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EU wheat producers' area response to prices, climate, and price risk

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Applied Economics and Sustainability

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Abstract

This thesis examines how changes in the wheat price, price risk and climate risk affect wheat producers' area decisions in the EU. Numerous studies have estimated the wheat area response in the US and in developing countries, but few have focused on the EU. The attention to risk in previous studies has also been limited. Greatly influenced by the Common Agricultural Policy, it is likely that producers in the EU respond differently to prices and risk than producers in the rest of the world. Understanding how these factors affect area allocation in the EU is important to be able to predict global food supply, as the EU is one of the world's main wheat producing regions. The study follows the Nerlovian partial adjustment approach and is conducted on panel data covering the period 2003 to 2022. The findings suggest that the wheat area response to wheat price is inelastic in both the short-run and the long-run. The estimated short-run elasticities vary from 0,09 to 0,15 and the estimated long-run elasticities vary from 0,57 to 0,82. The effect of climate risk on wheat area is negative, while the effect of price risk on wheat area is statistically insignificant. This suggests that risk mitigating measures in the EU are effective in terms of reducing price risk. However, with more frequent extreme weather events in the future due to climate change, different measures may be needed to reduce climate risk for wheat producers.

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1. Introduction

Since 2003 the world has experienced several surges in the global wheat price. During the food price crisis of 2007-2008, the wheat price increased by more than 120%. Then in 2011-2012, prices rose by 100% compared to 2010. Finally, in 2021-2022 the price reached an all-time high, doubling again compared to December 2020 (FAO, 2023). It is easy to think that an increase in price would give incentives to produce more, and this would push the price back down in time. But the speed and magnitude of this reaction depends on why the price increases and the responsiveness in supply. An increase in price caused by increased demand will obviously give a different reaction than an increase in price caused by higher production costs. The wheat price reached historical heights in May 2022, and even though it decreased during the second half of 2022 it was still almost 50% higher in the beginning of 2023 than it was in 2021(Tradingeconomics, 2023). To be able to predict whether the price will keep decreasing or whether it will stabilize at a higher level, we need detailed knowledge about how wheat supply responds to price changes.

Estimating supply response of agricultural commodities has been done in numerous studies. However, there has been limited focus on factors that can affect the responsiveness. Risk is one of the obvious factors to consider (Lin and Dismukes, 2007). More frequent price spikes make the market more volatile, and this will increase the output price risk for the producers. Changes in the perceived risk will affect the decisions made by the producers for the next period's investment (Kalkuhl, 2016). If the risk is perceived as high, the producers might alter their production. Climate risk may also influence production decisions. As a result of climate change, we will experience more extreme weather in the future (IPCC, 2021). More frequent extreme weather events will increase the risk of losing parts of the crop for each farmer. It may also have a more general effect on the global wheat price. Less stable weather can give more fluctuations in the price and increase price volatility.

Knowing the effect of climate risk and price risk on producers' production decisions is important for two reasons. First and foremost, this information is needed to be able to assess and predict the global food supply situation. It is also important for deciding which measures are most effective to incentivize farmers to increase production.

There is a substantial body of literature on agricultural supply response. Supply response can be studied by analyzing the relationship between price and either total output, yield or cultivated area (Coyle, 1993). It is important to note that supply response is used as a collective term for all these relationships. As yield can be strongly affected by weather and plant diseases, i.e., factors that the producer has no control over, this study will only focus on producer's wheat area decisions. The majority of existing literature is conducted on US data or from the perspective of different developing countries. Little empirical work has included data from the European Union (EU). The EU is one of the world's largest wheat producing and exporting regions. How producers in the EU react to price changes and risk has a big influence on the world's wheat market.

The main objective in this paper is to analyze how wheat price, price risk and climate risk have affected wheat area decisions in the EU during 2003-2022. The research will focus on the following questions: (1) How does an increase in the wheat price affect area decisions in the EU?; (2) Does increased wheat price volatility reduce the area response to increased prices?; and (3) Do more frequent extreme weather events reduce the area response to increased prices?

To estimate these relationships, I have constructed a panel dataset covering 27 EU countries over the period 2003 to 2022 and apply a Nerlovian model of agricultural supply response (Nerlove, 1956), which consists of estimating a partial adjustment model. This has been the most common approach to quantify agricultural supply response in previous literature (Thiele, 2000). As several of the variables are not observable, different proxies are tested in the model. Producer's price expectations formation is highly debated and requires careful consideration to create a proxy for price expectations. Area is used as an output measure and risk variables are included in the model to examine the effect of volatility and extreme weather on area decisions. In addition, the model includes variables for production costs and public support.

The EU wheat market is regulated and supported by the Common Agricultural Policy (CAP) and the estimated results are also used to examine the effect of CAP measures on area decisions. Wheat producers in the EU receive support both through direct payments (income support) and market price support (WTO, 2014). The support may cause producers in the EU to react differently to price and risk than producers in other countries. Haile et al. (2015)

estimated wheat area response to price and volatility in their global supply response study. This paper follows the same approach in terms of model and estimation method, and it is of interest to compare the estimated EU supply response with the global supply response estimated by Haile et al. (2015).

The study is organized in six sections. The next section dwells upon the background of price changes in the global wheat market, and how price volatility creates risk for the producers. It also describes the development of wheat production, agricultural support, and climate change in the EU since 2003.

Section 3 provides a discussion of the theory behind supply response analysis and elasticity estimation. The cobweb-theorem and its implications for the wheat market is presented, and a summary of the different price expectation formation hypotheses is given. It also reviews a selection of previous literature on supply response.

Section 4 explains how the data was collected and the different variables used in the model. It discusses the method applied to estimate the final specification and different statistical tests conducted to test the validity of the model. Section 5 presents and discusses the results of the estimation. A brief summary and the conclusions follow in section 6.

2. Background

2.1 The global wheat market

Wheat is produced and consumed all over the globe and is one of the world's most important staple foods. Global production was 781 million metric tons (mmt) in 2021/2022 and is estimated to increase to 801 mmt in 2022/2023. Both global production and consumption have an increasing trend, and since 2003 production has increased by more than 30% (FAO, 2023). During the last three years consumption has increased more than production, and wheat inventories have been drawn to meet the demand (IGC, 2023). As reported in figure 1, the tendency has been for about one quarter of total global production to be exported. This share remained fairly constant during 2003-22.

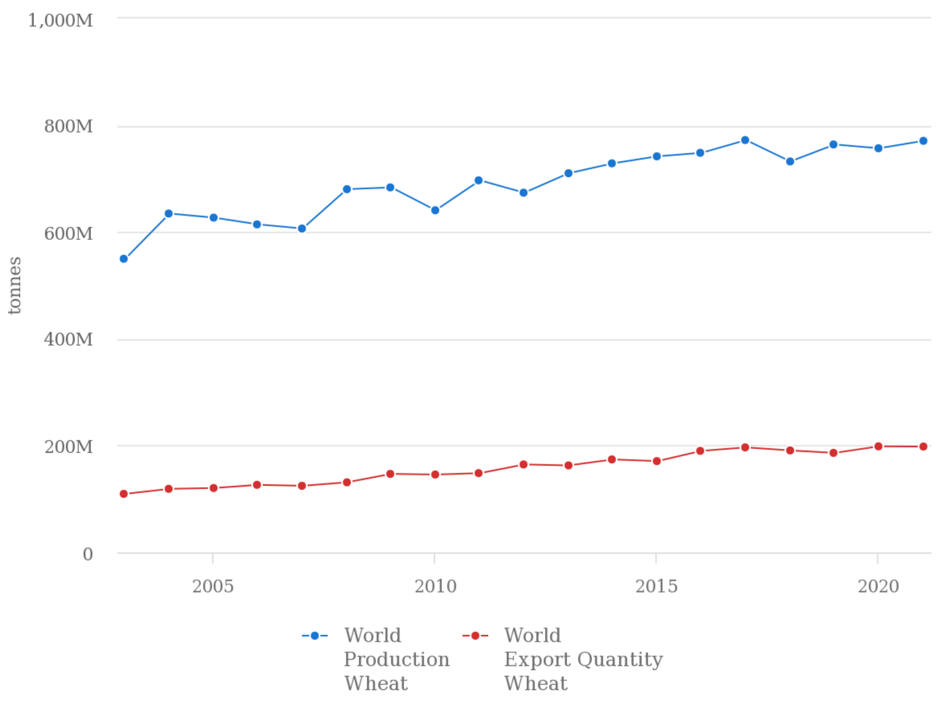

Figure 1 World production and export Source: FAO (2023)

According to OECD-FAO Agricultural Outlook (2022) the growth in both demand and production is expected to slow down in the next decade compared to the study period. The increase in demand will mainly be driven by population growth. Production is expected to increase by 10% in the next ten years. The cultivated area is projected to increase by 3%. Yield improvements are expected to drive the rest of the production growth. But there are many uncertainties behind these estimates. These projections are based on normal weather and policy assumptions, not accounting for any extreme events. They also assume increased investments in yield improving technology and no substantial increase in input prices (OECD/FAO, 2022).

The main part of wheat production is concentrated in a handful of regions. The shares remained relatively stable during the study period, with the same five regions as the largest producers. China, the EU, India, Russia, and the United States (US) accounted for about 70% of global wheat production per year during 2003-2022 (Indexmundi, 2023). The main exporters are Russia, the EU, Canada, Australia, and the US. The EU has had an increase in exports during the study period, from almost 30 mmt in 2003 to over 50 mmt in 2022. Russia also experienced an increasing trend, while the other countries have remained fairly stable (FAO, 2023).

2.2 Wheat prices

The global price of wheat is highly variable. This means that the price is likely to change quickly and suddenly. This is because the production level is uncertain and is affected by exogenous factors such as weather and plant diseases. A price spike can be described as a large and sudden increase in the price. In figure 2, if we compare 2003-2022 with 1980-2002, we see that the number of price spikes has increased in frequency and magnitude. Since 2000 there have been three major price spikes, where the price has increased by more than 100% within a year. The first one in 2008, followed by a second in 2011-2012 and third in 2022. These three events were all described as food price crises by the Food and Agriculture of the United Nations (FAO, 2022).

The 2008 price spike was caused by a series of events. The main causes were high energy prices, low yields caused by a combination of extreme weather events, increased consumption due to economic development in Asia, increased biofuel production and export restrictions (Mueller et al., 2011). Adverse weather conditions in the EU, Russia, and Australia in 2007 caused a decline in production. This was combined with an increase in fertilizer and fuel prices that drove up production costs. Both events led to a decline in supply. At the same time China and India increased their consumption of wheat. Rising biofuel prices and subsidies to biofuel production made many wheat producers shift from food production to biofuel production (Donald, 2008). This led to an increase in demand. The simultaneous change in both supply and demand led to a rapid increase in the global wheat price (Mittal, 2009). Export restrictions made less wheat available for the global market and drove the prices even higher.

The 2011-2012 price spike was caused by many similar factors (Coulibaly, 2013). Weather events, like the extreme drought in Russia and Ukraine in 2010, had a substantial impact on supply. Demand for biofuel was still increasing and energy prices started rising again after a decrease in 2009 (Trostle et al., 2011). Export restrictions amplified the effect also at that time. To what extent the different factors contributed to the price increase in 2008 and 2011-2012 is debated in the literature. This debate, however, is beyond the scope of this paper.

In 2022 the wheat price was driven up by high natural gas prices, problems with transporting wheat out of Ukraine, sanctions on Russia and many countries imposing export restrictions (Bentley et al., 2022). These issues were all connected to Russia's invasion of Ukraine. Both Russia and Ukraine are large wheat producers and exporters, and the war in Ukraine caused a lot of uncertainty in the wheat marked which drove the price up. The main difference between the price spikes in 2008 and 2011-2012 and the one in 2022 is that there was no large decrease in production. There was no lack of wheat on the world market, but logistics and export restrictions made global trade challenging.

Figure 2 Global price of wheat 1980-2022 in US dollars per bushel Source: Macrotrends (2023)

When analyzing the historical wheat price, it is important to distinguish between the price *level* and price *variation*. A high price level is not necessarily a problem. High prices benefit the producers and give them incentives to produce more. In the long run it can also benefit the consumers by the need for more employment.

Volatility describes price variation. It is a directionless measure of the extent of the variation (Gilbert & Morgan, 2010). There are a variety of approaches to measure volatility. Standard deviation (SD) of price changes is one of the most common. The higher the SD, the higher the volatility. Not all variation is bad, but when the changes are rapid and unexpected it causes uncertainty for both the producers and the consumers. Increased price volatility increases the price risk for the producers and makes it more difficult to plan production (Kalkuhl et al., 2016).

It is also important to distinguish between historical volatility and predicted volatility. Historical volatility is a measure of the variation in historical prices. Predicted volatility, also known as implied volatility, represents volatility expectations for the future based on the historical volatility. This is an important tool in the analysis of the financial markets. Thus, for the purpose of this study only measures of historical volatility are used.

Wheat price volatility has several drivers. Any kind of shock to supply, or demand can be transmitted into price volatility (Gilbert & Morgan, 2010). A supply shock can come of events such as extreme weather events, an outbreak of plant disease or a spike in input prices. A sudden change in demand can happen because of dietary changes, changes in policies (e.g., subsidies to biofuel production), or changes in income. Different measures can be taken to diminish price volatility. Policy intervention, trade and wheat storage can act as buffers of volatility in the global wheat market (Santeramo & Lamonaca, 2019). To what extent these different factors contribute to exacerbate or diminish price volatility is still debated.

In figure 3 wheat price volatility in the EU is measured as SD of monthly wheat prices. The volatility varied between 0,03 and 0,12 in the study period and has a slightly increasing trend. This is in line with previous studies on wheat price volatility. Steen et al. (2023) found that global wheat price volatility, measured as SD of daily prices, has had a small but significant upwards trend in the period 1971-2019. They conclude that climate change has had a small effect on wheat price volatility so far because of climate-adapted planting decisions, storage, trade, and use of risk mitigating instruments. Dawson (2014) estimates the volatility of wheat futures prices on Euronext for the period 1996-2012 and finds that wheat futures price has become more volatile during this period.

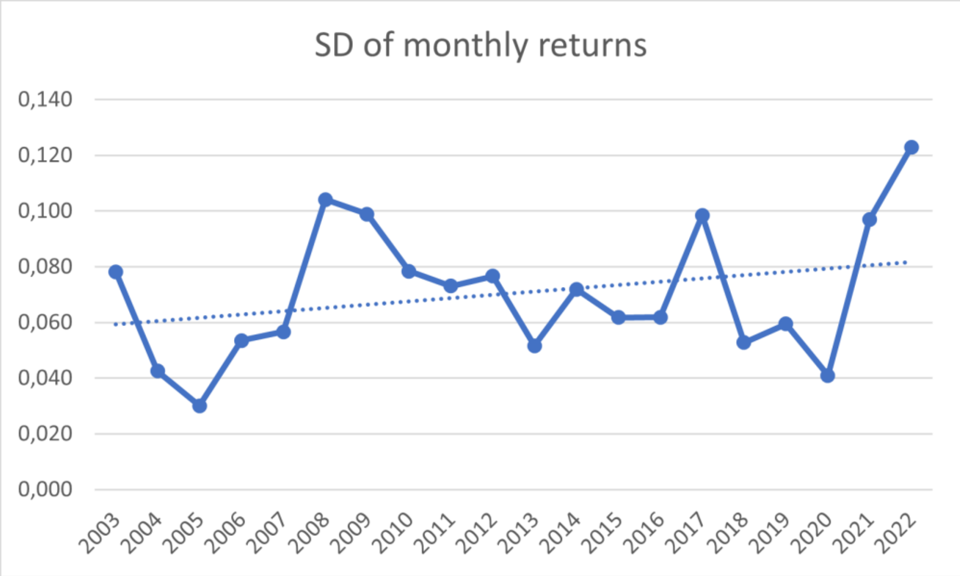

Figure 3 Standard deviation of monthly wheat prices Source: European Commission (2023a)

2.3 Wheat production in the EU

The EU is the second largest wheat producer and exporter in the world, with a total production of 133 million tons in 2022 (IGC, 2023). Total production, area, yield, average wheat price in the EU and global average wheat price is presented in table 1. The EU has increased production by an average of almost two million tons per year during 2003-22. The fluctuations in production can be explained by changes in either area or yield. Area is the number of hectares where the producers grow wheat. Yield is the amount of wheat harvested per hectare. The producers can influence both area and yield, but only to a certain extent. Producers do not have unlimited access to area, at least not in the short run. Therefore, they might not be able to extend their production as much as they believe is optimal. Yield can be affected by fertilizing and watering decisions made by the producers but is constrained by factors such as weather and technology improvements. Total supply is production plus last year's ending stocks. Since wheat can be stored, surplus from one year can be stored for several years and used in years with deficit.

The EU has the highest average yield in the world (Enghidad, 2017), with an average yield of 5,2 during the study period. Until the late 1990's the EU's increased production was driven by both area expansions and yield improvements (Erenstien, 2022). As we see from table 1, yield improvements have driven the increase in production since 2003. If we compare the first half of the period with the second half, the average yield has increased from 4,8 during 2003-2012 to 5,6 during 2013-2022. The wheat area has varied during this period, but with a slightly decreasing trend. The average area has decreased from 24,2 million hectares during 2003-2012 to 23,8 million hectares during 2013-2022.

We see that area exceeds 25 million hectares three times during the study period; in 2008, 2011 and 2012. These increases in area match the increases in average price and might suggest that higher prices incentivize producers to expand planted area. However, during the price spike in 2021-2022 the effect on area is not as prominent. The average wheat price in the EU increased by more than 50% from 2021 to 2022, while the increase in area was less than 0,5%. One explanation might be that the fertilizer price increased more, relative to the wheat price, in 2021-2022 than in 2008 and 2011-2012 (Baffes & Koh, 2022). This made wheat production less profitable despite higher wheat prices, compared to the two previous periods.

In table 1 the wheat price in the EU moves relatively close to the global wheat price. The Nominal Protection Coefficient (NPC) is the ratio between domestic price and global price (OECD, 2011). During the study period EU NPC is 1,03, which means that EU prices on average are 3% higher than global prices during this period. All three price spikes discussed above are obvious in both price series. In 2006 and 2007 we see that low yields in the EU drove total production down. Low production two years in a row resulted in low ending stocks, and a decrease in total supply. This, together with the factors discussed in 2.1, resulted in an increase in the wheat price in the EU in 2007. In 2008 production in the EU increased and the price decreased in the second half of 2008. The global price increased slower than the EU price in 2007. However, in 2008 the global price was 15% higher than the EU price. This might be due to policy adjustments made by the EU to mitigate the price increase (Mittal, 2009). Both the obligation of a 10% set-aside of arable land for wheat farmers and import duties on wheat were suspended (European Commission, 2008). These measures might have led to a faster decrease in the EU price than in the global price.

In 2011-2012 the global price was above the EU price in both years. A reason for this could be that unlike in 2008, the reductions in yield happened outside the EU. In 2021-2022 there is no reduction in yield in the EU that can explain the increase in the price series. The world price is above the EU price in the period 2020-2022. It is worth noticing that the EU price is above the global price during “normal” years, and below the global price during the periods we refer to as food price crises. In the remainder of this paper, the EU price series will be used when referring to the wheat price if nothing else is stated.

Table 1 Wheat production and prices from 2003 to 2022

Year	Production (m.tons)	Area (m.ha)	Yield (t/Ha)	Avg. price EU (€)	Avg. price global (€)
2003	100.89	22.65	4.4	143	123
2004	130.72	23.77	5.4	120	116
2005	117.14	23.72	4.9	131	121
2006	112.79	23.96	4.7	150	148
2007	106.84	24.16	4.4	205	195
2008	134.10	25.65	5.2	190	220
2009	125.71	24.12	5.2	130	129
2010	122.50	24.17	5.0	184	180
2011	123.63	25.00	4.9	200	228
2012	117.34	25.21	4.7	241	261
2013	132.51	24.67	5.4	183	229
2014	140.73	23.80	5.9	165	165
2015	144.77	24.90	5.8	170	161
2016	130.23	23.19	5.6	148	143
2017	137.50	24.21	5.6	150	145
2018	125.51	23.75	5.2	190	184
2019	139.43	23.21	5.9	173	170
2020	126.37	22.76	5.5	183	193
2021	138.07	24.02	5.7	222	280
2022	133.79	24.12	5.5	338	387

Note: Both price series are average annual prices in EUR pr ton. Area is the total area under cultivation.

Source: FAO (2023); European Commision (2023a); International monetary fund (2023a); IGC (2023)

France, Germany, and the UK were the main wheat producing countries in the EU until the UK withdrew from the EU in 2020. With an average production of respectively 26%, 15% and 10% of total production in the EU during 2003-2022 (FAO, 2023). After 2020, France, Germany and Poland have been the largest producers. France has the highest yield in the EU with an average yield of over 7 during 2003-22 (World Bank, 2023). Both winter wheat and spring wheat are cultivated in the EU. However, winter wheat accounts for almost 90% of the production (Schils, 2018). Winter wheat is planted in September/October and harvested in July/August, while spring wheat is planted in April/May and harvested in August/September (USDA, 2023). Estonia and Finland are the only two countries where winter wheat is most common. More than 50% of grain production in the EU is wheat, the remaining part consists of one third barley, one third maize and one third other grains (European Commision, 2022).

The EU supports wheat production through different measures. The World Trade Organization's Agreement on Agriculture classifies the measures into different "boxes" (WTO, 2023a). Amber box denotes the trade distorting measures, blue box denotes the measures that have some distorting effect on trade, but also have production requirements embedded in them and green box denotes the measures that has minimal trade or production distorting effects. There has been a transformation of the support program during the study period. Through the CAP farmers in the EU receive support from all three boxes (European Commision, 2023b). However, since the CAP reform in 2003 (gradually implemented between 2005 and 2007) the amount of amber box and blue box support has been reduced (European commission, 2023c) Figure 4 shows the amount of support received per year by the agricultural sector and distribution between the different boxes. Support from the blue box and amber box combined decreased from approximately 55 billion Euro in 2003 to 12 billion Euro on average per year for the rest of the study period (WTO, 2023b)

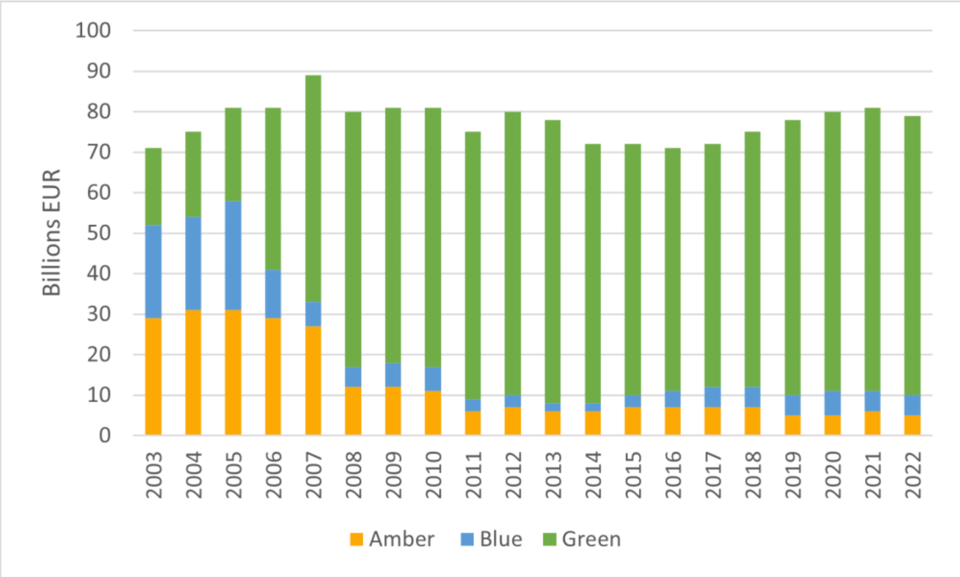

Figure 4 Agricultural support in the EU Source: European commission (2023); WTO (2023)

To understand the implications of the 2003 reform for the wheat producers, it is necessary to know how the different measures in the CAP function. The primary objectives of the CAP are to increase productivity, stabilize markets, guarantee stable food supply and reasonable prices for consumers (USDA, 2021). Historically, the CAP has mainly supported wheat farmers through market price support (MPS) (European Commision, 2023b). MPS is used to create a gap between prices within the EU and global prices, with the objective of protecting farmers from low prices. This is done by intervention buying through the government (Swinbank, 2008). Intervention buying implies an intervention price, often set far above the global price, that works as a guaranteed minimum price. If the wheat price falls below a certain threshold, the government will intervene.

MPS is considered to be one of the policies with the largest trade distorting effects and is classified as an amber box measure. It increases the producer surplus, and therefore has a strong effect on production (OECD, 2011). Since MPS can stimulate over-production, and the high prices make exports uncompetitive, MPS is often used in combination with export subsidies (WTO, 2014). Until 1992, MPS gave producers incentives to increase production of many commodities beyond what could be economically justified, and surplus was exported at prices below production cost (Bureau & Gohin, 2009). Export dumping has a highly distortional effect on global trade. MPS also affects consumers negatively through higher prices and higher tax burden (Pindyck & Rubinfeld, 2018). These negative consequences motivated the shift away from MPS.

Through CAP reforms in 1992 and 1999 the MPS for most products was reduced (Kelch & Normile, 2004). The intervention price for wheat was reduced by almost 50% between 1990 and 2000 (Pe'er et al., 2017). The 2003 reform further reduced MPS for some products, but the reduction was small for wheat. Export subsidies also declined after the 2003 reform, and after 2006 there were no export subsidies on wheat. Import tariffs have not been directly affected by the reform (WTO, 2014). During the study period the amount spent on MPS for wheat is fairly stable between 1,8 and 2,1 billion EUR pr year (WTO, 2023b). For the period before the reform (2003-2007) and the period after the reform (2008-2022) the support accounts for respectively 12% and 8% of the value of total wheat production in the EU per year on average. There is a clear consensus that MPS has a positive impact on production (OECD, 2011), but to what extent it affects area decisions during the study period is uncertain.

In addition to price support the farmers receive direct payments. Before 2003 the direct payments were coupled to production, and therefore classified as blue box. The new reform introduced a single farm payment (SFP), which is a payment to farmers based on historical payments. The SFP is not bound to any specific product and gives the farmers more flexibility in their planting decisions (Sckokai & Antòn, 2005). Since SPF is decoupled from production, it can be classified as green box (Binfield et al., 2004).

The changes made in 2003 resulted in a large shift of expenditure from blue box and amber box to green box for the agricultural sector in total. This made domestic markets in the EU more open to the global market and more responsive to international price variations. However, wheat farmers were mainly affected by the transition from direct payments that were coupled to production to SFP. With only a small reduction in MPS the wheat market is still protected during times of low global wheat prices. The introduction of SFP might affect wheat production both through changes in area and through changes in yield. Decoupling payments from production can result in a decrease in area since payments no longer require production of specific crops. If this is the case, it is likely that the area taken out of production is the area of lowest quality. Thus, transition to SFP might also lead to a yield increase (Kelch & Normile, 2004). It is debated in the literature how strong these effects are and to what extent SFP creates production incentives (Urban et al., 2016; Scokai & Moro, 2009).

2.4 Climate change and wheat production

Climate variations are a key driver of variability in wheat supply (Ray et al. 2015). There is a wide consensus that wheat production will, like all other agricultural production, be affected by climate change in the future. According to the Intergovernmental Panel on Climate Change (IPCC, 2021) it is very likely that global average temperature will increase by more than 2 degrees Celsius within the next 30 years. There is a lot of uncertainty related to how an increase in average temperature will affect wheat production (Zhang et al., 2022; Jägermeyr et al., 2021; Wilcox & Makowski, 2014). In addition to global warming, we will experience more frequent episodes of extreme weather in the future (IPCC, 2021). Heatwaves and droughts are often considered the most damaging consequence of climate change for wheat production. Liu et al. (2021) concludes that the frequency of extreme low yields will increase for several of the major wheat producers because of droughts and heat stress. The most obvious effect of more frequent episodes of extreme weather is the effect on yield but increased yield risk can also affect area decisions. If there is an increase in perceived risk of losing part of the crop due to extreme weather, this might dampen the effect of price increase on area.

However, extreme weather can increase the risk for producers even if they are not directly affected by the weather events. In addition to the direct effect on yield for each producer, the frequency of extreme weather events can affect the volatility of the wheat price. Zhang et al. (2022) estimates that even if the net effect of global warming on wheat yield is positive, increased frequency of extreme weather events and climate variability will make global wheat price spikes more frequent. Extreme weather can therefore affect production decisions in two ways, through increased yield risk and through increased price risk.

Bràs et al. (2021) found that the average impact of droughts and heatwaves on crop production in Europe has tripled over the last 50 years. The analysis was based on a crop response model using weather data from the Extreme Weather Disaster database (EM-DAT). This is in line with the findings of Lesk et al. (2016), which is also based on data from EM-DAT. In their global crop response study, they conclude that the negative effect of heatwaves and droughts on crops has increased in the period 1964-2007. They also find that production losses are due to a reduction in both yield and area. Thus, more common episodes of extreme drought and heatwaves can be a major threat to wheat production in Europe. Trnka et al. (2014) analyzes the possibility of increased frequency of weather events that negatively affects wheat production in Europe, based on climate models and different greenhouse gas emission estimates. They conclude that it is very likely that the frequency of such events will increase, and that this will lead to more frequent crop failure in Europe.

Figure 5 shows a summary of all reported droughts and heat waves in the EU from EM-DAT during the study period. The frequency of droughts and heat waves has an increasing trend in the figure. With a noticeable higher number of events in the last five years compared to the average.

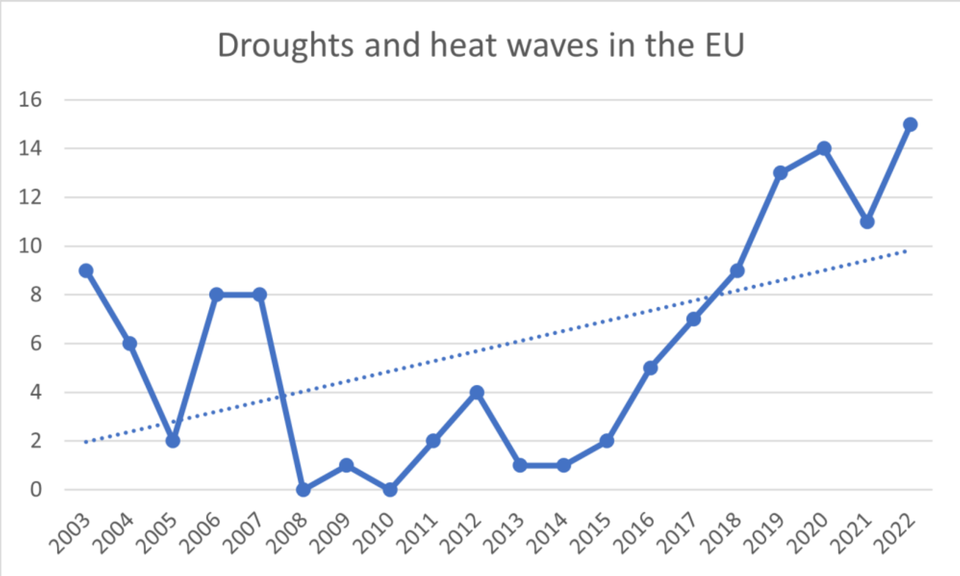

Figure 5 Number of droughts and heat waves in the EU reported in EM-DAT Source: EM-DAT (2023)

3. Theory and related literature

3.1 Producer theory

The supply response refers to the relationship between the expected price of the commodity and the quantity supplied. A fundamental principle of economic theory is the law of supply. This states that an increase in the price of a product leads to an increase in the quantity supplied, given that all other factors are constant. In economic theory, supply is defined as the total amount of a good that is available to consumers at a given time and at given prices. It is important to distinguish between this definition and the supply term used in supply response studies, as this term refers to the total output from the producers regardless of how much is released into the market (Coleman, 1983).

As discussed in chapter 2, supply can be decomposed into area and yield. As a measure of output in supply response models, it is possible to use total quantity, yield, or area. From the producer's perspective the total quantity is the crucial measure. An increase in quantity can be achieved by increasing yield, area or a combination of both. Applying area as an output measure in supply response functions will therefore capture only parts of the response. However, yield can be affected by external shocks and technological progress. The farmer has more control over decisions about area expansion and re-allocation. Area is therefore considered a better proxy for planned production than yield and total production (Coyle, 1993). Area has been the favorable output measure in supply response literature, but it is important to emphasize that this is only a lower bound for the total response (Halie et al., 2015).

One of the aims of supply response studies is to estimate the quantitative response in supply relative to price, i.e., the price elasticity of supply. Another aim is to investigate the effect of other explanatory variables, and supply response models normally include several different independent variables, like production costs, risk variables or policy variables (Thiele, 2000).

Price elasticity of supply is defined as the percentage change in quantity supplied resulting from a 1 percent increase in price (Pindyck & Rubinfeld, 2018). If the elasticity is greater than 1, it means that a 1 percent increase in price will result in more than 1 percent increase in supply. We refer to this as elastic supply. If the elasticity is less than 1, it means that a 1 percent increase in price will result in less than 1 percent increase in supply. We refer to this as inelastic supply. Elastic, inelastic and unitary supply are illustrated in figure 6.

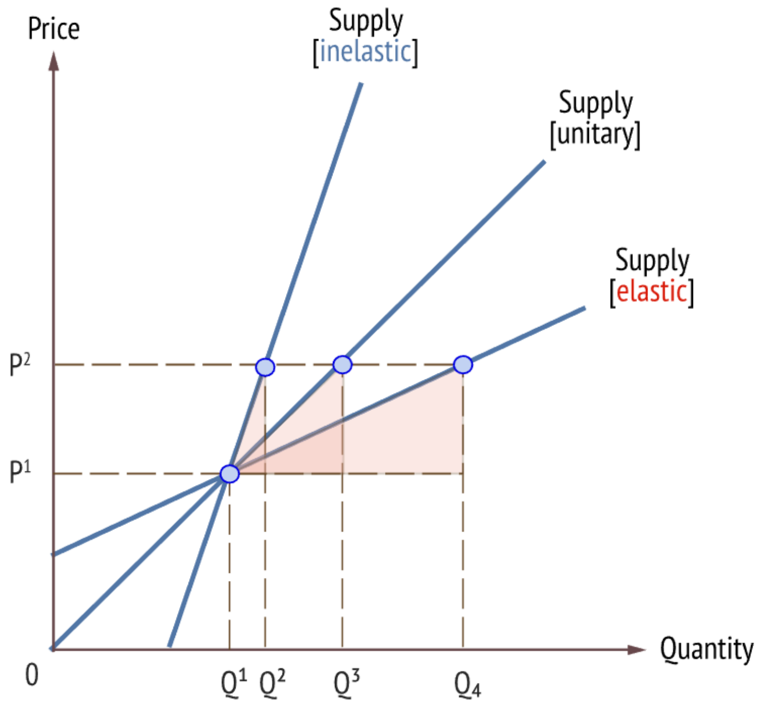

Figure 6 Elasticities Source: Economics (2023)

The elasticities of both supply and demand will decide how different shocks affect the wheat price. Empirical studies find that the elasticity of both wheat supply and wheat demand are low, i.e., relatively inelastic, at least in the short run (Bond, 1983; Rao, 1989). This means that a given change in supply or demand will have a relatively larger effect on the price. Looking back at the food price crises discussed in chapter 2, this explains the sharp increase in the wheat price caused by the shifts in supply and demand. Figure 7 illustrates a shift in supply when demand is elastic, unitary and inelastic. A shift in supply when demand is inelastic will result in a change in price that is larger relative to the change in quantity. When several countries in the EU were affected by extreme drought in 2007 supply decreased. This is illustrated in figure 7 by a shift of the supply curve to the left. If demand were elastic (graph to the left), the consumer would be price sensitive and a small increase in price would lead to a large decrease in quantity. However, since wheat is inelastic, the shift in supply results in a small decrease in quantity and a large increase in the wheat price (graph to the right).

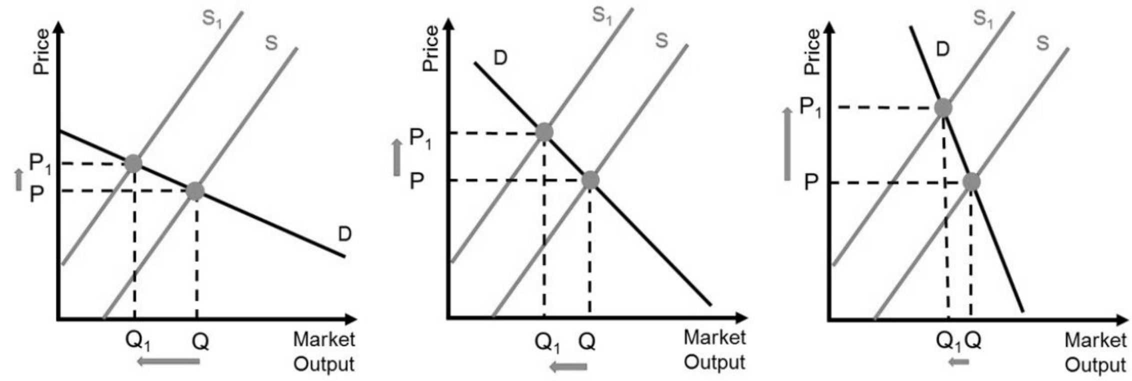

Figure 7 Inelastic, unitary and elastic demand Source: EzyEducation (2023)

Figure 8 illustrates a shift in demand when supply is inelastic, unitary and elastic. An increase in demand for wheat in Asia in combination with increased biofuel production, resulted in a shift in demand in 2008. Since the wheat supply is also inelastic, this led to a large increase in the price while the increase in production was modest. When supply is inelastic the shift in demand results in a relatively small change in quantity produced and a relatively large change in the price. This is explained by the fact that most factors in wheat production are fixed in the short-run (Binswanger, 1989).

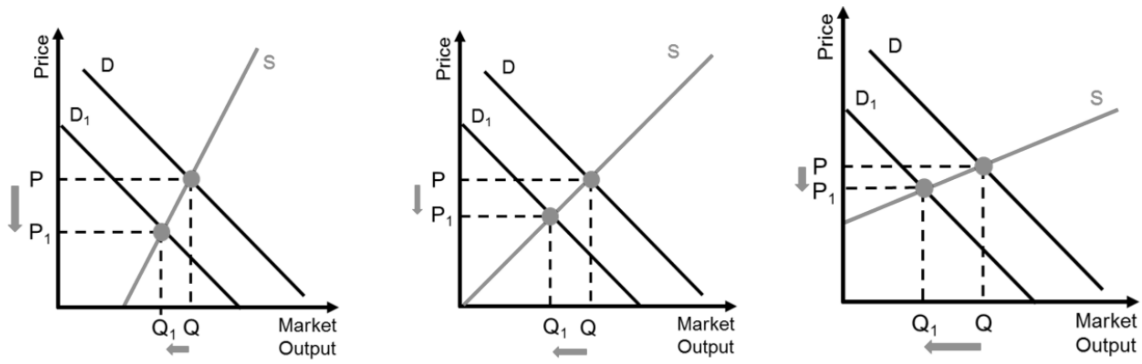

Figure 8 Elastic, unitary and inelastic supply EzyEducation (2023)

The wheat market differs from many other markets because production decisions are made a long time before the product is released to the market. Each farmer must allocate his land in the planting season, based on expectations about the future. The farmer does not get to alter his production until the next planting season. This makes it impossible to react fast to changes in price and supply is therefore inelastic in the short run. Reasons for wheat supply to be inelastic in the long run might be that land availability, climate or land degradation sets a cap on production (Roberts & Schlenker, 2013).

Another result of the time lag between production decisions and consumption is explained by the Cobweb theorem (Ezekiel, 1938). This economic model describes how a shift in supply or demand can lead to a cycle of rising and falling prices. Figure 9 shows how an increase in price in period 1 leads to increased production in period 2. The increase in production makes the price decrease in period 2. When production decisions are made in period 3, these are based on the low price in period 2. The decrease in production leads to an increase in price again and this cycle will continue.

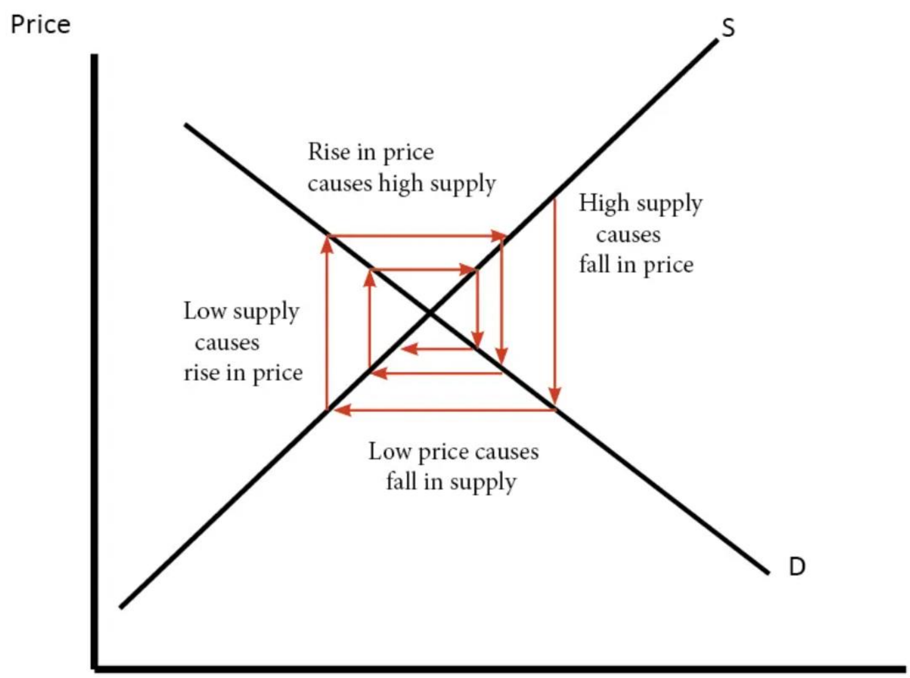

Figure 9 The cobweb theorem Source: EconomicsHelp (2023)

The outcome depends on the slope of the demand curve and the supply curve. If the supply curve is steeper than the demand curve, the market will eventually return to equilibrium (Poitras, 2023). For the Cobweb theorem to hold we must assume that production decisions are based solely on previous prices. This depends on how farmers form their price expectations. Expected prices might be different than current prices and, as we will see in the next chapter, there are different hypotheses regarding how price expectations are formed.

3.2 Formation of price expectations

The formation of price expectations is heavily debated in the supply response literature (Chavas, 2000; & Bessler, 2001). The most commonly applied expectations formation hypotheses are: (1) naïve expectations, where the expected price is set equal to the latest observed value of the price (Ezekiel, 1938; Houck & Gallagher, 1976); (2) adaptive expectations, where the expected price is assumed to be revised over time depending on the latest prediction error (Nerlove, 1956); (3) rational expectations, where producers are assumed to make efficient use of market information (Muth, 1961); and (4) quasi-rational expectations, where expected price is formed by a price prediction from a reduced-form dynamic regression equation (expectations are formed based on the observed historical pattern) (Nelson & Bessler, 1992; Nerlove et al., 1979).

Previous work suggests there is no a priori method to identify the correct price expectations. Both naïve and adaptive expectations have been criticized for underestimating the producer's ability to be forward-looking (Hommes, 1998). Using prices from past time periods also raises the question of which previous prices to use, and the literature does not give an unambiguous answer to this. The argument for using these types of expectations formations is often that market information is difficult or costly for producers to obtain. This might be the case for small-scale farmers in developing countries. For producers in the EU, obtaining relevant market information requires little resources.

Both the rational and quasi-rational expectations hypothesis assumes that producers utilize a variety of information when forming price expectations (Holt & McKenzie, 2003). Quasi-rational expectations partly correspond to fully rational expectations but differs in how it is based on historical data (Nelson & Bessler, 1992). Thus, quasi-rational expectations can be said to be more backward-looking than rational expectations. Rational expectations as described by Muth (1961), have been criticized for being too stringent (Nerlove & Fornari, 1998). This method implies that producers efficiently utilize all market information. This is a strong assumption. One approach that lies within the rational expectations framework is the use of futures prices as a proxy for price expectations. This builds on the hypothesis that futures prices reflect the market's estimate of the future cash price (Gardner, 1976). Following the rational expectations theory there is no reason for producers to have different expectations than the rest of the market.

3.3 Previous literature

There is a substantial literature on estimation of agricultural supply response (Bond, 1983; Lee & Helmberger, 1985; Rao, 1989). Previous literature provides a variety of approaches which may be employed to estimate supply response. The most common are different variations of the Nerlovian partial adjustment model. Following Coleman's (1983) classification, the Nerlovian model falls into the category of directly estimated models. The other two categories being two-stage procedures and directly estimated systems. These approaches build on the utility- and profit-maximizing framework. Which approach is most appropriate depends on available data and the objectives of the study. According to Coleman (1983) directly estimated models may be preferred if the objective is short-run supply forecasting of one or a subset of products. Models that build on the profit-maximizing framework are more time consuming and require more detailed data (Haile et al., 2015). This section will review some of the most influential supply response studies within all three categories, particularly focusing on which proxies are being used for price expectations and studies that include different risk variables.

Nerlove (1956) formulates the agricultural supply response model, known as the Nerlove model. This is one of the most frequently applied models in agricultural economics (Braulke, 1982). In addition to formulating the relationship between desired output and actual output, Nerlove (1956) focuses on how producers form their expectations of future prices and how this affects their decisions. He estimates short-run supply elasticities for wheat to 0,93. His estimates are based on US data from 1909-1932 and total production is used as an output measure. He criticizes earlier work that applies the price lagged one year as the price variable in their supply response models. Arguing that adaptive expectation formation gives a better proxy for expected price, and that naïve expectations formation will result in elasticity estimates that are biased downwards. Even though the Nerlovian method subsequently has been adopted by numerous authors, there has been a lot of variation in how the method has been applied.

Askari and Cummings' (1977) meta study contains more than 100 studies that follow the Nerlovian approach. They compare estimates on price responsiveness derived from the Nerlovian formulation from studies conducted between 1958 and 1976. There is a great diversity in the estimates. The short-run elasticity estimates for wheat vary from 0,01 to 0,96 and the long-run elasticities vary from 0,03 to 3. The studies differ in which control variables they include, what proxy they use for price expectations, and which measure they use for output. Askari and Cummings conclude that the wide range of estimates, also within the same type of crop or within similar countries, reveals a need for more research concerning which factors affect the responsiveness.

Several studies have been conducted to compare different proxies for price expectations. Gardner (1976) criticizes all use of lagged prices as a proxy for price expectations, also the way they are used in adaptive expectations formation. He argues that futures price is a better proxy. He compares soybean elasticity estimates from a model including lagged price with the estimates from a model including futures price, using data from the US for the period 1950-1974. Futures price as a proxy gives elasticity estimates of 0,73 and lagged price as a proxy gives elasticity estimates of 0,45. The standard error is lower when futures price is used. He concludes that futures price performs better than lagged price as a proxy for expected price.

Shideed & White (1989) compare alternative specifications in their study of corn and soybean area response in the US, using data covering the 1951-1968 period. They compare naïve price expectations, futures price and support price using a two-stage procedure. They find that the estimated elasticities are sensitive to the choice of proxy, but the performance of the alternative proxies are not consistent between corn and soybeans. Their conclusion is that the preferred proxy will vary from crop to crop. Chavas (2000) investigates different expectation formations, based on aggregate data on the US beef market covering 1948-92. Developing and estimating a model of price determination and dynamic market allocation he finds that 47% of producers based their production decisions on naïve expectations, 35% on quasi-rational expectations and 18% on rational expectations.

More recent supply response literature has focused on incorporating different explanatory variables. Risk variables have been included in several studies. Lin & Dismukes (2007) investigates the role of price risk and yield risk in their estimation of elasticities of corn, soybeans and wheat. To capture both price risk and yield risk they construct a variable for expected revenue variance. In addition to the risk variable, they include USDA estimates of production costs and a policy variable. The study is conducted on US data from 1991 to 2001, using two different utility-maximation models and with area as an output measure. The short-run area elasticity for wheat ranges from 0,248 to 0,336. The coefficient for the revenue variance variable was negative and statistically significant for soybeans, but not statistically significant for wheat and corn.

Roberts & Schlenker (2009) estimates supply elasticities for corn, soybeans, rice and wheat, based on global data from 1960 to 2007. They aggregate the four crops based on calories and follow a profit-maximation approach. They include yield shocks as an instrument for futures price in their model, measured as the deviation from country-specific trends in yield, arguing that futures prices incorporate yield expectations and therefore are endogenous to supply. They recommend the use of weather variables, instead of deviation from yield trends, if data on this is available. Short-run supply elasticities for wheat are estimated to lie between 0,078 and 0,116.

Hendricks et al. (2015) examines the use of instrumental variables (IV) in supply response models further. They replicate the work done by Roberts & Schlenker (2009) and show that the use of IV for futures price is not necessary, and that the preferred method is to add previous yield shocks or weather data as a control variable. They conclude that omitting this control variable when estimating the response of total production will give substantially biased estimates. This is due to the correlation between futures prices and expected yield. The bias will be reduced if area instead of total production is applied as the dependent variable, but it will not be eliminated. The recommended method for bias reduction is to use area as dependent variable, futures price as price expectation, and yield shocks as control variable.

Haile et al. (2015) estimates global aggregate yield and area response for wheat, rice, corn and soybeans. They follow the Nerlovian approach with a partial adjustment model, using both global and country-specific data covering the period 1961-2010. To estimate the model, they apply a generalized method of moments (GMM) estimator (Blundell & Bond, 1998). In addition to the lagged dependent variable and the price expectation variable, they include the fertilizer price as a proxy for production costs and price volatility measured as SD of monthly returns. As a proxy for price expectation, they use both the spot price at the time of planting and futures price. They fail to find a statistically significant relationship between area and futures price for wheat, corn and rice. Applying spot prices, they find a statistically significant relationship with area for all crops. According to the authors this might be due to lack of participation in the futures market by farmers in developing countries. The estimated short-run area elasticity of wheat is 0,075 and price volatility is found to have a statistically significant negative effect on area. The price volatility coefficient is estimated to -0,3. This estimate is not an elasticity, and is difficult to compare with the price elasticity. By standardizing the effect size of both volatility and price, they find that the positive effect of a one percent price increase on area is about twice as strong as the negative effect of a one percent increase in volatility.

Iqbal & Babcock (2018) also conducts an analysis of global area response of wheat, rice, corn and soybeans to global prices and price volatility. Their study differs from Haile et al. (2015) by applying the mean group (MG) estimator suggested by Pesaran and Smith (1995) instead of the GMM estimator. The study relies on data from 1961 to 2014 and follows the Nerlovian approach. They test the model with both futures price and spot price as a proxy for price expectations. In contrast to Haile et al. (2015), they find that only futures price is statistically significant. They estimate their model both with and without fertilizer price as a control variable. The estimated elasticities for wheat area are between 0,032-0,038 in the short run and 0,345-0,398 in the long run. The effect of price volatility on wheat area is not statistically significant.

Following a large part of previous literature, this study will use the Nerlovian partial adjustment model. It follows the work of Haile et al. (2015) closely, with the obvious distinction being the use of EU data instead of global data. Conducting the analysis based on the same model and method will make it easier to compare the estimated area response in the EU to the global area response estimated in their study. Based on the available literature there is no consensus regarding which price expectation formation is preferred. It gives reason to believe that further research is needed and that any supply response analysis should be conducted with alternative proxies for price expectations to compare the results. Both spot price and futures price have yielded statistically significant estimates. In this study both proxies will therefore be tested in the model.

There are a few examples of supply response studies that include price risk in their models, but the results are conflicting. Haile et al. (2015) obtained a statistically significant, negative effect of price risk on wheat area using SD of monthly prices as a measure of price risk. Iqbal & Babcock (2017) obtain statistically insignificant results with the same volatility measure. Lin & Dismukes (2007) use a variable that combines price risk and yield risk and does not obtain statistically significant results. Based on this I will use SD of prices as price risk variable. The supply response literature accounting for weather shocks is thin, which gives motivation to explore this further. Roberts & Schlenker (2009) argue that weather data preferably could be applied instead of a yield shock variable and Hendricks et al. (2015) concludes that a variable accounting for weather shocks should be included. I will therefore include a weather variable in the model. The reviewed studies include different control variables. Most common seems to be fertilizer price, to account for production costs. As discussed in 2.2, the wheat market in the EU is supported by different measures through the CAP. Following Lin & Dismukes (2007) I will also include a variable to account for public support.

3 Method and data

4.1 Data

The data used in this study consists of a constructed panel dataset covering 27 countries in the EU during 2003-2022. The UK is included, despite withdrawing from the EU in 2020. Malta is the only EU country not included, as they have minimal wheat production during the study period (no production reported in eight of the years). Data on planted area are obtained from the International Grains Council (IGC, 2023) and the Food and Agriculture Organization of the United Nations (FAO, 2023). Wheat prices in the EU are obtained from the European Commision (European Commision, 2023a) and Urea prices are obtained from the International Monetary Fund (2023b). Volatility measures are constructed by the author as SD of monthly prices based on the wheat price data from the European Commission (2023a). Alternative volatility estimates are obtained from IFPRI's Food Security Portal (2023). Futures prices on wheat are collected from Euronext (Euronext, 2023) and data on extreme weather events are obtained from the International Disaster Database (EM-DAT, 2023). EM-DAT is a comprehensive global database containing data on all events that reach a pre-determined level of severity. The level of severity is defined by the impact the event has on humans and infrastructure, e.g., loss of lives or economic cost. Prices are deflated using the Harmonized Index of Consumer Prices (HICP), which is obtained from Eurostat (Eurostat, 2023).

4.2 Variables

Area is used as an output measure, as this is the measure that is least affected by factors that cannot be controlled. Area is measured in hectares (ha). For the countries with no available data on planted area, the next year's harvested area is used as a proxy.

As described in 3.2, the price expectation variable has been a subject of debate. In the estimated models both a naïve and a rational expectations formation has been applied. The specification based on naïve expectations uses the monthly EU spot price of the month before planting, and the specification based on rational expectations uses harvest-time futures price of the month before planting. The futures price is the price of Euronext milling wheat no.2 (former Matif milling wheat). This contract is commonly used as an indication of wheat futures prices in the EU (Euronext, 2023). All countries except Spain starts the planting season in September (USDA, 2023). August prices are used for these countries. Spain starts the planting season in November. Thus, October prices are used for Spain. Finland and Estonia are the only two countries where spring wheat accounts for most of the production, respectively 80% and 70%. Their planting season starts in April and March prices are used.

The Urea price (EUR/t) is used as a proxy for production costs. Urea is the most common fertilizer for wheat production in the EU, and fertilizer accounts for approximately 50% of operating costs for wheat producers (Ericsson et al., 2009). The monthly Urea price one month before planting is used.

Price volatility is included as a proxy for price risk. As a measure of volatility SD of monthly prices in the last 12 months before planting is being used. SD is one of the standard measures of historical volatility (Diop & Traore, 2021). It measures the dispersion of values in a series relative to the mean, and it is easy to calculate and interpret. The SD can be expressed as

$$(1) \qquad SD = \sqrt{\frac{\sum_{t-1}^{T}(Pt-\bar{P})^2}{T-1}}$$

Where P_t is monthly wheat price in the EU at time t, $\bar{P}$ is the mean price in the sample and T is the number of months in the sample. Each sample is the last 12 months before planting. Time series with price data are often non-stationary because of seasonal patterns or trends. In a non-stationary time series, the statistical properties change over time. The standard deviation measure of volatility depends on the stationarity assumption. To avoid the issue of trends and seasonality volatility is measured as the SD of changes in logarithmic prices.

As an alternative proxy for price risk, the volatility measure derived by International Food Policy Research Institute (IFPRI) in their Excessive Food Price Variability Early Warning System (Food Security Portal, 2023) is used. When using the IFPRI measure, the volatility variable reflects the number of days ranked as “high volatility” by the warning system during the last 12 months before planting.

An extreme weather variable is included as a proxy for yield risk. Extreme weather is restricted to droughts and heat waves, as the previous literature has found no significant relationship between wheat production and other extreme weather events (Bras et al., 2021; Lesk et al., 2016). This is reflected by a dummy variable with the value 1 if the country has experienced episodes with extreme drought or heat waves reported in EM-DAT the last 12 months before planting and zero otherwise. As an alternative proxy for yield risk a variable reflecting yield shocks is being used. This is derived by estimating country-specific deviations from yield trends, following the method of Roberts & Schlenker (2009).

Support from the CAP is included by two variables. Amber box support is included by a variable that reflects the level of price support as a percentage of total production value. The shift from blue box payments to green box payments is included by a dummy variable reflecting the policy change following the 2003 CAP reform. This implies the implementation of SFP for wheat producers. The variable has a value of zero until 2006 and 1 all years after 2006. From 2007 the SFP was fully implemented, and the majority of wheat producers no longer received direct payments coupled to production.

4.3 General model

Following a substantial part of the most influential literature on agricultural supply response, the Nerlovian supply response model is applied in this paper. One of the advantages of this model is that it enables the determination of both short-run and long-run elasticities, and it is flexible in terms of which independent variables to include. The general form of the model is

$$(2)\ Y_t^* = \beta_0 + \beta_1\ P_t^e + \beta_2 Z + u_t$$

where Y_t^* is the desired output at time t and P_t^e is expected price at time t and Z is other exogenous factors affecting Y_t . Y_t^* cannot be observed, since most farmers have limitations on how fast they can change their production. We can only observe Y_t, which is the actual output. The actual change in Y is given by a parameter λ times the difference between Y_t^* and Y_{t-1}

$$(3)\ Y_t - Y_{t-1} = \lambda\ (Y_t^* - Y_{t-1})$$

The parameter λ, i.e., the adjustment coefficient, is between 0 and 1. If $\lambda = 1$ there would be a full, not a partial, adjustment. Because of adjustment costs, the change between the two periods is only a fraction of the change needed to achieve the optimal level of Y. If we replace Y_t^* in equation (2) with the expression from equation (3) we get

$$(4)\ Y_t = \lambda\beta_0 + \lambda\ \beta_1\ P_t^e + \lambda\ \beta_2 Z + (1-\lambda)\ Y_{t-1}$$

Equation (4) can be rewritten as

$$(5)\ Y_t = \delta_0 + \delta_1\ P_t^e + \delta_2 Z + \delta_3\ Y_{t-1}$$

Where δ_1 can be interpreted as the supply elasticity in the short run. 1-δ_3 is equal to λ, and β_1 is equal to δ_1 divided by λ. Thus, δ_1 divided by 1-δ_3 can be interpreted as the supply elasticity in the long run. The short-run estimate is the annual response, as it captures the change in area from year to year. The long-run response must be interpreted with some caution. It gives a good indication of the direction the estimate will move in, i.e., whether the elasticity will be higher or lower in the long term. The adjustment coefficient also tells us something about how fast the adjustment will happen. However, Peterson (1979) and Binswanger (1989) argue that more sophisticated lag structures are needed to be able to estimate the response to a permanent price increase.

4.4 Estimated model

The final model is estimated first with monthly spot price as a proxy for price expectations and then with futures price as a proxy for price expectations. The final specification of the model is

$$(6)\ log\ Y_{it} = \alpha log Y_{it-1} + \beta log P_{it} + \gamma log F_{it} + \delta V_{it} + \varepsilon E_{it} + \epsilon MPS_t + \theta SFP_t + \varphi T_t + \mu_i + \sigma_{it}$$

Where Y_{it} is planted acreage in time t for country i and Y_{it-1} is planted acreage lagged one year; P_{it} is the proxy for expected price; F_{it} is the Urea price as a proxy for production costs; V_{it} is volatility as a proxy for price risk; E_{it} is the extreme weather-dummy as a proxy for climate risk; MPS_t is the variable for price support as % of production; SFP_t is the dummy for SFP; T_{it} is a time dummy to account for time-specific fixed effects; μ_i is the country specific and time invariant part of the error term; and σ_{it} is the idiosyncratic error term. The dependent variable and all price variables are transformed into logarithms. By conducting log transformations, the parameter β can be interpreted as the short-run supply elasticity. The long-run supply elasticity can be calculated as α divided by 1-β.

4.5 Estimation strategy

Before estimating the model, the data is tested for unit roots to determine whether the series are stationary. Because N is larger than T, the Harris-Tzavalis test for panel data is being used (Harris & Tzavalis, 1999). This test is suitable for datasets with few time periods and many units (Stata, 2023).

In the next step, to detect possible multicollinearity, Pearsons correlation is computed for all combinations of all variables. Multicollinearity could cause less reliable results from the estimation and occurs if the independent variables are strongly correlated. If a strong correlation between any of the variables is detected, variance inflation factor (VIF) is used to further investigate the magnitude of the correlation. VIF computes an estimate of the severity of multicollinearity (O'brien, 2007).

After examining the data for stationarity and multicollinearity, a suitable estimator must be applied. The Nerlovian partial adjustment model includes a lagged dependent variable and therefore represents a dynamic panel model. Applying Ordinary Least Squares (OLS) to estimate a dynamic panel model will result in biased and inconsistent estimates because of the correlation between the lagged dependent variable and the time invariant part of the error term (Nickell, 1981). A solution to this problem could be to apply the Fixed Effects estimator (FE). This will transform the data and remove the fixed effects. However, this approach will also result in biased estimates, since the constructed de-meaned version of the lagged dependent variable still will be correlated with the idiosyncratic error term. Hence, the exogeneity assumption will still be violated (Phillips & Sul, 2007).

Andersen & Hsiao (1982) developed an IV approach for dynamic panel data. They applied First Difference (FD) to remove the fixed effects and used the second lag of the dependent variable as IV for the lagged dependent variable. This approach provides consistent estimates but is inefficient for a panel with a short time dimension (T). The Anderson-Hsiao estimator might be preferred if T is substantially large, but there is no consensus in the literature on how large T must be (Judson & Owen, 1996; Kiviet, 1995).

Arellano & Bond (1991) and Blundell & Bond (1998) suggest two alternative methods using GMM estimators. The general GMM method was first suggested by Hansen (1982) and these two methods are an extension of this framework. They are called difference GMM and

System GMM. The GMM approach has proven to have efficiency gains compared to the Anderson-Hsiao estimator (Arellano & Bond, 1991). Both difference and system GMM are designed for dynamic panel models with small T and a large number of units (N). In particularly the panel must have N>T to apply the GMM estimators. The estimators are suitable for situations with fixed individual effects, where some of the regressors are not strictly exogenous, and with heteroskedasticity and autocorrelation within individuals but not across them (Roodman, 2009).

The difference GMM method was first introduced by Holtz-Eakin et al. (1988) and developed further by Arellano & Bond (1991). This method transforms the variables by first differencing before using GMM. Since it subtracts each observation from the following one, it will create larger gaps in unbalanced panels. The system GMM allows for more instruments by adding the assumption that the transformed IVs are uncorrelated with the fixed effects. It transforms the instruments by subtracting the average off all future available observations of the variable. This creates minimal loss of data. The increased number of instruments can improve the efficiency of system GMM compared to the difference GMM (Blundell & Bond, 1998). Since the dataset in this study contains 27 countries (N=27) over 20 years (T=20), the GMM estimators is applied. Because of the possible efficiency gain, the system GMM estimator is chosen over the difference GMM estimator.

The model is estimated as a two-step system GMM and finite-sample correction for the covariance matrix is used, following Windmeijer (2005), to avoid downward biased standard errors. The results from system GMM will be biased downwards if the number of instruments outnumber the number of units (N). To avoid this, the instrument set is "collapsed". Without collapsing there will be created one instrument for each time period, variable and lag distance. With collapsing there will not be created instruments for each time period (Roodman, 2009).

Finally, different statistical tests are conducted to check the robustness of the model and the validity of the instruments. The Hansen test is used to test for overidentifying restrictions, and the difference-in-Hansen test is conducted to test the validity of the additional instruments necessary for system GMM. The Arellano-Bond test for autocorrelation is applied to test for first-order and second-order autocorrelation.

Following Roodman (2009) and Bond (2002), a robustness check of GMM is to also estimate the model using OLS and the FE estimator to compare the coefficient of the lagged dependent variable. The OLS estimate works as an upper bound, as this has proven to be biased upwards.

The FE estimate works as a lower bound, as this has proven to be biased downwards. A credible result from the GMM estimator should therefore lie between the OLS and the FE estimates.

4 Results

In this section I will evaluate the results from the statistical tests conducted on the data and the model. I will present the results from the two estimations and discuss these estimates considering the relevant background and theory.

The data was tested for stationarity using the Harris-tzavalis (1999) test. The null hypothesis is that the series contains a unit root and is therefore non-stationary. All variables provide a p-value below 0,05, and the null hypothesis is rejected at the 5% level. I therefore conclude that the series are stationary.

By computing the Pearson correlation, I find that spot price and futures price have a statistically significant correlation with volatility and Urea price. The correlation coefficient (CC) reflects the magnitude and direction of the correlation. For futures price and Urea price the CC is 0,42, for futures price and volatility the CC is 0,32, for spot price and Urea price the CC is 0,53 and for spot price and volatility the CC is 0,25. There is no exact limit for the strength of correlation, but following the guidelines provided by Cohen (1988) CC between 0,1 and 0,3 can be considered as small correlation, and CC between 0,3 and 0,5 can be considered as moderate correlation. VIF is calculated for all four combinations. A rule of thumb is to remove the variable if VIF is above 5. All VIF values are below the threshold of 5, which indicates that correlation between the variables is not a serious problem in the model.

To investigate the validity of the instruments and the robustness of the model, several tests were conducted. The Hansen test for exogeneity of the instruments fails to reject the null hypothesis of exogeneity with a p-value of 0,23. This supports the choice of instruments. Roodman (2009) recommends to not take comfort in p-values below 0,1 or above 0,25. The p-value of 0,21 is within the recommended limits. The Difference-in-Hansen test gives a p-value of 0,26. This supports the choice of system GMM as estimator.

The Arallano-Bond test for autocorrelation in the error term gives a p-value for AR (2) of 0,81. If AR (2) is significant it indicates that some of the lags of the dependent variable, that is used as instruments, are endogenous. A p-value above 0,05 indicates that the error term is serially uncorrelated and that the instruments are correctly specified.

By running the regression using OLS the coefficient of lagged area was estimated to 0,97. By using FE the coefficient was estimated to 0,20. Thus, the GMM estimate lies between the upper and lower bound. This gives confidence in the validity of the estimates.

Table 2 presents the results of the estimation and a summary of the test results. The estimation was done with different alternative proxies for price expectation, volatility, and extreme weather. No significant results were obtained with the IFPRI volatility measure as volatility variable or deviation from yield as extreme weather variable. These are therefore excluded in the final specification. SD of monthly returns and the extreme weather dummy based on events registered in EM-DAT are used instead in both the regressions. Regression (1) is a model with naïve expectations and includes spot price as a proxy for price expectations. Regression (2) is a model with rational expectations and includes futures price as a proxy for price expectations. Results for both regressions are reported in table 2.

Table 2 Estimation results of EU wheat area response

Variable	(1)	(2)
Lagged dependent variable	0,841***	0,830***
	(0,017)	(0,006)
Spot price	0,092*	-
	(0,032)	
Futures	-	0,151**
		(0,029)
Urea	-0,070	-0,133
	(0,042)	(0,023)
Volatility	- 0,212	-0,420
	(0,087)	(0,090)
MPS	0,021*	0,032*
SFP	-0,037*	-0,042**
	(0,018)	(0,020)
Extreme weather	- 0,017**	-0,012**
	(0,021)	(0,024)
Year dummy	Yes	Yes
Hansen test	0,21	
Difference-in-Hansen	0,26	
Arallano-Bond test AR(1)	0,02	
Arallano-Bond test AR(2)	0,81	
Number of instruments	20	
Number of countries	27	

Note: *, ** and *** indicate significance levels at 10%, 5% and 1%. Standard errors are reported in parentheses. Estimates are obtained using STATA's xtabond2 command.

Both regressions give identical results when it comes to signs and significance of the estimated coefficients. In line with previous studies on wheat area response, price expectations and area have a positive and statistically significant relationship. This indicates that an increase in price expectations gives incentives to increase production via area expansion. With the spot price as a proxy for price expectations the estimated short run area elasticity is 0,092. With the futures price as a proxy for price expectations the estimated short run area elasticity is 0,151. This suggests that a 10% increase in the pre planting spot price will result in a 0,9% increase in the area for wheat production and that a 10% increase in the harvest time future price will result in a 1,5% increase in the area for wheat production. Both results lie slightly above the global short-run elasticity at 0,07 estimated by Haile et al. (2015).

The response of area to changes in futures price is stronger than the response to changes in spot price. This might indicate that futures prices form price expectations to a larger extent than spot prices. This is in line with the results from Iqbal & Babcock (2018) and Gardner (1976). The estimated short-run elasticities are below 1 and therefore inelastic. This explains the large fluctuations in price discussed in chapter 2. An inelastic area response in the short run implies that high wheat prices will not be mitigated by increased production through area expansions in the short-run.

The long-run area elasticity is estimated to 0,57 when spot price is applied and 0,82 when futures price is applied. This accounts for an increase in area of respectively 5,7% and 8,2% if prices increase by 10%. As expected, wheat area is more elastic in the long run than in the short run. This is in line with economic theory and implies that an increase in price over time eventually will result in larger area expansions. The long-run elasticity is higher than comparable estimates from previous studies. Haile et al., (2015) did not estimate long-run elasticities, so these cannot be compared. However, Iqbal & Babcock (2018) estimated global long-run elasticities for wheat to 0,35. As mentioned above, the long-run elasticities should be interpreted with some caution. The key insight from these estimates is that the area response will be larger if the price increase lasts longer.

Maize and Barley prices were tested as additional variables in the model, as it is reasonable to assume that the wheat price relative to the prices of competing crops affects land allocation decisions. These variables turned out to be statistically insignificant and highly correlated with the wheat price. With multicollinearity it can be difficult to separate own price elasticities from cross price elasticity (Roberts & Schlenker, 2013). They were therefore not included in the final specification. This limits the analysis to some extent, as we cannot tell if the area expansions come from substitution within these crops or from expansions into new land.

The first research question of interest was how an increase in the wheat price affects area decisions in the EU. From the estimated results I find that farmers respond by increasing planted area when prices increase. The wheat area response to prices is inelastic, both in the short-run and the long-run. When the results are compared to previous studies, it looks like both the short-run and the long-run response is stronger in the EU than in what is found in global studies. The abolishment of the compulsory 10% set-aside for producers in response to the price increase in 2008 made more land available and might affect the results. According to Iqbal & Babcock (2017), countries with high yield also respond more to price in terms of area expansion compared to countries with low yield.

The Urea price is not statistically significant in the model. According to economic theory, an increase in production costs is expected to have a negative effect on area. This might suggest that Urea price is not a good proxy for production costs. If obtained, a more general fertilizer price index may be a better proxy. It is also possible that other costs should have been included. Fertilizer only accounts for parts of the production cost. Other input prices, like those of pesticides and energy, will also have a large effect. Fluctuations in fertilizer price alone might not have a significant effect on planting decisions. By using a variable that includes different input prices and captures total production costs better, the model would more likely obtain a significant result. Iqubal and Babcock (2018) estimated their area response model both with and without controlling for fertilizer price. They found that the estimated area response was marginally higher without fertilizer as control variable. This might suggest that the estimated elasticities in this model are slightly overestimated.

The volatility estimates are not statistically significant in any of the specifications. This was not the expected result, as economic theory shows that price uncertainty has a negative effect on production (Sandmo, 1971). This also contradicts the findings of Haile et al. (2015). A possible explanation might be that price risk affects producers in the EU differently than the global average. By participating more in the futures market and absorbing risk through different risk management tools, EU producers are able to mitigate price risk to a greater extent than producers in developing countries. The substantial amount of public support through both price support and SFP might also mitigate price risk for EU producers to the extent that price volatility does not affect area decisions (Tangermann, 2011). When comparing the global wheat price to the EU wheat price it was obvious that the EU price was higher in general, except for the three periods of abnormal price spikes. If EU wheat producers are protected against very low prices and have come to expect this support, price risk will affect area decisions to a limited extent. Lin & Dismukes (2007) explains the limited risk response found in their study by structural changes in the agricultural sector. Arguing that the transition to larger, commercial farms has shifted the farmers focus away from avoiding risk in the short-run and towards wealth accumulation in the long-run. These producers might associate price risk with the opportunity for higher returns. This might also be part of the explanation of the limited risk response for EU farmers. An alternative explanation is that the chosen volatility measures do not capture price risk as intended. SD of monthly prices and the IFPRI volatility measure might not reflect the risk in the same way as it is perceived by the farmers. However, as SD is the most common measure of volatility it is likely that producers' assessment of price risk will not deviate too far from this.

How price risk affects wheat area decisions in the EU was the second research question of interest. Based on the volatility estimates it seems like price risk does not affect area decisions to a large extent. Haile et al. (2015) found a statistically significant, negative effect of price risk on global wheat area. This suggests that wheat area decisions in the EU are less affected by price variation than what is found in the global study. This has implications for policy design, as it is obvious that the response to price risk is not homogenous across markets. Measures to reduce food price volatility might have a positive effect on production in some markets, but not in others.

MPS has a statistically significant, positive effect on planted area. This result is supported by economic theory, as an increase in support should give incentives to increase area. It also implies that despite several rounds of reduction, MPS still influences wheat production decisions. A reduction of the MPS variable equal to 1, with everything else constant, would result in a reduction of wheat area of approximately 2%. The transition from payments coupled to production to SFP turns out to have a negative effect on area. The effect is small, but statistically significant. The coefficients suggest that the shift to SFP, if all other factors were fixed, would have resulted in a reduction in wheat area of between 3.7% and 4.2%. This indicates that when farmers are no longer bound to produce wheat to receive payments, some of the area is taken out of production. One of the aims of the CAP reform in 2003 was to decouple the direct payments from production. These findings support the idea that introducing SFP is at least a step in the right direction. This study does not consider the effect of SFP on yield, but it is easy to assume that the land taken out of production is the least productive land. If this is the case, SFP has also led to an increase in yield, which is one of the aims of the CAP. What these estimates do not capture is to what extent SFP influences production. As previously stated, SPF's degree of decoupling is debated. This study only examines the effect of shifting from coupled direct payments to SFP.

Extreme weather is estimated to have a small, but statistically significant, negative effect on area. Producers that have experienced extreme droughts or heat waves during the last 12 months before planting are expected to reduce wheat area by between 1.2% and 1.7%. This is in line with the findings of Lesk et al. (2016), who found that droughts and heat waves had caused reductions in wheat area in their global study. The effect is small but knowing that extreme weather events will become more frequent, this might have an impact on production development in the EU in the future. One thing to keep in mind is that yield risk (caused by weather events) and price risk might be negatively correlated. Especially as the frequency of extreme weather events increases. If several large wheat producers experience yield loss in the same season, the wheat price will increase. This might diminish the total risk for the producers. However, there is no correlation between these two variables in this dataset. Local extreme weather events can be devastating for the affected farmers without having an impact on the price in the EU.

Due to lack of available data, the climate risk variable is a dummy variable. This limits the analysis, as it only allows us to compare the response of farmers who have experienced some sort of extreme weather during the last year with farmers who have not experienced any extreme weather. More detailed data would have allowed us to distinguish between different sorts of weather, severity of the event and to what extent it affected wheat production.

The final, stated research question was how climate risk affected farmers area decisions. The results implies that the farmers that have experienced extreme weather during the previous crop season are less incentivized to increase cultivated area when the price increases, compared to other farmers. In other words, if the perceived risk of losing parts of the crop increases, a higher price is needed to give incentives for area expansions.

6 Summary and conclusions

The aim of this study is to examine to what extent wheat producers in the EU reallocates area as a response to price changes, price risk and climate risk. The EU is one of the main wheat producers and exporters in the world, and changes in their production level have big implications for the global wheat market. A more detailed understanding of how area decisions are made is important to design effective policies and to be able to predict future production levels.

The study is conducted using panel data for the period 2003-2022, and the estimations are done by system GMM on a dynamic panel data model. The model is a Nerlovian partial adjustment model, which makes it possible to derive both short-run and long-run area responses. An important consideration in area response models is which price expectations proxy to use. The model therefore is estimated with both naïve expectations (spot price) and rational expectations (futures price) to compare the results. During the study period the EU has experienced three periods defined as food price crises. In addition, the wheat price volatility and the number of droughts and heat waves have increased. By examining the wheat producer's area response to these events, we gain valuable information.

The specification with naïve expectations and the specification with rational expectations give the same results in terms of sign and statistical significance of the coefficients. Using spot price as a price expectations proxy, the estimated short-run elasticity is 0,09 and the estimated long run elasticity is 0,57. Using futures price, the estimated short-run elasticity is 0,15 and the estimated long-run elasticity is 0.82. Thus, the area response to price is inelastic. The short-run elasticities are similar to those obtained from global area response studies. The low elasticity explains why the periods with high wheat prices have not resulted in a large increase in production. There is more uncertainty related to the long-run estimates, but they suggest that area responds more to prices in the long-run.

Area response to price risk, measured as wheat price volatility, turns out to be statistically insignificant. This does not correspond with previous, global studies and implies that price risk has not affected farmers area decisions in the EU during the study period. This can be explained by the widespread use of risk mitigating instruments in the EU and by the high level of protection through the CAP. There is also a possibility that some producers see high price risk as an opportunity to gain higher returns. Price volatility has been found to have a negative effect on wheat area decisions globally, but the result from this study gives reason to believe that the picture is more nuanced. Measures that reduce price volatility might not have the same impact on wheat production in the EU as in developing countries.

Climate risk, measured as the frequency of extreme droughts and heat waves, has a statistically significant and negative effect on area. The effect is small, but as the frequency of extreme weather is expected to increase due to climate change, this might have a larger effect on area allocation in the future. Public support, like SFP and MPS, is likely to protect farmers from climate risk to some extent. However, if extreme weather creates more risk for the farmers in the future, other types of insurance might be necessary to keep the same level of production.

The main limitation of the study is the assumptions made about the producer's perception of the market. Both in terms of price expectations and in terms of risk assessment. It is assumed in the model that farmers have either naïve or rational price expectations, and that their risk assessment is based on events that have occurred during the preceding 12 months. If these assumptions do not hold, and the price and risk variables do not capture the real expectations of the producers, we cannot have confidence in the results. Another limitation is that only the area response is estimated. Inclusion of yield response would give a more nuanced picture. Lack of available data also limits the analysis. Preferably, more detailed data on weather and production costs would have been used.

Further research should focus on differences within the EU. There might be a great diversity in area response across the different countries. The relationship between exports and area response should also be examined further. If the trend of more frequent extreme weather continues, more detailed weather data should be used to analyze the effect on wheat area. Based on the results of this study, risk mitigating measures in the EU have a better effect on price risk in the EU than on climate risk. Future research should therefore examine how climate risk can be reduced for wheat producers.

References

Anderson, T.W., Hsiao, C. (1982). Formulation and estimation of dynamic models using panel data. Journal of Econometrics, 18 (1), 47-82. https://doi.org/10.1016/0304-4076(82)90095-1

Arellano, M., Bond, S. (1991). Some Tests of Specification for Panel Data: Monte Carlo Evidence and an Application to Employment Equations. *The Review of Economic Studies*, 58(2), 277–297. https://doi.org/10.2307/2297968

Askari, H., & Cummings, J. T. (1977). Estimating Agricultural Supply Response with the Nerlove Model: A Survey. International Economic Review, 18(2), 257–292. https://doi.org/10.2307/2525749

Baffes, J., Koh, W.C. (2022, May 11). Fertilizer prices expected to remain higher for longer. World bank blogs. https://blogs.worldbank.org/opendata/fertilizer-prices-expected-remain-higher-longer

Bentley, A.R., Donovan, J., Sonder, K. Baudron, F., Lewis, J.M., Voss, R., Rutsaert, P., Poole, N., Kamoun, S., Saunders, D.G., Hodson, D., Hughes, P.D., Negra, C., Ibba, M.I., Snapp, S., Sida, T.S., Jaleta, M., Tesfaye, K., Reshef, I., Govaerts, B. (2022). Near- to long-term measures to stabilize global wheat supplies and food security. Nat Food **3**, 483–486. https://doi.org/10.1038/s43016-022-00559-y

Binfield, J., Donnellan, T., Hanrahan, K., Hart, C., Westhoff, P. (2004). CAP reform and the WTO: Potential impacts on EU agriculture. FAPRI-UMC, Report 08-04. http://hdl.handle.net/10355/3066

Binswanger, H. (1989). The policy response of agriculture. The world bank economic review, 4(1). http://dx.doi.org/10.1093/wber/3.suppl_1.231

Blundell, R. & Bond, S. (1998). Initial conditions and moment restrictions in dynamic panel data models. Journal of Econometrics, 87(1), 115-143. https://doi.org/10.1016/S0304-4076(98)00009-8.

Bond, M.E. (1983). Agricultural Responses to Prices in Sub-Saharan African Countries. Staff papers (international monetary fund), 30(4). 703-726. https://doi.org/10.2307/3866783

Bond, S. (2002). Dynamic panel data models: A guide to micro data methods and practice. Working Paper CWP09/02, Cemmap, Institute for Fiscal Studies. https://www.cafed.sssup.it/~federico/etrix_allievi/Bond2002.pdf

Braulke, M. (1982). A Note on the Nerlove Model of Agricultural Supply Response. International Economic Review, *23*(1), 241–244. https://doi.org/10.2307/2526474

Bràs, T.A., Seixas, J., Carvalhais, N., Jägermeyr, J. (2021). Severity of drought and heatwave crop losses tripled over the last five decades in Europe. Environmental research letters, 16(6). https://iopscience.iop.org/article/10.1088/1748-9326/abf004/meta#erlabf004s2

Bureau, J. C. & Gohin, A. (2009). Farm support policies in the European Union: an appraisal of their non-distortionary effects. FAO. Trade and Markets, 978-92-5-106388-0. https://www.fao.org/3/i1098e/i1098e10.pdf

Chavas, J.P., (2000). On information and market dynamics: The case of the U.S. beef market. Journal of Economic Dynamics and Control, 24 (5), 833-853. https://doi.org/10.1016/S0165-1889(99)00027-5.

Cohen, J. (1988). Set Correlation and Contingency Tables. Applied Psychological Measurement, 12(4), 425–434. https://doi.org/10.1177/014662168801200410

Coleman, D.R. (1983). A review of the arts of supply response analysis. Review of marketing and agricultural economics. 51(3), 201-230. https://ageconsearch.umn.edu/record/12516/

Coulibaly, A.L. (2013). The food price increase of 2010-2011. Causes and impacts. Library of parlament. Canada. Publication No. 2013-02-E. https://publications.gc.ca/collections/collection_2016/bdp-lop/bp/YM32-2-2013-2-eng.pdf

Coyle, B.T., (1993), On modeling systems of crop acreage demands, Journal of Agricultural and Resource Economics, 18(1). https://EconPapers.repec.org/RePEc:ags:jlaare:30823

Dawson, P.J. (2014). Measuring the volatility of wheat futures prices on the LIFFE. Journal of agricultural economics, 66(1), 20-35. https://onlinelibrary.wiley.com/doi/abs/10.1111/1477-9552.12092

Diop, I. & Traore, F. (2021). Measuring food price volatility. Agrodep, Technical note 0019. https://ebrary.ifpri.org/utils/getfile/collection/p15738coll2/id/134399/filename/134607.pdf

Donald, M. (2008). A note on rising food prices. World Bank Policy Research Working Paper. No.4682. https://ssrn.com/abstract=1233058

Economics (2023, February 18). Price elasticity of supply. https://www.learn-economics.co.uk/Price-elasticity-of-supply.html

EconomicsHelp (2023, March 17). Cobweb theory. https://www.economicshelp.org/blog/glossary/cobweb-theory/

EM-DAT (2023, January 27). The international disaster database. CRED/UCLouvain. https://public.emdat.be/

Enghiad, A., Ufer, D., Countryman, A.M., Thilmany, D.D. (2017). An Overview of Global Wheat Market Fundamentals in an Era of Climate Concerns. International Journal of Agronomy, Article ID 3931897, https://doi.org/10.1155/2017/3931897

Erenstein, O., Jaleta, M., Mottaleb, K.A., Sonder, K., Donovan, J., Braun, HJ. (2022). Global Trends in Wheat Production, Consumption and Trade. In: Reynolds, M.P., Braun, HJ. (eds) Wheat Improvement. Springer, Cham. https://doi.org/10.1007/978-3-030-90673-3_4

Ericsson, K., Rosenqvist, H., Nilsson, L.J. (2009). Energy crop production costs in the EU. Biomass and Bioenergy, 33(11), 1577-1586. https://doi.org/10.1016/j.biombioe.2009.08.002

European Commision (2008, April 17). Tackling the challenge of rising food prices; The direction for EU action. Brussels, COM (2008) 321 final. https://eur-lex.europa.eu/LexUriServ/LexUriServ.do?uri=COM:2008:0321:FIN:EN:PDF

European Commision (2022). Agriculture and rural development. Cereals, oilseeds, protein crops and rice. https://agriculture.ec.europa.eu/farming/crop-productions-and-plant-based-products/cereals_en

European Commission (2023a, February 7). Directorate-general for agriculture and rural development. Cereals prices. https://agridata.ec.europa.eu/extensions/DashboardCereals/ExtCerealsPrice.html

European Commission (2023b, February 20). Agriculture and rural development. Common agricultural policy. https://agriculture.ec.europa.eu/common-agricultural-policy_en

European Commission (2023c, April 14). Agriculture and rural development. The WTO and EU agriculture. https://agriculture.ec.europa.eu/international/agricultural-trade/wto-and-eu-agriculture_en

Euronext (2023). MATIF milling wheat price. Retrieved from ZMP. https://www.zmp.de/en/exchanges/matif-milling-wheat-no-2-price_future

Eurostat (2023, April 2). Harmonized Index of Consumer Prices. Retrieved from FRED, Federal Reserve Bank of St. Louis (CP0000EZ19M086NEST). https://fred.stlouisfed.org/series/CP0000EZ19M086NEST

Ezekiel, M. (1938). The Cobweb Theorem. *The Quarterly Journal of Economics*, 52 (2), 255–280, https://doi.org/10.2307/1881734

EzyEducation (2023, May 2). EzyEconomics, Elasticity. https://www.ezyeducation.co.uk/ezyeconomicsdetails/ezylexicon-economic-glossary/1304-elasticity-of-demand.html

FAO (2022). 2022 Global Report on Food Crises. https://www.fao.org/3/cb9997en/cb9997en.pdf

FAO (2023, January 10). Faostat, compare data. https://www.fao.org/faostat/en/#compare

Food Security Portal (2023, January 8). Volatility warning. https://www.foodsecurityportal.org/

Gardner, B. L. (1976). Futures Prices in Supply Analysis. American Journal of Agricultural Economics, *58*(1), 81–84. https://onlinelibrary.wiley.com/doi/abs/10.2307/1238581

Gilbert, C. L. & Morgan, C. W. (2010). Food price volatility. Phil. Trans. R. Soc. 365(1554). 3023-3034. https://doi.org/10.1098/rstb.2010.0139

Haile, M. G., Kalkuhl, M., Braun, J. V. (2013). Inter- and intra-seasonal crop acreage response to international food prices and implications of volatility. Agricultural economics. 45(6). https://doi.org/10.1111/agec.12116

Haile, M.G., Kalkuhl, M., Braun, J.V. (2015). Worldwide acreage and yield response to international price change and volatility: A dynamic panel data analysis for wheat, rice, corn and soybeans. Food price volatility and its implications for food security and policy. Springer, Cham. https://doi.org/10.1007/978-3-319-28201-5_7

Halvorsen, R. & Palmquist, R. (1980). The interpretation of dummy variables in semilogaritmic equations. American economic review, 70(3), 474-475. https://econpapers.repec.org/article/aeaaecrev/v_3a70_3ay_3a1980_3ai_3a3_3ap_3a474-75.htm

Hansen, L. P. (1982). Large Sample Properties of Generalized Method of Moments Estimators. Econometrica, 50(4), 1029–1054. https://doi.org/10.2307/1912775

Harris, R. & Tzavalis, E. (1999). Inference for unit roots in dynamic panels when time dimension is fixed. Journal of econometrics, 19(2), 201-226. https://econpapers.repec.org/RePEc:eee:econom:v:91:y:1999:i:2:p:201-226

Hausman, C. (2012). Biofuels and Land Use Change: Sugarcane and Soybean Acreage Response in Brazil. Environ Resource Econ, 51, 163–187. https://doi.org/10.1007/s10640-011-9493-7

Hendricks, N. P., Janzen, J. P., & Smith, A. (2015). Futures Prices in Supply Analysis: Are Instrumental Variables Necessary? American Journal of Agricultural Economics, 97(1), 22–39. http://www.jstor.org/stable/24476999

Holt, M. T., & McKenzie, A. M. (2003). Quasi-Rational and Ex Ante Price Expectations in Commodity Supply Models: An Empirical Analysis of the US Broiler Market. Journal of Applied Econometrics, 18(4), 407–426. http://www.jstor.org/stable/30035343

Holtz-Eakin, D., Newey, W., & Rosen, H. S. (1988). Estimating Vector Autoregressions with Panel Data. Econometrica, *56*(6), 1371–1395. https://doi.org/10.2307/1913103

Hommes, C. H. (1998). On the consistency of backward-looking expectations: The case of the cobweb. Journal of Economic Behavior & Organization, 33 (3), 333-362. https://doi.org/10.1016/S0167-2681(97)00062-0.

Houck, J. P., & Gallagher, P. W. (1976). The Price Responsiveness of U.S. Corn Yields. American Journal of Agricultural Economics, 58(4), 731–734. https://doi.org/10.2307/1238817

Indexmundi (2023, January 24). Wheat production by country. https://www.indexmundi.com/agriculture/?commodity=wheat

IGC (2023, January 8). Market data. Wheat. https://www.igc.int/en/members-site/markets/igc_markets_ayp.aspx

International monetary fund (2023, January 10). Global price of wheat. Retrieved from FRED, Federal reserve bank of St. Louis (PWHEAMTUSDM). https://fred.stlouisfed.org/series/PWHEAMTUSDM

International monetary fund (2023, January 10). Global price of natural gas, EU. Retrieved from FRED, Federal reserve bank of St. Louis (PNGASEUUSDM). https://fred.stlouisfed.org/series/PNGASEUUSDM

IPCC (2021). Sixth assessment report. Working group 1: The physical science basis. https://www.ipcc.ch/report/ar6/wg1/

Iqbal M. Z. & Babcock, B.A. (2018). Global growing-area elasticities of key agricultural crops estimated using dynamic heterogenous panel methods. Agricultural economics, 49(6), 681-690. https://doi.org/10.1111/agec.12452

Judson, R.A., Owen, A.L. (1999). Estimating dynamic panel data models: a guide for macroeconomists. Economics Letters, 65 (1), 9-15. https://doi.org/10.1016/S0165-1765(99)00130-5.

Jägermeyr, J., Müller, C., Ruane, A.C. et al. (2021). Climate impacts on global agriculture emerge earlier in new generation of climate and crop models. Nature food, 2. 873–885. https://doi.org/10.1038/s43016-021-00400-y

Kalkuhl, M., Braun, J., Torero, M. (2016). Food price volatility and its implications for food security and policy. Springer Cham, 1. https://doi.org/10.1007/978-3-319-28201-5

Kelch, D., Normile, M.A. (2004). CAP reform of 2003-04. USDA, WRS-04-07. https://view.ckcest.cn/AllFiles/ZKBG/Pages/285/Csgk0FvYNBiAezaQAAFWvbwD1wc413.pdf

Kiviet, J.F. (1995). On bias, inconsistency, and efficiency of various estimators in dynamic panel data models. Journal of Econometrics, 68 (1), 53-78. https://doi.org/10.1016/0304-4076(94)01643-E.

Lee, D.R., Helmberger, P.G. (1985). Estimating supply response in the presence of farm programs. American journal of agricultural economics. 67(2). https://doi.org/10.2307/1240670

Lesk, C., Rowhani, P., Ramankutty, N. (2016). Influence of extreme weather disasters on global crop production. Nature 529, 84–87. https://doi.org/10.1038/nature16467

Liang, Y., Miller, J.C., Harri, A., Coble, K.H. (2011). Crop Supply Response under Risk: Impacts of Emerging Issues on Southeastern U.S. Agriculture. Journal of Agricultural and Applied Economics, 43(2), 181-194. https://ageconsearch.umn.edu/record/104615/

Lin, W., & Robert Dismukes. (2007). Supply Response under Risk: Implications for Counter-Cyclical Payments' Production Impact. Review of Agricultural Economics, 29(1), 64–86. http://www.jstor.org/stable/4624821

Liu, W., Ye, T., Jagermeyr, J., Muller, C., Chen, S (2021). Future climate change significantly alters interannual wheat yield variability over half of harvested areas. Environmental research letters, 16(9), 45-62. https://iopscience.iop.org/article/10.1088/1748-9326/ac1fbb

Macrotrends (2023, January 24). Wheat prices. https://www.macrotrends.net/2534/wheat-prices-historical-chart-data

Mittal, A. (2009) The 2008 food price crisis: Rethinking food security policies. G-24 discussion paper series. United nations publications. https://unctad.org/system/files/official-document/gdsmdpg2420093_en.pdf

Mueller, S. A., Anderson, J.E., Wallington, T.J. (2011). Impact of biofuel production and other supply and demand factors on food price increases in 2008. Biomass and Bioenergy, 35 (5), 1623-1632. https://doi.org/10.1016/j.biombioe.2011.01.030

Muth, J. F. (1961). Rational Expectations and the Theory of Price Movements. Econometrica, *29*(3), 315–335. https://doi.org/10.2307/1909635

Nelson, R., & Bessler, D.A. (1992). Quasi-rational expectations: Experimental evidence. *Journal of Forecasting, 11*, 141-156. https://doi.org/10.1002/for.3980110205

Nerlove, M. (1956). Estimates of the elasticities of supply of selected agricultural commodities. Journal of farm economics, 38(2). https://doi.org/10.2307/1234389

Nerlove, M. (1979). The dynamics of supply: Retrospect and prospect. American journal of agricultural economics, 61(5). https://doi.org/10.2307/3180340

Nerlove, M., Fornari, I. (1998). Quasi-rational expectations, an alternative to fully rational expectations: An application to US beef cattle supply. Journal of Econometrics, 83(1), 129-161, https://doi.org/10.1016/S0304-4076(97)00067-5

Nerlove, M., Grether, D.M., Carvalho, J.L. (1979). Analysis of Economic Time Series. Academic Press, New York. https://www.sciencedirect.com/book/9780125157506/analysis-of-economic-time-series

Nerlove, M & Bessler D.A. (2001). Chapter 3 Expectations, information and dynamics, Handbook of Agricultural Economics, Elsevier, 155-206, https://doi.org/10.1016/S1574-0072(01)10006-X.

Nickell, S. (1981). Biases in Dynamic Models with Fixed Effects. Econometrica, 49(6), 1417–1426. https://doi.org/10.2307/1911408

O'brien, R.M. (2007). A Caution Regarding Rules of Thumb for Variance Inflation Factors. Quality and Quantity 41, 673–690. https://doi.org/10.1007/s11135-006-9018-6

OECD (2011). Evaluation of agricultural policy reforms in the European Union. https://doi.org/10.1787/9789264112124-en

OECD/FAO (2022). OECD-FAO Agricultural Outlook 2022-2031. OECD Publishing, Paris. https://doi.org/10.1787/f1b0b29c-en

Pe'er, G., Lakner, S., Passoni, G., Azam, C., Berger, J., Hartmann, L., Schüler, S., Müller, R., von Meyer-Höfer, M., Zinngrebe, Y. (2017). Is the CAP Fit for purpose? An evidence-based, rapid Fitness-Check assessment - Preliminary Summary of key outcomes. Leipzig, EEB. https://www.idiv.de/fileadmin/content/iDiv_Files/Documents/peer_et_al_2017_cap_fitness_check_final_20-11.pdf

Pesaran, M. H., Smith, R. (1995). Estimating long-run relationships from dynamic heterogeneous panels. Journal of Econometrics, 68(1), 79-113. https://doi.org/10.1016/0304-4076(94)01644-F.

Peterson, W. L. (1979). International Farm Prices and the Social Cost of Cheap Food Policies. American Journal of Agricultural Economics, 61(1), 12–21. https://doi.org/10.2307/1239495

Phillips, P.C.B., Sul, D. (2007). Bias in dynamic panel estimation with fixed effects, incidental trends and cross section dependence. Journal of Econometrics, 137(1), 162-188. https://doi.org/10.1016/j.jeconom.2006.03.009.

Pindyck, R. & Rubinfeld, D. (2018). Microeconomics, 9th edition. Pearson Education. 58-62.

Poitras, G. (2023). Cobweb theory, market stability, and price expectations. Journal of the History of Economic Thought, 45(1), 137-161. https://doi:10.1017/S1053837222000116

Rao, J.M., (1989). Agricultural supply response: A survey. Agricultural economics, 3(1). 1-22. https://doi.org/10.1111/j.1574-0862.1989.tb00068.x

Ray, D., Gerber, J., MacDonald, G., West, P.C. (2015). Climate variation explains a third of global crop yield variability. Nature communictions, 6. 5989. https://doi.org/10.1038/ncomms6989

Roberts, M.J. & Schlenker, W. (2009). World Supply and Demand of Food Commodity Calories. American Journal of Agricultural Economics, 91(5). http://www.jstor.org/stable/20616288

Roberts, M.J., & Schlenker, W. (2013). Identifying Supply and Demand Elasticities of Agricultural Commodities: Implications for the US Ethanol Mandate. American Economic Review, 103 (6), 2265-95. https://www.aeaweb.org/articles/pdf/doi/10.1257/aer.103.6.2265

Roodman, D. (2009). How to do xtabond2: An introduction to difference and system GMM in Stata. The Stata Journal, 9(1), 86-136. https://journals.sagepub.com/doi/pdf/10.1177/1536867X0900900106

Sandmo, A. (1971). On the theory of the competitive firm under price uncertainty. The American economic review, 61(1), 65-73. https://www.jstor.org/stable/pdf/1910541.pdf

Santeramo, F.G. & Lamonaca, E. (2019). On the drivers of global grain price volatility: An empirical investigation. Agricultural economics – Czech, 65. 31-42. https://www.old-aj.cz/publicFiles/76_2018-AGRICECON.pdf

Schils, R., Olesen, J. E., Kersebaum, K., Rijk, B., Oberforster, M., Kalyada, V., Khitrykau, M., Gobin, A., Kirchev, H., Manolova, V., Manolov, I., Trnka, M., Hlavinka, P., Palosuo, T., Peltonen-Sainio, P., Jauhiainen, L., Lorgeou, J., Marrou, H., Danalatos, N., Archontoulis, S., … Ittersum, M. (2018). Cereal yield gaps across Europe. European Journal of Agronomy, 101, 109-120. https://doi.org/10.1016/j.eja.2018.09.003.

Sckokai, P., & Antón, J. (2005). The Degree of Decoupling of Area Payments for Arable Crops in the European Union. American Journal of Agricultural Economics, *87*(5), 1220–1228. http://www.jstor.org/stable/3697698

Sckokai, P & Moro, D (2009). Modelling the impact of the CAP Single Farm Payment on farm investment and output. *European Review of Agricultural Economics*, 36 (3), 395–423, https://doi.org/10.1093/erae/jbp026

Shideed, K. H., & White, F. C. (1989). Alternative Forms of Price Expectations in Supply Analysis For U.S. Corn and Soybean Acreages. Western Journal of Agricultural Economics, 14(2), 281–292. http://www.jstor.org/stable/40988107

Sowell, A., Swearingen, B., Sauer, C. & Hutchins, C. (2022). Wheat outlook: December 2022. USDA. https://www.ers.usda.gov/publications/pub-details/?pubid=105461

Stata (2023). Panel-data unit-root tests. https://www.stata.com/features/overview/panel-data-unit-root-tests/

Steen, M., Bergland, O., Gjølberg, O. (2023). Climate Change and Grain Price Volatility: Empirical Evidence for Corn and Wheat 1971–2019. Commodities, 2(1), 1-12. https://doi.org/10.3390/commodities2010001

Subervie, J. (2008). The Variable Response of Agricultural Supply to World Price Instability in Developing Countries. Journal of Agricultural Economics. 59. 72-92. https://onlinelibrary.wiley.com/doi/abs/10.1111/j.1477-9552.2007.00136.x

Swinbank, A. (2008). Potentil WTO challenges to the CAP. Canadian journal of agricultural economics, 56(4), 445-456. https://doi.org/10.1111/j.1744-7976.2008.00140.x

Tangermann, S. (2011). Risk management in agriculture and and the future of the EU's common agricultural policy. International center for trade and sustainable development. Issue paper no. 34. https://www.files.ethz.ch/isn/138400/tangermann_risk_management.pdf

Thiele, R. (2000). Estimating the aggregate agricultural supply response: a survey of techniques and results for developing countries, Kiel Working Paper, No. 1016, Kiel Institute of World Economics. https://www.econstor.eu/bitstream/10419/2516/1/kap1016.pdf

Tradingeconomics (2023, January 11). Wheat. https://tradingeconomics.com/commodity/wheat

Trnka, M., Rötter, R., Ruiz-Ramos, M. Kersebaum, K.C., Olesen, J.E., Zalud, Z., Semenov, M.A. (2014). Adverse weather conditions for European wheat production will become more frequent with climate change. Nature Climate Change, 4. 637–643. https://doi.org/10.1038/nclimate2242

Trostle, R., Marti, D., Rosen, S., Westcott, P. (2011). Why have food commodity prices risen again? WRS-1103, Economic research service/USDA. https://d35t1syewk4d42.cloudfront.net/file/1934/USDA-food-prices.pdf

Urban, K., Jensen, H.G., Brockmeier, M. (2016). How decoupled is the Single Farm Payment and does it matter for international trade? Food Policy, 59, 126-138. https://doi.org/10.1016/j.foodpol.2016.01.003.

USDA (2021). International markets and US trade. European Union. https://www.ers.usda.gov/topics/international-markets-u-s-trade/countries-regions/european-union/

USDA (2023). Crop calendar. Europe. https://ipad.fas.usda.gov/rssiws/al/crop_calendar/europe.aspx

Wilcox, J. & Makowski, D. (2014). A meta-analysis of the predicted effects of climate change on wheat yields using simulation studies. Field Crops Research, 156. 180-190. https://doi.org/10.1016/j.fcr.2013.11.008

Windmeijer, F. (2005). A finite sample correction for the variance of linear efficient two-step GMM estimators. Journal of Econometrics, 126 (1), 25-51. https://doi.org/10.1016/j.jeconom.2004.02.005.

World Bank (2023). Data. Cereal yield. https://data.worldbank.org/indicator/AG.YLD.CREL.KG

WTO (2014). Trends in domestic support – Market price support. Doc. 14-3238, G/AG/W/131. https://docs.wto.org/dol2fe/Pages/FE_Search/FE_S_S006.aspx?MetaCollection=WTO&Serial=%2214-3238%22&Language=ENGLISH&SearchPage=FE_S_S001&languageUIChanged=true#

WTO (2023). Agreement on Agriculture. https://www.wto.org/english/docs_e/legal_e/14-ag_01_e.htm

WTO (2023). Agriculture Information Management System. https://www.wto.org/english/tratop_e/agric_e/transparency_toolkit_e.htm

Zhang, T., van der Wiel, K., Wei, T., Screen, J., Yue, X., Zheng, B., Selten, F., Bintanja, R., Anderson, W., Blackport, R., Glomsrød, S., Liu, Y., Cui, X., Yang, X. (2022). Increased wheat price spikes and larger economic inequality with 2°C global warming. One Earth, 5(8). 892-906. https://doi.org/10.1016/j.oneear.2022.07.004

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