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Climate change and the US wheat commodity market ☆

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ABSTRACT

We study the impact on the workings of the wheat commodity market of increasing weather variability, one of the direct consequences of climate change. After finding strong evidence of an increase in the variance of weather and harvest for wheat in the US, we develop a structural time series model of the commodity market to investigate the sources and consequences of this increased variability. Exploiting this model, we devise a novel empirical procedure to analyze the impact on price and the potential adjustments of the speculative demand for inventories, as predicted by the rational storage theory. We find that speculation in the physical market for wheat at annual frequency adapted to the greater uncertainty about harvest stabilizing the market price.

1. Introduction

An important dimension in which climate change influences weather patterns across the planet is the increase in weather variability, with a rise in the frequency and intensity of extreme temperature and precipitation events (IPCC, 2021). The consequences of this change for agricultural commodity prices are not yet clear. In this paper, we first investigate if weather and harvest variability have actually increased in the US land cultivated for wheat, the most important food grain in the country, and then we analyze the implications of this event for the workings of the wheat commodity market and the dynamics of wheat price.

We are interested, in particular, in uncovering the response of storage and speculation in the physical market for wheat, which is the mechanism by which competitive markets of storable agricultural commodities prevent unpredictable fluctuations in harvest from affecting price variability. While the presence of a speculative demand for wheat inventories dampens the impact of supply shocks on price by raising total market demand elasticity, it also introduces a new exogenous shock, which might be driven by self-fulfilling beliefs and sunspot variables amplifying existing price variability. Therefore, we are also interested in understanding to what extent speculation in the physical market for wheat is stabilizing or destabilizing in the face of increasing weather and harvest variability.

The overwhelming majority of the research effort in this area has focused on the characterization of the long-run trend in agricultural commodity prices using univariate econometric techniques, and some studies have also considered the link between

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weather fluctuations and food price volatility, but mostly relying on reduced-form types of analysis.[1] A correct understanding of the effects that weather variability produces on price dynamics, however, requires the estimation of a structural model of the commodity market for at least two reasons. First, because we need to unravel the impact of weather shocks on agricultural production from that produced by a set of simultaneous economic shocks associated with both the demand and supply sides of the market. Second, because a permanent change in the statistical characteristics of weather, a key source of variation in crop production, is very likely to trigger permanent adjustments in the structure and functioning of the agricultural commodity market.

The novelty of our contribution consists in developing a dynamic structural model of the wheat commodity market that is well designed to identify the different economic shocks that simultaneously determine the price level of the commodity and to capture the important role played by the speculative demand for inventories. Our study falls within a very recent strand of research that uses a multivariate structural time series approach to model agricultural commodity prices. Carter et al. (2017) and Smith (2018) build a Structural Vector Autoregression (SVAR) model to study the implications of biofuel policies for the commodity markets of maize, wheat, and soybeans, with an explicit consideration of the demand for storage. Peersman (2022) and DeWinne and Peersman (2021) use an SVAR model to study the effects of weather-related changes in global grain commodity prices on economic activity and the general price level in different countries. But this class of models has also been widely used to describe the historical developments of oil markets (Kilian, 2009; Kilian and Murphy, 2014). We use the same empirical framework based on SVAR modeling and we adopt an identification strategy that is built on insights from the economic theory of commodity markets and the rational storage demand to uncover the relevant causal relationships within the US wheat commodity market, and then we use such framework to explore the evidence of adjustments in the speculative demand for inventories.[2]

It is worth clarifying from the beginning that in this paper we look at the physical market for wheat and its price dynamics at annual frequency, which is the timescale relevant to its production process. Therefore, the speculative activities we refer to consider exactly this time frame, which is different from the high frequency that is relevant instead for speculation in derivative financial products related to agricultural commodities. By speculation we intend the use of storage and inventories to transfer the physical commodity across periods. So, the definition of speculator we adopt here is very general, as we refer to the storer that buys physical wheat not to satisfy current consumption needs, but for future use in light of anticipation of future price increases, for precautionary motives in response to uncertainty about future market conditions, or simply following market trends.

In the first part of our investigation, we will look at some preliminary facts about the unconditional variance of crop-specific weather, harvest, and price. We use a test for structural breaks in the variance that allows us to control for the effects of global warming, here modeled as a long-run deterministic trend in average temperature, subject to an acceleration as uncovered in recent research. While this test has power against more general time patterns of changes in variance, it offers us the advantage of identifying a date around which the change occurred. We find strong evidence of an upward shift around 1974 in the variance of temperature and harvest, but not price.

Motivated by this preliminary evidence, in the second part of our investigation, we build a dynamic structural model (SVAR) of the wheat commodity market to answer three main questions: 1) how much of the detected rise in harvest variability is due to weather compared to other determinants; 2) what is the potential role of different economic shocks in the determination of production and price; 3) does the speculative demand for inventories respond endogenously to permanent increases in harvest variability. To identify the relevant structural equations and the associated economic shocks we impose a set of theoretical restrictions, the validity of which is confirmed by estimated parameters that deliver a plausible description of the dynamics of the observables.

In addition to providing quantitative insights into the functioning of agricultural commodity markets, this paper also offers a methodological contribution consisting in the development of a novel econometric procedure to uncover the presence of endogenous adjustments in the structural parameters of a market. In the core part of this procedure we adapt to our SVAR model an econometric test for structural change when estimation is performed using instrumental variables. We apply this novel procedure to test the prediction from rational storage theory that speculators change their systematic behaviour in response to a permanent rise in weather and harvest variability. But this procedure has a general applicability and can be employed whenever one is interested in studying the evolution of a market as it changes in response to an event with permanent consequences such as climate change.

We find sufficient evidence that at the same time that weather and harvest became more volatile in 1974, the speculative demand for inventories experienced a permanent change in its main elasticities, and in its price elasticity in particular. To understand the implications of this structural change for the price dynamics, we study the impulse response functions of the model before and after the 1974 structural change. We uncover that the size of the price fluctuations produced by all economic shocks has diminished as a result of such adjustment. Finally, when we assess the overall contribution of speculation to price volatility at annual frequency, we conclude that it plays a fundamental stabilizing role thanks to its ability to adapt to the increasing uncertainty caused by growing harvest variability.

The structure of the paper is the following. In section 2, we perform a univariate analysis of the historical time series of weather, harvest, and price. In section 3, we summarize the main features of the wheat sector in the US, which will inform our model specification. In section 4, we develop our SVAR model and motivate our set of identifying restrictions. In section 5, we describe in detail the methodology behind our novel econometric procedure, which hinges on a structural change analysis of the SVAR model.

[1] A few examples are: Gilbert and Morgan (2010), Roache (2010), Abbott et al. (2011), Diffenbaugh et al. (2012).

[2] Some of the most prominent examples of the literature on competitive rational storage theory is Williams and Wright (1991), Deaton and Laroque (1996), and more recently Bobenrieth et al. (2014). For a recent overview, see Wright (2014).

In section 6, we present and discuss the results we obtain from the application of our procedure on the US wheat commodity market. Section 7 comprises a summary of the key results and some concluding remarks.

2. Univariate analysis

We begin our empirical investigation by exploring the statistical evidence for historical changes in the annual variability of weather. An increase in variability is one specific dimension in which climate change is expected to alter weather patterns. In this paper, however, we do not investigate whether such a change is due to climate change or not, but rather we study its consequences for the commodity market. It is worthwhile to stress that we do not make use of a general definition of temperature and precipitation, but rather focus on measures that are specific to wheat crops both in terms of geography and time periods of the year, reflecting the crop's growing season.

As weather fluctuations represent a key determinant of interannual changes in crop yield and agricultural output, we are also interested to understand the extent to which a change in weather variability is reflected in the harvest and ultimately in the price of wheat. Therefore, we extend our analysis of the unconditional variance also to this latter couple of variables. In the following, we first describe how our data are constructed (2.1), and then we explain the methodology we use and our results (2.2).

2.1. Data

We construct a dataset that contains three sets of variables, nine in total, at the US national level, with annual frequency from 1950 to 2018. The first set is a group of variables that relate to the agricultural side of wheat production (temperature, precipitation, and wheat crop area); the second reflects the wider economic conditions (real oil price, real interest rate, and GDP change); and the third describes the wheat commodity market (wheat harvest, inventory change, and real price of wheat).[3]

The purpose of this paper is to study the US wheat market, so we work with aggregate national variables. This approach carries important limitations, since national aggregation necessarily hides the spatial heterogeneity in weather and harvest that exists across the US territory. However, we highlight that while the US covers an immense surface, the wheat crop is heavily concentrated in the area of the Great Plains and the Northwestern states, which limits considerably the spatial heterogeneity. In addition, the existence of a well-developed transportation network made up of roads, rails, and rivers implies that the wheat market is well integrated at the national level. To reduce as much as possible the information loss from ignored spatial heterogeneity, we construct our national weather variables using a crop-specific weighted average across only the relevant time and space, as described in the following.

The temperature and precipitation values are constructed by taking a crop-specific weighted average across the months of the growing season and across the US territory. Temperature is measured in degree Celsius, and precipitation is measured in millimeters per month. For this we follow the standard practice of combining three gridded datasets: the monthly average of temperature and precipitation defined on a grid of 30 min resolution, collected from the Climate Research Unit of the University of East Anglia (Harris et al., 2014); the map of cropland at 5 min resolution (Monfreda et al., 2008) used to identify the cells with wheat crop land; and the growing season calendar for wheat at 5 min resolution (Sacks et al., 2010), which is used to select the months that are relevant to the wheat crop. In particular, we include data for the months between April and July to capture the effect of weather on the most important varieties cultivated in the US.[4]

Since there is strong theoretical and empirical support for a non-linear description of the impact of weather on crop yield, we also consider an alternative measure of temperature that we construct based on the concept of *growing degree days*. We find that the results of the paper are robust to this alternative definition of temperature. Details of this assessment can be seen in Appendix B. To construct the annual growing degree days variable we use a different weather dataset, namely the one provided by Livneh et al. (2013), which includes daily minimum and maximum temperatures for the US. For the crop area we use the harvested acreage, collected from the USDA and measured in million acres.

The real oil price is the ratio between the West Texas Intermediate spot crude oil price, obtained from the Federal Reserve Bank of St Louis, and the annual GDP deflator, collected from the OECD with 2012 as the base year. The real interest rate, measured in percent units, is obtained as the difference between the rate on the Treasury Bills with maturity of 3 months, collected from the IMF International Financial Statistics, and the GDP deflator inflation rate. The GDP is the real chained volume estimate, expressed in 2012$ million, extracted from the OECD.

Harvest and inventory are obtained from the USDA National Agricultural Statistics Service, both measured in millions of bushels. The real price of wheat is the ratio between the nominal farm price in dollars per bushel and the GDP deflator. The first variable represents the annual season-average of the monthly prices received by the farmers weighted by monthly sales, also collected from the USDA, while the GDP deflator has 2012 as the base year. The reference period of weather is the last four months prior harvest,

[3] We decide to use all variables in their original level, rather than taking log-transformation for a set of reasons. First, since the purpose of our analysis is to explore the presence of changes in the variances, we prefer not to use a transformation, the primary effect of which is to reduce heteroskedasticity. Second, the time series of harvest does not suggest an exponential growth path. Third, we exclude the presence of a multiplicative error term, as the increase in harvest variance appears abrupt rather than gradually following a rising harvest level (this will also be evident from our structural change analysis). Fourth, there are no clear indications from economic theory on whether to prefer a model of the commodity market with constant elasticities or derivatives, but a practical reason motivates our preference for the latter option, since our set of identifying restrictions prevents the use of variables expressed in logs.

[4] Three varieties of wheat are cultivated in the US: winter, spring and durum. The first two comprise most of the production, with winter accounting for at least two thirds of total harvest. Winter and spring varieties are planted, respectively, in September-October and April-May and harvested in June-July and August.

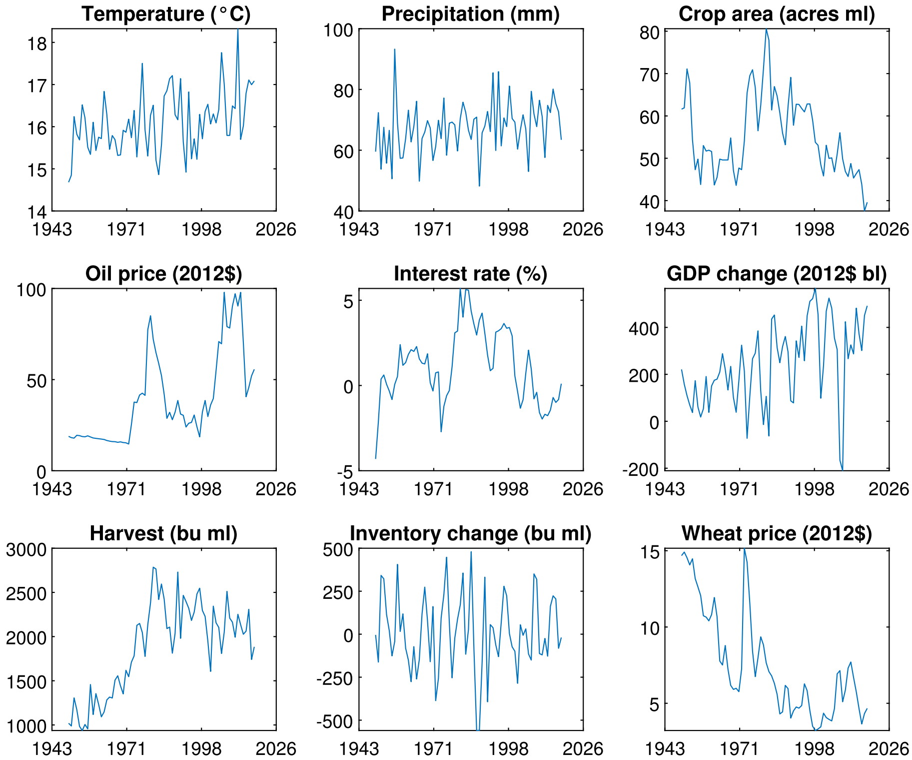

Fig. 1. Time series of the variables.

occurring between June and August, while that of GDP is from April to March of the following year. For all the other variables, the reference period is the wheat marketing year, which spans June of one year to May of the following year.

2.2. Testing for a break in variance

Before assessing the presence of a change in the variance of a variable, we first need to characterize the nature of its long-run trend. This is important to avoid misrepresenting long-run movements as short-run fluctuations, and also because the distribution of the test statistics used to ascertain a change in variance depends on the stochastic nature of the trend. An initial look at the plot of the data in Fig. 1 reveals the likely existence of deterministic trends, which sometimes appear to be subject to a break at a certain point in time. This is not surprising, especially for the time series of temperature, as substantial amount of evidence suggests that its long-run behavior is adequately represented by a trend-break stationary model (see e.g. Gay et al., 2009, Estrada et al., 2013, Agnolucci et al., 2021).

Hence, we adopt a two-stage procedure to study the variance of harvest, price and the two weather variables. In the first stage, we run a test for unit root allowing for a break in the trend at an unknown point in time both under the null of unit root and the alternative of stationarity (Perron and Vogelsang, 1992, and Vogelsang and Perron, 1998). In the second stage, we take the appropriately detrended variable and we use it to test for a break in the variance using a Wald statistic.[5]

More formally, in the first stage the variable of interest is modeled as

$$y_t = \mu + \beta t + \theta DU_t + \gamma DT_t + \tilde{y}_t, \tag{1}$$

where μ is a constant, β is the slope of the trend, $DU_t = 1\left\{t > T_{tr}\right\}$ and $DT_t = 1\left\{t > T_{tr}\right\}\left(t - T_{tr}\right)$ are two dummy variables, with $1\{\cdot\}$ being an indicator function taking the value of 1 when the event in curly brackets occurs and 0 otherwise, T_{tr} is the break point, and $\tilde{y}_t$ is a finite-order ARMA process. Following Perron and Vogelsang (1992) and Perron (1997), we take the residuals from equation (1) and estimate the following model

$$\tilde{y}_t = \alpha \tilde{y}_{t-1} + \sum_{i=1}^{k} a_i \Delta \tilde{y}_{t-i} + \sum_{i=0}^{k} d_i D\left(t_b\right)_{t-i} + u_t, \tag{2}$$

[5] While there is no particular reason to expect that a change in variance occurs abruptly, we highlight that a test for a structural break has power against more general time patterns of change, and it allows us to define a clear date for this change.

Table 1
Analysis of trend and variance.

	t_α	T_{tr}	supWald	p-value	T_v	σ_1^2	σ_2^2
Temperature	−7.523	1976	9.004	0.043	1974	0.203	0.564
Precipitation	−7.024	1992	1.501	0.916	1966	-	-
Harvest	−6.581	1978	8.742	0.048	1974	22806	61124
Price	−5.181	2003	2.267	0.732	1961	-	-

Note: The 5% and 1% critical values of the unit root test are −5.13 and −5.82. We denote by σ_i^2, with $i = 1, 2$, the variance of each variable before and after the break.

where $D(\cdot)_{t-i}$ are pulse dummies needed to ensure that the asymptotic distribution is invariant to the lag truncation parameter k and $u_t \sim iid(0, \sigma^2)$ with finite fourth moment. The relevant test statistic is the t ratio for $\alpha = 1$ in equation (2), which we indicate by t_α. Since the break point is unknown, it is estimated by minimizing the t ratio for $\alpha = 1$ across all possible years, after selecting the lag order at each year using a sequential testing on the coefficient of the last lag, starting with a maximum of 10 and adopting a 5% significance level.

If the above test rejects the null, we conclude that the variable is stationary and, as a consequence, in the second stage we take the detrended variable $\tilde{y}_t$ and fit an autoregressive model of the same lag order selected in the unit root test. The residuals from this regression are squared and regressed on a constant on which we perform a test for one break at an unknown point using the supWald statistic that is robust to heteroskedasticity (see Andrews, 1993).[6] We indicate by T_v the break point for the variance estimated by the supWald statistic.

The results of both stages of the analysis are shown in Table 1. All variables are stationary once we allow for a deterministic trend that is potentially breaking.[7] There is also evidence of a change in the variance of temperature and harvest at 5% significance, but clearly no sign of a change in the case of precipitation and price, as indicated by the p-value of the supWald test. Interestingly, the estimated break point for the variance is 1974 for both temperature and harvest, and the magnitude of the change in the variances is also the same, in both cases almost trebling. This is remarkable as the test on temperature and harvest has been implemented separately.

We conclude that wheat-specific temperature has trebled its variability around 1974, and this has been accompanied by a contemporaneous rise in the variability of harvest, but surprisingly without any consequence for the price of wheat. We attribute this constant price variability to the workings of the wheat commodity market and possibly its endogenous adaptation to the observed higher variability of harvest.

Attributing the detected change in harvest variability to weather alone would be unwarranted at this stage of the analysis. However, this evidence offers strong motivation for a deeper analysis of the determinants of harvest variability, which requires a structural model of the wheat commodity market. The remainder of the paper is exactly devoted to this, developing a structural model that describes the key relations of the wheat commodity market, and which will allow us to uncover the presence of potential cofactors other than weather in explaining the increased harvest variability and to clarify the reasons why this change did not have a consequential impact on the price of wheat.

3. The US wheat sector

Before setting up our model of the physical wheat commodity market, it is useful to describe the US wheat sector in its main characteristics. This description will help us justify the choices that we will make later at the modeling stage. In particular, we indicate the main demand and supply factors with their potentially long-lasting effects on price (3.1), the importance of demand for inventories (3.2), and the prominent role of forward-looking expectations (3.3).

3.1. Production and demand

Wheat is an important crop in the US, mostly used for food production, with a small fraction becoming animal feed and no utilization as feedstock to generate biofuel, which means that the main buyers of wheat are flour mills, food processors, and direct consumers. As it represents a basic staple commodity, it is well known that in developed countries the demand for wheat as food consumption accounts for a very small fraction of households' expenditure and thus is inelastic to income changes. For these reasons, aggregate demand for wheat has been fairly stable in recent US history.

Modifications in dietary behavior tend to last several years, potentially contributing to the generation of slow cycles that is not uncommon to observe in commodity prices, an aspect that suggests the use of a model capable of capturing long-lasting dynamics. Due to dietary habits and the fact that wheat constitutes a small fraction of the final retail processed food, demand is expected to show a relatively low price elasticity.

[6] For a similar procedure see Stock and Watson (2002). Notice that if the unit root test fails to reject, we have to proceed differently by taking the first differences of the variable.

[7] We also run the same unit root test on the other remaining variables, and we always reject the null except for the real interest rate and the real oil price.

Like other agricultural commodities, supply shocks are believed to dominate wheat price dynamics, with the short run influenced by weather fluctuations, planting decisions, and pest outbreaks, while the long run is determined by relative land scarcity, input availability, and technological progress. During most of the time period of our sample (1950-2018), the United States was a major producer and exporter of grains and the largest exporter of wheat. Holding a dominant position as a swing producer on the global wheat market for many years, the domestic US price was also the main benchmark for wheat produced in other countries. This situation allows us to focus on the US domestic market conditions when studying the determination of the US domestic price of wheat. The influences produced by events that changed world market conditions will be captured by a shock that we identify from the demand function.

3.2. Inventories

The winter wheat variety, which accounts for most of the production, is cultivated throughout the country, planting in September-October and harvesting in June-July of the following year. This lengthy growing process, the inherent randomness of weather as a key determinant of harvest, and the high degree of storability (which could potentially reach 30 years) are three features that explain the important role played by storage and forward-looking expectations in this market. Uncertainty about future production and prices explains the opportunity to hold inventories with the aim of smoothing consumption over time but also to bet on market trends in a speculative fashion.

A long-standing theoretical literature that dates back to Gustafson (1958) and Williams and Wright (1991) has examined the optimal intertemporal decision problem behind the demand for inventories. Storage offers a mechanism to transfer production across periods, in this way buffering consumption against unpredictable fluctuations in harvest, which are mainly driven by weather (Deaton and Laroque, 1996). This mechanism explains, at least for the most part, why agricultural commodity prices exhibit strong serial correlation despite the fact that weather is largely uncorrelated from year to year.[8]

For our purposes, it is important that our model of the wheat market includes an explicit consideration of the demand for inventories. Indeed, one of our aims is to verify the extent to which the storage mechanism has acted to dampen the effects of increased weather and harvest variability, uncovered in the previous section, thus stabilizing the price dynamics. We need to identify two distinct demand functions, a flow demand driven by current food consumption and a speculative demand associated with storage (or stockholding). Distinguishing between these two components of demand is crucial for any correct estimation but is particularly important in our case. Only by separating the forward-looking part that depends on the expectations about future prices from that part that is related to current consumption needs, we will be able to assess the role of the storage mechanism and also explore its ability to adapt to a new regime of higher harvest variability.

As anticipated in the Introduction, we are interested in studying the role of speculation in physical inventories at annual frequency, and not the high-frequency speculation in financial markets linked to the wheat commodity.[9] However, financial speculation in the futures market plays an indirect role here by influencing the expectations of physical speculators (or storers), and thus their choice with respect to the wheat stocks to carry from one year to another. Hence, expectations of the physical speculators might include a sunspot component generated in the financial market.

According to the traditional storage theory, demand for inventories has two main determinants, expectations of the future price relative to the current market price and the cost of carry (Williams and Wright, 1991). Expectations about the future price level are influenced by news and beliefs about the prevailing market conditions in the following periods. The cost of carry is the cost of holding physical wheat inventories for a certain period of time, which includes storage, insurance, and capital costs.

Storage includes warehousing cost (often in the form of a rental), and maintenance activities such as the drying and the aeration process to remove moisture and keep a specific temperature, shrinkage, physical handling of the grain, and pest control. Capital costs are the interest payments on existing loans used to invest in physical inventories or the opportunity cost of foregone returns from a risk-free investment. While storage costs do not vary much over time, capital costs are the most variable component of the cost of carry and are typically summarized by the market interest rate on government bonds.[10]

3.3. Expectations

Expectations about future commodity market conditions are a key determinant in both the production and inventory decision. In our modeling strategy, we derive such expectations indirectly as an unobserved shock from a model that includes the forward-looking variable “change in inventories” and is subject to a set of theoretical restrictions. Such an approach has been advocated by Kilian and Murphy (2014) as a way to solve the non-fundamentalness problem of SVARs that is alternative to the inclusion of a financial asset price, such as futures prices, which is supposed to incorporate all relevant forward-looking information.

We prefer the solution of Kilian and Murphy (2014) to that of including the futures price of wheat for a number of reasons. First, we do not know precisely to what extent the expectations of financial traders are representative of those of the physical market participants, which is our focus here. Only a small fraction of wheat farmers participate in futures and option contracts, with, for

[8] For a recent overview of this literature see Wright (2014).

[9] Notice that while speculation in commodity markets is recognized to have a stabilizing role at low frequencies smoothing the price dynamics across periods, at high frequencies it can have destabilizing effects even under the assumption of rational economic agents (Hart and Kreps, 1986).

[10] There is substantial evidence that storage fees charged for wheat and other grains are quite stable across long time intervals. See, for instance, the evidence discussed in Cafiero and Wright (2011).

example, 5% of all farms in 2016 (USDA, 2020). Second, the amount of arbitrage activities between the financial and physical markets of wheat is unclear, and this depends, among other things, on the liquidity of the futures market, which may have varied substantially over time. Fourth, there is no compelling evidence that the futures price is the best forecast as dictated by the efficient market hypothesis.[11] Fifth, we found data on hard wheat futures only from 1970, which would cut considerably the already not vast number of degrees of freedom that we have available to perform inference on our SVAR model.

4. A model of the commodity market

Considering the aspects of the wheat sector discussed in the previous section, a natural choice to answer our questions about the influence of climate change on the price of wheat, along with the role of the other market forces, is to rely on a Structural VAR model (SVAR). The strengths of this econometric approach which are relevant to our investigation are at least three: the clear benefits of thinking about identification in a coherent and systematic fashion; the possibility of representing the effects over time thanks to the intrinsically dynamic features of the model; the attractive ability to estimate the influence of expectations without the need to model the specific mechanism that generates them.[12] In the following, we present our model, first indicating how we deal with potential non-linear effects (4.1), and then explaining our identification scheme (4.2).

4.1. Non-linear effects

Despite the advantages mentioned earlier, the linear nature of an SVAR modeling approach could represent a major limitation when the subject of investigation is weather and agricultural production. Supported by agronomic science, there is extensive evidence, indeed, that the impact of temperature on crop yield is highly non-linear. We address this evident limitation of the SVAR approach first by introducing an additional quadratic component for temperature level, but we find that its contribution is negligible, with the consequence that results are virtually identical to the model without a quadratic component. Then, we replace our average temperature level with *growing degree days*, a variable that incorporates the non-linear impact of heat on plant growth. Also in this case, results do not change in any noticeable way, confirming the robustness of the main conclusions reached using the average temperature level (see Appendix B for more details). Nevertheless, we have to admit that detection of significant non-linear effects would probably require an investigation at a more disaggregated level.

4.2. Identification scheme

We consider an SVAR model in 9 variables, temperature (T_t), precipitation (P_t), crop area (A_t), real oil price (o_t), real interest rate (r_t), GDP change (Y_t), wheat harvest (H_t), inventory change (I_t), and real price of wheat (pr_t), which can be represented as

$$B_0 z_t = v + \sum_{i=1}^{m} B_i z_{t-i} + \varepsilon_t \tag{3}$$

where $z_t = \left[T_t, P_t, A_t, o_t, r_t, Y_t, H_t, I_t, pr_t\right]'$ is the vector containing our nine variables, v is a vector of intercepts with v_j indicating the j-th element, B_0 is the matrix of structural contemporaneous parameters, B_i is the matrix of the structural parameters associated with the i-th lag of the same variables, m is the lag order, which, following standard information criteria (BIC and HQ), we set equal to 1, and ε_t is the vector of mutually and serially uncorrelated structural shocks that have distinct economic meanings.

The SVAR model is identified by means of a set of exclusion restrictions on B_0, indicated by the following system

$$\begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ b_{21} & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & b_{54} & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & b_{64} & b_{65} & 1 & 0 & 0 & 0 \\ b_{71} & b_{72} & b_{73} & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & b_{84} & b_{85} & 0 & b_{87} & 1 & b_{89} \\ 0 & 0 & 0 & 0 & 0 & b_{96} & b_{97} & b_{98} & 1 \end{bmatrix} \begin{bmatrix} u_t^T \\ u_t^P \\ u_t^A \\ u_t^o \\ u_t^r \\ u_t^Y \\ u_t^H \\ u_t^I \\ u_t^{pr} \end{bmatrix} = \begin{bmatrix} \varepsilon_t^T \\ \varepsilon_t^P \\ \varepsilon_t^A \\ \varepsilon_t^o \\ \varepsilon_t^r \\ \varepsilon_t^Y \\ \varepsilon_t^S \\ \varepsilon_t^{SD} \\ \varepsilon_t^{FD} \end{bmatrix}, \tag{4}$$

where u_t^j denotes the reduced-form VAR error of the j-th variable.

We can distinguish three blocks of equations corresponding to our three groups of variables: 1) an agricultural block that defines the main determinants of agricultural production (T_t, P_t, and A_t); 2) a macroeconomic set of factors (o_t, r_t, and Y_t); 3) a set of

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[11] Alquist et al. (2013) find that futures prices are worse than the random walk model at predicting the nominal and real oil prices one year or more ahead. Chinn and Coibion (2014) show that the futures price for wheat helps to predict the sign of the future change in price, but reduces only marginally the squared forecast errors compared to the random walk model.

[12] Apart from a wide literature on the oil market, an example of which is Kilian (2009), the use of SVAR models to study agricultural commodity markets remains quite rare, with the exception of, for instance, Hausman et al., 2012 and Carter et al., 2017. Kilian and Murphy (2014) highlight the opportunity of using an SVAR model to capture expectations shocks.

market-specific forces for wheat commodity (H_t, I_t, pr_t). The first two blocks are strongly exogenous with respect to the third block, with the exception of A_t. This assumption is trivial for the two weather variables, but is also unquestionable for the macroeconomic variables, given that the wheat sector represents only a tiny fraction of the US economy.

As for the first block, we assume that both T_t and P_t are functions of only their own lags, but we allow P_t to depend contemporaneously on T_t to capture potential comovements. A_t is largely the result of the planting decision taken the year before the current marketing year (Sep-Oct), so it does not depend on any contemporaneous variable, but it is function of the lagged values of all the other variables, including in particular past values of oil price, interest rate, wheat price, and inventories, but also previous crop area choices and past weather conditions that might have long-lasting effects on soil conditions.[13] From this block, we identify a *temperature shock* ε_t^T which coincides with the unexpected change in temperature given observation of the previous period's temperature, a *precipitation shock* ε_t^P that captures unexpected changes in precipitation that are orthogonal to temperature, and a *crop area shock* ε_t^A which amounts to the corresponding VAR reduced-form error.

For the second macroeconomic block, we have no strong a priori belief given the annual frequency. So, we simply impose a triangular structure where the oil price is ordered first, considering that the oil price is determined by global market conditions, but without any ambition to identify the interest rate shock or the GDP shock. Moreover, we restrict to zero all the lagged variables that originate from the first and third blocks, given the irrelevance of the wheat sector in the overall US economy. From this block we identify an *oil price shock* ε_t^o.

The third block describes the wheat commodity market, so we analyze one equation at a time. The first equation describes harvest as a function of current T_t, P_t, and A_t. We exclude all current macroeconomic factors, but also current wheat price pr_t. The reason to assume a vertical supply curve is simple: the wheat production process starts with the planting decision in September-October of the previous year, so at least eight months earlier, which means that most of the input decisions have already been taken (land rental, seeds, soil preparation and management, irrigation, fertilizers, pesticides), and thus most of the costs are sunk when we arrive to June at the start of the wheat marketing year. Even if the farmer is able to observe the price in the first month of the marketing year, it is very unlikely that he significantly modifies the amount of harvest depending on the current price of wheat or the current price of oil.[14] Having said that, the harvest decision remains a function of the lagged values of all variables. In particular, we include the oil price in the previous period, which is the relevant time for most of the production decisions. Oil price affects the production process indirectly through its influence on natural gas price, used to produce fertilizers, such as nitrogen and other chemicals, and directly as a fuel for agricultural machinery. The residual ε_t^S is the *supply shock*, which captures other omitted supply factors, such as changes in labor supply and technological innovation.

The second equation of the third block describes the speculative demand for inventories. This year's change in inventories is a function of the current value of oil price, interest rate, harvest, and wheat price. The price of oil influences the storage costs, while the interest rate is a proxy for capital costs (see discussion in the previous section). We include current harvest since speculators are likely to take their inventories decision after observing this year's harvest. We exclude current T_t, P_t, A_t, and Y_t as they are not of direct relevance to the speculator. The demand for new inventories is also a function of all lagged values, except for past T_t, P_t, A_t, and o_t, which are not relevant for current inventories decisions. The residual ε_t^{SD} is the *speculative demand shock*, which captures the change in expectations about the future price of wheat. These expectations reflect the conditional mean of the future price level, the uncertainty about future demand and supply conditions, and possibly also the prevailing market beliefs about ongoing market trends.

The third equation of the third block represents the demand for wheat for food consumption, written in its inverse form with price as dependent variable. In this equation, the flow demand is obtained using the equilibrium market condition between the supply (H) and the total demand, which is made up of the two components, the flow demand (FD) and the speculative demand for inventories (I): $H = FD + I$. From this equilibrium condition we obtain the flow demand as the difference between harvest and demand for inventories, $FD = H - I$. Hence, we impose the restriction that $b_{98} = -b_{97}$. We assume that the current price of wheat is the main determinant, along with the current change in GDP, but we exclude current weather conditions, interest rate, or oil price as important factors. As for the previous equation, we assume that flow demand is also a function of all lagged values, except the past T_t, P_t, A_t, and o_t, which are not relevant to the current consumption decision. The associated ε_t^{FD} is the *flow demand shock*, which includes shifts in preferences and tastes, as well as changes in global market conditions.

5. A structural change analysis

Our novel econometric procedure is centered on a structural change analysis of our SVAR model represented by equations (3) and (4). Therefore, in this section, we first provide the motivation for such analysis (5.1), then we describe how it is implemented (5.2), and finally, we illustrate its implications for our SVAR model (5.3).

[13] Considering that A_t is harvested rather than planted crop area, in a previous estimated version of the model we also allowed A_t to depend on contemporaneous T_t and P_t to capture the potential impact of extreme events such droughts, but their coefficient turned out to be largely not significant.

[14] Given that most of the costs are sunk, it makes sense to destroy the crops only if the market price falls below the variable cost of the harvesting activity, which is a rare event. During the Great Depression, for instance, the price plummeted to an unprecedented low level that might have justified crop destruction, but this was mainly the consequence of the government encouraging this act to clear the overproduction of the previous years. Note also that the grain market is widely considered to be closer to competition than any other market structure, which means that farmers do not have much power to influence the price by choosing a lower harvest. Finally, if the price is too low, the farmer who does not want to sell has always the option to store some of the harvest, which is equivalent to buying speculative inventories.

5.1. Motivation

As for many other annual agricultural commodities, the supply side represents the main source of variation for wheat price. Of these supply-side factors, weather is the key random unpredictable driver, with respect to which stockholding constitutes a buffer mechanism.[15] Introducing a speculative demand component on top of the demand for current consumption implies, by definition, a higher total market demand elasticity to price, which *per se* has the effect of reducing price variability. However, rational storage theory also suggests that the equilibrium level of inventories is an increasing function of the standard deviation of harvest and thus weather volatility (Deaton and Laroque, 1996).

The intuition is simple. A change in the conditional mean of harvest does not modify the systematic storage behavior of the storers, but it simply produces a one-time modification in consumption and so in the price level, which, if anticipated, is spread over time. On the contrary, an increase in the conditional variability of harvest entails a change in the opportunities to profit from speculation in inventories, given that the probability that future prices will exceed the level that makes it profitable to hold inventories is now higher. If future harvest is expected to be more volatile as a result of higher weather variability, it is optimal for the risk-neutral profit-maximizing stockholder to respond to this greater harvest uncertainty by increasing its demand for inventories.[16]

In the case of US wheat production, we found that there has been a permanent increase in weather variability around 1974. As speculators realize that such change is permanent and not simply unusually high temporary shocks in the weather process, we expect some permanent adjustment in the speculative demand for inventories to follow. Deaton and Laroque (1996) claim that the equilibrium level of inventories should be higher if the harvest has a higher variance. We expand this theoretical insight and explore whether there has been a more general change in the systematic behavior of speculators. If the idea is that equilibrium inventories are higher because there are larger opportunities to profit from holding inventories, we should also expect a stronger reaction of the speculators to new emerging profit opportunities generated by a change in the economic conditions, for instance, as a result of a decrease in current spot price (relative to the expected future spot price), a fall in the cost of carry driven by a decline in the interest rate, or a drop in energy price.

In our representation of the speculative demand for wheat, the ninth equation of model (4), new inventories are a function of the current values of oil price, interest rate, harvest, and wheat price, in addition to all lagged variables. We want to test the hypothesis that the systematic relationship between demand for inventories and all these factors changed in response to the higher profit opportunities generated by the observed higher harvest volatility. And if this change occurred, we want to know how the weight assigned to each factor shifted. In particular, we are interested to know whether there was an increase in the elasticity of inventories to the current wheat price. In econometric terms, we want to verify whether there is enough evidence of a structural change in the relevant parameters of the speculative demand equation of model (4).

In addition to modifying the systematic behavior of the speculative demand for wheat, a permanent change in harvest volatility may also influence the size of the speculative demand shock ε_t^{SD}. This is because the speculative demand shock incorporates all the forward-looking expectations of future prices, and in particular the perceived uncertainty about future market conditions. If harvest becomes more volatile, this can translate into greater uncertainty about future market conditions, and so the residual expectations-driven component of the speculative demand for wheat may increase in size. Therefore, it is also important to verify whether there is evidence of a structural change in the standard deviation of the speculative demand shock ε_t^{SD}.

It is worth stressing that, while an increase in price elasticity has evident stabilizing effects on the equilibrium price, an increase in the typical size of the speculative demand shocks, perhaps driven by self-fulfilling trends or sunspots, is obviously destabilizing. Therefore, examining the evidence of a possible change in these two dimensions of the speculative demand for wheat provides a way to answer the more general question of whether speculation is capable of beneficial effects by dampening the impact of climate change on price variability or is instead detrimental by amplifying the increased random variations originating in the weather process.

Before illustrating in detail the methodology we use to explore the evidence that the speculative demand for inventories changed in response to the increase in weather and harvest variability, it is useful to have a comprehensive look at all the possible sources of price variability implied by our model (4). If we solve this model for the equilibrium level of the unexpected part of wheat price, we obtain

$$\begin{aligned} u_t^{pr} = {} & \frac{b_{97}\left(b_{71}-b_{72}b_{21}\right)}{1+b_{89}b_{97}}\varepsilon_t^T + \frac{b_{97}b_{72}}{1+b_{89}b_{97}}\varepsilon_t^P + \frac{b_{97}b_{73}}{1+b_{89}b_{97}}\varepsilon_t^A - \frac{b_{97}b_{84}}{1+b_{89}b_{97}}\varepsilon_t^o \\ & - \frac{b_{87}b_{97}+b_{96}}{1+b_{89}b_{97}}u_t^Y - \frac{b_{97}b_{85}}{1+b_{89}b_{97}}u_t^r + \frac{1}{1+b_{89}b_{97}}\left[b_{97}\left(\varepsilon_t^{SD}-\varepsilon_t^S\right)+\varepsilon_t^{FD}\right], \end{aligned} \tag{5}$$

where we have all the relevant structural parameters and structural shocks, apart from the interest rate (u_t^r) and GDP (u_t^Y), which on purpose we leave unsolved since we do not identify proper corresponding economic shocks.

From equation (5) it is evident that price variability depends first of all on the price elasticity of both the speculative demand (b_{89}) and the flow demand ($1/b_{97}$). Then, it is clearly a function of the variance of all structural shocks of the model, the agricultural

[15] Other supply factors like land allocation and availability, technological improvements, and labor supply changes, are more relevant for the long-run horizon and are largely anticipated or observed by the speculator.

[16] In the case of a linear demand function, Deaton and Laroque (1996) find that the optimal amount of storage is exactly proportional to the standard deviation of harvest.

block (ε_t^T, ε_t^P, ε_t^A), the macroeconomic block (ε_t^o), and the wheat market block (ε_t^S, ε_t^{SD}, ε_t^{FD}). For the sake of completeness, we will examine the evidence of a possible shift also in this set of shock variances.

5.2. Estimation approach

Model (3) with the accompanying theoretical restrictions in (4) is a standard SVAR model with constant parameters. We use this model to achieve two objectives. First, to verify the extent to which the break in the unconditional variance of harvest, found in Section 2, is due to weather alone or other determinants play a significant role. Second, to explore the hypothesis that the relevant elasticities of the speculative demand for inventories have shifted as a result of increased weather and harvest variability. We perform such analysis by estimating the SVAR model via a single-equation approach based on instrumental variables (IV), and by applying a partial break version of the stability test developed by Hall et al. (2012).

Following the order of the equations in model (3), we estimate one equation at a time and we use the resulting estimated shocks as instruments in the estimation of the following equations. Once we arrive at the harvest equation, we use the corresponding IV residuals to test for a break in the variance of ε_t^S (the conditional variance of harvest).[17] A rejection of the null would imply that an omitted factor, not included in the model, is also contributing to the observed increase in harvest variability.

Once we arrive at the speculative demand equation, we run a test for a partial break at the known year 1974, which involves the intercept (v_8), the coefficients of oil price (b_{84}), interest rate (b_{85}), harvest (b_{87}), and wheat price (b_{89}). To account for heteroskedasticity we choose a Wald-type test constructed via a 2SLS estimation, following Hall et al. (2012). In Appendix A we describe in detail how this test is constructed. After performing this test, we use the IV residuals from the speculative demand equation to test for a break in the variance of the speculative demand shock.[18]

5.3. The SVAR model with break

The break test analysis above produces one of two possible outcomes: there is evidence of a structural change in the elasticities of the speculative demand for wheat and possibly in the size of the associated shock, or we conclude that the same set of parameters is constant over the whole sample period. In the latter case, the SVAR model represented in equation (3) retains its validity, and the dynamic features of the model can be analyzed via a unique set of impulse response functions (IRFs). In the first case, on the contrary, we have to modify the SVAR model by incorporating the shift in parameters occurring at 1974. In this case, equation (3) is replaced by the following SVAR model with break

$$B_0^{(1)} I\,(t \le \tau)\, z_t + B_0^{(2)} I\,(t > \tau)\, z_t = v + \sum_{i=1}^{m} B_i z_{t-i} + \varepsilon_t \tag{6}$$

where $I\,(\cdot)$ is an indicator function that takes on the value of 1 when the event in brackets occurs and 0 otherwise, and $B_0^{(l)}$ represents the regime-specific contemporaneous correlation matrix, with $l = 1, 2$.

Apart from the one-time episode of non-linearity, the model remains linear within each of the two segments $[1..\tau]$ and $[\tau + 1..T]$. As a consequence, there are two reduced-form VAR representations, each associated to respectively the period before and the period after the structural change occurs

$$\begin{cases} z_t = \mu^{(1)} + \sum_{i=1}^{m} A_i^{(1)} z_{t-i} + C_0^{(1)} \varepsilon_t,\ E\left[\varepsilon_t \varepsilon_t'\right] = \Sigma_\varepsilon^{(1)} & \text{for } t \le \tau \\ z_t = \mu^{(2)} + \sum_{i=1}^{m} A_i^{(2)} z_{t-i} + C_0^{(2)} \varepsilon_t,\ E\left[\varepsilon_t \varepsilon_t'\right] = \Sigma_\varepsilon^{(2)} & \text{for } t > \tau \end{cases} \tag{7}$$

where $\mu^{(l)} = C_0^{(l)} v$, $A_i^{(l)} = C_0^{(l)} B_i$, $C_0^{(l)}$ is the inverse of $B_0^{(l)}$, $\Sigma_\varepsilon^{(l)}$ is the regime-specific covariance matrix of the structural shocks, and the superscript $l = 1, 2$ indicates the regime.

Notice, in particular, that a structural change in B_0 or in Σ_ε implies that we now have two regime-specific reduced-form error covariance matrices $\Sigma_u^{(l)}$

$$\begin{cases} \Sigma_u^{(1)} = C_0^{(1)} \Sigma_\varepsilon^{(1)} C_0^{(1)\prime} & \text{for } t \le \tau \\ \Sigma_u^{(2)} = C_0^{(2)} \Sigma_\varepsilon^{(2)} C_0^{(2)\prime} & \text{for } t > \tau. \end{cases} \tag{8}$$

From these two essentially distinct SVAR models we obtain two sets of IRFs, which allows us to study how the dynamics of the wheat market changed as a consequence of the increase in weather and harvest variability and the ensuing adjustment of the speculative demand for inventories.

[17] This test is constructed similarly to the one used in the univariate analysis of section 2 and consists in regressing the squared residuals on a constant, and then using a Wald statistic for one break in this constant at the same year 1974.

[18] To exclude the risk that results are confounded by modeling a spurious break in price elasticity, we run this test conditioning both on constant and breaking parameters.

Table 2
Break in typical size of shocks.

	Wald	pvalue	σ_1	σ_1	unit
ε_t^T	7.686	0.006	0.477	0.759	C
ε_t^P	2.073	0.150	9.375	7.126	mm
ε_t^A	0.880	0.348	4.642	3.880	acres ml
ε_t^o	8.632	0.003	3.610	11.439	2012$
ε_t^r	0.018	0.891	1.084	1.044	%
ε_t^Y	6.950	0.008	94.102	160.310	2012$ bl
ε_t^S	2.384	0.122	122.670	157.350	bu ml
ε_t^{SD}	0.039	0.843	138.050	132.370	bu ml
ε_t^{FD}	1.480	0.224	1.855	0.919	2012$

6. Results

In this section, we present the results that we have obtained by implementing the empirical approach described in the previous section. First, we examine the evidence of instability in the structural parameters of the B_0 matrix and the variance of all structural shocks (6.1). Then, we discuss the dynamic implications for the whole system of the detected parameter instability (6.2). Finally, we perform a counterfactual calculation that provides a numerical measure of the contribution of speculation in offsetting or amplifying the impact on price of weather and harvest variability (6.3). Standard validation checks of our SVAR model can be found in Appendix C, Tables 8–10.

6.1. Evidence of instability

The Wald tests for a break in the variance of each structural shock identified in our model are displayed in Table 2, along with the magnitude of the standard deviation before and after the break. Even using a relatively generous significance level of 10%, we found a break in the variance of only three shocks, ε_t^T, ε_t^o, and ε_t^Y. The first confirms our preliminary reduced-form analysis on temperature; the second reflects a highly more volatile period that begins with the oil price crisis of 1973; and the third is probably related to the 2008 Great Recession. The Wald test for a break in the residual variance of harvest is 2.384 with a p-value of 0.122, suggesting that, apart from weather, energy price and GDP, there are no other factors behind the increased harvest variability.

When we analyze the speculative demand for inventories, we find that the Wald test for a fixed partial break in the set of relevant parameters (v_8, b_{84}, b_{85}, b_{87}, b_{89}) is 3.398 with a p-value of 0.004. This implies that there is strong evidence of a shift in all relevant elasticities of the speculative demand for wheat. If we test for a partial break only in the price coefficient b_{89} we obtain a statistic of 3.866 with a p-value of 0.049, which is still significant at 5%, confirming the presence of an adjustment in the price elasticity in particular.

The Wald test for a break in the variance of the speculative shock fails to reject, with a statistic equal to 0.039 and a p-value of 0.844, so we can conclude that there is no significant change in the size of the speculative shock.[19] In fact, the standard deviation calculated before and after 1974 shows a tiny decrease.

As an additional check, we also test for a partial break in the relevant parameters of the flow demand equation (v_9, b_{96}, b_{97}). The Wald statistic is 1.388 with a p-value of 0.244. The test on a break only in the corresponding price coefficient is 1.809 and the p-value is 0.179. Also for this equation there is no evidence of a break in the residual variance.

Considering that the unstable shock variances are only three, those associated with ε_t^T, ε_t^o, and ε_t^Y, and they all increased after 1974, we can safely conclude that there are no sources, other than the shift in the regression parameters, responsible for offsetting the effects of higher weather variability. On the other hand, we have to recognize that weather was not the only source of increased harvest variability. Contemporaneously to the increase in the typical size of a temperature shock, there was also an increase in the variance of the oil price shock and the macroeconomic conditions represented by the GDP shock. The relative importance of these different sources of variability can be uncovered by calculating their structural impact on harvest and price, which we do in the following two sections.

6.2. Dynamic implications of instability

Following the strong evidence of a break in the structural parameters of the speculative demand equation, as well as in the variance of ε_t^T, ε_t^o, and ε_t^Y, the correct representation of our system is the SVAR model with break defined in equation (6).

The estimates of the relevant rows of the matrix B_0 are shown in Table 3. The first two rows represent the two weather equations; the third row is the harvest equation; the fourth and fifth rows are the speculative demand for inventories before 1974 (regime 1) and after (regime 2); and finally, the sixth row is the flow demand equation. Once we express each equation in terms of the corresponding dependent variable (and thus change sign), we observe that the estimated signs and magnitudes are broadly consistent with what is predicted by economic theory and intuition.

[19] Same conclusion is reached if the test is run conditional on constant parameters. In this case, the statistic is 0.873 with a p-value of 0.350.

Table 3
B_0 matrix.

	T	P	A	o	r	Y	H	I	pr
T	1	0	0	0	0	0	0	0	0
P	3.276 (0.014)	1	0	0	0	0	0	0	0
H	17.906 (0.589)	−5.334 (0.019)	−37.913 (0.000)	0	0	0	1	0	0
I_1	0	0	0	27.776 (0.010)	4.028 (0.850)	0	−0.888 (0.000)	1	12.413 (0.610)
I_2	0	0	0	0.756 (0.717)	37.087 (0.031)	0	−0.448 (0.000)	1	62.786 (0.000)
pr	0	0	0	0	0	4e-07 (0.700)	0.001 (0.143)	−0.001 (0.143)	1

Note: entries are IV estimates, with heteroskedasticity-robust p-values in brackets.

As expected, in the equation for P_t temperature enters significantly and with a negative sign, reflecting the typical negative correlation. In the equation for H, the contemporaneous coefficient on temperature is negative, although not significant, while that on precipitation is positive and significant, both results of which match the marginal effect typically estimated by existing empirical studies on wheat crops that include non-linear specifications. The crop area, the most important decision of the farmer, enters the harvest equation positively and with strong statistical significance.

In both regimes, the speculative demand for inventories presents coefficients with meaningful signs. The marginal effect of oil price is negative, as it affects storage costs; that of interest rate is negative, reflecting the capital cost of holding inventories; that of harvest is positive, suggesting that a higher harvest creates incentives to accumulate more wheat stocks; and that of price is negative, since the returns from holding stocks increase whenever the current price falls *ceteris paribus*.

Moving from one regime to the other, there are important changes in the parameters that describe the systematic behavior of the speculators. After the break, the coefficient on oil price decreases and loses its significance, whereas that on the interest rate increases in size and gains significance. Harvest remains important in the decision of the speculator, although it loses some of its weight. The price coefficient is not significant before the break but becomes larger and strongly significant after the break. In absolute value and with respect to inventories level, the price elasticity of speculative demand increases from 0.132 to 0.669.

This shift in parameters appears plausible and in line with economic intuition. As harvest is more volatile and less predictable in the future, the speculator decides its new inventories level by giving less weight to current economic conditions, such as storage costs and this year's harvest, while more importance is assigned to those factors that determine its future expected returns, such as interest rate and current price relative to the expected future price. Before the break, the speculators were absorbing a higher fraction of the current harvest in a rather mechanical fashion; now, after learning about the higher harvest volatility in the future, this mechanical fraction is smaller, because current production is less important.

The increased responsiveness to price enhances the stabilizing effect on price, whereas the lower responsiveness to harvest reduces such effect. So the net effect of this adjustment on price variability is *a priori* unclear at this stage, but can be uncovered by looking at the IRFs and calculating the conditional variance under different counterfactual scenarios.

In the flow demand equation, Y_t is not significant, while the coefficient on H_t and I_t is negative as expected, but fails to be significant as the p-value is 0.143. This result is not surprising given the well-known characteristics of wheat consumption described in section 3.

In sum, we found strong statistical evidence of two regimes in the structural parameters of the model and also a large numerical difference in the size of these parameters. Conditional on this result, we have two regime-specific IRFs that describe the dynamics of the system before and after the break. To evaluate the numerical difference in this dynamics, we display in Fig. 2 and 3 the IRFs to a typical shock (one standard deviation), in regime 1 (red line) and in regime 2 (blue line), along with the one standard deviation confidence band to highlight the statistical significance of the dynamic responses in each regime.[20]

We first comment on the effects of the three agricultural shocks, shown in Fig. 2. A positive temperature shock is accompanied by a decrease in precipitation, which negatively affects harvest in the same year. The contemporaneous effect on price is positive, but not significant. There is a difference between the two regimes: after the break the size of the shock is larger, 0.76 degree Celsius instead of 0.48, and so is the decrease in precipitation; the immediate impact on harvest is -27 million bushels rather than -17; in both regimes there is a decline in inventories that is equal to 15 million bushels, and it is significant only in regime 1. After one year, there is a decrease in crop area of 1 million acres in regime 2 and 0.38 in regime 1. Reflecting this difference, harvest decreases by 57 million bushels in regime 2 and 32 in regime 1, while inventories shrink by 29 million bushels in both regimes. After two years,

[20] We choose a 68% confidence band since this is a common choice in many studies and is reasonable considering the aggregate data, the sample size, and the relatively loose parameterization of VAR models (Kilian and Lutkepohl, 2017). Moreover, while we obviously loose in statistical confidence, a 68% confidence band tend to have a substantially higher coverage accuracy than those based on 95% (Sims and Zha, 1999). However, except for weather shocks, most of the statistical significance in the dynamic effects on harvest, inventories, and price is maintained using a 90% confidence level. It should be underlined that overlapping confidence bands between the two regimes do not imply a lack of statistically significant differences between IRFs.

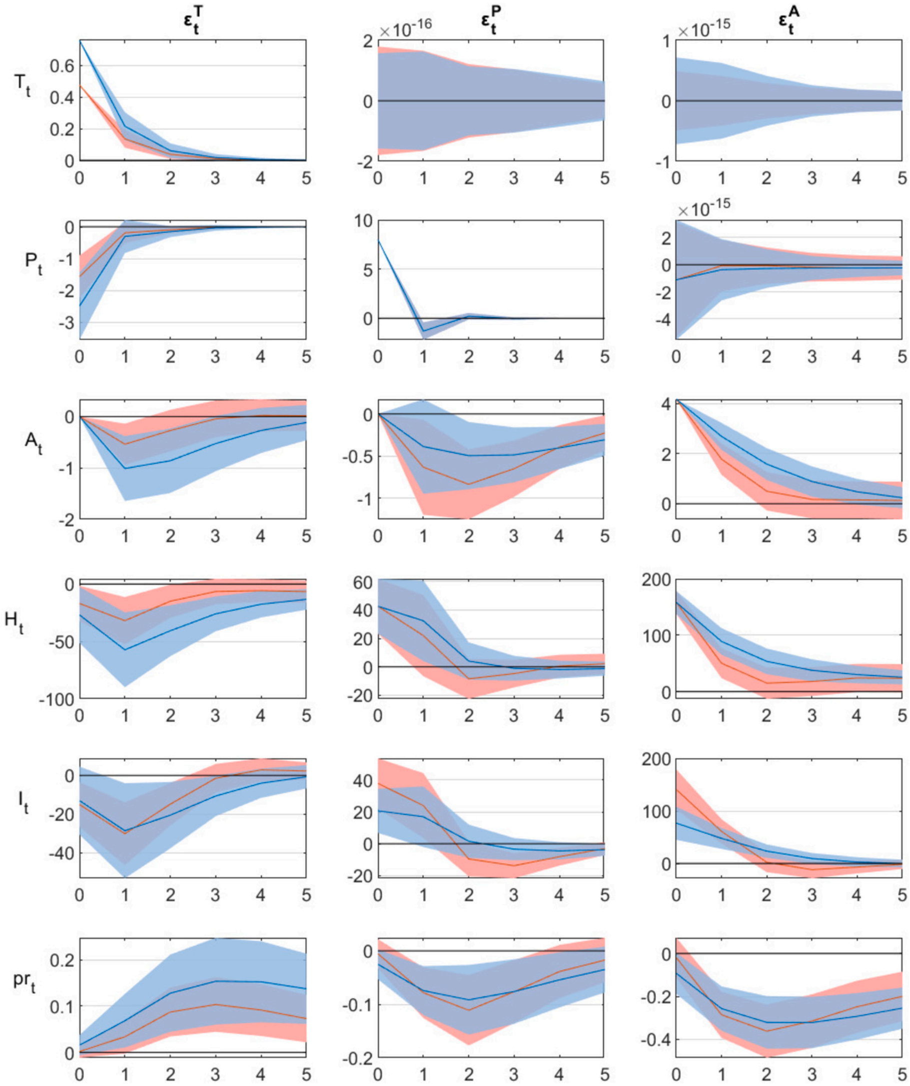

Fig. 2. IRFs of regime 1 (red) and regime 2 (blue). T_t is measured in °C, P_t in mm/month, A_t in million acres, H_t and I_t in million bushels, and pr_t in 2012$.

crop area, harvest, and inventories start their path back to equilibrium. Notable is the dynamics of wheat price, which increases after one year in both regimes, but more strongly in regime 2 reaching a peak of $0.15 after three years.

A positive precipitation shock of 8 mm has a strongly significant contemporaneous impact on harvest under both regimes, triggering a increase of 43 million bushels. At the same time, inventories increase by 21 and 38 million bushels in regime 2 and 1 respectively. There is no significant impact on price under either regime. After one year, the harvest is still higher in regime 2, but not in regime 1, before declining back to the starting point in year 2. The inventories return to the starting point after one year in regime 2 and after two years in regime 1. The price falls under both regimes after one year, reaching a peak of -$0.10 after two years under regime 2, before gradually reverting back to its initial level.

A positive crop area shock amounts to an increase in 4 million acres and is highly persistent over time, although more persistent in regime 2. Harvest follows the same pattern, with an initial increase of 158 million bushels under both regimes. Inventories increase by 77 million bushels in regime 2 and 141 in regime 1, and then gradually decline back to the initial level. The effect on wheat price is negative and significant after one year in both regimes, reaching a peak at -$0.32 after two years in regime 2.

We now turn to the wheat market block, displayed in Fig. 3. A positive supply shock increases harvest by 146 million bushels under both regimes, before returning to the starting point after two years in regime 2 and one year in regime 1. There is a contemporaneous increase in inventories, 71 million bushels in regime 2 and 130 in regime 1. There is also a contemporaneous significant drop in wheat price by $0.09 under regime 2, while this drop is significant under regime 1 only after one year. The peak decline in price is higher in regime 1 equaling -$0.27 after two years rather than -$0.23 in regime 2.

A positive speculative demand shock increases inventories by 125 million bushels under both regimes. The contemporaneous effect on wheat price is an increase of $0.14, which is almost significant under both regimes. After one year, there is a drop of 1.8

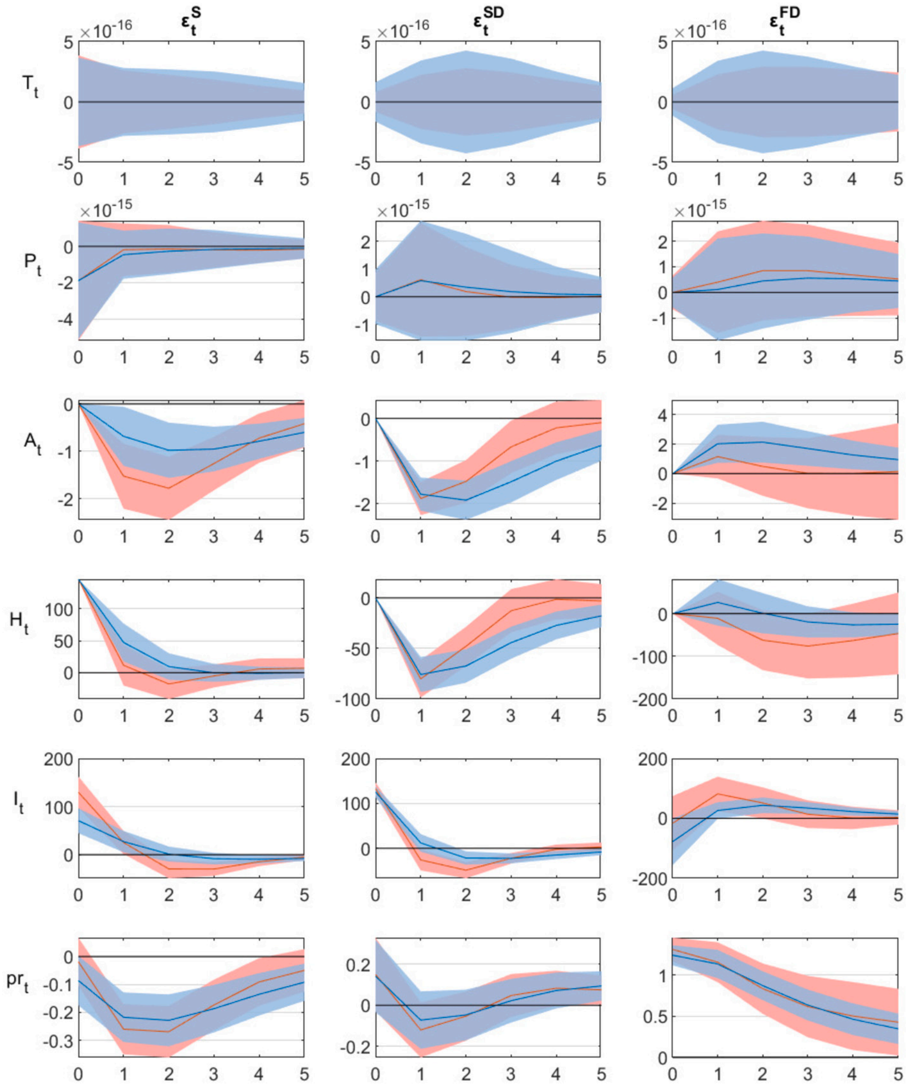

Fig. 3. IRFs of regime 1 (red) and regime 2 (blue). T_t is measured in °C, P_t in mm/month, A_t in million acres, H_t and I_t in million bushels, and pr_t in 2012$.

million acres in crop area under both regimes, which causes a decrease of 76 million bushels in harvest. This decline in harvest is very persistent in both regimes and more so under regime 2. The price is unaffected after one year onwards.

A positive flow demand shock is responsible for a decline in inventories, which is significant only under regime 2 amounting to -78 million bushels. After one year there is a significant increase in crop area under regime 2, but this is not followed by a significant rise in harvest. In the same year of the shock, the wheat price jumps by $1.24 in regime 2 and $1.36 in regime 1. In the following years, the price remains very persistently at a higher level, only gradually declining to its starting point.

An interesting aspect emerging from these results is the different response of crop area to a speculative demand shock and to a flow demand shock. Both shocks push up the price level in the same year of the shock, but while crop area and so harvest decline after one year in the case of a speculative demand shock, the opposite occurs for the flow demand shock. A possible explanation for this different dynamics lies in the very different information conveyed by the initial increase in price in the two cases. After a price increase driven by speculation, farmers reduce crop area and harvest knowing that there is no actual and persistent increase in demand for wheat, while inventories available for the following years are higher. In contrast, after a price increase driven by higher consumption, farmers try to increase crop area and harvest, recognizing a persistently higher demand also in the future, as well as a lower availability of inventories.

Considering the overall pattern of dynamic responses, there are three aspects worth mentioning. First, after 1974 weather shocks have become more important for harvest and wheat price, with potentially long-lasting effects, perhaps related to the persistent modifications that weather events can produce on the soil condition for more than one year. Second, with the exception of weather, all shocks tend to produce smaller fluctuations in price after 1974. This is presumably the result of the increase in price elasticity of the speculative demand for inventories. Third, the flow demand shock dominates over all the other shocks in terms of magnitude of the effects on wheat price.

6.3. Effects of speculation

Our empirical analysis so far has delivered two important findings: 1) the observed increase in harvest variability is most likely the result of higher weather and oil price variability; 2) the adjustment of the speculative demand for inventories has dampened the dynamic effects on price of most economic shocks. In this section, we look at these two aspects in more depth.

With respect to the increased variability of weather and oil price, we can obtain a quantitative measure of their relative importance by calculating a counterfactual variance, namely what the variability of price would have been had the variance of ε_t^T or ε_t^o not increased as it did, conditional on the existence of speculation and its adjustment.

With respect to the permanent change in the speculative actions, it is important to understand to what extent the speculation's adjustment to higher harvest variability counterbalanced the effects of a more volatile harvest on price, and what is the contribution to price variability of speculation altogether. To answer this question we have to calculate what the price variability would have been in the absence of the speculative adaptation, and then in the total absence of speculation.

As for the speculative adaptation, the result is predictable because with a lower price elasticity of total demand, we expect that price variability would have been higher. As for the role of speculation altogether, instead, the answer is uncertain because speculation is comprised here of two components, a systematic part that reacts to price changes and a speculative shock, with the latter adding a new source of variability for the price of wheat. Hence, we use our estimated structural model to calculate the variance of the one-step-ahead forecast error of price under two counterfactual scenarios. In the first, we remove the adaptation by switching off the change in price elasticity of the speculative demand. In the second, we completely remove the speculative demand equation by setting all its coefficients to zero so that we can uncover the overall contribution of speculation to price variability.

Table 4
Counterfactual standard deviation of price error.

pre-break	post-break	no adapt	no spec	no cc	no (o,Y)
1.3229	1.2558	1.3672	1.3387	1.2557	1.2549

The outcome of this counterfactual exercise is shown in Table 4. In the first two columns we show the standard deviation of the one-step-ahead forecast error of price, estimated in the time segments 1950-1974 and 1975-2018, respectively. In the following columns we switch off, one at a time, some of the parameter change that occurred in 1974, so removing the adaptive adjustment of the speculative demand equation (third column), the speculative demand altogether from the system (fourth column), the increased weather variability (fifth column), and the increased variability in oil price and GDP (sixth column).

In the structural change analysis of our SVAR model of the wheat commodity market we found evidence that around 1974 there was a break in the shock variance of temperature, oil price, and GDP. Since all of these three variances increase, we would also expect an increase in the residual variance of wheat price to follow. As a matter of fact, the opposite occurs, as can be seen from the first two columns of the table, where the standard deviation of the one-step-ahead forecast error of wheat price falls from 1.3229 to 1.2558. Clearly, this fall can be explained by the shift in the parameters of the speculative demand function that we uncovered in our structural change analysis above. Indeed, we see that in the absence of speculative activities altogether, the variance would have been much higher (1.3387 instead of 1.2558). But it is interesting to notice that in the presence of speculative activities, this time of the old type (pre-break period), the price variance would have been even higher compared to not having speculation at all (1.3672 instead of 1.3387).

Hence, we obtain a more nuanced picture of the contribution of speculation to price variability. Speculation based on physical inventories is not necessarily stabilizing with respect to the commodity price, but it rather depends on the value of the parameters that govern its behavior. Until 1974, the speculative demand for inventories has been of a destabilizing type, whereas after that year, it has become stabilizing as a result of its adaptation to a more volatile regime of weather and harvest. When we consider the contribution of increased weather variability conditional on the new speculative demand for inventories, we find that this has been positive but negligible, while that of increased variability of oil price and GDP is slightly higher but still very small.

As to our question about the contribution of increased weather variability to the increased variability of harvest, we showed that once we control for temperature (and other factors) in the harvest equation, we find no evidence of an increase in the residual variance of harvest. So, it is useful to provide a quantitative assessment of how the contribution of weather and other factors to wheat price fluctuations changed after the structural break in 1974. For this purpose, we calculate the forecast error variance decomposition (FEVD) before and after the break, and present it in Tables 5 and 6, respectively.

In the short term, before the break, the conditional variance of wheat price is dominated, in decreasing order of importance, by the shocks in flow demand (94%), oil price (4.8%), and speculative demand (1.3%). After the break, the flow demand shock remains the main factor (97%), while the oil price shock loses completely its importance, and the speculative demand shock maintains its contribution (1.3%).

In the long term, before the break, the variance of wheat price is influenced, in decreasing order of importance, by the shocks in oil price (56%), flow demand (32%), the combination of interest rate and GDP (3.9% + 2.4%), crop area (3.3%), and supply factors (1.2%). After the break, the contribution is spread across a wider set of shocks. The flow demand shock now becomes dominant

Table 5
Pre-break FEVD of wheat price.

h	ε_t^T	ε_t^P	ε_t^A	ε_t^o	ε_t^r	ε_t^Y	ε_t^S	ε_t^{SD}	ε_t^{FD}
0	0.00	0.00	0.02	4.84	0.03	0.16	0.02	1.25	93.67
1	0.03	0.18	2.46	2.71	0.04	0.24	2.04	1.12	91.18
2	0.21	0.43	4.99	2.11	0.28	0.46	3.28	0.94	87.30
5	0.56	0.44	6.97	9.60	1.09	0.82	3.05	0.93	76.54
10	0.47	0.29	5.51	34.17	0.85	1.51	2.04	0.72	54.44
∞	0.29	0.17	3.33	55.91	3.94	2.38	1.20	0.44	32.35

Table 6
Post-break FEVD of wheat price.

h	ε_t^T	ε_t^P	ε_t^A	ε_t^o	ε_t^r	ε_t^Y	ε_t^S	ε_t^{SD}	ε_t^{FD}
0	0.02	0.04	0.55	0.00	0.22	0.16	0.47	1.30	97.24
1	0.17	0.21	2.50	0.03	0.22	0.15	1.83	0.86	94.04
2	0.54	0.37	4.50	0.23	0.45	0.30	2.70	0.71	90.22
5	1.64	0.46	8.11	2.47	1.83	0.68	3.16	0.80	80.85
10	2.04	0.41	9.18	7.47	3.05	0.82	2.85	1.25	72.94
∞	1.98	0.38	8.81	12.94	3.17	0.97	2.64	1.28	67.82

(68%), while the oil price shock loses most of its importance (13%), and is followed by the crop area shock (8.8%), the combination of interest rate and GDP shocks (3.2% + 0.97%), the supply shock (2.6%), and for the first time the temperature shock (2%), with the last contribution provided by the speculative demand shock (1.3%).

When we look at the contribution of each shock to the long-term variance of both harvest and inventories, shown in Table 7, we notice that there has been a substantial increase in the importance of weather, crop area decisions, and speculators' expectations, while the contribution of oil price variations has declined considerably.

Table 7
Long-term FEVD of harvest and inventories.

h	ε_t^T	ε_t^P	ε_t^A	ε_t^o	ε_t^r	ε_t^Y	ε_t^S	ε_t^{SD}	ε_t^{FD}
$H^{(1)}$	0.17	0.23	2.88	83.52	5.78	2.6	2.09	0.86	1.87
$H^{(2)}$	5.25	2.12	29.3	27.73	5.13	0.61	17.33	10.12	2.42
$I^{(1)}$	0.78	1.35	13.48	52.24	2.65	0.64	11.13	12.03	5.69
$I^{(2)}$	3.01	1.51	17.13	6.85	3.03	2.42	11.73	33.37	20.95

7. Concluding remarks

We found strong statistical evidence of an increase in the weather variability faced by US wheat farmers, which we estimate to occur around 1974. We exploited this evidence to understand the role of storage and speculation in physical stocks of wheat as a stabilizing device for market price. To perform such an analysis, we built a structural time series model of the wheat commodity market on which we developed a novel empirical procedure to explore the potential adjustment of speculation to increasing weather and harvest variability. As this study largely disregards the potential role of spatial heterogeneity, we would welcome studies that investigate at the micro-level the mechanisms that we uncover at the aggregate national level.

There is strong evidence that speculators in the physical market for wheat adapted their demand for inventories in response to the observed increase in the magnitude of weather and harvest fluctuations. This adaptation we discovered in the data is in line with the predictions of the rational storage theory, but it also offers additional insights into the role and evolution of the speculative demand for physical inventories. In the decision to store, the importance of oil price and harvest declines, while that of interest rate and wheat price rises.

This result has a plausible intuitive explanation. As long as harvest volatility is moderate, the storer is willing to absorb rather mechanically the excess production, since producing a bit more simply implies that one is able to sell it the year after with not much implications for the market price; but when harvest volatility becomes significant, the size of these potential excess productions or shortages starts to become important, and so the storer has to assess more carefully the market conditions before deciding how much to store.

Simultaneously to these changes, we found that expectations about future market conditions did not become more volatile. There is no increase in the variability of speculators' expectations, and thus there is no evident sign of spillovers on the physical market of potentially destabilizing self-fulfilling trends generated in the financial market, at least at the annual frequency.

We uncovered that the contribution of weather shocks to wheat price variability has increased as the frequency of more extreme weather events rises, but the adaptive adjustment in the workings of the wheat commodity market has caused a reduction in the impact on wheat price of all demand and supply shocks. However, using a counterfactual analysis, we discovered that physical speculation is not necessarily stabilizing with respect to the commodity price, but it rather depends on the value of the parameters that govern its behavior. In terms of relative contribution to price variation, we found that after 1974, and as a result of the adjustment of the speculative demand for inventories, wheat price fluctuations are no longer dominated by oil price shocks and are more driven by a wider set of shocks that include weather and consumption demand.

Our findings indicate that for a country like the US, which can rely on an advanced farming sector, a well-developed infrastructure with sufficient storage capacity, and a liquid futures market, the observed greater weather variability does not represent a substantial threat for the price of wheat. But this conclusion implies two, perhaps more important, considerations. First, our results indirectly suggest that climate change will most likely cause greater volatility in wheat price if any of the above conditions is missing.[21] Second, our findings pertain to the increased weather variability experienced by US farmers up to 2018. Therefore, it is hard to predict if the storage mechanism will work equally well when faced with unprecedented levels of weather variability, with extreme events that can potentially disrupt the transport network and so the very infrastructure on which it is based.

Appendix A. A fixed partial break point test

The test for a fixed partial break, so a break involving only a subset of the parameters, is constructed as follows. Denote by τ the break point and distinguish two groups of regressors, those featuring a breaking parameter, the $p_B \times 1$ vector $w_{B,t}$, and those with a constant parameter, the $p_C \times 1$ vector $w_{C,t}$. If we indicate the dependent variable with y_t, our structural equation can be written as

$$y_t = \overline{w}'_{B,t}\beta_B + w'_{C,t}\beta_C + v_t \tag{9}$$

where $\overline{w}_{B,t} = \iota_t \otimes w_{B,t}$, ι_t is a 2×1 indicator vector that is equal to $[1,0]'$ if $t \in [1,\tau]$ and $[0,1]'$ if $t \in [\tau+1, T]$, and T is the number of observations in our sample. After deriving the fitted values $\widehat{w}_{B,t}$, in the second stage of the 2SLS procedure we construct its block-diagonal partition $\breve{W}_B = diag\left(\widehat{W}_{B,\tau}, \widehat{W}_{B,T}\right)$, where $\widehat{W}_{B,\tau} = \left(\widehat{w}_{B,1}, ..., \widehat{w}_{B,\tau}\right)'$ and $\widehat{W}_{B,T} = \left(\widehat{w}_{B,\tau+1}, ..., \widehat{w}_{B,T}\right)'$. We indicate by $M_C = I - W_C\left(W'_C W_C\right)^{-1} W'_C$ the matrix that partials out the constant-parameter regressors and by Y the $T \times 1$ vector of observations on y_t. Once we define $\widetilde{W}_B = M_C \breve{W}_B$, the 2SLS estimator of β_B is

$$\hat{\beta}_B = \left(\widetilde{W}'_B \widetilde{W}_B\right)^{-1} \widetilde{W}'_B Y. \tag{10}$$

The Wald test statistic for one partial break is then

$$Wald = R'\hat{\beta}'_B\left(RVR'\right)^{-1} R\hat{\beta}_B \tag{11}$$

where V is the covariance matrix of $\hat{\beta}_B$ and $R = I_{p_B} \otimes (1, -1)$.[22] Under the null of no break, $Wald \overset{a}{\sim} \chi^2_{p_B}$, where p_B is the number of breaking parameters.

Appendix B. Robustness to non-linear effects

In this section, we evaluate the possible differences in results from using an alternative measure to average temperature, used in the main estimation. We show that apart from marginal variations, the findings from the main estimation remain unchanged.

We construct an aggregate annual time series of *growing degree days* following the procedure described in the agronomic literature. In particular, we follow Schlenker et al. (2006) and Tack et al. (2015) in defining the piecewise non-linear function that converts daily temperature into growing degree days. The threshold above which heat is absorbed by the plant is set to 8 degrees Celsius, the threshold above which the absorbed heat is constant is set to 32, and the level beyond which higher temperatures are harmful is set to 34. Between 8 and 32 the contribution is equal to the number of degrees above 8, between 32 and 34 the contribution is equal to 24, and above 34 degrees we use a squared root specification to reflect the assumption that the marginal damage of higher temperatures is decreasing.

To capture the impact of extreme temperature events we follow Schlenker and Roberts (2009) in using minimum and maximum daily temperature to estimate an approximate distribution of temperatures across the 24 hours via linear interpolation. Tack et al. (2015) have shown the advantages in model predictive performance from interpolating the distribution of temperatures within each day, rather than using average daily temperature levels.

Data on daily minimum and maximum temperature levels for the US are obtained from the dataset constructed by Livneh et al. (2013), which spans the period 1915-2011 with a resolution of 1/16 of a degree. To match the resolution of the crop area and calendar datasets we regrid all maps up to 1/4 of a degree. Like in the main estimation, we consider the last 120 days before harvest as the relevant days to calculate the annual level of growing degree days, and we take the weighted average across cells using crop area as weights to obtain an aggregate national value of growing degree days (GDD).

[21] The alternative strategy to storage for ensuring domestic food security is to rely on imports, although recent evidence has shown that climate change is likely to increase the occurrence of extreme weather events that hit simultaneously multiple regions of the planet, not to mention geopolitical conflicts that render such route unfeasible.

[22] We estimate V via a fixed-design wild bootstrap with 1,000 replications.

When we estimate our SVAR model of the wheat commodity market, the structural change analysis delivers the same outcome as in the main model. The resulting IRFs for the two regimes are shown in Fig. 4 and 5.

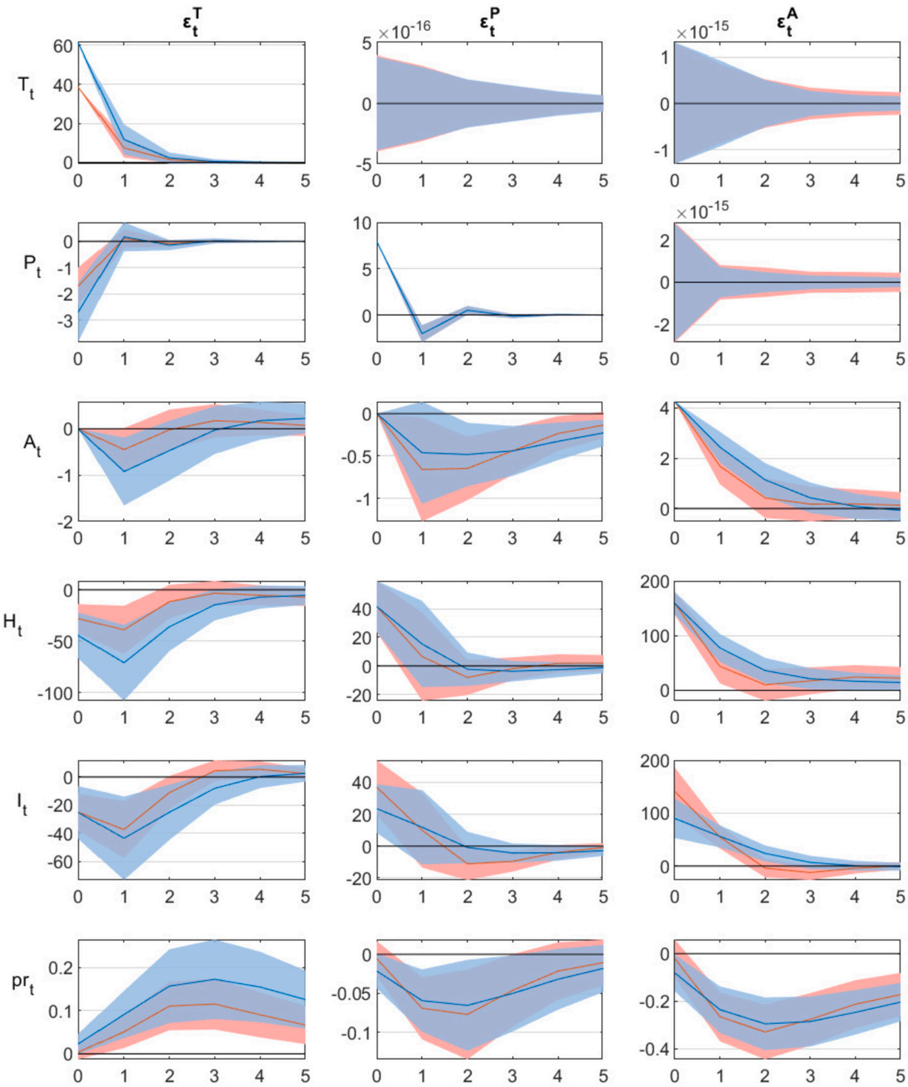

Fig. 4. IRFs in the two regimes using GDD.

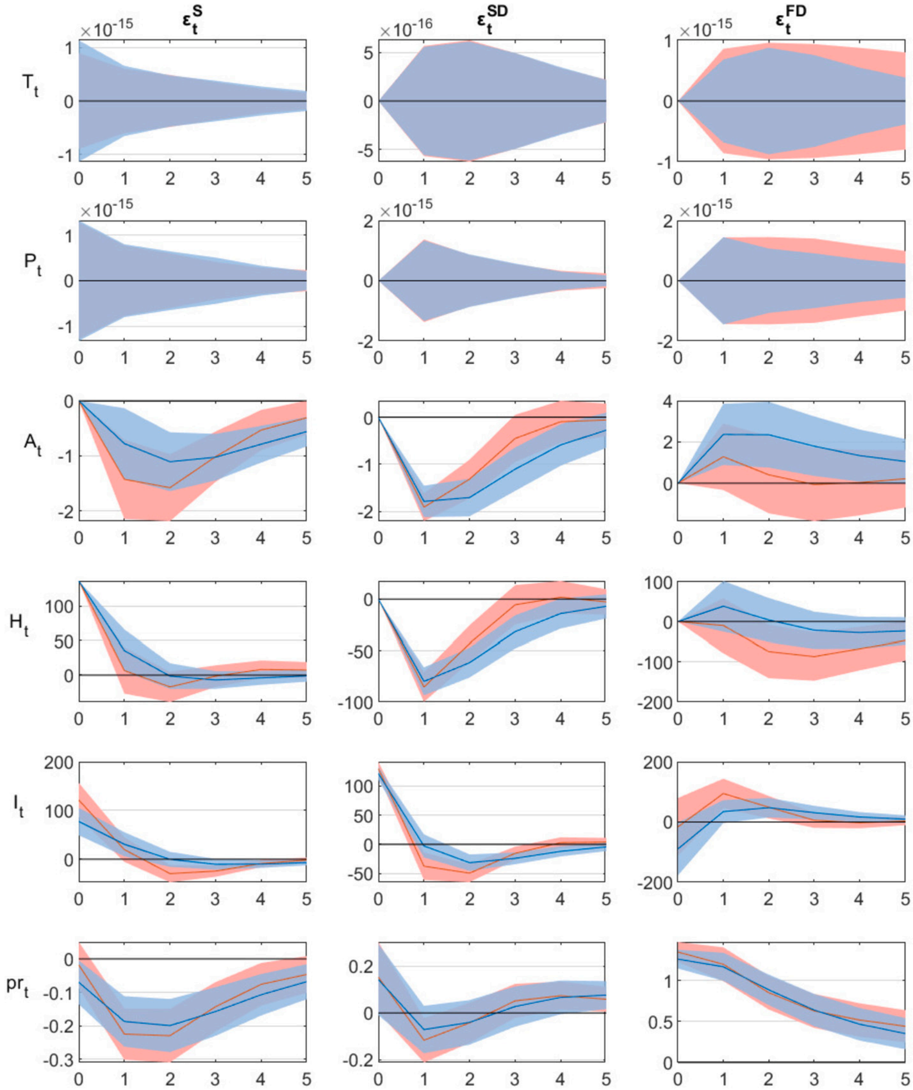

Fig. 5. IRFs in the two regimes using GDD.

Appendix C. Validation checks of SVAR model

Table 8
Pseudo-R^2 for each individual equation.

T	P	A	o	r	Y	H	I	pr
0.08349	0.10974	0.79842	0.85132	0.72593	0.35034	0.91569	0.57253	0.84984

Table 9
Residual ARCH heteroskedasticity test on individual equations.

h	T	P	A	o	r	Y	H	I	pr
1	0.75086	0.8869	0.63819	0.14252	0.40095	0.39215	0.99959	0.70879	0.88113
2	0.90272	0.96502	0.17703	0.31024	0.49439	0.15364	0.64015	0.83540	0.98825
3	0.92911	0.93344	0.24238	0.50137	0.62402	0.10930	0.82079	0.53057	0.99684
4	0.97919	0.96881	0.35169	0.65401	0.75472	0.19055	0.71141	0.67531	0.99535
5	0.97691	0.91397	0.13216	0.73298	0.83340	0.26033	0.84240	0.41934	0.99915
6	0.35810	0.82534	0.19487	0.82163	0.65463	0.31538	0.82403	0.33779	0.99952
7	0.40636	0.96211	0.39914	0.48100	0.14019	0.37294	0.87009	0.46686	0.99959
8	0.38269	0.97789	0.31070	0.38375	0.20447	0.39411	0.92128	0.09839	0.99964
9	0.49145	0.90980	0.30538	0.45580	0.29782	0.16078	0.94899	0.11857	0.99057
10	0.55525	0.42699	0.18527	0.55995	0.37871	0.19890	0.96128	0.16203	0.99572
11	0.62612	0.51654	0.20666	0.64969	0.42687	0.25713	0.97654	0.09338	0.99807
12	0.60028	0.55296	0.22755	0.71619	0.36331	0.27872	0.98719	0.12596	0.99895
13	0.67728	0.57168	0.26065	0.75749	0.41872	0.35698	0.07032	0.16733	0.99945

Note: entries are p-values, with h indicating the lag length.

Table 10
Portmanteau test for autocorrelation.

h	Q_1	pv_1	Q_2	pv_2
5	328.03	0.42707	391.47	0.00601
6	377.22	0.83544	470.69	0.01331
7	432.24	0.96172	550.92	0.02183
8	488.06	0.99271	622.10	0.05416
9	539.71	0.99925	684.77	0.15358
10	584.97	0.99997	736.26	0.41807
11	627.75	1.00000	785.97	0.72121
12	660.90	1.00000	833.00	0.91760
13	694.66	1.00000	881.15	0.98270

Note: Q_i refers to regime i and h indicates the lag length.

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