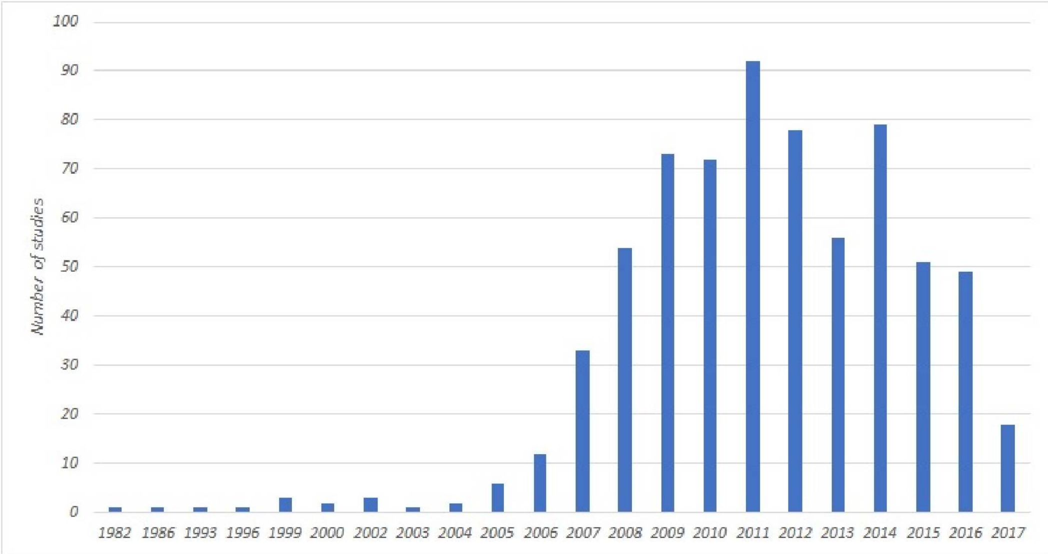


Source: Quandl

The junction of the two trends (production of biofuels and agricultural prices) started a loud discussion about the trade-off between fuel resources and food. Especially in the United States, biofuel policies have been talked over quite heavily since then, which is understandable considering the "leading exporter" role of the United States in the agricultural commodities sector. However, governments were not the only ones who decided to take a closer look at the effects of biofuel expansions on corn or other agricultural commodity prices. Other organizations and academics started to pay considerably higher attention to these correlations as well. Figure 1.2 reflects the development of the number of studies published on the topic of the relationship between agricultural prices and biofuels in time.

In the last 10 years, more than 30 studies bringing over 170 medium-to-long run estimates of the effect of corn ethanol production on corn prices have been published. A systematic method of making use of all these studies and the precious information they contain is to collect all available estimates and summarize them quantitatively. One of the most suitable methods for this purpose is the so-called meta-analysis (Stanley 2001). I will use this powerful

Figure 1.2: Number of published studies



tool to obtain the best possible estimate of the true effect of ethanol expansions on corn prices.

The main objective of this thesis is the detection of selective reporting that is very probable to be present in the literature and to have a significant effect on the reported estimates. According to Stanley *et al.* (2008), selective reporting (sometimes also called publication selection) has been found throughout many areas of empirical economics. Selective reporting causes exaggeration of the sizes of the mean reported effects and thereby biases our conclusions based on the available literature. Necker (2014) performed a survey on the fields of European Economic Association that brought a disturbing conclusion: More than 30% of European economists admit an engagement in methodically unsound procedures like searching for variables until the desired outcome is obtained. According to a meta-analysis by Havranek *et al.* (2012a), more than a third of the gasoline demand price elasticity estimates are never reported because of either counter-intuitive signs or statistical insignificance. After correcting for this large selective reporting bias authors conclude that the mean reported price elasticity was exaggerated twofold. Considering how often publication bias occurs, Stanley (2005) recommends that we should include the assumption of the presence of publication bias into every meta-analytical study. However, this has not been done in the previous meta-analyses on this topic conducted by Condon *et al.* (2015).

I will use both graphical and empirical methods of testing for selective reporting. Among others, meta-regression, funnel asymmetry test, fixed-effects model, and mixed-effects multilevel model will be employed. If I detect a significant influence of selective reporting in the literature, I will also estimate the size of the bias caused by it. Furthermore, I will correct for it, which will allow us to obtain the "true" impact of ethanol expansions on corn prices. An unpleasant complication on the way towards the detection of selective reporting and correction for the bias induced by it will probably be the absence of any precision measures of estimates reported by primary studies. This issue will be addressed in accordance with the method proposed by Havranek *et al.* (2015). This approach, however, will have an unfortunate impact on the data set, because only studies that present more than one estimate can be examined.

In addition, I will include the most recent studies, which could not have been incorporated into the previous meta-analysis, in my data set. Furthermore, I will also control for different sizes of corn ethanol expansions and other study or estimate-level characteristics by including new explanatory variables as well as some that were already used in the previous meta-analysis.

The thesis is structured as follows. Chapter 2 summarizes the most recent literature examining the relationship between biofuel policies and agricultural commodity prices. Chapter 3 presents additional information about biofuel policy tools, development of the biofuels markets, global transportation forecasts, the relationship between biofuel policies and biofuel markets, and shortly discusses the food prices crisis in 2008. Chapter 4 explains the collection of the data, describes the data set and discusses variables. Chapter 5 shortly describes and evaluates the meta-analysis method, explains the methods used for detecting selective reporting, and clarifies the computation of approximate standard errors. Chapter 6 presents the results of meta-regression analysis and compares the results to the previous literature. Chapter 7 concludes the thesis.

Chapter 2

Literature Review

As already mentioned, the literature dealing with the effects of biofuel expansion on agricultural commodity prices is very diverse in the sense of inconsistent findings and a broad range of estimated effects. Let me mention a few examples here. Zhang *et al.* (2013) examined the relationship between the price of corn and the U.S. biofuel policies and came up with a wide range of results between 5 – 53 %. Such variation is not very useful for making any conclusions on this topic. Unfortunately, many other primary studies suffer from the same inaccuracy as well. For example, the (NRC) presented a study on this topic and their estimates were ranging from 17% to 70% while working with data from the 2007-2009 period. Of course, such contradictory estimates are very difficult to interpret, which makes the evaluation of the relative strengths and weaknesses of the biofuel policies that either expand, reduce or change the biofuels production trends, almost impossible.

This thesis builds upon the recently conducted meta-analysis (Condon *et al.* 2015) and should try to further deepen the understanding of the precise impacts of biofuels on agricultural commodity prices. Unlike the previous reviews on this topic, Condon *et al.* (2015) employed a few new strategies "to place studies on more equal footing to facilitate such comparisons". Moreover, they restricted the extent of their study to a single commodity – corn – which I will examine as the only one in this thesis as well. The work of Condon *et al.* (2015) focused largely on the effects of U.S. biofuel policy.

Condon *et al.* (2015) normalized the impacts of corn prices by ethanol quantity to control for huge differences between individual ethanol volumes in various scenarios. This way they were able to calculate two basic metrics: "The percent change in corn prices per one billion gallons increase in corn ethanol production (a semi-elasticity measure), and the percent change in corn prices per one percent increase in corn ethanol production (an elasticity measure)" (Condon *et al.* 2015). They found out that each billion-gallon increase in production of ethanol made from corn results into a 3-4% increase in corn prices depending on the individual scenarios.[1] In this thesis, I normalize the data in the same way.

Even though this normalization changed the dataset to a much more useful state allowing for easier comparison of different primary studies, the most important variances remained present. Therefore, Condon *et al.* (2015) conducted a formal meta-analysis "to parse the contribution of other key assumptions besides ethanol expansion scenario, such as corn yields and oil prices, as well as structural modelling framework". This meta-analysis will be the already mentioned "cornerstone" of my thesis.

According to Condon *et al.* (2015), one of the advantages of a meta-analysis is that it allows us to relax the assumption of linear price response per unit of corn ethanol expansion, which the normalization imposes. The authors of the 2015 meta-analysis also managed to identify a few key factors driving the variety of corn price effects between the primary studies. Among others, Condon *et al.* (2015) included variables representing the treatment of ethanol co-products, projection year, and assumptions about non-corn ethanol biofuels in their models. All of these were found to be very important as they explain a lot of the variation in price effects across scenarios and studies. However, here comes one of the weaknesses of any meta-analysis in action. As Stanley rightly mentions in his papers[2], every meta-analysis is only as good as the underlying primary studies. Condon *et al.* (2015) used both fixed and random effects models in their meta-regression. This way they addressed the dependency of many estimates coming from the same authors/study.

There is also quite a lot of studies examining the relationship between the production of ethanol and prices of gasoline. The proponents of ethanol production usually say that gasoline prices are greatly lowered by ethanol production. Their estimates were around $1 per gallon in the year 2011, and these estimates have been mentioned and used in numerous studies. Many of them are based on the study by Xiaodong *et al.* (2011). However, the study of Knittel & Smith (2012) called "Ethanol Production and Gasoline Prices: A Spurious Correlation" stands up against these findings claiming that the estimates provided by

[1] Such an increase in corn ethanol production is equivalent to a 10% expansion.

[2] For example: Stanley & Jarell (1989), Stanley (2008), or Stanley (2005).

Xiaodong *et al.* (2011) are "driven by implausible economic assumptions and spurious statistical correlations". Knittel & Smith (2012) use the very same statistical models as Xiaodong *et al.* (2011) did and prove that ethanol production decreases the prices of natural gas *but* at the same time it increases unemployment in both Europe and the US. They also show that the empirical results of Xiaodong *et al.* (2011) are "extremely sensitive to the empirical specification; however, empirical models that are most consistent with economic theory suggest effects that are near zero and statistically insignificant" (Knittel & Smith 2012). This is another fact that should be considered when evaluating the pros and cons of ethanol policies.

The paper called "Abolishing biofuel policies: Possible impacts on agricultural price levels, price variability and global food security" is a recent study published by Enciso *et al.* (2016). The authors of this study are trying to estimate the impact of abolishing all types of biofuel policies (including tax credits, mandates, export and import tariffs) on agricultural price levels, price variability and some aspects related to global food security. They claim that previous studies of the effects of biofuels on the development in the agricultural market (especially price levels and price variability) were based on either economic approaches like time-series analysis or the use of economic partial or general equilibrium models. Time-series models usually make use of prices and other explanatory variables like macroeconomic indicators while needing relatively large amounts of observations to be able to estimate the desired parameters (Enciso *et al.* 2016).[3] According to the authors, paying attention to the empirical analysis of linkages between various prices and markets without imposing a theoretical structure is a common limitation of studies based on time-series. Although they are very strong in the means of analysing the behaviour of examined prices, these studies leave various market fundamentals and their relationships unexplored (De Gorter *et al.* 2013).[4][5] Concerning studies using partial or general equilibrium models, the authors appreciate the focus on understanding how uncertainty may influence the relationship between

[3]For more information about agricultural price volatility and its analysis see Brümmer *et al.* (2013).

[4]For more information about economic modelling used for estimation of price levels see Zhang *et al.* (2013).

[5]Analysing price variability is usually performed with the use of stochastics. For more information about stochastics and estimation of price variability in the agricultural prices see Taya (2012) who makes use of the Aglink-Cosimo model or Artavia *et al.* (2014) who also incorporate uncertainty in their modelling framework.

biofuel policies and biofuel market determinants.[6]

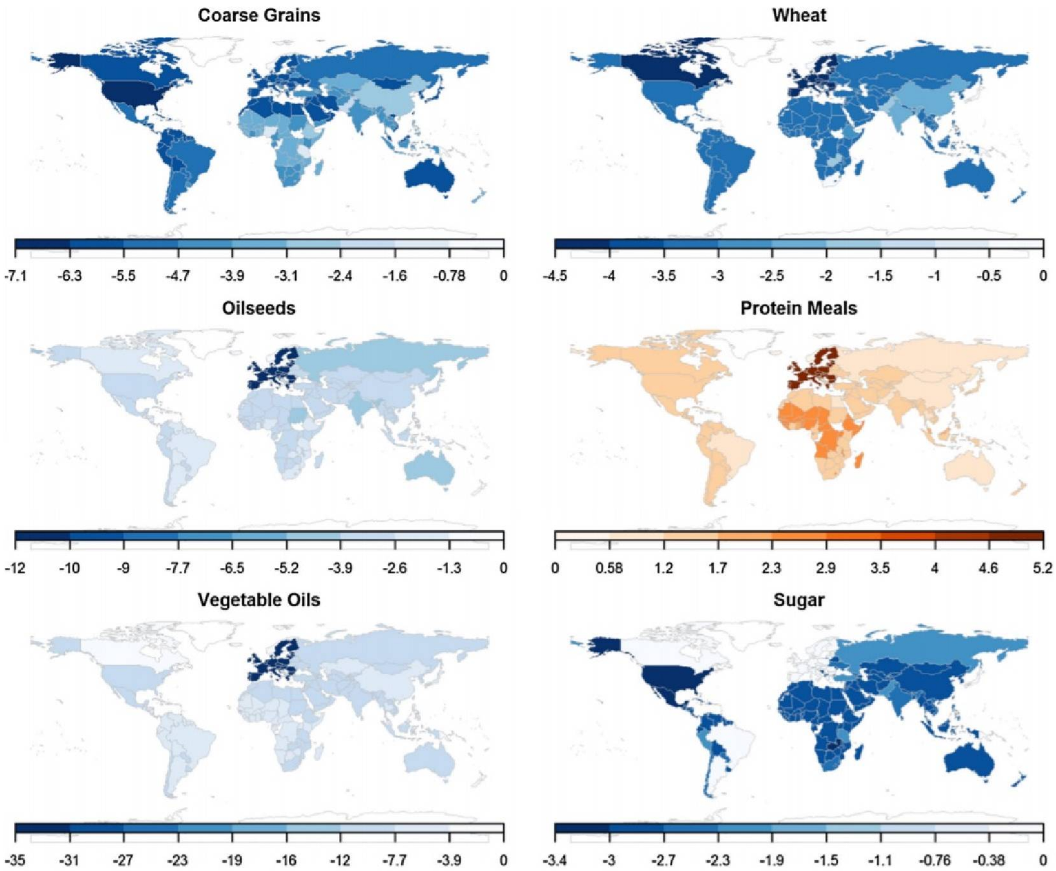
Given all the types of studies mentioned above, Enciso *et al.* (2016) employ a recursive-dynamic agricultural multi-commodity model within a stochastic framework in their analysis to complement the previous literature. Using a scenario working with the upcoming 10 years period while employing the Aglink-Cosimo model, they obtain estimates that suggest that the abolishment of all of the biofuel policies would have a large impact on the variability of biofuel prices, but only a slight effect on the price variability of agricultural commodities. One of the most important estimates this study brings is that the global demand for biofuels would drop by around 25 percent in the case of ethanol and by 32 percent in the case of biodiesel, if the biofuel policies would have been abolished. According to authors' forecasts, prices would behave differently for ethanol feedstock commodities and biodiesel feedstock commodities. In the first case of ethanol feedstock commodities (wheat or coarse grains), prices would react just by a slight decrease, whereas in the second case of biodiesel ethanol feedstock commodities (vegetable oils), prices would react more violently. In Figure 2.1, we can see a very nice graphical representation of how violently prices of different agricultural commodities would react in various regions if the assumed scenario of abolishing all biofuel policies would occur (projection year 2024). Interestingly, European prices seem to be much more sensitive according to Figure 2.1. We can clearly see that especially in the case of oilseeds, wheat, and vegetable oils, prices in Europe would react by a substantial fall if biofuel policies were abolished. Similarly violent reaction would probably occur in the case of protein meals market, however, prices would jump in the opposite direction. Authors also say that "due to competing uses of crop production such as feed and industrial use, abolishing biofuel policies would not necessarily lead to an increase in global food security, as food use increases would remain low for most crops and regions" (Enciso *et al.* 2016).

In addition, they also make a prediction of the world consumption shares for the top five biofuels consuming regions (projection year 2024) which is represented in Figure 2.2.

The world food prices doubled between 2000 and 2011 (Carter *et al.* 2012). The question is, how much of this significant jump can be assigned to the growing usage of land and food crops for the production of ethanol? Since

[6]Examples of studies using partial or general equilibrium models to understand the mentioned relationship are the following: McPhail & Babcock (2008), McPhail & Babcock (2012), Hennessy (1998), and Debnath *et al.* (2014).

Figure 2.1: Projection of agricultural prices



Note : Change in domestic agricultural price due to the abolishment of biofuel policies (difference in percentage points compared to the reference scenario).

Source: Enciso *et al.* (2016)

Figure 2.2: World consumption share for the top five biofuels consuming regions

Biodiesel		Ethanol	
Region	Share (%)	Region	Share (%)
EU	35	US	41
US	17	Brazil	29
Indonesia	15	EU	8
Brazil	13	China	7
Argentina	4	India	2
Accumulated share of the top five consuming regions	84	Accumulated share of the top five consuming regions	87

Note: Although Canada is the fifth largest consumer of ethanol in the world, the authors decided to put the sixth largest consumer India into the table instead. They justify this decision in a way that India is at the same time one of the largest producers of sugar in the world and there are some potential linkages between these two markets that should be examined (Enciso *et al.* 2016).

Source: Enciso *et al.* (2016)

2007 there is a legislation in the US that requires huge amounts of corn to be transformed into ethanol and used for fuel purposes. The impacts of this legislation and of the many others that came after is stunning because the amount of corn-based ethanol produced in the United States has quadrupled between 2005 and 2012 (from 3.9 to 13.9 mil. gallons per year). Moreover, the number of ethanol plants grew up from 81 to 204 over the same period. Another interesting fact is that the ethanol production in the United States used more than 15% of all corn produced in the world (Carter *et al.* 2012).

Therefore, Carter *et al.* (2012) came up with a study called "The Effect of the US Ethanol Mandate on Corn Prices", where they try to estimate what the real price of corn would have been if there were no mandates for the increase of corn-based production of ethanol. Their estimation is based on a few time series methods. Their results show that if there was no mandate for ethanol production, the prices of corn between 2006 and 2011 would have been lower by about 30 percent. A significant issue that the authors of this paper had to fight with was the occurrence of a severe drought in the midwestern United States in 2012. This natural disaster had, of course, a very significant effect on corn prices. This led the authors to the idea of estimating the magnitude to which ethanol production worsened the impacts of the natural disaster. In this particular case, they found out that the prices of corn were about 40 percent higher that year than they would have been if there was no mandate. All in all, they conclude that "the impact of US energy policy on global corn prices is considerable, particularly for the world's poor" (Carter *et al.* 2012).

Serra & Zilberman (2013) made a comprehensive overview of studies using time-series to estimate the effects of biofuels on agricultural commodity prices in their paper "Biofuels-related price transmission literature: a review". According to their conclusions, crude oil and biofuel prices have significant effects on the levels of agricultural prices. Moreover, according to a majority of primary studies examined by Serra & Zilberman (2013), there is an interconnection between energy and agricultural markets, which results into transfers of price volatility between them.

Chapter 3

Biofuels - Production, Policies, Markets

In 2003, only 3% of total ethanol production was made from corn. This share is rising steadily and it was more than 10% in the year 2012. This dramatic increase was spurred by policy initiatives such as the Renewable Fuel Standard (RFS) and state-level blend mandates, and supported by direct subsidies such as the Volumetric Ethanol Excise Tax Credit[1]. Moreover, an average American household was spending more than 8% of its total income on gasoline back in 2011. It is clear that decisions made by governments about policies affecting the prices of gasoline will have significant impacts on households' budgets (Knittel & Smith 2012). All these facts only strengthen the importance of studying the relationships between ethanol production and corn and gasoline prices. The most important benefits of using ethanol instead of gasoline are the lower emissions resulting from burning ethanol, diversification of the fuel mix, and an increase of the wealth of farmers. There is one more additional potential benefit: "It may relieve gasoline refining capacity constraints during peak demand periods; this would, in turn, lead to lower gasoline prices" (Knittel & Smith 2012).

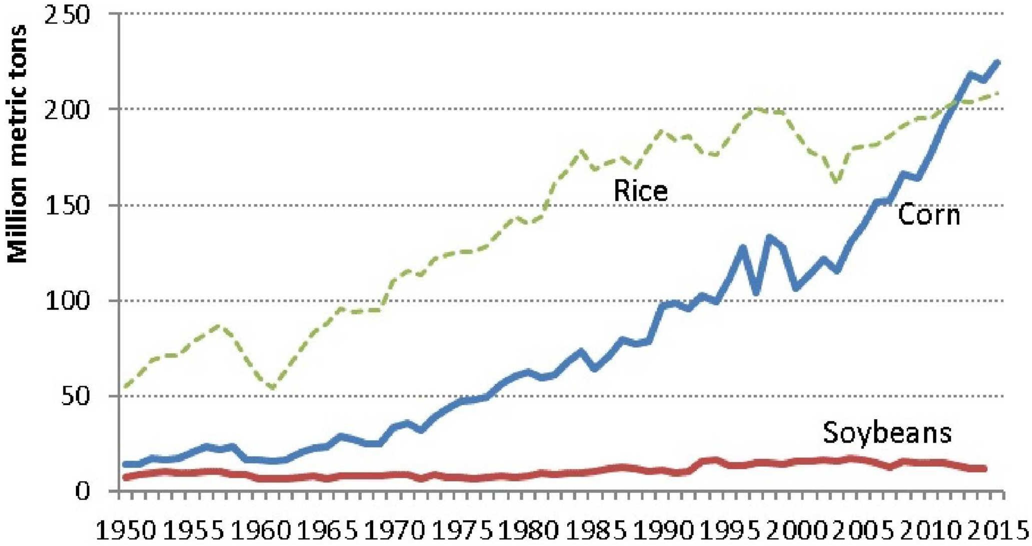
3.1 Biofuels Production

Over the last 17 years, the global production of biofuels has grown substantially. For example, the world ethanol production was equal to 46 billion litres

[1]For more information about these subsidies and state-level blend mandates and their effects on corn prices and agricultural markets in the US see Carter *et al.* (2012).

in 2005, whereas in 2010, it was already 101 billion litres which means that it more than doubled. Concerning biodiesel, the situation is even more shocking – in the period 2005-2010, the world production went up from 3.7 to 20 billion litres, which means it grew more than fivefold in five years (Enciso *et al.* 2016). According to the newest available data, the state of affairs did not change a lot since then. The numbers representing biofuel production kept on rising and in 2014 ethanol production was already above 110 billion litres and biodiesel ended up above 30 billion litres. This means that the amounts are still rising but the growth is slowing down (especially in the case of ethanol production) (OECD 2015). According to OECD, the production of biofuels has been considerably encouraged by many different kinds of biofuel policies that have been accepted and implemented in many countries around the world during the last decade. From this perspective, the most important countries/regions that had the largest scope of biofuel policy agendas were the United States, European Union, Argentina, Brazil and Australia. These countries/regions favoured the increased production and usage of biofuels with many different aims. In general, the objective with the highest priority was the reduction of greenhouse gas emissions together with increasing the degree of independence on fossil fuels (OECD 2008). Figure 3.1 depicts the significant increase in corn production in recent years. Moreover, it also includes information about rice and soybeans production for comparison purposes.

Figure 3.1: Corn production in comparison to rice and soybeans



Source: Quandl

3.2 Policy Tools

As already mentioned before, there is a broad range of policy tools and measures that have been used and implemented during the last two decades to promote biofuels. Let us focus on three key mechanisms that are used the most. According to OECD, this trinity is represented by tax credits (sometimes also called concessions), trade restrictions, and usage of mandates (OECD 2008).[2] Tax credits can grant tax concessions both to end users or to the biofuel refineries (producers). This mechanism does not restrict nor obligate either the production or consumption. Instead, it encourages the consumption of biofuels by making them more competitive with fossil fuels in terms of prices. According to a study published by Rajcaniova *et al.* (2013), the efficiency of this mechanism is not solely dependent on the extent of the tax credit. It is also greatly influenced by the overall situation on the market (especially on the relative competitiveness of various fuel types on the market).

On the contrary, blending or usage of mandates behave differently as they potentially may create an obligation for refineries to produce or for end-users to consume. This may happen because these mechanisms involve defining a certain minimum amount of biofuels to be represented in the market. The quantitative threshold can also be defined in the way of a given market share that biofuels should represent with respect to fossil fuels. Both approaches have their weaknesses. In the United States, the biofuel mandate is represented by a threshold of minimum biofuel consumption. This could be potentially binding in a situation when the optimal consumption according to the market equilibrium would be below the quantity required by the mandate.

The second approach is applied in the European Union where an obligation in the form of reaching a particular share of biofuels in the transport fuel consumption is present. The result of this method is the co-movement between fossil fuels and biofuels demand which in turn adds an upward pressure on the price of biofuels which will reach higher levels than they would in the case of no mandates. Enciso *et al.* (2016) also add that "other factors like production costs and imports might help to reduce the pressure, but production costs in the EU are higher than in other regions of the world and the EU imposes preferential tariffs to biodiesel imports, which makes it more likely that biofuel mandates in the EU result in a binding mandate".

[2]For further information about other policy measures and mechanisms that are not mentioned here see Blanco *et al.* (2010) or Sorda *et al.* (2010).

The third key mechanism of promoting biofuels are the trade restrictions. These are usually in the form of import tariffs that may be designed to protect a less competitive domestic fuel industry from foreign lower-cost biofuel suppliers, resulting in higher domestic biofuel prices and restrained development perspectives for more competitive foreign suppliers (Enciso *et al.* 2016).[3]

3.3 Linkage between Biofuel Policies and Biofuel Markets

The strong interconnection between biofuel markets and government policies and measures discussed above was clearly observable in recent years both in the US and EU (OECD 2015). For example, in the European Union, there is a policy concerning biofuels called Renewable Energy Directive (RED) which should be fulfilled in 2020. RED should be replaced by new biofuels policies at that time, but it is still unclear how these policies will look like after 2020. The uncertainty stemming from the indecisiveness of EU institutions regarding biofuel policies is reflected on the market. One of the most serious issues on the market within this topic is the lack of investments in the production of biofuels which even endangers the successful compliance of currently valid mandates. Moreover, the sustainability of the first generation of biofuels is also unclear and their future is a hot topic of many ongoing debates. According to OECD (2015), the policy dependency is also visible in the United States. Similarly to the EU, there is an important institution called Environmental Protection Agency whose decisions and assumptions largely influence the future of biofuels in the US.

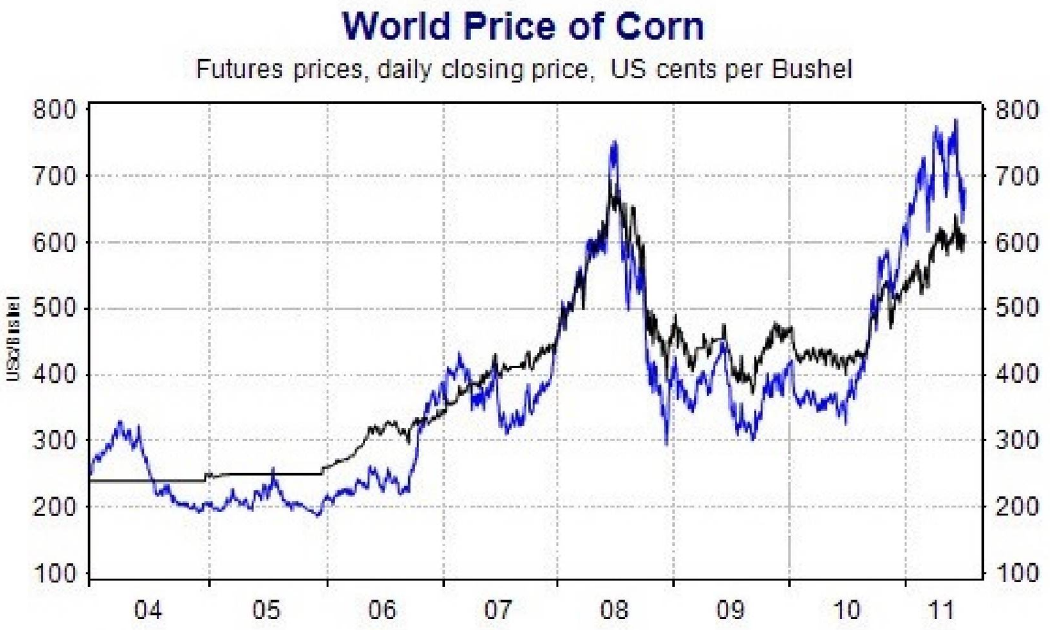
3.4 Food Price Crisis

After the food price crisis that arose in 2008 and the related substantial rise and subsequent fall in prices of agricultural commodities and food a lot of studies were published on the topic of what drivers may be behind the higher prices in agricultural markets and what causes the increased variability of prices. Fig-

[3]For more detailed information and discussion on the topic of different biofuel policies and other mechanisms affecting the quantity of biofuels produced see for example OECD (2008), de Gorter & Just (2009), Ziolkowska *et al.* (2010), Rajcaniova *et al.* (2013), Janda *et al.* (2012).

ure 3.2 depicts the development of the world price of corn including the substantial rise and subsequent fall in 2008.

Figure 3.2: World price of corn



Source: Reuters EcoWin

Many studies[4] made a research on this topic and came up with the following conclusion: "Regarding the drivers, researchers come to different conclusions on the relative importance of the underlying causes, but there is a general consensus that biofuel policies are one of the culprits along with a combination of factors, comprising harvest failures in various parts of the world, subsequent export restrictions or bans for some agricultural commodities by several countries, increasing crude oil prices, slowing down of crop yield trends, global stock declines of several agricultural commodities in the years preceding the price peak, increasing investment in commodity funds and related financial speculation, decreasing economic growth, and the depreciation of the US dollar" (Enciso *et al.* 2016). The increase of prices and their variability led to the return of the topic of food security. Especially the Food and Agriculture Organization of the United Nations (FAO) strengthened their efforts towards this topic which can be observed in the studies published right after the crisis.

[4]Including Headey & Fan (2008), Trostle *et al.* (2008), Baffes & Haniotis (2010), Gilbert (2010), Naylor & Falcon (2010), FAO *et al.* (2011), and Tadasse *et al.* (2016).

3.5 Global Transportation

International Energy Agency made a forecast in 2011 concerning biofuels in the global transportation area. The estimates were quite surprising as they projected the share of biofuels in global transportation fuel to increase from 2% in 2010 to 27% in 2050 (IEA 2011). That is another reason why paying special attention to this topic and examining it properly is of major importance. On the other hand, the situation around biofuels and transportation slowly changes. The projections of the International Energy Agency presented in 2010 may seem to be too optimistic today. This change of circumstances is caused by various reasons. Without any doubt, electric cars are in some sense "competitors" to biofuels driven vehicles. Now, in 2017, the research concerning electricity driven cars is way more advanced than it was seven years ago, at the time of publication of the International Energy Agency's study.

Chapter 4

Data Set

4.1 The Collection of Data

The starting point of every meta-analysis is the collection of data provided by primary studies. Even though we are usually interested in one specific estimate of a primary study (for example price or income elasticity of demand for electricity), there are usually many other results reported that we can make use of. Very often authors include other explanatory variables in their models and these can be useful for a meta-analysis as well. Moreover, there are dozens of other interesting attributes of every primary study that we should cautiously observe and collect.

Reading and understanding the primary study is of major importance in this regard. Nobody can collect the optimal data set without fully understanding the author's ideas and approaches. Talking about an optimal data set, I do not only mean the largeness of the resulting table. More importantly, the structure of the data, the decisions about including or not including a variable into the data set or the form of the inclusion of the variables into our data set is what really matters. Mistakes can easily be made while collecting the data because of many reasons. For example, different studies may use different currencies (*USD* vs *EUR*), lengths (*cm* vs *feet*), volumes (*litres* vs *gallons*)[1], etc. Some studies work with percentages throughout their analysis including the reported results and some other prefer reporting their estimates in decimals.

Another problematic issue that cannot be dealt with without careful reading of the paper is the definition of variables. To give an example again, let us

[1]This is exactly one of the issues that I had to deal with while collecting data for this analysis because primary studies published both in the United States and Europe are used.

assume that one study uses a dummy variable called *US* that is equal to 1 if an observation is based on data collected in the United States (among others). The second study in our comparison also uses a dummy variable called *US* but this time, authors decided to define it in a different way - it equals to 1 if an observation is based on data collected in the United States *only*. Of course, there is a large difference in the two definitions and this difference will not usually be recognizable at the first sight and therefore it is of major importance to read the whole study and understand it, instead of just looking at the table of results, to be able to create a well-specified data set for a meta-analysis.

Until now, I was discussing the variables and estimates used or reported by the authors of the primary studies in their results. A correct approach to the process of collecting the variables presented in results tables by authors is not the only fact influencing how successful a meta-analysis will be. There is a lot of other information about a primary study that should be collected - especially concerning the methodology. A common approach in this regard is the collection of information about models used in a primary study. The same can be said about scenarios assumed or year of prediction (for example in studies that estimate the magnitude of an effect to some future date) and others. With regards to all the obstacles discussed above that lie in every meta-analyst's way, it is clear that the collection of data is a very lengthy and difficult process.

This thesis builds upon the latest meta-analysis on this topic conducted by Condon *et al.* (2015). I use the same primary studies as a cornerstone as Condon *et al.* (2015) did and I add new studies from recent years that could not have been accounted for back in 2015. On the other side, I have to drop some primary studies that reported only one estimate as their result. This is necessary because the aim of this meta-analysis is the detection and removal of the selective reporting bias which, in this case, disallows the usage of single-estimate primary studies (this problem is further discussed in Chapter 5).

4.2 Description of the Data Set

The final data set covers studies published between 2008 and 2017 and includes 23 papers. All primary studies together with a short description of methods used, policy scenarios assumed, a number of reported estimates and their range are listed in Table 4.1. For further information about the estimates of all types of corn price responsiveness see Table 4.2. Most studies are represented by multiple estimates of the corn price responsiveness as they report results of different data-sorting (such as regions or periods), different scenarios, or projection years. Choosing only one estimate from each study that would be the "best" in my opinion would, of course, lead to a loss of objectivity and information. Moreover, as Havranek & Irsova (2010) say, such an approach would also lead to other distortions of results. Another possible approach would be to compute a simple average of all estimates within a study and include this one number into our data set. Again, this would lead to a loss of precious information and therefore I include every single estimate of the impacts of biofuel policies on corn prices.

The collection of all estimates stemming from non-single-estimate studies resulted into 155 observations that will be used for this analysis. With respect to the number of observations, the data set belongs to the category of smaller ones which, of course, is a subject of possible improvements in the future.

4.3 Adjustments

Aside from adding new observations and dropping some of them I also made a few more adjustments to the data set. In comparison to Condon *et al.* (2015), I decided not to include the dummy variables for modelling approaches because the data set is too small and many of the models were used only once. I also decided not to collect information about corn yields because majority of the studies did not account for corn yields and when they did, it was often unclear what concrete values of corn yield they assumed in their analysis. Collection of these additional characteristics would probably make more sense if the data set was larger and could consist of single-estimate studies (the data set used by Condon *et al.* (2015) includes single-estimate studies). I also collected additional variables that I expected to be helpful in explaining the heterogeneity of reported estimates of the impacts of ethanol policies on corn prices. A clear majority of the studies is based on the data from the United States which led me to a decision to keep all the volumes in billions of gallons (*bgal*) and prices in US Dollars.

As already mentioned, the first estimate in the data set was reported in 2008, the last study was added to the data set in May 2017 and the median study comes from 2011. Concerning different study types, 20 out of the 23 primary studies included in the sample were published in peer-reviewed journal articles and only the remaining 3 came from government or international

Table 4.1: Summary of literature statistics

Study	No. of est.	Model	Policy instrument	Price change (%)
Babcock (2012)	2	FAPRI-CARD	removal of tax credit, mandates	7-17
Bento & Klotz (2014)	12	Dynamic multi-market model	RFS, tax credits	7–85
Chen & Khanna (2012)	6	BEPAM multi-market model	RFS, tax credits, tariffs	23-52
Cui *et al.* (2011)	6	Multi-market model	RFS; other optimal biofuel policies	-23-44
Enciso *et al.* (2016)	8	AGLINK-COSIMO	removal of all policies	3-7
Gehlhar *et al.* (2010)	6	USAGE	RFS	3–5
Gohin & Tréguer (2010)	6	Stochastic PE model	RFS, tax credits	17–50
Hayes *et al.* (2009)	3	FAPRI-CARD	RFS, tax credits, import tariffs	19-26
Hertel *et al.* (2010)	2	GTAP-BIO	RFS	16-18
Hochman *et al.* (2010)	2	CON multi-market model	100% decrease in ethanol production	7–12
Huang *et al.* (2012b)	8	GTAP	RFS, EU, and Brazilian biofuel policy	0.7–45
Huang *et al.* (2012a)	3	BEPAM multi-market model	RFS, tax credits, import tariffs	7-40
Meyer & Thompson (2012)	3	FAPRI-MU	RFS	-0.2-13
Mosnier *et al.* (2013)	14	GLOBIOM	Deviations from RFS	1-13
Nuñez *et al.* (2013)	2	BEPAM multi-market model	RFS, ethanol mandates	2-17
OECD (2008)	2	AGLINK-COSIMO	RFS and EU biofuel policy	6–7
Roberts & Schlenkera (2013)	2	Supply and demand model	RFS	20–30
Rosegrant *et al.* (2008)	2	IMPACT	RFS, EU, and Brazilian biofuel policy	26–72
Taheripour *et al.* (2011)	4	GTAP-BIO	RFS and EU mandates	12–24
Tyner & Taheripour (2008)	40	Purdue partial equilibrium model	RFS, fixed and variable subsidies	5–84
Tyner *et al.* (2010)	14	Purdue partial equilibrium model	RFS, tax credits	7-70
Agency (2010)	2	FAPRI-CARD, FASOM	RFS	3–8
Zhou & Babcock (2017)	6	Competitive storage model	RFS, E85 stations	4-6

Notes: Four primary studies examine the price change of a different commodity, such as coarse grains or a weighted average of grains and soy: OECD (2008), Hertel *et al.* (2010), Taheripour *et al.* (2011), Roberts & Schlenkera (2013). Those studies were part of the previous meta-analysis by Condon *et al.* (2015) and therefore I decided to incorporate them into my analysis as well.

In this table, I use absolute values for reporting corn price changes to only show their magnitudes. It means that studies whose scenarios were based on a decrease of corn ethanol volumes are represented by positive corn price changes even though their estimates were negative. This concerns Mosnier *et al.* (2013), OECD (2008), Hochman *et al.* (2010), Cui *et al.* (2011), Huang *et al.* (2012a), Chen & Khanna (2012), Nuñez *et al.* (2013) and Enciso *et al.* (2016).

Table 4.2: Three types of corn price responsiveness

Study	Price change (%)	Price change per billion gallon increase in ethanol (%)	Price change per 1% increase in ethanol (%)
Babcock (2012)	7-17	10.6-10.8	1.32-1.35
Bento & Klotz (2014)	7-85	6.4-10.5	0.35-1.05
Chen & Khanna (2012)	23-52	3.1-5.7	0.12-0.22
Cui *et al.* (2011)	-23-44	2.1-3.8	0.13-0.23
Enciso *et al.* (2016)	3-7	0.3-7.8	0.13-0.26
Gehlhar *et al.* (2010)	3-5	0.4-0.7	0.04-0.05
Gohin & Tréguer (2010)	17-50	4.4-11.0	0.10-0.40
Hayes *et al.* (2009)	19-26	1.8-2.9	0.26-0.46
Hertel *et al.* (2010)	16-18	1.2-1.3	0.02
Hochman *et al.* (2010)	7-12	1.9	0.07-0.12
Huang *et al.* (2012b)	0.7-45	1.2-2.9	0.06-0.14
Huang *et al.* (2012a)	7-40	0-4.1	0-0.22
Meyer & Thompson (2012)	2.9-13	-2.5-3.1	0.45-0.49
Mosnier *et al.* (2013)	1-13	-0.3-2.0	-0.04-0.26
Nuñez *et al.* (2013)	2-17	3.2	0.5
OECD (2008)	6-7	2.0-2.9	0.24-0.35
Roberts & Schlenkera (2013)	20-30	1.8-2.7	–
Rosegrant *et al.* (2008)	26-72	2.2-2.6	0.08-0.10
Taheripour *et al.* (2011)	12-24	1.3-2.4	0.07-0.13
Tyner & Taheripour (2008)	5-84	3.6-5.8	0.02-1.02
Tyner *et al.* (2010)	7-70	3.7-4.8	0.05-0.79
Agency (2010)	3-8	1.3-3.1	0.15-0.38
Zhou & Babcock (2017)	4-6	4.7-5.5	0.66-0.77

Notes: Four primary studies examine the price change of a different commodity, such as coarse grains or a weighted average of grains and soy: OECD (2008), Hertel *et al.* (2010), Taheripour *et al.* (2011), Roberts & Schlenkera (2013). Those studies were part of the previous meta-analysis by Condon *et al.* (2015) and therefore I decided to incorporate them into my analysis as well.

In this table, I use absolute values for reporting corn price changes to only show their magnitudes. It means that studies whose scenarios were based on a decrease of corn ethanol volumes are represented by positive corn price changes even though their estimates were negative. This concerns Mosnier *et al.* (2013), OECD (2008), Hochman *et al.* (2010), Cui *et al.* (2011), Huang *et al.* (2012a), Chen & Khanna (2012), Nuñez *et al.* (2013) and Enciso *et al.* (2016).

It is mathematically impossible to calculate a price change per percentage increase in ethanol volume for scenarios which start with zero baseline ethanol production. Roberts & Schlenkera (2013), therefore, do not dispose with any estimates of elasticity.

organisation articles. I decided to include the very small group of government and international organisation articles following the advice of Stanley (2001), who recommends including these studies into a meta-analysis. On the other hand, 3 studies of one type do not allow for an efficient analysis of possible differences in selective reporting between articles published in peer-reviewed journals on one side and the government and international institutions one the other. The data collection has been performed in accordance with instructions and advice presented in the Meta-Analysis of Economics Research Reporting Guidelines (Stanley *et al.* 2013).

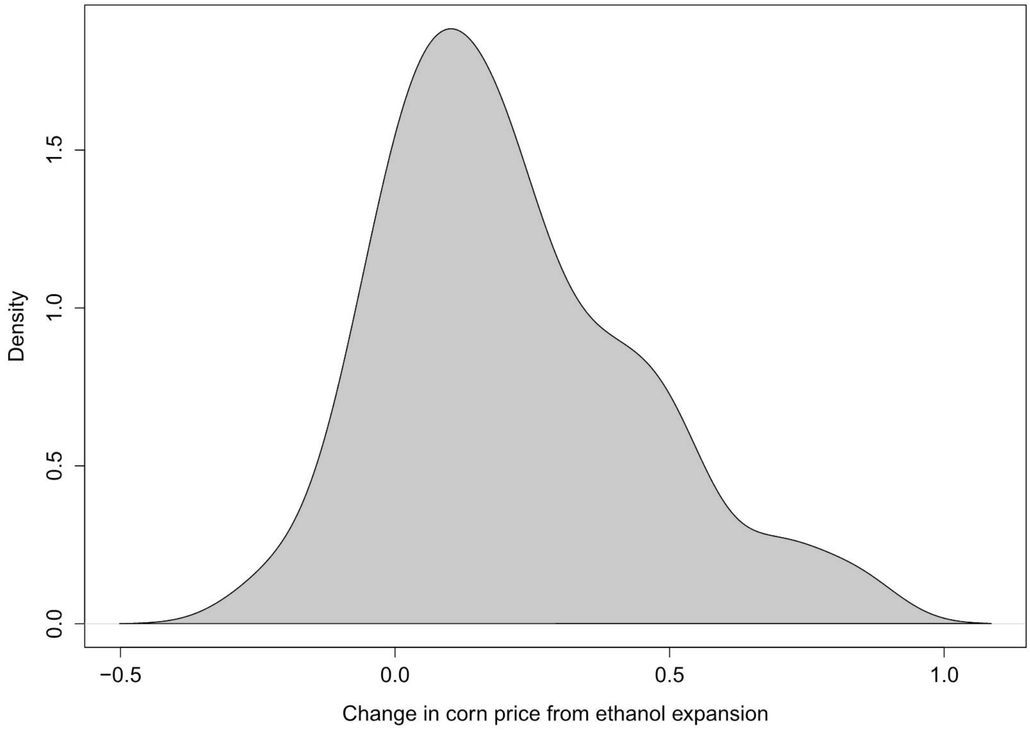
4.4 Distribution of Estimates of Corn Price Responsiveness

For the purpose of depicting the distribution of estimates of corn price responsiveness, I decided to use the Kernel density function. Figure 4.1 presents the distribution of *raw price change* estimates in the data set (i.e. the raw percent change in corn price resulting from ethanol expansion assumed in the primary study – for example, the value of 0.5 on the x-axis represents an estimate of 50% increase of the price of corn resulting from ethanol expansion). The distribution is clearly asymmetric and skewed to the right which is also reflected in the difference between the mean estimate (21.3%) and the median estimate (16.3%). This may be considered as one of the first symptoms of possible selective reporting.

Figure 4.2, on the other hand, presents the distribution of semi-elasticity estimates in the data set (i.e. the percent change in corn price resulting from one billion gallons increase in ethanol volume – for example, the value of 0.05 on the x-axis represents an estimate of 5% increase of corn price as a result of one-billion-gallon ethanol expansion). The distribution is asymmetric again. Moreover, there seem to be two peaks; one close to zero and another one close to 5%. The mean and median estimate are not much different in this case – mean estimate equals to 3.7%, median estimate equals to 3.8%.

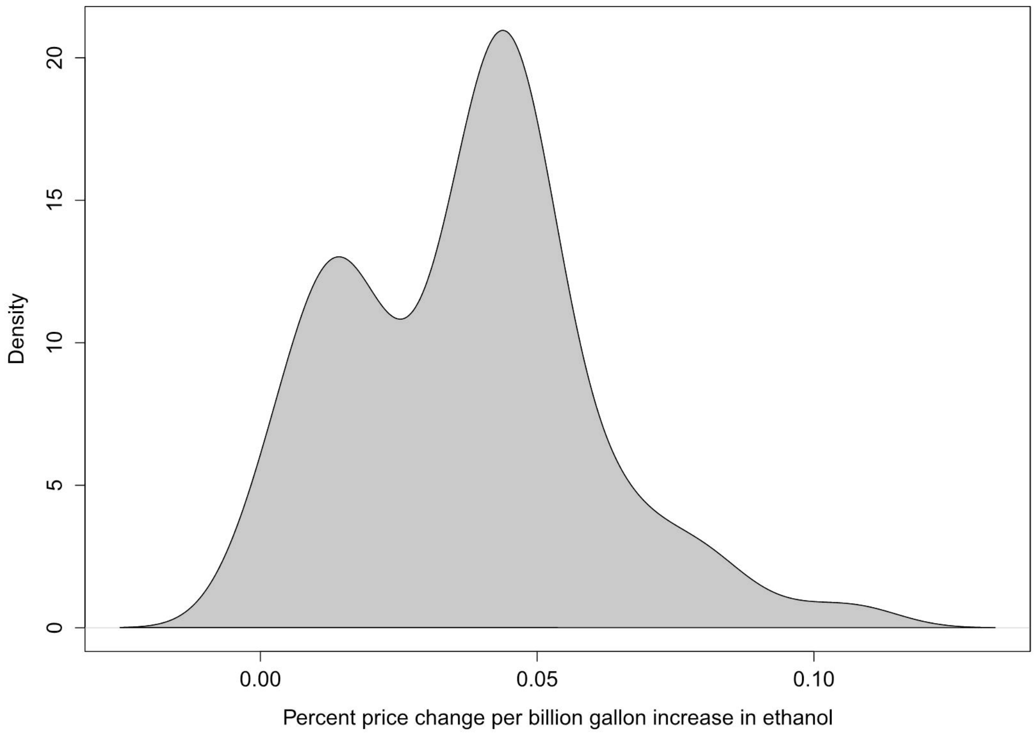
Finally, Figure 4.3 depicts the distribution of elasticity estimates in the data set (i.e. the percentage change in corn price resulting from one percent increase in ethanol volume – for example, the value of 0.005 on the x-axis represents an estimate of 0.5% increase of corn price as a result of 1% increase in ethanol volume). The distribution is, again, asymmetric and skewed to the

Figure 4.1: Kernel density of raw price change



Note: The raw percent change in corn price resulting from ethanol expansion assumed in the primary study – for example, the value of 0.5 on the x-axis represents an estimate of 50% increase of price of corn resulting from ethanol expansion.

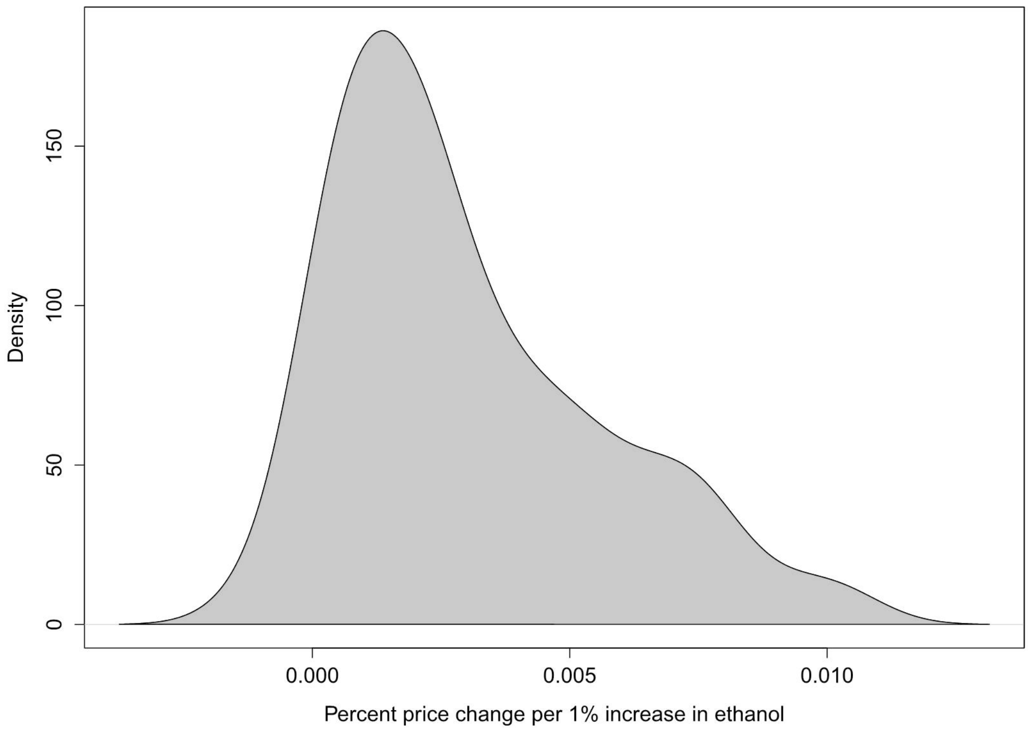
Figure 4.2: Kernel density of semi-elasticity



Note: The percent change in corn price resulting from one billion gallons increase in ethanol volume – for example, the value of 0.05 on the x-axis represents an estimate of 5% increase of corn price as a result of one-billion-gallon ethanol expansion.

right. This fact is also reflected in a significant difference between the mean estimate (0.32%) and median estimate (0.23%). Selective reporting is likely to be present. In addition, it is clearly visible how "dissuasive" the zero-value of the elasticity is for the authors. This phenomenon occurs frequently in the case of studies examining elasticities because the zero value usually creates a border between estimates that are and are not in accordance with the widely-accepted theory. It is manifested by the highly-sloped decreasing kernel density curve when approaching the zero value from the right. The asymmetry that it induces could be explained in two basic ways. The first possible explanation is that authors do not report their results when obtaining counter-intuitive estimates. The second possible explanation is that the publishers are the ones who are unwilling to publish counter-intuitive outcomes. Be it any of these two reasons or a different one, selective reporting is likely to be present and will be investigated further in the next sections of this study.

Figure 4.3: Kernel density of elasticity



Note: The percentage change in corn price resulting from one percent increase in ethanol volume – for example, the value of 0.005 on the x-axis represents an estimate of 0.5% increase of corn price as a result of 1% increase in ethanol volume.

4.5 Description of Variables

Table 4.3 summarizes all variables I collected for this meta-analysis and explains their definitions. Furthermore, it also includes a basic statistical description of each variable as it shows their mean, minimum and maximum estimate, the standard deviation, and number of observations for which the variable is defined. One fact that is worth mentioning in this regard is the smaller amount of observations in the case of elasticity variable. This is because some studies build some of their scenarios on the assumption of zero baseline corn ethanol volume. As far as elasticity is calculated from percentage changes of price and quantity, it is not possible to obtain it for these scenarios, as we cannot divide by zero. In total, fourteen observations do not present any estimate of elasticity due to this reason.

Standard errors of the estimates of the impacts of ethanol volume expansion on corn price (the fourth item in Table 4.3) were not reported in any of the 23 primary studies included in this analysis. Therefore, I had to additionally construct them. Their construction was performed in accordance with Havranek *et al.* (2015) and will be described more in detail in Chapter 5.

To make the comparison between the results of this meta-analysis and the previous one done by Condon *et al.* (2015) possible, I include many of the explanatory variables used in the mentioned meta-analysis and add some more as already explained in the previous sections. The variable *baseline corn ethanol* represents the ethanol volume in billions of gallons assumed in the baseline scenario and is one of the most important ones because Condon *et al.* (2015) found it to be significant in all types of corn price responsiveness to biofuels expansion (absolute price change, price change per billion gallons increase, price change per percentage increase). In addition, this variable was significant while using both random and fixed-effects models. The same can be said about the variable *year* which represents the year assumed in the policy scenario (in other words – the year when the expansion or reduction policy is fulfilled). Almost the same applies in the case of variable *co-product* which is a dummy variable equalling to 1 if the authors accounted for ethanol co-products. Co-product was also found significant in all types of corn price responsiveness and models apart from the fixed-effects model estimation of elasticity. The last explanatory variable that was found significant by Condon *et al.* (2015) in the majority of model specifications is the *change in other biofuels* which represents the expansion/reduction (in billions of gallons) of other biofuels (for example

Table 4.3: Description and summary statistics of regression variables

Variable	*Description*	*Mean*	*Std.dev.*	*Min*	*Max*	*Obs*
Price change	The reported estimate of the raw price change of corn	21.3%	0.235	-27%	85.4%	155
Semi-elasticity	The price change of corn per billion gallon increase in ethanol	3.7%	0.024%	-0.3%	11%	145
Elasticity	The price change of corn per 1% increase in ethanol	0.32%	0.003	-0.04%	1.3%	125
Standard error	The approximate standard error of the estimate	0.104	0.068	0.004	0.260	155
Baseline corn ethanol	The assumed baseline corn ethanol volume in billions of gallons	9.07	6.76	0.00	35.49	155
Policy corn ethanol	The assumed policy corn ethanol volume in billions of gallons	14.72	7.32	0.00	40.05	155
Change in ethanol	The difference between the baseline and policy ethanol volumes in billions of gallons	5.64	6.68	-8.39	35.19	155
Ethanol decrease scenario	= 1 if the scenario assumes a decrease in ethanol production volumes	16%	0.37	0	1	155
Mandate policy	= 1 if the authors assume a mandate type of policy instrument	68%	0.46	0	1	155
US mandate only	= 1 if the assumed scenario consists only of changes in US mandates	41%	0.49	0	1	155
Co-product	= 1 if the authors account for ethanol co-products	93%	0.25	0	1	155
Year	The year assumed in the policy scenario	2013	8.05	2005	2035	155
Change in other biofuels	Volume of biofuels produced from non-corn feedstocks in billions of gallons	0.703	2.222	-2.180	13.020	155
Year published	Year when the study was published	2011	2.66	2008	2017	155
Oil price	Baseline crude oil price (USD/barrel)	84	30.4	40	160	123
Repec	= 1 if the primary study was present among the published studies on the Research Papers in Economics (RePEc) web site	79%	0.41	0	1	155
Scopus	= 1 if the primary study was present among the published studies in the Elsevier's Scopus abstract and citation database of peer-reviewed literature	91%	0.28	0	1	155
Citations	The number of Google Scholar citations of the study	66	64.3	1	395	155

Note: Four primary studies examine the price change of a different commodity, such as coarse grains or a weighted average of grains and soy: OECD (2008), Hertel *et al.* (2010), Taheripour *et al.* (2011), Roberts & Schlenkera (2013). Those studies were part of the previous meta-analysis by Condon *et al.* (2015) and therefore I decided to incorporate them into my analysis as well.

biodiesel) accounted for by the authors. All the variables mentioned in this paragraph were found significant by Condon *et al.* (2015) and are included in this meta-analysis.

I also include a dummy variable called *ethanol decrease scenario* to take into account whether the estimate of corn price responsiveness is based on a scenario that assumes a decrease in ethanol production volumes. I also control for the difference between the baseline and policy ethanol volumes (in billions of gallons) by including an explanatory variable called *change in ethanol*. *Mandate policy* is a dummy variable whose value indicates whether the given estimate is or is not based on a scenario including a mandate type of policy instrument. Regarding oil prices, I decided to use the same attitude towards their inclusion as Condon *et al.* (2015) did. That is, I report the *oil price* only if the primary study accounted for oil markets in their modelling approach. In many of the primary studies, baseline oil prices had to be estimated or obtained elsewhere because they were not reported. In the case of the study by Hochman *et al.* (2010) I was able to find historic data of the oil prices from the U.S. Energy Information Administration (*EIA*) in the same way as Condon *et al.* (2015) did. In the case of the study by Chen & Khanna (2012), assumptions about gasoline prices were taken from Chen (2010) and converted to oil prices using the assumption that each $1 per barrel increase in oil translates to a 2.4 cent per gallon increase in gasoline (EIA) - again, this approach was used in the previous meta-analysis on this topic by Condon *et al.* (2015). All the variables mentioned in this paragraph were sometimes found significant and sometimes insignificant by Condon *et al.* (2015) - depending on what corn price responsiveness was estimated and what model was used for the estimation. All those variables are included in the data set and will be a subject of investigation.

Corn yield is a variable which was used in the previous meta-analysis and which represented bushels of corn per acre. Because *corn yield* was found insignificant in the previous meta-analysis and its values were missing for most observations I decided not to include this variable into my meta-analysis.

4.6 New Variables

On the other hand, I add some new variables that I think they could have some potential explanatory abilities regarding the estimation of the price responsiveness of corn. Apart from the already discussed addition of *standard error* variable, I newly include a dummy variable called *US mandate only* to take into account whether the estimate is based on a scenario considering an ethanol expansion only in the form of US mandates. I also newly control for the publication year of the primary study (variable *year published*). The idea behind the inclusion of this variable is that perhaps novel methods of estimating the responsiveness of corn price to biofuels expansions deliver systematically distinct results and the literature may converge to some particular "consensus value".

Finally, I control for the "quality" of the primary study in three ways using three variables. Two of them are dummy variables called *repec* and *scopus*. The first one is equal to one if the given primary study was present among the published studies on the Research Papers in Economics (*RePEc*) website and the second one equals to one if the primary study was present among the published studies in the Elsevier's Scopus Abstract and Citation Database of Peer-reviewed Literature. The third one, called *citations*, stands for the number of citations of a given study according to Google Scholar. The idea behind the inclusion of these three study characteristics is that they may capture some aspects of quality not covered by the methodology variables introduced above (Havranek *et al.* 2015). All the variables mentioned in this paragraph were not included in the previous meta-analysis performed by Condon *et al.* (2015).

Chapter 5

Methodology

5.1 Meta-Analysis

Meta-analysis is a statistical method of combining and contrasting outcomes of multiple scientific studies. Moreover, it also has capabilities to find relationships between them. Meta-analyses are usually employed to estimate the true effects of various relationships. Meta-analyses can be done in various ways, scopes, and complexities. Taking a weighted average of all estimates reported by all studies published on a topic of particular relationship can be considered as a very simple meta-analysis. A common practice in these analyses is weighting by standard errors of estimates or by sample sizes of primary studies. The famous phrase by Glass (1976) says that meta-analysis is an "analysis of analyses".

Indisputably, meta-analyses dispose with widespread advantages including aggregation of information resulting in statistically powerful estimates and possibility of generalization of its outcomes to wider populations than in the case of single primary study. With meta-analysis, we are also able to easily assess the inconsistencies among the results of different studies, like between-study heterogeneity. Another huge advantage of meta-analyses, that I will benefit from in this study, is that they can detect and correct for selective reporting, which is a serious problem throughout the literature.

On the other hand, performing a complex meta-analysis correctly is not easy. Researchers face many tough judgements starting from deciding about the way of search for studies, setting objective criteria for inclusion of a study into the analysis, dealing with unbalanced data sets, and ending with interpreting the outcomes. As Slavin (1986) says, meta-analysis is not omnipotent; running a well-structured meta-analysis of methodologically unsound studies results in bad statistics.

5.2 Selective Reporting

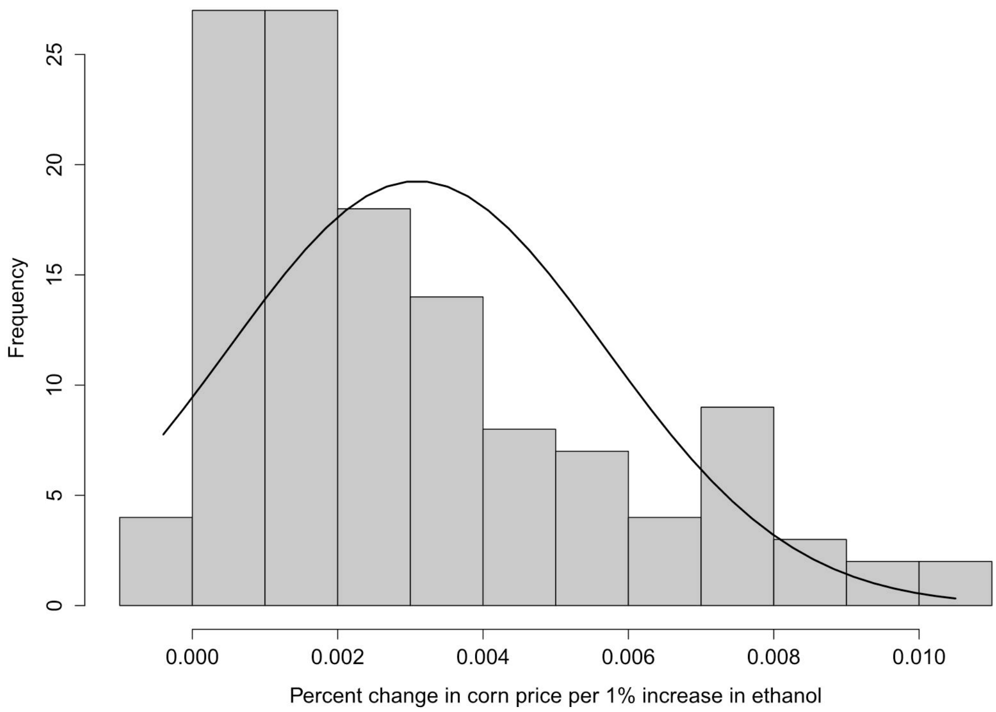
Selective reporting is one of the most serious problems that meta-analysts encounter when conducting their analysis. Every meta-analysis is heavily dependent on the available set of published primary studies. Therefore, the so-called selective reporting bias is a serious threat and often leads to false (biased) results when not accounted for. Selective reporting occurs when articles reporting estimates that are counter-intuitive, insignificant or inconsistent with traditional theories and opinions suffer from a lower probability of being published. Studies examining the relationships between agricultural markets, ethanol production, and biofuel policies are undoubtedly also affected. According to Havranek *et al.* (2012b), selective reporting can be especially devastating in the case of studies estimating elasticities. For example, price elasticities are usually assumed to be negative according to widely-accepted theories and positive estimates of price elasticity are inconsistent with these traditional theories.

In this meta-analysis, I am examining three types of relationships between ethanol volumes expansions and prices of corn. One of them is typologically similar to the concept of elasticity as it describes the corn price responsiveness to biofuels expansion in the means of percentage price change of corn per percentage increase in ethanol volumes. The values of this elasticity, from the perspective of widely-accepted theories, should be positive. The idea behind this theoretical point of view is that an increase in ethanol volume[1] results in an increase of farmland used for producing ethanol, which, in turn, leaves less space for growing crops for food purposes. Less space for growing corn for food purposes inevitably leads to a decrease in the quantity of corn grown for food purposes which, in accordance with a common theory, results in higher prices of corn on agricultural markets. The outcomes of primary studies support this theory very significantly as there is only a single negative estimate of this elasticity out of the 125 available elasticity estimates in the data set. Figure 5.1 depicts the histogram of elasticity together with a normal curve following the mean and variance of the variable.

Another type of relationship that is subject to examination in this meta-analysis describes the corn price responsiveness to biofuel expansions in the

[1]In this meta-analysis, ethanol volumes expansions are usually caused by biofuels policies like mandates or tax credits.

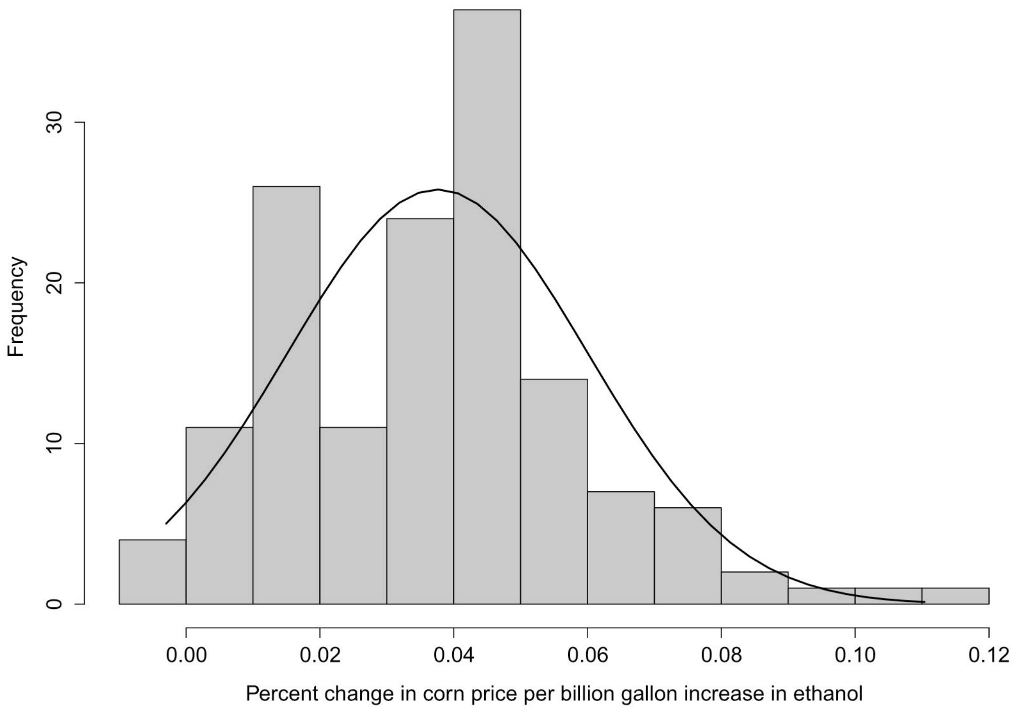
Figure 5.1: Histogram of elasticity with normal curve



Note: The percentage change in corn price resulting from one percent increase in ethanol volume - for example, the value of 0.005 on the x-axis represents an estimate of 0.5% increase of corn price as a result of 1% increase in ethanol volume.

means of percentage price change of corn per one billion gallons increase of ethanol volume. This, on the other hand, is typologically similar to the concept of semi-elasticity. Theories expect the values of this semi-elasticity to be also positive, following the same pattern of effects described in the paragraph devoted to elasticity above. Again, results of primary studies support this expectation significantly as there is only a single negative estimate of this semi-elasticity out of the 145 available semi-elasticity estimates in the data set.[2] Figure 5.2 depicts the histogram of semi-elasticity together with a normal curve following the mean and variance of the variable.

Figure 5.2: Histogram of semi-elasticity with normal curve



Note: The percent change in corn price resulting from one billion gallons increase in ethanol volume - for example, the value of 0.05 on the x-axis represents an estimate of 5% increase of corn price as a result of one-billion-gallon ethanol expansion.

The last type of corn price responsiveness to biofuel expansions is defined as percentage price change of corn resulting from the change in biofuel volume according to scenarios assumed by the authors of the primary study (irrespective

[2]The single negative estimates of both elasticity and semi-elasticity come from the same study by Mosnier *et al.* (2013) and they are both very close to zero. For further information about the ranges of reported estimates of semi-elasticities and elasticities by particular studies see Table 4.2.

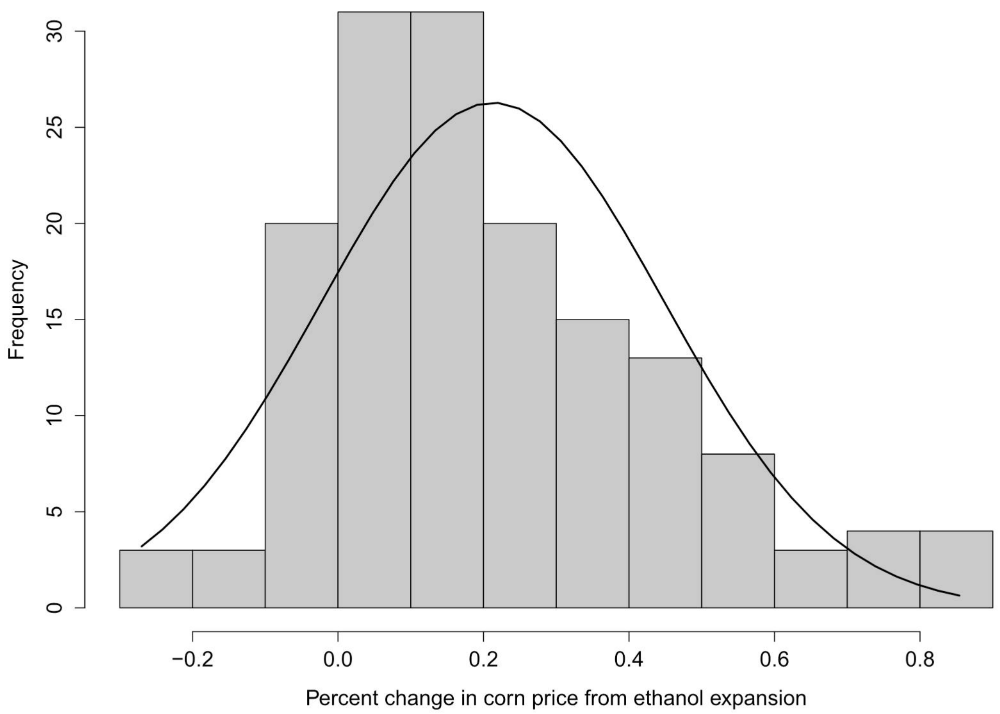
of the magnitude of the volume change). I refer to this type of corn responsiveness as to *raw price change*. Intentionally, I use the term "change in biofuel volume" instead of "biofuel volume expansion" as some studies assume scenarios of decreasing the volumes of ethanol. As a result, negative estimates of corn price change are in accordance with theory in cases of decreasing ethanol volumes scenarios. Therefore, there are 22 negative estimates of corn price change out of the 155 available estimates in the data set. To address these scenarios, I created a dummy variable called *ethanol decrease scenario* which equals to one if such a scenario was assumed by the authors.[3] Interestingly, there are 22 negative estimates of corn price change while altogether 25 scenarios work with decreasing ethanol volumes. This means there are some results indicating that prices of corn would rise even if there was a policy enforcing a reduction in ethanol volumes. One note that should be mentioned here is that most of the 25 scenarios of ethanol reduction assume total abolishment of all biofuel policies or at least cancellation of some. Enciso *et al.* (2016) is one of these studies and it is described more in detail in Chapter 2. Figure 5.3 depicts the histogram of raw price change together with a normal curve following the mean and variance of the variable.

As already mentioned, Havranek *et al.* (2012b) argue that selective reporting can cause seriously biased estimates of price elasticities because positive estimates are not consistent with the widely-accepted theory. This analysis does not study this type of elasticity, but it is very probable that we will find some serious bias among the results because, in our case, negative estimates of the three dependent variables described above are usually inconsistent with the theory. In addition, Stanley *et al.* (2008) warn the academics that not only price elasticities are the victims of selective reporting. According to their study, selective reporting has been found throughout various areas of empirical economics. Stanley also published a study called "Beyond Publication Bias" in which he claims that the price elasticity of water demand is one of the deterrent examples of how devastating the publication bias can be as it seems to be exaggerated more than fourfold because of selective reporting (Stanley 2005). We can hardly compensate for this bias without knowing how many of the insignificant or counter-intuitive studies were not published or, in other words, ended in file drawers.[4]

[3]For further information about this and other variables included in the analysis see Table 4.3.

[4]Publication bias is also sometimes referred to as to the "file drawer problem" or "file drawer effect". This phrase was firstly used by a psychologist Rosenthal (1979).

Figure 5.3: Histogram of raw price change with normal curve



Note: The raw percent change in corn price resulting from ethanol expansion assumed in the primary study - for example, the value of 0.5 on the x-axis represents an estimate of 50% increase of price of corn resulting from ethanol expansion.

According to Hunter & Schmidt (1982), we should always consider the possible occurrence of selective reporting carefully when interpreting the results of any meta-analysis. The presence of selective reporting usually results in biased, skewed or sometimes even completely one-sided distribution of estimates. This, in turn, leads to overestimation of the significance of studies that were truly published because their "counter-intuitive" counterparts are usually unseen.

Publication selection bias is often attributed to journal practices of preferring significant results over the insignificant ones, but there are also other potential sources. One of them may be the practice of "statistical significance hunting" which may occur when researchers try to achieve publication of their study irrespective of methodological correctness. Stanley *et al.* (2008) admit that this social aspect may be linked with selective reporting as well. They also claim that researchers are very often "rewarded" with respect to the quantity of published studies rather than their quality. All in all, Stanley (2005) concludes that meta-analysts should account for the possible presence of selective reporting in every meta-analysis.

5.3 Detecting Selective Reporting

This section presents an overview of available tools for detection of selective reporting and its potential elimination. Selective reporting bias is most commonly examined with the use of the three following methods: Hedges' model, the funnel plot, and meta-regression analysis (Havranek *et al.* 2015).

5.3.1 Hedges' Model

The first one, Hedges' model, assumes the logical reasoning that statistical significance of obtained estimates determines the probably of reporting them. In other words, estimates have a higher probability of being reported when some psychologically important p-values are reached. In economics, these threshold values are commonly assumed to be 0.01, 0.05, and 0.1 (Havranek *et al.* 2015). Theoretically, if there was no reporting bias at all, all estimates should have the same chance of being published, irrespective of their significance at conventional levels. Ashenfelter and his colleagues developed an augmented model allowing for heterogeneity in the estimates of the underlying effect in 1999. The proposed augmented log-likelihood function is (Ashenfelter *et al.* 1999):

$$
\begin{aligned}
L = & c + \sum_{i=1}^{n} \log w_i(X_i, \omega) - \frac{1}{2} \sum_{i=1}^{n} (\frac{X_i - Z_i\Delta}{\eta_i})^2 - \\
& \sum_{i=1}^{n} \log(\eta_i) - \sum_{i=1}^{n} \log[\sum_{j=1}^{4} \omega_j B_{ij}(Z_i\Delta, \sigma)],
\end{aligned} \tag{5.1}
$$

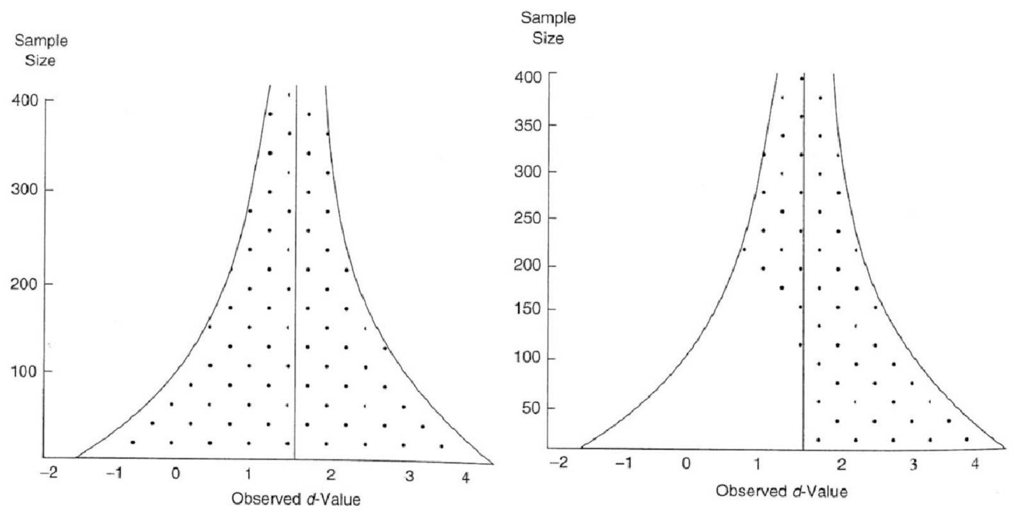
where $X_i \sim N(\Delta, \eta_i)$ are the estimates of the corn price responsiveness, Δ is a parameter of the average underlying corn price responsiveness, and $\eta_i = \sigma_i^2 + \sigma^2$, where σ measures heterogeneity in the estimates and σ_i stands for the standard errors of estimates. The $w(X_i)$ is a step function associated with the p-values of the estimates and determines the probability of reporting. As already mentioned before, four different intervals of statistical significance are usually investigated by analysts: $p - value < 0.01$, $0.01 < p - value < 0.05$, $0.05 < p - value < 0.1$, and $p - value > 0.1$. The probability that an estimate X_i will be assigned with weight ω_i is represented by $B_{ij}(\Delta, \sigma)$. Firstly, ω is normalized to 1 for the first interval ($p - value < 0.01$), then the author decides whether the remaining three weights differ from this value. Characteristics of the X_i estimates are included in the Z_i vector. In case there is no selective reporting in the literature, estimates with different levels of statistical significance must have the same probability of being reported, and therefore the analyst should not be able to reject the $\omega_2 = \omega_3 = \omega_4 = 1$ hypothesis (Ashenfelter *et al.* 1999; Havranek *et al.* 2015).

5.3.2 Funnel Plot

A very simple method of detecting selective reporting is based on the graphical representation of the data set. Funnel plot is a graphical representation used most frequently, which may serve very well for an introductory visual inspection. The funnel plot is a simple scatter plot of the estimated effect sizes and their precision. In our case, the estimated coefficients of percentage corn price change resulting from a change in ethanol volume are on the horizontal axis and the variable describing their precision is on the vertical axis. The precision of the estimates may be defined in various ways. The inverse of the estimate's standard errors ($\frac{1}{se}$) is probably the most common one. When used, we can observe that the most precise estimates gather tightly at the top of the funnel whereas the less precise estimates (at the bottom of the funnel) are more dispersed. One of the advantages of the funnel plot is the possibility of replacing the precision parameter for another one when, for example, standard errors are not available. In that case, Stanley (2005) proposes to use the sample size (n) as a substitute. He also suggests, that in some cases, using the square root of the sample size ($\sqrt{n}$) may be more representative.

In an ideal state (absence of any selective reporting), the funnel plot should be symmetrical and should look like an upturned funnel with a sharp tip on the top and a wide base on the bottom. In the case when the funnel is symmetrical, we can allege that all the imprecise observations have the same probability of being reported (Havranek *et al.* 2015). An example of such an ideal funnel plot showcasing the absence of any selective reporting can be found in the left part of Figure 5.4. A worrying experience with many meta-analyses is that if the true effect is positive and reasonably close to zero, the y-axis (x=0) creates a significant barrier between a densely observations-filled right side and sparsely observations-filled left side of the axis. Even in this case, we should find some significant number of negative estimates due to the laws of chance (the same theory applies for large positive estimates with low precision). The funnel becomes asymmetrical as soon as some estimates are systematically omitted. This is exactly the consequence of not publishing the counter-intuitive estimates or, in other words, selective reporting. An example of a funnel plot suffering from this asymmetry, where the negative side of the funnel is almost missing, can be found on the right-hand side of Figure 5.4. Such a serious bias will inevitably lead to false interpretations and hypotheses when not accounted for.

Figure 5.4: Ideal vs. biased funnel plot



Source: Scherer (2012).

5.3.3 Meta-Regression Analysis

Even though graphical testing of selective reporting is very straightforward and powerful, it is not omnipotent. According to Gorg & Strobl (2001), graphical tests are usually unable to detect all types of publication selection bias. The third method of detecting selective reporting is based on the same idea as the previous funnel plot method. It uses meta-regression analysis to statistically examine the degree of funnel asymmetry (Havranek *et al.* 2015). In the ideal scenario of no selective reporting in the examined literature, the estimates of the corn price responsiveness CPR to biofuel expansions should be distributed randomly around the true value of corn price responsiveness CPR_0. But if authors discard some estimates because they are statistically insignificant or have a sign that is inconsistent with the theory or the mainstream prior, the reported estimates of the corn price responsiveness will be correlated with their standard errors (Card & Krueger 1995):

$$CPR_i = CPR_0 + \beta_0 \cdot Se(CPR_i) + \epsilon_i, \tag{5.2}$$

where CPR_i is the estimate of the corn price responsiveness to biofuel expansions[5], CPR_0 is the average underlying value of the corn price responsiveness, $Se(CPR_i)$ is the standard error of CPR_i, β_0 measures the magnitude of selective reporting, and ϵ_i is an error term. In practice, formula(5.2) tests for funnel plot asymmetry as the regression follows from rotating the axes of the plot and inverting the values on the new horizontal axis (Havranek *et al.* 2015). In the ideal case of a symmetric funnel plot, β_0 should be statistically insignificant. On the other hand, if the estimate of β_0 turns out to be statistically significant, we have a formal evidence of an asymmetric funnel plot and of the presence of selective reporting in the literature. According to Havranek *et al.* (2015), estimates of β_0 that are close to 2 are consistent with a situation when only positive and statistically significant estimates of corn price responsiveness are reported. In other words, only the estimates whose 95% confidence intervals exclude zero are reported and the rest ends up in file drawers.

Nevertheless, Doucouliagos & Stanley (2009) argue that specification(5.2) suffers from heteroskedasticity because of the dispersion of the explained vari-

[5] Corn price responsiveness (CPR) is a term I decided to use as an aggregate term for all of the three types of corn price responsiveness (raw percentage corn price change resulting from a given scenario assumed by the authors of a primary study, percentage corn price change per billion gallons increase in ethanol volume, and percentage corn price change per percentage increase in ethanol volume) instead of writing them repeatedly.

able which increases and decreases at the same time as the values of the explanatory variable. Therefore, Stanley (2005) proposed an estimation based on the method of weighted least squares (WLS), where precision (usually the inverse of standard errors) is taken as the weight:

$$\frac{CPR_i}{Se(CPR_i)} \equiv t_i = CPR_0 \cdot \frac{1}{Se(CPR_i)} + \beta_0 + \xi_i, \qquad \xi_i \mid Se(CPR_i) \sim N(0, \sigma^2). \tag{5.3}$$

In equation(5.3) above, t_i is the approximate t-statistic of an estimate and the new error term ξ_i is now homoscedastic. In this case, the intercept β_0 measures the magnitude of publication selection bias. Testing its significance is analogous to testing the funnel plot asymmetry because it is based on the rotation of the funnel plot and division of the estimates by their standard error. The estimate of CPR_0 is representing the true corn price responsiveness to ethanol expansion corrected for selective reporting.

5.4 Mixed-Effects Multilevel Model

When conducting a meta-analysis, we should keep in mind that primary studies usually present more than one estimate of the corn price responsiveness[6] and these estimates are likely to be correlated. The correlation can be quite significant and could potentially distort our estimation, if not accounted for. A way how to cope with this issue is to employ the so-called mixed-effects multilevel model proposed by Doucouliagos & Stanley (2009), which allows for unobserved between study heterogeneity. The mixed-effects model is specified according to Havranek & Irsova (2011) and Havranek *et al.* (2012a) in the following way:

$$\begin{gathered} t_{ij} = \beta_0 + \beta \cdot (\frac{1}{Se(CPR_{ij})}) + \zeta_j + \epsilon_{ij}, \\ \zeta_j \mid Se(CPR_{ij}) \sim N(0, \theta), \qquad \epsilon_{ij} \mid Se(CPR_{ij}), \zeta_j \sim N(0, \psi), \end{gathered} \tag{5.4}$$

where i and j denote estimate and primary study subscript respectively and t_{ij} is the approximate t-statistic. The overall error term (ξ_{ij}) now breaks down into study-level random effects (ζ_j) and estimate level disturbances (ϵ_{ij}).

[6] In our case, every single study included in the data set presents more than one estimate of corn price responsiveness because studies that report only one estimate could not be included in the analysis as their standard errors could not be approximated.

Interestingly, the variance of both error terms is additive as they are assumed to be uncorrelated.

The mixed-effects multilevel model and the random-effects model used in panel data econometrics are similar, but the terminology for mixed-effects multilevel models follows hierarchical data modelling. The mixed-effects model incorporates both random and fixed effects. Nevertheless, mixed-effects multilevel framework, which uses the restricted maximum likelihood estimator, is more suitable for a meta-analysis than the random effects model, which uses generalized least squares, because it allows us to account for the unbalancedness of the data and for nesting multiple random effects (Havranek *et al.* 2012b). One of the most serious drawbacks of mixed-effects models is that it does not assume any correlation between study-level random effects and the explanatory variables. According to Havranek *et al.* (2015), this assumption is rarely tenable in practice, and they thus prefer to run the fixed-effects model and cluster standard errors at the study level.

5.5 Computation of Standard Errors

To be able to detect and estimate the publication selection bias by employing the methods based on the funnel plot, standard errors of the estimates of corn price responsiveness are needed. None of the primary studies report their estimates' standard errors, confidence intervals or any other measure of uncertainty. Therefore, I decided to choose an alternative way of computing the approximate standard errors. Following the approach of Havranek *et al.* (2015), I take the median estimate of the corn price responsiveness from each study and then compute the approximate standard error as the difference between the 50th and 16th percentile of the distribution of estimates. This is the reason why studies reporting only one estimate of corn price responsiveness could not be included in this analysis. A lot of studies had to be dropped from the data set because of this reason. Dropping these studies is very unfortunate considering the small number of studies which present more than one estimate in the available literature, but detecting and estimating the possible selective reporting without knowing the standard errors or any other precision measure is not possible. This method of computing standard errors is performed under the simplifying assumption of normal distribution of estimates in each primary study. Havranek *et al.* (2015) argue that most studies produce an asymmetric distribution of estimates, but quantification of the confidence of the authors that their estimate of the corn price responsiveness is different from zero, which is analogous to statistical significance for classical regression estimates used in economic meta-analyses, is what we should be interested in.

5.6 Meta-Regression Analysis and Heterogeneity of Estimates

Equations that were discussed until now do not consider any possible heterogeneity of characteristics of primary studies apart from selective reporting. Nevertheless, different types of biofuel policies (mandates vs non-mandates), baseline ethanol volumes, policy ethanol volumes together with the difference between them, usage of US-data only, the inclusion of co-products in the analysis, and other additional aspects of estimates and studies may explain some of the heterogeneity in corn price responsiveness estimates. One way of controlling for these additional characteristics it the employment of an enhanced model of equation(5.3) proposed by Doucouliagos & Stanley (2009):

$$\frac{CPR_i}{Se(CPR_i)} \equiv t_i = \beta_0 + CPR_0 \cdot (\frac{1}{Se(CPR_i)}) + \sum_{k=1}^{K} \frac{\beta_k Z_i k}{Se(CPR_i)} + \xi_i, \qquad (5.5)$$
$$\xi_i \mid Se(CPR_i) \sim N(0, \sigma^2),$$

where Z represents a vector of all additional explanatory variables like *year published*, *oil price*, etc.[7] Again, we must keep in mind that individual estimates of a single study are most probably correlated. Havranek *et al.* (2012a) specify a mixed-effects multilevel model, which can address this issue by controlling for unobserved between-study heterogeneity, as follows:

$$t_{ij} = \beta_0 + CPR_0 \cdot (\frac{1}{Se(CPR_i)}) + \sum_{k=1}^{K} \frac{\beta_k Z_i k}{Se(CPR_i)} + \zeta_j + \epsilon_{ij}, \qquad (5.6)$$

where $\quad \zeta_j \mid Se(CPR_i) \sim N(0, \theta), \qquad \epsilon_{ij} \mid Se(CPR_i), \zeta_j \sim N(0, \psi).$

[7] For complete summary and description of explanatory variables included in this analysis see Table 4.3.

The results of employment of these models will be presented in the next chapter.

Chapter 6

Results

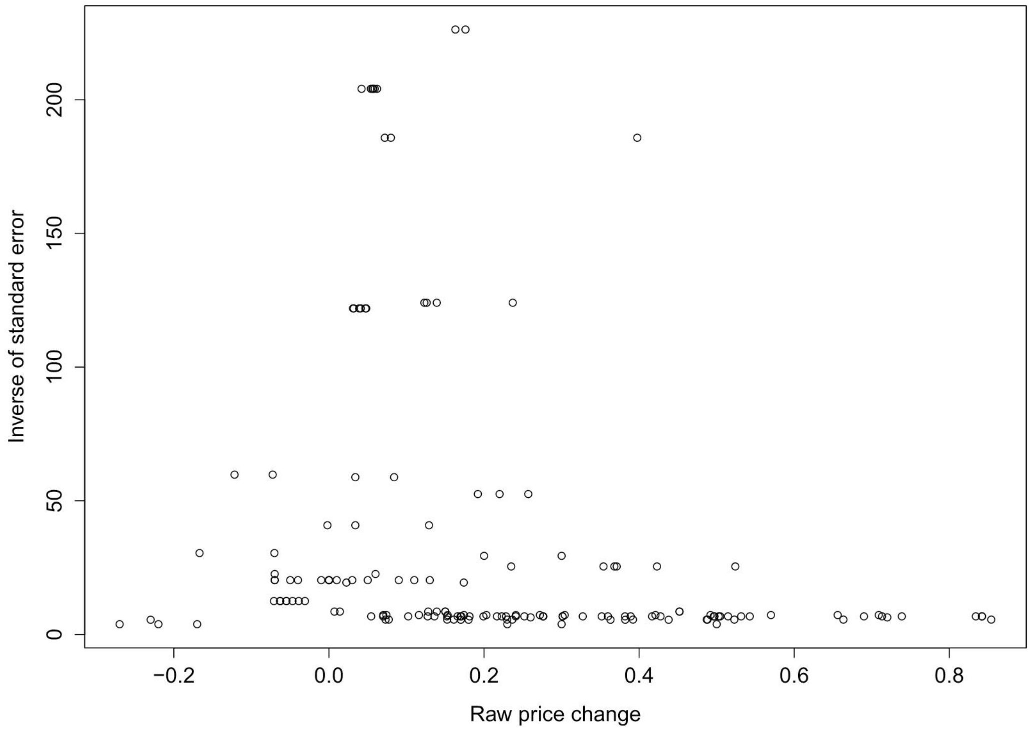
6.1 Funnel Plots

Figure 6.1 depicts the funnel plot of estimates of *raw price change* in our data set (i.e. the percentage change in corn price resulting from ethanol expansion assumed in the primary study – for example, the value of 0.2 on the x-axis represents an estimate of 20% increase of price of corn resulting from assumed ethanol expansion scenario). We can see that the funnel is slightly asymmetrical as the right-hand side tail seems to be longer and denser. Only a few negative estimates, in comparison to the amount of large positive estimates, are reported. Smaller estimates (in the range between 0 and 20 percent) create the top of the funnel as they are the most precise ones. Large estimates of raw price change are associated with lower inverses of standard errors (lower precision).

The second funnel plot (Figure 6.2) in our analysis reflects the estimates and their precision of the *semi-elasticity* (i.e. the percentage change in corn price resulting from one billion gallons increase in ethanol volume – for example, the value of 0.02 on the x-axis represents an estimate of 2% increase of corn price as a result of one-billion-gallon ethanol expansion). The funnel plot is even more asymmetric this time, practically omitting the left-hand side. As already mentioned once in this analysis, only one estimate "dares" to be negative, whereas the right-hand part of large positive estimates is quite populated. The top of the funnel is between 0 and 2 percent.

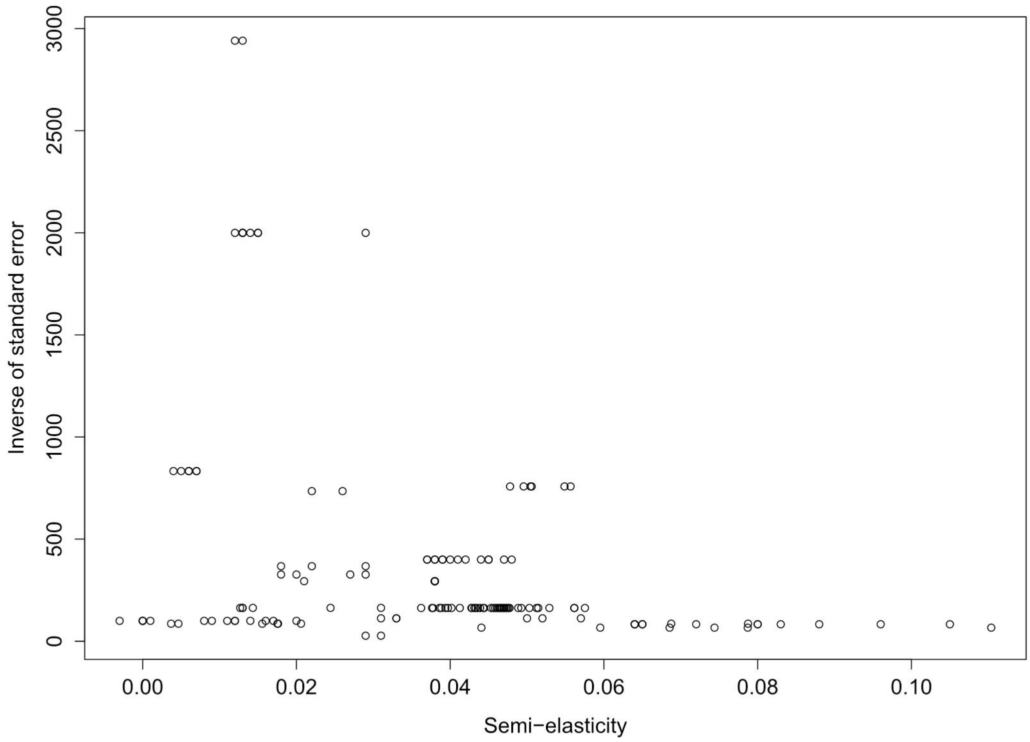
The last funnel plot (Figure 6.3) reports the estimates of elasticity (i.e. the percentage change in corn price resulting from one percent increase in ethanol volume – for example, the value of 0.002 on the x-axis represents an estimate of 0.2% increase of corn price as a result of 1% increase in ethanol volume). In

Figure 6.1: Funnel plot - raw price change



Note: If there was no selective reporting, observations would be symmetrically spread around the highest-precision estimate of raw price change. Precision is computed as the inverse of approximate standard errors.

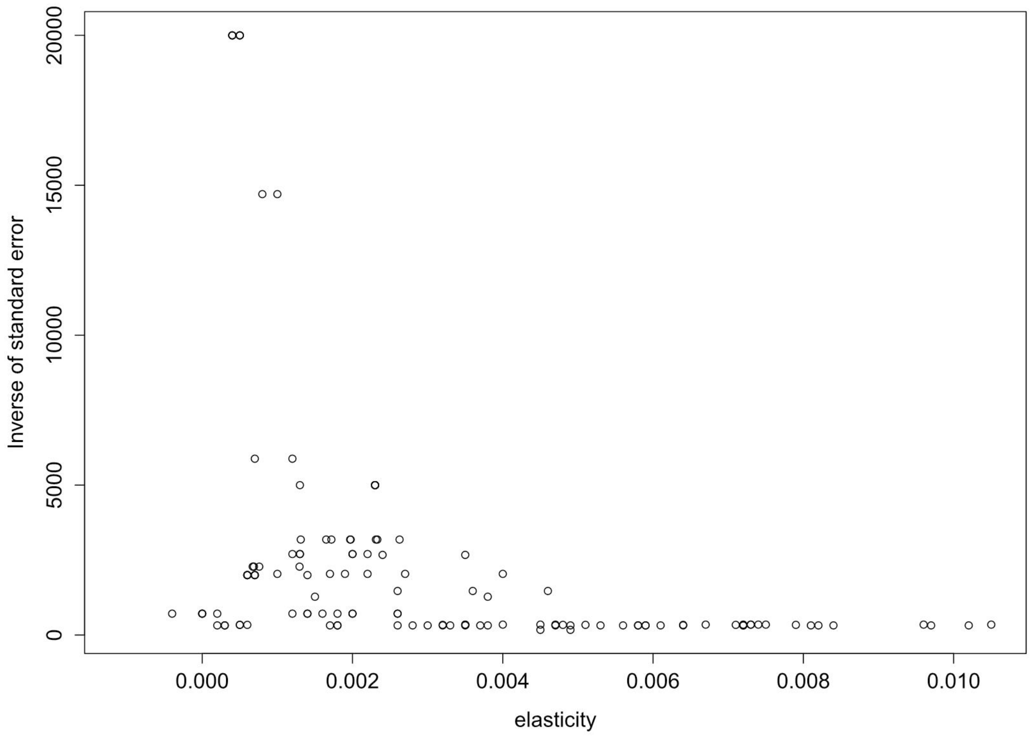
Figure 6.2: Funnel plot - semi-elasticity



Note: If there was no selective reporting, observations would be symmetrically spread around the highest-precision estimate of semi-elasticity. Precision is computed as the inverse of approximate standard errors.

the case of *elasticity*, the funnel plot is totally asymmetric and the left part of the funnel is completely missing.

Figure 6.3: Funnel plot - elasticity



Note: If there was no selective reporting, observations would be symmetrically spread around the highest-precision estimate of elasticity. Precision is computed as the inverse of approximate standard errors.

The asymmetry of all funnels indicates the presence of selective reporting in the literature. In case there was no selective reporting, the estimates would be symmetrically spread around the highest-precision estimates.

6.2 Funnel Asymmetry Tests (FAT)

The results of funnel asymmetry tests defined in the equation(5.3) for *raw price change*, *semi-elasticity*, and *elasticity* are shown in Table 6.1, Table 6.2, and Table 6.3 respectively. The first column (OLS) presents the results of running a simple Ordinary Least Squares regression of point estimates of the corn price responsiveness on standard errors. The second column (FE) is a result of controlling for all study-specific aspects that could possibly affect the estimates. The filtering of these effects is done by incorporating study-level fixed effects.

The outcomes of weighting estimates by their precision (in our case, precision is represented by the inverse of standard errors) are recorded in the third column called (*Precision*). Weighting has the form of employing the Weighted Least Squares method (*WLS*) which, according to Havranek *et al.* (2015), has two significant advantages. It corrects for heteroskedasticity in the baseline regression, where the independent variable (standard error of the estimate of the corn price responsiveness) is a measure of dispersion of the dependent variable (the magnitude of the estimate of the corn price responsiveness). Furthermore, it gives more weight to more precise results, which means a further alleviation of the selective reporting effects (Havranek *et al.* 2015). Finally, the results of the mixed-effects multilevel model are reported in the last column (*ME*). With the help of mixed-effects multilevel model, it is possible to assign more similar weights to each study. At the same time, the model accounts for random differences in the size of corn price responsiveness across individual studies.

Turning our attention to the first type of price responsiveness, Table 6.1 reports the results obtained for *raw price change* (the percentage change in corn price resulting from ethanol expansion assumed in the primary study). According to the *OLS* regression outcomes, the slope coefficient (coefficient of standard error) is positive and statistically significant at 1% level. This result supports our presumptions about the association between the size of the raw price change estimate and its uncertainty. The slope coefficient is above 1.2 which, according to Stanley *et al.* (2013), is referred to as "substantial" selective reporting bias. As Havranek *et al.* (2015) argues, "the slope coefficient close to 2 would be consistent with a situation when researchers systematically omitted estimates for which the 95% confidence interval included zero". The mean estimate of the raw price change corrected for selective reporting is supposed to be slightly above 8% as the constant parameter suggests.

The FE specification, however, estimates the slope coefficient to be close to 0.8, which according to Stanley *et al.* (2013) belongs into the interval of "little to modest" selective reporting bias. The true effect (*constant*) is estimated to be slightly under 10% in this case.

The results of *Precision* specification based on weighting the variables by the inverse of standard error are very similar to the ones obtained from simple *OLS* regression. Mixed-effects model, however, reports a slightly higher slope of almost 1.5. This value still means substantial selective reporting bias. Due to the estimation of slightly larger publication bias, the true effect is estimated to be about 6%, which is the lowest of all.

Table 6.1: Funnel asymmetry test - raw price change

	OLS	*FE*	*Precision*	*ME*
Standard Error	1.2582***	0.8028***	1.2308***	1.4973***
	(0.2579)	(0.0945)	(0.2345)	(0.2360)
Constant	0.0822**	0.0975***	0.0850***	0.0593**
	(0.0321)	(0.0015)	(0.0129)	(0.0246)
Observations	155	155	155	155

Notes: Table presents the results of $CPR_{ij} = CPR_0 + \beta_0 \cdot Se(CPR_{ij}) + \epsilon_{ij}$ regression. CPR_{ij} is the i-th estimate of j-th study of corn price responsiveness and $Se(CPR_{ij})$ is the related standard error. Study level clustered standard errors in parentheses. OLS = Ordinary Least Squares, FE = fixed-effects, $Precision$ = weighted by $1/SE$, ME = mixed effects. Levels of 1%, 5%, and 10% are denoted by ***, **, and * respectively.

The results of funnel asymmetry tests for the second type of price responsiveness examined in this analysis, *semi-elasticity* (the percentage change in corn price resulting from one billion gallons increase in ethanol volume), are shown in Table 6.2. Interestingly, the coefficients estimates vary significantly. The highest slope coefficient (over 4.8) is the outcome of the fixed-effects model. Together with the estimate provided by Weighted Least Squares method of over 2.6, they expect the literature to be "severely" biased because of selective reporting according to the classification by Stanley *et al.* (2013). On the other hand, *OLS* and *ME* specifications estimate the slope coefficient to be close to 1.1 and 1.6 respectively, which would suggest a somewhat minor influence of selective reporting. The estimates of the true semi-elasticity vary as well. The lowest true effect is reported by *FE* method, other methods expect that the one billion gallons increase in ethanol volume would most probably result in an increase of corn prices by 2-3%.

The last table in this subsection (Table 6.3) shows the outcomes of funnel asymmetry tests for the last type of corn price responsiveness – *elasticity* (the percentage change in corn price resulting from one percent increase in ethanol volume). In contrast with *semi-elasticity* funnel asymmetry tests, the estimated true effects and magnitudes of selective reporting bias do not vary that much across various specifications. The fixed-effects method reports the highest presence of selective reporting in the literature again. It is the only coefficient of standard error that is above 2, indicating severe bias. Other estimates are in a considerably narrow range between 1.1 and 1.4. A similar conclusion can

Table 6.2: Funnel asymmetry test - semi-elasticity

	OLS	*FE*	*Precision*	*ME*
Standard Error	1.0614***	4.8400***	2.6803***	1.6140***
	(0.3372)	(0.1009)	(0.4029)	(0.3779)
Constant	0.0304***	0.0138***	0.0196***	0.0271***
	(0.0029)	(0.0002)	(0.0017)	(0.0027)
Observations	145	145	145	145

Notes: Table presents the results of $CPR_{ij} = CPR_0 + \beta_0 \cdot Se(CPR_{ij}) + \epsilon_{ij}$ regression. CPR_{ij} is the i-th estimate of j-th study of corn price responsiveness and $Se(CPR_{ij})$ is the related standard error. Study level clustered standard errors in parentheses. OLS = Ordinary Least Squares, FE = fixed-effects, $Precision$ = weighted by $1/SE$, ME = mixed effects. Levels of 1%, 5%, and 10% are denoted by ***, **, and * respectively.

be done in the case of estimates of the true *elasticity*. The fixed-effects method expects it to be about 0.05%, whereas the other three methods expect an increase of corn price by 0.08-0.11% as a result of one percent increase in ethanol volume.

Table 6.3: Funnel asymmetry test - elasticity

	OLS	*FE*	*Precision*	*ME*
Standard Error	1.1674***	2.1455***	1.3253***	1.4211***
	(0.1361)	(0.1022)	(0.1272)	(0.1196)
Constant	0.0011***	0.0005***	0.0008***	0.0010***
	(0.0003)	(0.0000)	(0.0001)	(0.0001)
Observations	125	125	125	125

Notes: Table presents the results of $CPR_{ij} = CPR_0 + \beta_0 \cdot Se(CPR_{ij}) + \epsilon_{ij}$ regression. CPR_{ij} is the i-th estimate of j-th study of corn price responsiveness and $Se(CPR_{ij})$ is the related standard error. Study level clustered standard errors in parentheses. OLS = Ordinary Least Squares, FE = fixed-effects, $Precision$ = weighted by $1/SE$, ME = mixed effects. Levels of 1%, 5%, and 10% are denoted by ***, **, and * respectively.

6.3 Controlling for Heterogeneity

In this subchapter, I control for additional characteristics of individual estimates and studies by including all the explanatory variables presented in Table 4.3 into the models described in the previous subchapter. Table 6.4, Table 6.5, and Table 6.6 include results of running these enhanced models for *raw price change*, *semi-elasticity*, and *elasticity* as dependent variables respectively. One important fact that should be explained is the omission of the fixed-effects specification. *FE* method cannot be used in this setting because of some independent variables, especially the dummy ones, which have the same value for all estimates presented by one primary study, which would induce perfect correlation with study dummies.

Let us turn attention towards Table 6.4 which reports the results of the first type of corn price responsiveness – the *raw price change*. The most important coefficients for our analysis are the ones of standard errors. Surprisingly, this coefficient changed significantly in the simple *OLS* specification as it became less significant in comparison to the results of funnel asymmetry testing. On the other hand, standard error coefficients remained significant and close to 1 in the cases of *Precision* and *ME* specifications. In general, selective reporting bias after controlling for additional aspects of estimates and studies seems to be somewhat less severe, but still significant. According to the estimates of *Precision* and *ME* models, its magnitude is on the edge between "little to modest" and "substantial" (Stanley *et al.* 2013).

Regarding the rest of the explanatory variables, *Absolute change in corn ethanol* is significant throughout all the models, which is clear because *raw price change* is not normalized towards any given quantity (*semi-elasticity* and *elasticity*, however, are normalized from definition to one-billion-gallon expansion in ethanol volume and one percent increase in ethanol volume respectively). In addition, change in other biofuels seems to also have a significant (negative) effect on *raw price change*. Interestingly, presence of a study among the published studies on the Research Papers in Economics (RePEc) web site together with increasing number of *citations* seems to have a negative effect on reported *raw price change*. This means that, on average, publications reporting smaller impacts on corn price as a result of ethanol expansion are cited more often.

Table 6.5 reports the results for the second type of corn price responsiveness – the *semi-elasticity*. Same pattern as in the case of raw price change concerning the standard error occurs here. *OLS* method reports modest selective reporting bias and *Precision* and *ME* report the coefficients close to 1.3 and 1.5 respectively, showing substantial selective reporting bias. Concerning other explanatory variables, coefficients of *year*, *change in other biofuels*, and *repec* are all negative and statistically significant. Effects of *change in other*

Table 6.4: Controlling for heterogeneity - raw price change

	OLS	*Precision*	*ME*
Standard error	0.3779*	1.0408***	0.8877***
	(0.2239)	(0.2158)	(0.2541)
Baseline corn ethanol	-0.0023	-0.0043**	-0.0043**
	(0.0019)	(0.0017)	(0.0019)
Absolute change in corn ethanol	0.0326***	0.0227***	0.0244***
	(0.0027)	(0.0027)	(0.0030)
Ethanol decrease scenario	-0.0041	-0.0239	-0.0134
	(0.0411)	(0.0402)	(0.0410)
Mandate policy instrument	-0.0300	-0.0396	-0.0116
	(0.0306)	(0.0328)	(0.0351)
US mandate only	0.0256	-0.0021	-0.0045
	(0.0280)	(0.0232)	(0.0256)
Co-products	0.0896*	-0.0288	-0.0027
	(0.0480)	(0.0298)	(0.0440)
Year	0.0047**	0.0052***	0.0039*
	(0.0022)	(0.0017)	(0.0021)
Oil price	-0.0004	0.0004	0.0001
	(0.0005)	(0.0004)	(0.0005)
Change in other biofuels	-0.0421***	-0.0223***	-0.0249***
	(0.0062)	(0.0060)	(0.0064)
Year published	-0.0150*	-0.0124*	-0.0131*
	(0.0077)	(0.0063)	(0.0076)
Repec	-0.1007***	-0.0525**	-0.0567**
	(0.0311)	(0.0212)	(0.0278)
Scopus	0.2499***	0.1648***	0.1611***
	(0.0546)	(0.0367)	(0.0457)
Citations	-0.0005**	-0.0003***	-0.0004**
	(0.0002)	(0.0001)	(0.0002)
Constant	20.5848	14.2898	18.5098
	(14.1047)	(11.5272)	(14.0564)
Observations	155	155	155

Notes: Table presents the results of $CPR_{ij} = CPR_0 + \beta_0 \cdot Se(CPR_{ij}) + \lambda \cdot Z_{ij} + \epsilon_{ij}$ regression. CPR_{ij} is the i-th estimate of j-th study of corn price responsiveness, $Se(CPR_{ij})$ is the related standard error. Z represents a vector of additional explanatory variables. Study level clustered standard errors in parentheses. OLS = Ordinary Least Squares, FE = fixed-effects, $Precision$ = weighted by $1/SE$, ME = mixed effects. Levels of 1%, 5%, and 10% are denoted by ***, **, and * respectively.

biofuels and *repec* were described in the previous paragraph. The negative coefficient of *year* means that studies assuming longer scenarios (their fulfilment occurs in further future) report, on average, less significant impacts of ethanol expansions on of corn price.

The results for the last type of corn price responsiveness, *elasticity*, are displayed in Table 6.6. Once again, coefficients of standard errors are smaller compared to funnel asymmetry test results as some of their magnitudes was taken over by other explanatory variables that were previously not accounted for. *Precision* and *ME* methods still show a presence of selective reporting bias that is on the edge between "little to modest" and "substantial" according to the scale created by Stanley *et al.* (2013).

To conclude this subchapter, it is important that the results for all three types of corn price show the presence of selective reporting, as the results of funnel asymmetry tests predicted. In general, the magnitude of selective reporting bias slightly decreased after controlling for additional characteristics of individual estimates and studies, but remained significant. One last note regarding the evaluation of results presented by tables in this subsection: keep in mind, that it is not very reasonable to interpret the *constant* in these regressions – they do represent the mean of corn price responsiveness while removing the selective reporting bias, but it is very dependent on the sizes of all other explanatory variables included in the model.

6.4 Comparison with the previous Meta-Analysis by Condon et al. (2015)

In this subchapter, I will briefly compare my results with the previously published meta-analytical study by Condon *et al.* (2015). Their meta-analysis included 29 studies published between 2007 and 2014. This meta-analysis works with almost the same amount of studies (23) that were published between 2008 and May 2017. Even though I added a few studies from recent years, which Condon *et al.* (2015) could not account for, I ended up with fewer studies because I had to drop all studies that reported only one estimate. For more information about why this had to be done, see Chapter 5. Both my and the previously published study work with approximately 150 estimates of the impacts of corn ethanol production expansion on corn prices.

The biggest contribution of this study is the detection of selective reporting

Table 6.5: Controlling for heterogeneity - semi-elasticity

	OLS	*Precision*	*ME*
Standard error	0.6308*	1.3330***	1.4905***
	(0.3461)	(0.3772)	(0.4131)
Baseline corn ethanol	-0.0011***	-0.0003	-0.0008***
	(0.0002)	(0.0002)	(0.0002)
Absolute change in corn ethanol	0.0003	0.0003*	0.0003
	(0.0003)	(0.0001)	(0.0003)
Ethanol decrease scenario	-0.0052	-0.0079	-0.0090*
	(0.0059)	(0.0050)	(0.0053)
Mandate policy instrument	-0.0027	-0.0017	-0.0064*
	(0.0042)	(0.0025)	(0.0036)
US mandate only	-0.0060	-0.0028	-0.0015
	(0.0037)	(0.0030)	(0.0033)
Co-products	0.0001	-0.0088*	-0.0063
	(0.0066)	(0.0044)	(0.0056)
Year	-0.0009***	-0.0008***	-0.0008***
	(0.0003)	(0.0002)	(0.0003)
Oil price	0.0001	0.0000	0.0001
	(0.0000)	(0.0000)	(0.0001)
Change in other biofuels	-0.0030***	-0.0018***	-0.0022***
	(0.0008)	(0.0005)	(0.0008)
Year published	0.0002	0.0000	0.0000
	(0.0011)	(0.0008)	(0.0010)
Repec	-0.0163***	-0.0136***	-0.0133***
	(0.0053)	(0.0046)	(0.0048)
Scopus	0.0175**	0.0163***	0.0142**
	(0.0080)	(0.0058)	(0.0069)
Citations	0.0000***	0.0000***	-0.0001***
	(0.0000)	(0.0000)	(0.0000)
Constant	1.5540	1.7020	1.7054
	(1.9350)	(1.4020)	(1.5841)
Observations	145	145	145

Notes: Table presents the results of $CPR_{ij} = CPR_0 + \beta_0 \cdot Se(CPR_{ij}) + \lambda \cdot Z_{ij} + \epsilon_{ij}$ regression. CPR_{ij} is the i-th estimate of j-th study of corn price responsiveness, $Se(CPR_{ij})$ is the related standard error. Z represents a vector of additional explanatory variables. Study level clustered standard errors in parentheses. OLS = Ordinary Least Squares, FE = fixed-effects, $Precision$ = weighted by $1/SE$, ME = mixed effects. Levels of 1%, 5%, and 10% are denoted by ***, **, and * respectively.

Table 6.6: Controlling for heterogeneity - elasticity

	OLS	*Precision*	*ME*
Standard error	0.5303**	0.8880***	0.9796***
	(0.2083)	(0.1879)	(0.1500)
Baseline corn ethanol	0.0001***	0.0000**	0.0000*
	(0.0000)	(0.0000)	(0.0000)
Absolute change in corn ethanol	0.0000	0.0000	0.0000***
	(0.0000)	(0.0000)	(0.0000)
Ethanol decrease scenario	-0.0012**	0.0001	0.0004***
	(0.0005)	(0.0003)	(0.0002)
Mandate policy instrument	0.0003	-0.0002	-0.0004*
	(0.0004)	(0.0003)	(0.0002)
US mandate only	-0.0010**	-0.0005*	-0.0002
	(0.0004)	(0.0003)	(0.0001)
Co-products	0.0012	0.0007	0.0014***
	(0.0010)	(0.0006)	(0.0003)
Year	0.0001***	0.0000*	0.0000
	(0.0000)	(0.0000)	(0.0000)
Oil price	0.0000***	0.0000	0.0000
	(0.0000)	(0.0000)	(0.0000)
Change in other biofuels	0.0000	-0.0001**	-0.0002***
	(0.0000)	(0.0000)	(0.0000)
Year published	0.0003*	0.0001	0.0001
	(0.0001)	(0.0001)	(0.0001)
Repec	-0.0015**	-0.0006	-0.0008***
	(0.0005)	(0.0004)	(0.0002)
Scopus	-0.0011	-0.0004	0.0004
	(0.0010)	(0.0007)	(0.0004)
Citations	0.0000**	0.0000	0.0000***
	(0.0000)	(0.0000)	(0.0000)
Constant	0.3330	0.2009	-0.1588
	(0.2956)	(0.2204)	(0.1073)
Observations	125	125	125

Notes: Table presents the results of $CPR_{ij} = CPR_0 + \beta_0 \cdot Se(CPR_{ij}) + \lambda \cdot Z_{ij} + \epsilon_{ij}$ regression. CPR_{ij} is the i-th estimate of j-th study of corn price responsiveness, $Se(CPR_{ij})$ is the related standard error. Z represents a vector of additional explanatory variables. Study level clustered standard errors in parentheses. OLS = Ordinary Least Squares, FE = fixed-effects, $Precision$ = weighted by $1/SE$, ME = mixed effects. Levels of 1%, 5%, and 10% are denoted by ***, **, and * respectively.

that has been found in the literature published on this topic. Controlling for selective reporting yields unbiased estimates of the true effect of corn ethanol production on corn prices. Results of Condon *et al.* (2015) indicate that a one-billion-gallon expansion in the corn ethanol production would lead to a 3-4% increase in corn prices. After controlling for selective reporting bias, the results of this study show that the same expansion in the corn ethanol production would lead to a 2-3% increase in corn prices. In absolute terms, the difference seems negligible, but in relative terms, the difference is significant. Another type of corn price responsiveness that is investigated in both studies is the percentage change in corn price resulting from one percent increase in ethanol production. While Condon *et al.* (2015) report an estimate of 0.24%, this study shows one percent increase in ethanol production would lead to 0.05-0.11% increase in corn prices.

Following the example of Condon *et al.* (2015), I decided to include some additional explanatory variables into this analysis as well. For comparison purposes, I chose many of the same variables as they did. Moreover, I also added a few new variables representing factors that could potentially explain some of the remaining variation of estimates across studies. Both studies found out that *baseline corn ethanol* is a statistically significant variable and they both report very similar estimates of its coefficient. The same accordance of results applies for the variable *year*, indicating that smaller price changes are projected in future years. Variables *mandate policy* and *co-products* are statistically significant in the previous meta-analysis, but this study does not find them significant. Both studies are in accordance considering the variable oil price as both report negligible estimates of its coefficient. The only contradiction among the significant results is connected to *change in other biofuels*. Condon *et al.* (2015) report small but statistically significant positive effect of an expansion in other biofuels on corn prices, but this study comes up with negative, statistically significant estimates, although they are small in magnitude as well.

Chapter 7

Conclusion

According to economic theory, deflecting a significant portion of corn production to ethanol for fuelling purposes will increase the prices of corn. The relationship between corn ethanol expansions and corn prices has been examined many times during the last decade. Although empirical analyses published on this topic confirm the theory, the reported estimates vary broadly (from nil to 85%). In this thesis, I conduct a meta-analysis of literature estimating the impacts of ethanol policies on corn prices. I collect and examine 155 estimates of the percentage change in corn price resulting from various scenarios of ethanol expansions reported in 23 studies published between 2008 and 2017. I control for different sizes of corn ethanol expansions and other study or estimate level characteristics to make them more comparable. Among others, I employ meta-regression methods to detect potential selective reporting in the literature. The results suggest that estimates for which the 95% confidence interval excludes zero are preferred by the authors. Smaller estimates of the impacts of ethanol policies on corn prices are usually connected with higher precision while for larger estimates the opposite is true. With regards to an overwhelming consensus about the positive impacts of corn ethanol expansions on corn prices, it may make sense to ignore negative (counter-intuitive) estimates. From this perspective, the zero value creates a natural lower boundary for small estimates. On the contrary, there is no such boundary preventing the unintuitively large estimates to be reported. This is reflected by an upward bias in the literature.

Unfortunately, none of the studies reported their estimates together with standard errors or any other measure of uncertainty. Therefore, an alternative approach, following Havranek *et al.* (2015), of computing approximate standard errors is applied. Because of this limitation, I could not include studies reporting a single estimate of the impact of ethanol policies on corn prices, which significantly reduces the available data set.

Using the methods of ordinary least squares, fixed-effects, weighted least squares, and mixed-effects multilevel model I can control for the selective reporting bias. I show that the true effect of a one-billion-gallon corn ethanol expansion on corn prices is between two and three percent. In addition, the true effect of one percent increase in corn ethanol on corn prices is between 0.05 and 0.11 percent. The results of the meta-analysis also show that projection year, baseline corn ethanol volume, and other than corn-ethanol biofuel production explain a significant portion of the variance in the estimates.

The outcomes of this study may be of use for researchers conducting future analysis, as well as policymakers creating new or reforming the existing policies and measures. Readers should not only look at the estimated true effect but should also consider other factors that are assumed to have a significant impact. For example, policymakers may find short-term estimates more useful considering the significance of projection year. Furthermore, indirect impacts of non-corn ethanol biofuels production on corn prices should be always accounted for.

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