



AgEcon SEARCH
RESEARCH IN AGRICULTURAL & APPLIED ECONOMICS

The World's Largest Open Access Agricultural & Applied Economics Digital Library

This document is discoverable and free to researchers across the globe due to the work of AgEcon Search.

Help ensure our sustainability.

Give to AgEcon Search

AgEcon Search
<http://ageconsearch.umn.edu>
aesearch@umn.edu

*Papers downloaded from **AgEcon Search** may be used for non-commercial purposes and personal study only. No other use, including posting to another Internet site, is permitted without permission from the copyright owner (not AgEcon Search), or as allowed under the provisions of Fair Use, U.S. Copyright Act, Title 17 U.S.C.*



IATRC

INTERNATIONAL AGRICULTURAL
TRADE RESEARCH CONSORTIUM

Commissioned Paper

Anomalies and Recoveries in Agricultural Trade

Savin Khadka, Munisamy Gopinath, and Feras Batarseh

November 2022
IATRC Commissioned Paper 30

International Agricultural Trade Research Consortium

Commissioned Paper No. 30

Anomalies and Recoveries in Agricultural Trade

This Commissioned Paper was co-authored by a working group which responded to a call for Commissioned Papers from the Executive Committee of the IATRC. The members of the group are:

Savin Khadka
University of Georgia – Athens, GA, USA
Sk56027@uga.edu

Munisamy Gopinath
University of Georgia – Athens, GA, USA
m.gopinath@uga.edu

Feras A. Batarseh
Virginia Tech – Arlington, VA, USA
batarseh@vt.edu

The views expressed should not be taken to represent those of the institutions to which the authors are attached, nor to the IATRC and its funding agencies. Correspondence regarding the content of the paper should be directed to the author(s).

The International Agricultural Trade Research Consortium (IATRC) is an organization of approximately 220 economists from 28 different countries, interested in research, policy analysis, and current developments in international agricultural trade. It is supported by the United States Department of Agriculture (ERS, FAS, and OCE), Agriculture and Agri-Food Canada, and the participating organizations. Funding for this commissioned paper comes from Agriculture and Agri-Food Canada.

Anomalies and Recoveries in Agricultural Trade

St. Paul, Minnesota: University of Minnesota, Department of Applied Economics, International
Agricultural Trade Research Consortium

Copies of this paper and other IATRC Publications are available on the website
www.iatrcweb.org

This volume contains information which was presented at an
International Agricultural Trade Research Consortium Annual Meeting,
which was held December 12-14, 2021 in San Diego, CA.

Anomalies and Recoveries in Agricultural Trade

Savin Khadka, Munisamy Gopinath*, Feras A. Batarseh

August 19, 2022

Abstract: While uncertainty effects on macroeconomic indicators such as consumption, production, and investment have been well-studied, much remains to be known about the relationship between uncertainty and international trade. Some early explorations into this topic have revealed that high economic uncertainty can have detrimental impacts on trade, but the evidence is not conclusive, particularly that on the heterogeneity of uncertainty effects across sectors. This study provides one of the first investigations into the uncertainty-agricultural trade nexus. Application of a novel data-driven methodology - anomaly detection and classification - to monthly trade data at the HS-4 level finds that imports of agricultural commodities are reduced when economic uncertainty is high. Evidence also suggests that economic policy-related uncertainty has larger and more persistent impacts on agricultural trade than structural uncertainty arising from supply-side fluctuations. Interestingly, anticipatory stock-piling occurred, like in durable goods, when uncertainty is specific to trade policy.

Key Words: *policy uncertainty, agricultural trade, anomaly detection, and machine learning*

JEL Classification: F14, C45, Q17

*Corresponding author: m.gopinath@uga.edu; 706-542-0748.

Khadka is PhD student and Gopinath is Distinguished Professor of Agricultural Marketing in the Department of Agricultural and Applied Economics at the University of Georgia; Batarseh is Research Associate Professor in the Department of Electrical and Computer Engineering at Virginia Tech. Authors acknowledge funding support from the International Agricultural Trade Research Consortium.

I. Introduction

International trade has grown remarkably over the past few decades facilitated, in part, by global economic growth and sustained efforts to lower barriers to cross-border exchange of goods and services. However, alongside unprecedented levels, recent years have also seen a marked increase in the volatility associated with international trade. While idiosyncratic production shocks are a significant contributor to trade volatility, it is clear that variance in international trade is not explained by output volatility alone. Between 2008 and 2009, for instance, a 5.1 percent decline in global Gross Domestic Product (GDP) coincided with a 22.9 percent decrease in international merchandise trade (World Bank and World Trade Organization, WTO, 2020). This so-called magnification is particularly severe in the case of agricultural commodities. Global corn and wheat production fell by around 8 and 11 percent, respectively, during the 2008-09 great recession whereas the simultaneous contraction in their trade volume was far greater at 26.3 and 28.0 percent, respectively. Overall, the decline in total agricultural imports (13.2 percent) was also more pronounced than the drop in production (7.9 percent) for the same period.

The role of uncertainty in guiding economic behavior has been an active area of literature following early contributions by Bernanke (1983)[1], McDonald and Siegel (1986)[2], and Pindyck (1991)[3] among others. Previous work has established that when decisions are irreversible or adjustment costs are large (which they often are, per Ramey and Shapiro (2001) [4] and Bloom (2009)[5]), high economic uncertainty can lead to a contraction in economic activity as the real-option value of delaying key decisions is increased. More recent work by Kellogg (2014)[6] also highlights the importance of uncertainty in investment decisions by noting that the cost of failing to respond to volatility shocks is economically significant.

The role of uncertainty in agriculture, arising from unpredictable weather conditions and unstable agricultural markets, has been well documented (Binswanger (1981)[7] and Chavas (2018)[8]. Chavas and Holt (1990)[9] examined production decisions under uncertainty by developing an acreage supply response model under expected utility maximization. Their work showed that both risk and wealth effects are important determinants of corn and soybean acreage allocations with the latter being more risk responsive than the former. In a similar vein, Chavas and Holt (1996)[10] noted that risk effects are important for agriculture because producers tend to be relatively risk-averse i.e., corn-soybean farmers are risk averse, when facing price and production risk, and exhibit decreasing absolute risk aversion and downside risk aversion.

Investigations of uncertainty effects on trade in general, however, are relatively new. Handley (2014)[11] provided one of the first explorations of the impacts of trade policy uncertainty (TPU) on exports and reported that increased TPU will delay the entry of exporters into new markets while also making them less responsive to applied tariff reductions. Subsequent work by Handley and Limao (2017)[12] confirmed TPU effects on trade and welfare using evidence from China’s accession to the WTO. Their work showed that the decision by the United States to grant permanent most favored nation (MFN) status to China, and thus end the annual threat of raising tariffs on Chinese imports, contributed significantly to the increase in exports of Chinese goods to the U.S. “through

a reduction in US policy uncertainty” (pp. 2732). On the other hand a study by Alessandria et al. (2019)[13] on the annual tariff uncertainty about China’s Most Favored Nation (MFN) status found that trade increased strongly in anticipation of uncertain future increases in tariffs, suggesting that policy uncertainty may also lead to expansion in trade. However, this discrepancy arises, as the authors mention, from their choice of data- this study uses within-year variation in trade flows of firms as opposed to annual trade flows employed by most other studies. In addition, they also compared the trade-dampening effects of uncertainty with the trade-boosting effects of an expected tariff increase, finding that the latter is larger and explained the anticipatory growth in imports. A recent study by Novy and Taylor (2020)[14] extends seminal work by Bloom (2009)[5] in modeling uncertainty as second-moment shocks to investigate uncertainty effects on trade. Using an (s,S) inventory model, Novy and Taylor (2020)[14] illustrate the significance of economic uncertainty effects on trade. Their empirical findings confirmed that uncertainty affected trade more than domestic production and that the effects are the most prominent in the case of trade in durables. However, their claim that these effects are unlikely to influence other sectors such as non-durables – due to more frequent and recurring consumer demand – requires further investigation. Such effects take on critical policy significance in domestic and multilateral contexts, e.g., WTO’s principle of predictability through binding and transparency.

Recent shifts in the global political landscape, most notably the tariff wars between the U.S. and China during the Trump administration, have significantly stressed international agricultural markets leading to high variability in exports. However, the resulting volatility in agricultural trade has not been explored adequately, just as that occurred during the Great Recession (2008-09). More specifically, this is the first study that links volatilities in international agricultural trade with policy uncertainties in general and specific to trade. The key goal of this work is to present an argument that trade in agriculture is severely impacted by the uncertainty created due to the potential for shift(s) in future policy, regardless of whether or not the policy pertains directly to agriculture, in addition to the idiosyncrasies associated with production and supply fluctuations. To illustrate, the effects of economic policy uncertainty (EPU) shocks are compared with those of production-related shocks using a novel methodology guided by monthly data on soybean imports at the four-digit Harmonized System (HS-4) level spanning the period between 2000 and 2020. The appendix (Figures/Tables A3-A6) presents the case of corn and beef imports. Analysis on the effects of the more recent trade policy uncertainty (TPU) is also presented. In the first step, anomalies or outliers in imports of agricultural commodities are identified using a machine learning (ML) technique called the Naive Bayes Classifier (NBC) (Mitchell, 2010)[15]. Next, the identified anomalies are classified as structural or policy-related via two methods, one of which relies on simple quarterly percentage changes while the other uses NBC. World Agricultural Supply and Demand Estimates (WASDE) reports from USDA’s World Agricultural Outlook Board (WAOB) are used to verify the classification where possible. Then, heterogeneities between the two classes of anomalies are inspected in terms of intensity and duration of effects. Results reveal that agricultural trade responds differently to policy-uncertainty shocks than supply-side changes. anomalies attributable

to EPU are, on average, more likely to show a negative deviation from the trend suggesting that increased uncertainty can prompt importers to reduce their quantity demanded. Like in durables [14], TPU leads to anticipatory stock-piling, i.e., increased trade as a response to uncertainty about future policy changes. Both results suggest significant distortions to markets with likely efficiency losses.

The rest of the paper proceeds as follows: Section II provides background and the literature relating uncertainty to agricultural trade, Section III describes the data and methods used in this study, Section IV reports findings and Section V concludes.

II. Background

While the role of uncertainty in determining several key indicators of the economy such as investment and market entry is examined by a well-developed literature, the effects of policy uncertainty (PU) remained largely out of focus until relatively recently. Instead, the majority of early empirical exercises on studying uncertainty effects were directed towards exchange rate volatility- perhaps due to convenience in terms of quantification of key variables and data availability- leading to mixed results. Clark et al. (2004)[16], for instance, report that there exists a negative effect of exchange rate volatility on aggregate trade flows but the effect, however, is “fairly small and by no means robust”. As the literature on PU matured, new quantitative measures were devised that led to a surge of scholarship on PU effects. Born and Pfeifer (2014)[17] was one of the first works to empirically investigate the role of PU in explaining business cycles. They used a New Keynesian model on aggregate data to conclude that output effects of monetary and fiscal policy risk are relatively small because policy-risk shocks are too small and not sufficiently amplified. In a similar dynamic and stochastic general equilibrium (DSGE) exercise, Fernandez-Villaverde et al. (2015)[18] find that fiscal volatility shocks have an adverse effect on economic activity. The present study is focused particularly on economic and trade policy uncertainty and the remainder of this section will provide a brief review of some of the empirical work done in this regard.

Economic Policy Uncertainty

Departing from commonly-used models relying on structural vector autoregressive (SVAR) formulations to quantify PU, Baker, Bloom, and Davis (2016) [19] construct a new measure relying instead on the frequency of uncertainty-related keywords in major U.S. newspapers. Their index pertains to both near- and long-term concerns about the future of economic policy and provides quantitative measurements of EPU for the U.S., the U.K., and 11 other major economies. They then use this index to investigate the relationship between PU and various outcomes (such as investment rates, aggregate investment, output and employment), further reinforcing the negative economic effects of uncertainty shocks on economic performance. In a related work, Pastor and Veronesi (2011)[20] use the same index to show that high levels of policy uncertainty lead to a stronger co-movement

of firm-level equity returns, suggesting that such effects are not restricted to individual firms and also affect market-wide volatility.

More recent work by Li et al. (2016)[21] further extends these ideas by providing evidence, albeit weak, for bidirectional causal relationships between EPU and stock market returns in China and India in several sub-periods of their sample. Similarly, Antonakakis et al. (2014)[22] also identify spillover effects from EPU on international oil price changes in a group of countries, particularly China. In addition, Andreasson et al. (2016)[23], in their study of EPU effects on international commodity markets, find that U.S. EPU has a weak impact on most commodities traded, supplementing an earlier Wang et al. (2015)[24] study that explored the inverse relationship and showed that commodity price changes can help predict EPU. This study is closely related to and extends Novy and Taylor (2020)[14] who develop a theoretical model to examine the effects of economic uncertainty on trade and use vector autoregression (VAR) to show trade contraction under heightened economic uncertainty with significant implications to understand the Great Trade Collapse of 2008-09.

Trade Policy Uncertainty

The literature on the effects of TPU, although recent, has had several important contributions. In one of the first studies focusing on TPU, Handley (2014)[11] empirically examines the impact of tariff-binding commitments on trade and export market entry. While previous research had explored the impacts of WTO membership with varied results (for instance, Rose (2004)[25] argues that the effects of GATT/WTO are not substantial, while Subramanian and Wei (2007)[26] claim that WTO does promote trade), Handley (2014)[11] directly quantifies the role of Australian trade policy on exports to Australia between 1991 and 2001 using detailed product level trade data, and those on applied and bound tariffs for the same period. His analysis shows that lowering bindings, while holding applied tariffs fixed, helps in promoting export-market entry and that the cautionary effect of uncertainty reduces responsiveness of entry decisions to tariff reductions by up to 70 percent on average. Moreover, the combined effect of reducing uncertainty- by restricting tariffs to zero and binding them through WTO commitment- would result in a 17 percent increase in the number of traded products.

The model used by Handley (2014)[11] is similar to the one constructed in Handley and Limao (2017)[12] that provides structural estimations of PU parameters and quantifies the effects of PU on aggregate prices and welfare of US consumers alongside other outcomes. The theoretical foundation for their work relies, again, on Bernanke (1983)[1] and Dixit (1989)[27] and relates uncertainty to investment via a real-options approach, modelling investment as sunk costs that incentivize firms to postpone significant decisions under high uncertainty. They exploit variation in policies, export values, and prices across a large number of products for estimating TPU effects and provide evidence that the threat of imposing higher tariffs alone can lead to significant consumer welfare losses, even in the absence of actual tariff adjustments. Specifically, the removal of the threat of revoking

China’s Most Favored Nation (MFN) status alone had substantial impacts on Chinese export entry (by about 60 log points), and export growth (by 32 log points).

Caldara et al. (2020)[28] offer a firm-level measure of TPU linked to firm-level investment data and show that, in 2018, increase in TPU resulted in a one percent drop in investment in the U.S. with VAR estimates alluding to larger effects. Their findings, based on a two-country general equilibrium model with heterogeneous firms and endogenous export decisions, also highlight the role of increased uncertainty about future tariffs wherein the the fixed costs of export serve as a channel via which the effects of TPU are transmitted.

On the other hand, Alessandria et al. (2019)[13] argue in favor of expansion of trade as a result of TPU due to anticipatory effects. Their study leverages the annual renewal of Normal Trade Relations (NTR) status of China by the U.S. (prior to China’s accession to the WTO) to examine the impact of uncertainty about future changes to trade policy. However, it should be noted, as the authors do, that their findings, based on a (\underline{s} , s) inventory model, may be a consequence of the difference in frequency compared to most of the literature- they use variations in within-year trade flows instead of annual trade flows- and these frictions arising from the fixed costs of ordering inventory contribute to the negative effects of TPU often observed in annual trade flows. Their results help in contextualizing those from Steinberg (2019)[29] that studies the effects of the decision by the U.K. to leave the European Union (E.U.). His analysis is based on a DSGE model featuring three countries (the U.K., the E.U., and the rest of the world), heterogeneous firms, and uncertainty about trade costs where TPU affects trade flows due to firms’ forward-looking decision on export participation. The model is calibrated by using an input-output matrix from 2011, before the first discussions on a potential U.K. exit. His findings- considering both “soft” and “hard” exits where trade costs with the E.U. rise slightly and substantially, respectively- suggest that there would be substantial implications of Brexit on the U.K. economy in the long run with a possibility of trade flows falling by up to 44.8 percent, while the impacts may be minimal in the short run. He ultimately concludes that the welfare cost of the uncertainty regarding Brexit is small compared to the overall welfare cost of Brexit itself, and that the cost of the former is comparable to the cost of unpredictability of yearly fluctuations in macroeconomic activity.

Essentially, the literature reviewed above provides a formal mechanism relating uncertainties, e.g. demand shock arising from trade wars, to trade. A variety of methods can be employed to quantify or uncover that relationship, and the following section provides a novel approach to do so.

III. Data and Methods

III.1 Data

Exploration of the relationship between policy-related uncertainty and trade requires three streams of data: production, trade, and uncertainty. Furthermore, data need to be finer – monthly or quarterly – to quantify this relationship as previous studies have suggested that annual data usually mask uncertainty effects on trade (Alessandria et al. (2019)[13]). As noted earlier, the following

presentation primarily focuses on soybean (HS-1201), but three other major agricultural commodities (HS-4 digit products) are also analyzed: corn (HS-1005), fresh/chilled beef (HS-0201) and frozen beef (HS-0202).

Imports: Monthly imports data are acquired from the Global Trade Atlas database maintained by IHS Markit®, and shown in pink in [Figure 1](#). As with data similarly large in scope, there are some important considerations. Some observations have non-standard units of measurement¹ and were dropped from the dataset (206 in total). While the choice of using imports data over exports is made for the benefit of reliability, there still remain concerns about the accuracy of the reports, particularly in the case of small economies. However, the large size of the panel dataset (1.08 million observations after pre-processing) and the relatively minor share of small economies in the global trade market assuage most of the concerns. The data show that global soybean imports have been increasing in value at a high rate over the past two decades, in spite of a large contraction following the Global Financial Crisis and another period of slowdown around the time of the 2016 U.S. Presidential Election. Also evident are the steep drops in trading activity coinciding with the ongoing COVID-19 pandemic.

Production: Production data are obtained from the Production, Supply and Distribution (PSD) database, curated by the United States Department of Agriculture Foreign Agricultural Service (USDA-FAS), and illustrated in teal in [Figure 1](#). Acquiring high-quality dis-aggregated global production data is difficult, particularly at the monthly or quarterly levels. Owing to the nature of the agricultural production process, maintaining a timely year-round collection of data is not possible for all crops. Moreover, PSD does not provide data at the HS-4 level. Thus, global supply of soybean oilseeds is used as the production metric. Soybean production exhibits a similar trend of steady growth over time despite some minor variation over the last decade. It is immediately obvious, upon comparing the two series in [Figure 1](#), that volatilities in imports are not entirely attributable to output variance alone. Notably, three major spikes in imports (around 2008, 2014, and 2018) do not correspond to any commensurate shifts in production.

Uncertainty: The availability of big data and machine learning (artificial intelligence) techniques have enabled innovations on measuring uncertainty. Baker, Bloom and Davis (2016)[[19](#)] provides a new index of EPU based on newspapers’ policy coverage frequency. Their monthly index is a weighted average of newspaper articles which included terms such as “economic” or “economy”; “uncertain” or “uncertainty”; and one or more of “Congress,” “deficit,” “Federal Reserve,” “legislation,” “regulation,” or “White House” from 10 leading newspapers since 1985. Several sensitivity analysis including a human audit indicate that the Baker, Bloom and Davis (2016)[[19](#)] index proxies for movements in policy-related economic uncertainty: tight presidential elections, Gulf Wars I and II, the 9/11 attacks, the failure of Lehman Brothers, the 2011 debt ceiling dispute, and other major battles over fiscal policy. Advancing further, Baker et al. (2019)[[30](#)] provide EPU indexes for several categories including trade, fiscal, monetary, regulatory and other policies. Quantified

¹*viz.* BOX, M3, NO, NOC, PK, and ST

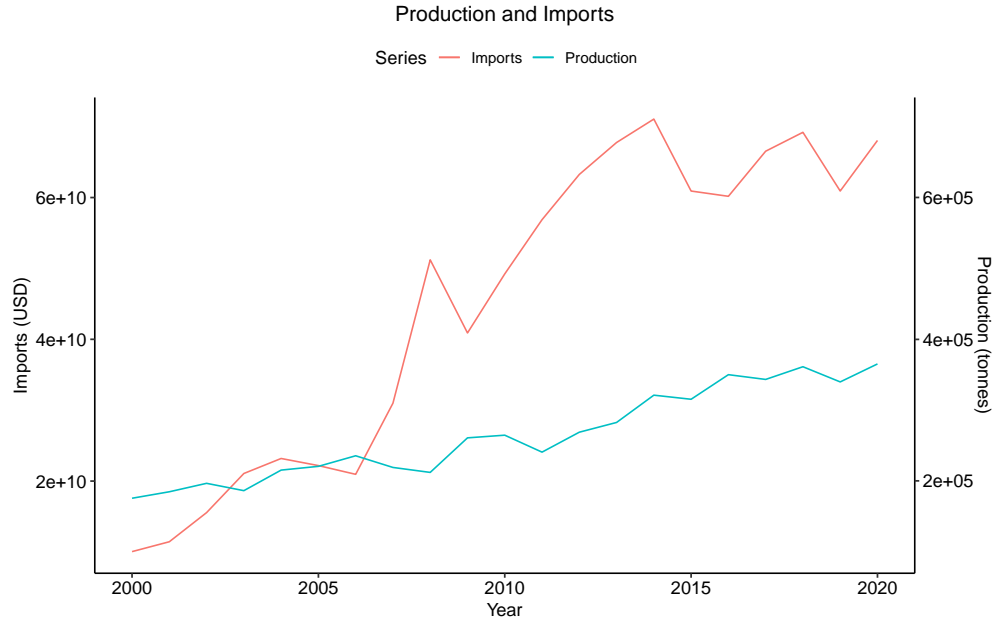


Figure 1: Global Annual Soybean Production and Imports

monthly metrics on economic and trade policy uncertainty, obtained from the dataset developed by Baker, Bloom, and Davis (2016[19], retrieved from www.policyuncertainty.com), are shown in Figure 2.

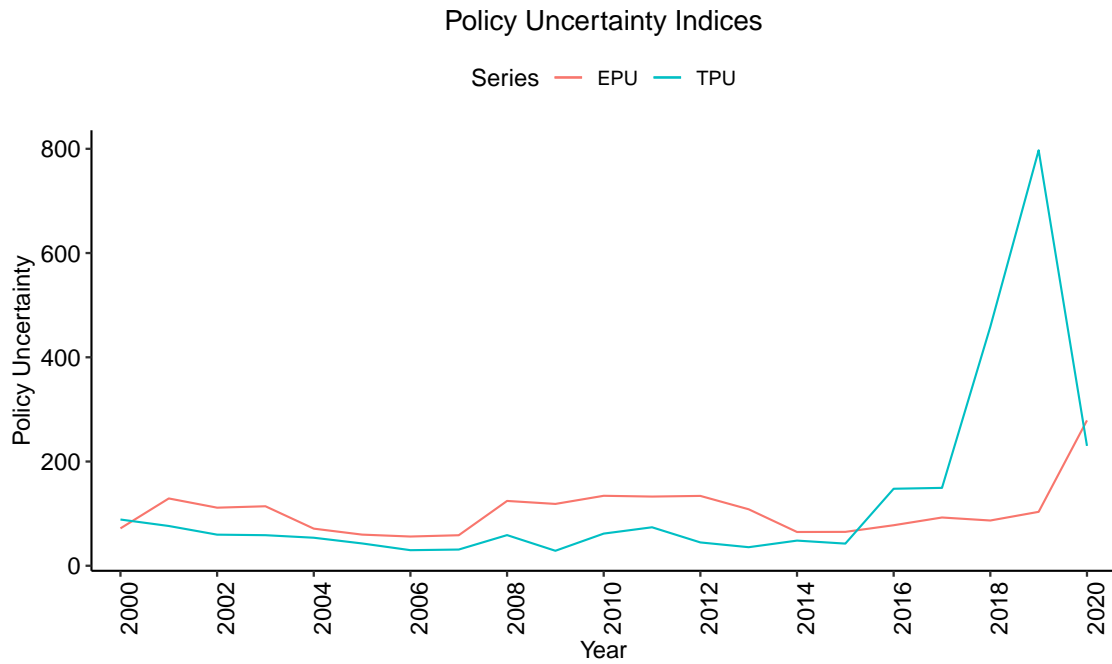


Figure 2: Policy Uncertainty

III.2 Methods

Empirical analysis begins by de-seasonalizing the data via lagged differencing and encompasses three major steps: anomaly identification, anomaly classification, and heterogeneity analyses. The following discussion provides methodological details for each of those three steps.

Step 1: Anomaly Identification

As noted above, trade data were de-seasonalized by taking the difference between current monthly values and that of the corresponding month in the previous year. Anomalies are usually defined as the values in a series that show considerable deviations from other observations, such that they might have been generated by a different underlying data-generating mechanism. However, they encompass anomalies as well, i.e., resulting from measurement, reporting, or recording errors. In this study, the terms anomaly and outlier are used interchangeably. Many methods are available for detecting anomalies: Isolation Forest (Liu et al. (2008)[31]), Kernel Density Estimation (KDE, Chacon and Duong (2018)[32]), Density-Based Spatial Clustering of Applications (DBSCAN; Hashler, Piekenbrock, and Doran (2019)[33]), and support vector machines (SVM, Chang and Lin (2011)[34]), among others. This study primarily uses the Naive Bayes Classifier (Mitchell, 2010 [15]) which is a supervised ML technique (i.e., it uses labeled datasets) compared to others that are unsupervised (and do not use labeled data). Nonetheless, appendix Table A1 provides results from unsupervised classifiers. A brief discussion on the NBC is provided below.

Naive Bayes Classifier (NBC): NBC is a supervised ML technique frequently used in prediction and classification exercises that operates by constructing a Bayesian probabilistic model. Consider Bayes’ Rule which provides the conditional probability of y given X :

$$P(y|X) = \frac{P(X|y)P(y)}{P(X)}, \quad (1)$$

where $X = x_1, x_2, \dots, x_n$ represents data features and y is the outcome variable. As an example, in an application where credit-worthiness with regards to a personal loan offer is the variable of interest (y), several factors such as income, marital status and home ownership status may be considered as features (X).

The term “naive” is meant to denote the fact that it assumes that features are independent. Then, substituting for X and using the chain rule gives:

$$P(y|x_1, x_2, \dots, x_n) = \frac{P(x_1|y)P(x_2|y)\dots P(x_n|y)P(y)}{P(x_1)P(x_2)P(x_3)\dots P(x_n)} \quad (2)$$

Note that the denominator is the same for all instances of the class variable y and thus behaves as a scalar. It may be removed to introduce proportionality as:

$$P(y|x_1, \dots, x_n) \propto P(y) \prod_{i=1}^n P(x_i|y) \quad (3)$$

For a *crisp* classifier where each instance is to be assigned to exactly one class, a simple calculation of the RHS for each class can identify the class for which this value is maximized. This *maximum a posteriori* (MAP) class is calculated in simple NBCs as:

$$y = \operatorname{argmax}_y P(y) \prod_{i=1}^n P(x_i|y) \quad (4)$$

The assumption of independence among features may not hold true under most scenarios, but it has been shown that classification based on NBC is credible even if the independence assumption does not hold. Domingos and Pazzani (1997)[35] show that even when independence is violated, NBC is competitive with other classification techniques although the probability estimates- given by Equation 4 may not be optimal. Further, Zhang (2005)[36] investigates the optimality of NBC under the Gaussian distribution, and shows that it can be optimal even if dependencies among attributes exist.

As mentioned above, NBC is a supervised technique which requires labelled datasets as inputs. To train the model, an out-of-sample dataset is used. Imports in the training dataset are labelled as anomalies if their (lag-differenced and scaled) values lie above the 95th or below the 5th percentiles. Then, the labelled dataset is used to construct a NBC model which can be subsequently used to identify anomalies in the actual dataset. To avoid overfitting and ensure that the results are not sensitive to specifications and choice of training datasets, three different versions of training data spanning different years are used (1990-2000, 1995-2005, and 2000-2010). The three trained models are then used on three different testing periods: 2001-2010, 2006-2015, and 2011-2020. Results are reported for all specifications.

After tuning the NBC model to optimize performance, the final model is constructed by using the bootstrap method for training over 10 resampling iterations. The final model used for anomaly detection (in the 2011-2020 period) has an overall accuracy of 91.89 percent with an F1 score of 0.9524, which suggests that it performs well. A confusion matrix constructed from training on 2000-2010 data is provided in Table 1 which shows that 30 normal observations and four anomalies are accurately classified while two anomalies are mistakenly attributed as being normal and one normal observation is incorrectly labelled as anomalies.

Table 1: Confusion Matrix for Anomaly Detection)

Prediction	Reference	
	0	1
0	30	2
1	1	4

Step 2: Anomaly Classification

Having identified anomalous imports or anomalies, the next step is to classify the shocks as structural and policy-uncertainty related. This is performed via two methods: baseline and NBC. The

baseline method uses quarterly percentage changes from the preceding quarter in EPU and production for classification. Having computed the percentage changes, an anomaly is attributed as being related to policy-uncertainty if the quarterly percentage change in the uncertainty measure is larger than the corresponding percentage change in production, and as being structural otherwise. To validate the classification, WASDE reports for the months identified as anomalies are analyzed for notable shifts in production levels.

In addition to the baseline method, a NBC classifier is also used. To construct the NBC classification model, labeled datasets are created by using the baseline method. The labeled dataset (with the source of anomaly included) is then used to train the model using the bootstrap method and 10-fold cross-validation as in the previous step. The final model (used to classify 2010-2020 data) has an accuracy of 81.08 percent with an F1 score of 0.74. Confusion matrix from the training step is provided in [Table 2](#) below.

Table 2: Confusion Matrix for Anomaly Classification)

Prediction	Reference	
	0	1
0	10	4
1	3	20

The results from an EPU-based classification are highlighted in Section IV, while those from a TPU-based classification are discussed in a separate subsection within Section IV.

Step 3: Recovery Pattern Analysis

Upon identifying anomalies and classifying them on the basis of their origin, heterogeneities in anomalies according to their sources of origin is examined. To do so, imports data are grouped by months and a separate trend line is fitted for each month for every commodity.

Two features of are of interest in evaluating the effects of anomalies and subsequent patterns of recovery: intensity and duration. The distance from the trend line to the anomalous data points is used as the measure of intensity of disruption associated with each anomaly. Either class of anomalies being more likely to be significantly farther away from the trend line than the other would imply that the corresponding source of origin (structural or PU) has more severe effects. To examine persistence or duration of effects, the four-month period following each anomaly is considered. An NBC model is trained to detect the recurrence of an anomaly of the same class within the following four-month period. A sensitivity analysis of results to variations in the lag window, i.e. 3- or 5-month period is also conducted. From the anomalies set, those anomalies that are likely to be succeeded by another of the same class in the near future are selected. Finally, average residual scores over the four-month period across the two groups are compared. A statistically significant difference in residual scores across the two classes has the implication that structural and policy-related anomalies differ in the duration of effects.

IV. Results

IV.1 Anomaly Detection

Anomalies in monthly soybean imports detected by the NBC model for the period between 2010 and 2020 are shown in [Figure 3](#) below, where each line represents imports for a particular month while the blue dots represent anomalies. There are a few months that account for a significant share of anomalies. For instance, the month of July accounts for nine anomalies out of the 80 total anomalies in the 2011-2020 sample, the highest share among all months. Soybean is usually planted in the U.S. between early May to early June in the states lying to the south while planting occurs between the middle of May and July for the northern states, where the optimum temperature for planting is reached a few weeks later. The crop is then harvested around October or November, about 90-120 days after planting. The Brazilian summer crop, likewise, is planted around mid- to late-September, and harvesting usually begins in mid- to late-December. The months of August, September and November are also associated with a relatively large share of anomalies (eight each) which, in tandem with June (seven anomalies), might be a consequence of predictions about the outlook about the harvest. The high number of anomalies observed for the months of February and March (seven anomalies each), however, do not correspond to usual growing cycles in any of the major soybean producing regions and may be driven more by factors outside of production.

A few other things also stand out. First, NBC is able to capture anomalies lying in the interior region as well as those on the extremities, while statistical measurement of anomalies is restricted to the identification of the latter group. Secondly, the significant growth in trading activity over the last decade also coincided with a high frequency of anomalies. As noted earlier, production levels have been rising relatively steadily during the last two decades. On the other hand, major economic powers of the world have shown signs of moving away from free-trade and promoting protectionism, e.g. Brexit. The resulting uncertainty about future policies, accentuated by trade disputes such as the recent U.S.-China tariff wars likely played a large role in determining international trade flows. Closely observing the occurrence of anomalies in [Figure 3](#) confirms that possibility. Note that periods of high policy-uncertainty such as Eurozone crisis (2014), the U.S. Presidential Election (2016) and the ensuing trade war years (2017-18) are all marked by anomalies. Some signs of recovery, following the U.S.-China phase 1 deal, is observed in 2020.

This study also used other ML-based techniques besides NBC to detect anomalies. Results from those methods are provided in the appendix. All of the analysis that follows is conducted on the set of NBC anomalies. The reason for this preference is that NBC is known to perform better in classification when the training data is sparse (as in this application). Moreover, it also outperforms other supervised methods in terms of efficiency and is better equipped to accommodate categorical variables.

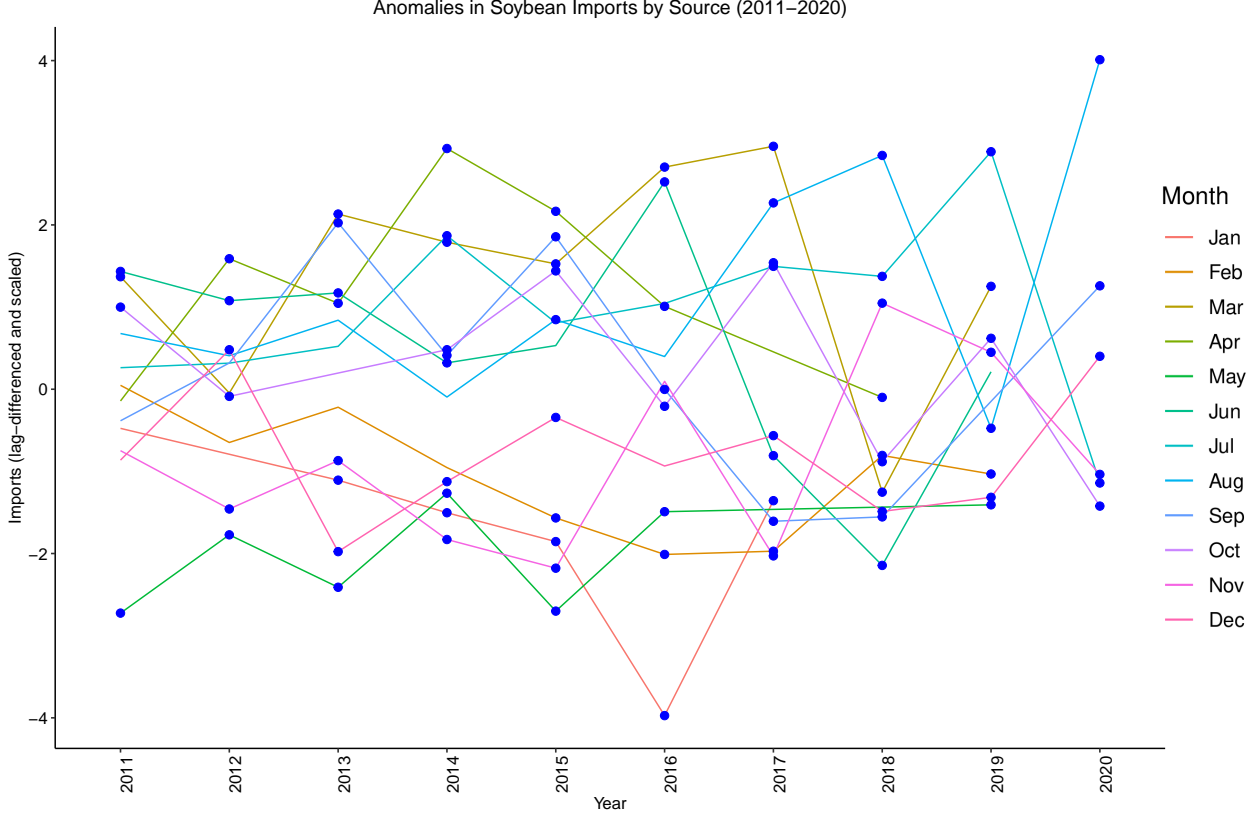


Figure 3: Anomalies in Soybean Imports

IV.2 Anomaly Classification

Classification based on the baseline and NBC methods, across the three training and testing regimes, are provided in Table 3. Essentially, the blue dots in Figure 3 are classified into structural and PU-related anomalies. In all cases, we find that the number of anomalies attributable to policy-uncertainty is comparable to structural anomalies (i.e., those arising from idiosyncratic production shocks). When the model is trained on data from 2000 and 2010, 80 anomalies are identified in soybean imports between 2011 and 2020. It is clear from both baseline and NBC classifications that policy-related anomalies tend to be more frequently observed in recent years. For the 2006–2015 testing period, 27 anomalies are classified differently by the two models. This discrepancy is expected given that the NBC model is more informed than the baseline model. While the latter relies in raw percentage changes alone in production and uncertainty metric alone, the NBC classifier also relies on data features pertaining to both production and uncertainty and, as such, leads to more accurate predictions. Classification of anomalies is relatively unchanged for the other two training-testing regimes.

Table 3: Classification

Method	Structural	PU
<i>1990-2000 Training/ 2001-2020 Analysis</i>		
Baseline	25	42
NBC	25	42
<i>1995-2005 Training/ 2006-2020 Analysis</i>		
Baseline	29	51
NBC	56	24
<i>2000-2010 Training/ 2011-2020 Analysis</i>		
Baseline	27	53
NBC	26	54

The classification of anomalies for the period between 2011 and 2020 is shown in Figure 4. In each figure, a red dot corresponds to a PU-related anomaly while structural anomalies are shown in black.

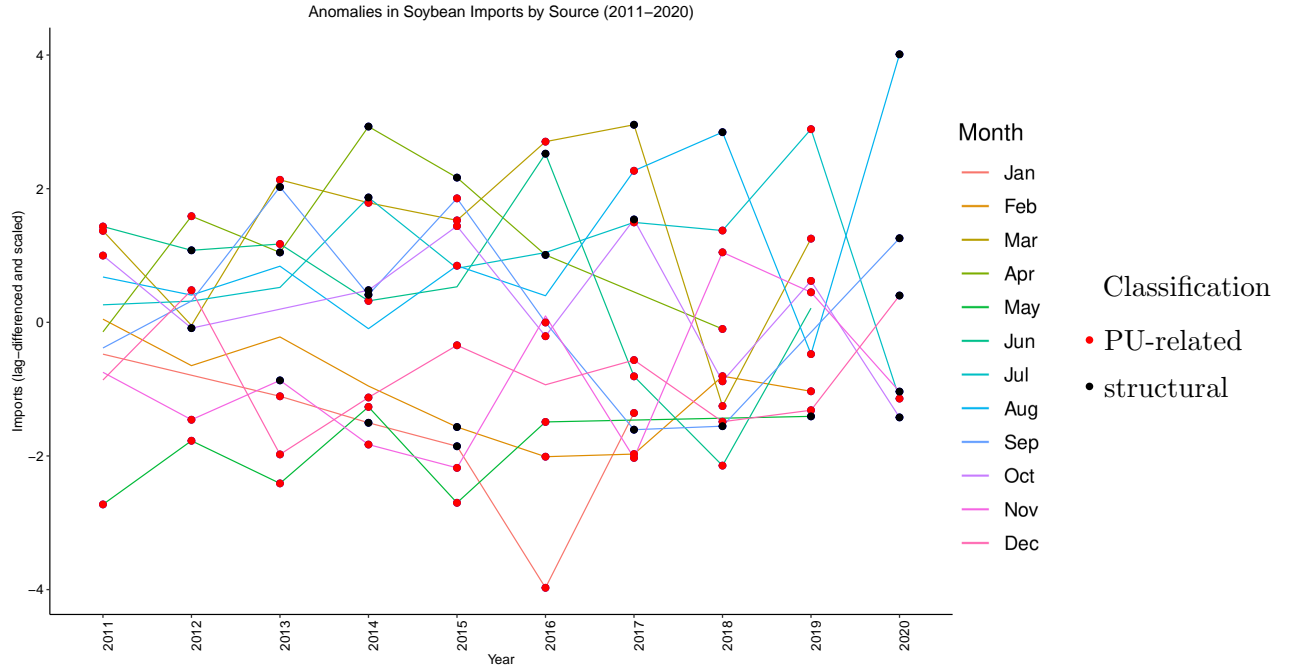


Figure 4: Anomaly Classification

IV.3 Heterogeneities and Recovery Patterns

IV.3.1 Deviation from Trend

Given that policy-uncertainty is also a determinant of trade flows and, as seen above, is a frequent source of anomalies, the next step is to investigate heterogeneities in effects according to anomaly source. Evidence strongly suggests that the average deviation from the trend differs according to

anomaly class. Figure 5 below shows the residuals obtained from fitting linear trends for each month and computing the deviation from trend for each of the anomalies.

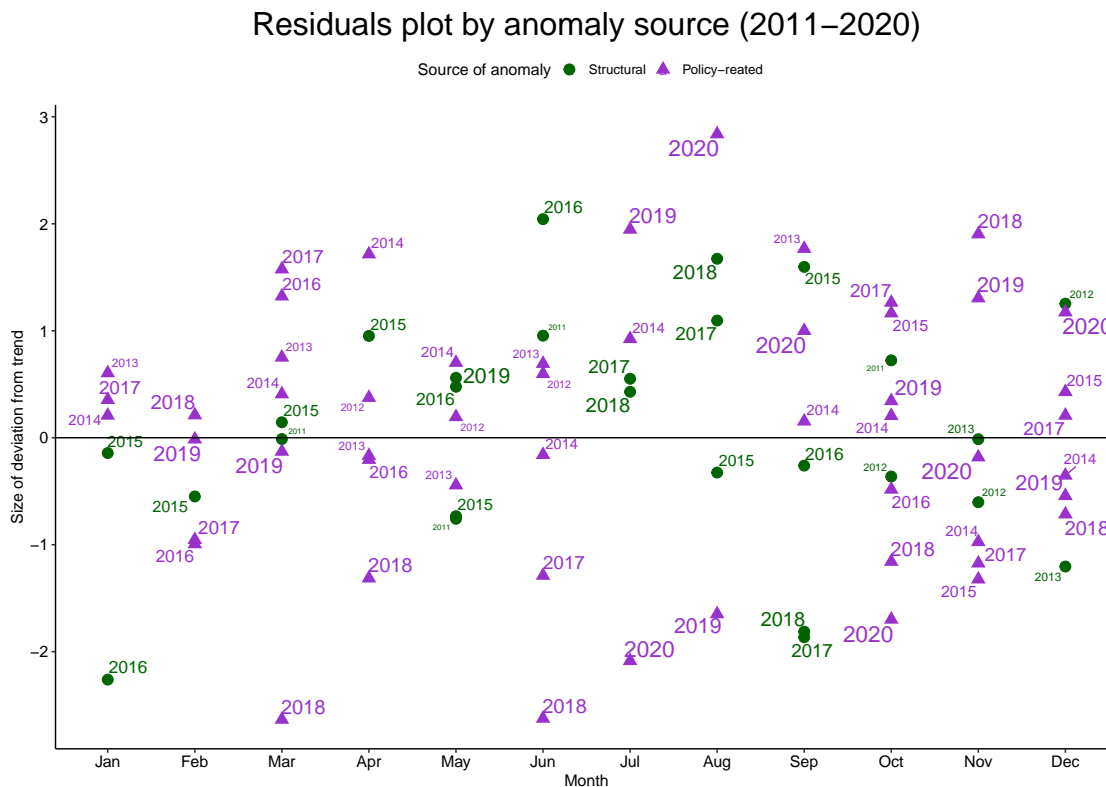


Figure 5: Residuals Plot

Results for differences in mean residual size across the two classes of anomalies are provided in Table 4. It is clear that the size of the residuals (which represent the intensity of deviation from the mean) vary across anomaly classes. Residuals from policy-uncertainty are, on average, negative while structural anomalies have positive residuals with the difference in means being statistically significant at the five-percent level for two of the three specifications. A negative residual implies that the imports for that month were lower in that year, compared to the trend for that month from previous years. Thus, the negative sign on residuals corresponding to policy-uncertainty anomalies suggests a decline in trade due to hesitancy on part of the importers to maintain their normal demand levels when faced with high EPU. Soybean trade, especially, is a unique case since it was at the heart of China’s retaliatory tariffs on the U.S., and a later section will focus on this topic.

Table 4: Heterogeneities

Method	Residuals		
	Structural	PU	Difference
<i>1990-2000 Training/ 2001-2010 Analysis</i>			
Baseline	0.151	-0.011	
NBC	-0.019	0.089	
<i>1995-2005 Training/ 2006-2015 Analysis</i>			
Baseline	-0.11	-0.010	
NBC	0.090	-0.326	**
<i>2000-2010 Training/ 2011-2020 Analysis</i>			
Baseline	0.057	0.058	
NBC	0.448	-0.130	**

Note: * = $p\text{-val} < 0.1$, ** = $p\text{-val} < 0.05$, *** = $p\text{-val} < 0.01$

Novy and Taylor (2020)[14] find that in response to an uncertainty shock, firms disproportionately cut orders of foreign inputs, leading to a magnification effect. They quantify these effects in durables goods trade, arguing that the magnification effect should be muted in goods with high depreciation rates such as nondurables (e.g., food and agriculture). Results here suggest that, contrary to their claim, the magnification effect is also present in agricultural commodities. This is in line with traditional economic theory that uncertainty suppresses demand. EPU, by definition, is high when there is growing uncertainty among stakeholders about the future of international markets. Thus, under high EPU, firms may be inclined to cut down on their foreign orders because they are not sure of the business conditions and may perceive demand for their products to fall significantly as customers decrease consumption. Thus, the adverse effects of EPU are not limited to durables but also apply to non-durables such as agricultural commodities.

Another point of emphasis here is that the EPU measures used in this study encompass uncertainty about the whole economy and thus are not restricted to developments regarding the goods under study alone. This has the important implication that trade in agriculture is affected not only by policies and decisions pertaining to agricultural goods but also by any other policy that causes EPU to change. In other words, any policy that affects confidence about the future also, inadvertently but definitely, affects international trade by virtue of causing shifts in the EPU, regardless of whether or not the policy pertains directly to trade. In the modern world, with its highly integrated global financial and trade networks, this serves to further highlight the importance of careful consideration that must be given with regards to any policy decisions, as evidence indicates that they may have more widespread effects in the economy than previously thought.

IV.3.2 Trade Policy Uncertainty (TPU)

This section of the paper discusses results from a classification based on TPU instead of EPU as before. Table 5 shows that for 2011-2020 period, residuals from TPU-anomalies were, on average, positive while structural residuals were negative, with the difference in means being statistically significant at the ten-percent level. A positive residual implies higher imports for than usual for a particular month compared to previous months. Thus, the positive sign on policy-uncertainty anomalies suggests a tendency towards stockpiling, i.e., opportunistic behavior by importers to protect against potential disruptions in the future. Results for the other two specifications were not statistically significant, which might suggest that the role of TPU is now much more pronounced than in previous years.

Table 5: Heterogeneities (TPU-classification)

Method	Residuals		
	Structural	PU	Difference
<i>1990-2000 Training/ 2001-2010 Analysis</i>			
Baseline	0.007	0.028	
Naive-Bayes	0.226	-0.063	
<i>1995-2000 Training/ 2006-2015 Analysis</i>			
Baseline	0.304	-0.015	
Naive-Bayes	0.179	0.083	
<i>2000-2010 Training/ 2011-2020 Analysis</i>			
Baseline	-0.143	0.022	
Naive-Bayes	-0.387	0.288	*

Note: * = $p\text{-val} < 0.1$, ** = $p\text{-val} < 0.05$, *** = $p\text{-val} < 0.01$

These results are also in contradiction with Novy and Taylor (2020) [14], and are more in line with Alessandria et al. (2019)[13]. While they claim that the magnification effect is minimal or entirely absent in the case of non-durables, results here suggest that instead of the effect being smaller, it actually runs in the opposite direction. That is, in response to potential uncertainty about future trading prospects, buyers will seek to acquire more agricultural commodities than usual. This is in line with the stockpiling behavior observed in other goods during times of uncertainty such as the recent COVID-19 pandemic according to subjective risk perceptions of the buying party (Wang et. al (2020) [37]. This type of forward-looking behavior has also been seen in the case of machinery used in agriculture (for instance, Farm Equipment (2021) [38] and Verdin (2019)[39]). Thus, the results point towards an asymmetry in the response of imports of durables and non-durables wherein trade contracts under uncertainty in the case of durables whereas trade in agricultural commodities increases when uncertainty is high.

IV.3.3 Persistence

Persistence analysis is conducted to investigate if the effects of either class of anomalies lasts longer than the other. The figures in the last two columns in [Table 6](#) and [Table 7](#) represent the number of times where an EPU-anomaly and TPU-anomaly of a particular class is predicted to have been followed by an anomaly of the same class over the next four periods. It is apparent that policy-uncertainty related anomalies are at least comparable in frequency of repetition to structural anomalies across all specifications. Moreover, when the analysis is restricted to the last decade alone after training the model on the period between 2000 and 2010, the share of persistent PU-anomalies in the data are found to be increasing and outnumber structural anomalies by a large margin. This is to be expected, as international relations among large economies have seen extreme levels of fracture. This growing strain has led to an increase in protectionism worldwide and, consequently, policy uncertainty has rocketed to unprecedented levels and is playing an increasing role in international trade flows.²

Table 6: Persistence of EPU-anomalies

Data	Structural	PU
<i>1990-2000 Training/ 2001-2010 Analysis</i>	17	34
<i>1995-2005 Training/ 2006-2015 Analysis</i>	52	15
<i>2000-2010 Training/ 2011-2020 Analysis</i>	18	50

Table 7: Persistence of TPU-anomalies

Data	Structural	PU
<i>1990-2000 Training/ 2001-2010 Analysis</i>	21	19
<i>1995-2005 Training/ 2006-2015 Analysis</i>	40	17
<i>2000-2010 Training/ 2011-2020 Analysis</i>	13	50

[Table 8](#) shows the averages for residuals over the four-month period, for those anomalies that are succeeded by an anomaly of the same class during that period. Two out of the three specifications show a persistent contractionary effect of EPU on international agricultural trade, in line with economic theory. These negative effects are also accompanied by positive residuals that correspond to structural fluctuations. In combination, the data over from the two samples suggest that while firms may be more willing to increase imports to mitigate issues related to idiosyncratic fluctuations in production, EPU has persistent dampening effects. The effect however runs in the opposite direction for the 2001-2010 decade. This apparent contradiction is also seen in the response to high TPU, as presented in the first row of [Table 9](#). In the first decade of the 2000's, increases in TPU were associated with a decline in trading activity. However, in the most recent decade,

²While anomaly detection, classification and residual analyses can be thought of as examinations of the second moment, the determinants of the trend (i.e. the first moment) can also be identified using traditional methods. OLS estimates from linear regressions involving some variables that usually feature in gravity models (e.g., population, GDP, tariff rates) for the period between 2000 and 2020, show expected signs.

high TPU led to a growth in trade instead of a decline, a result that is statistically significant at the one-percent level. A possible explanation for this change in firms' behavior may be that when facing policy uncertainty in previous years, importers may not have maintained usual levels of ordering due to wariness about future prospects and employed a strategy to wait until the period of uncertainty subsided to make significant purchases. In recent years, however, trade policy has been so volatile that firms', fearing extreme changes in the near future (including tariff hikes and other restrictions), may be induced to prepone purchases and complete their orders before the situation is exacerbated. This adds to the evidence towards the claim that policy-uncertainty and its consequences are both increasing in severity, and, in order to limit damages to both firms as well as consumers, steps must be taken to address this concern .

Table 8: Heterogeneities in Persistence (EPU)

Data	Residuals		
	Structural	EPU	Difference
<i>1990-2000 Training/ 2001-2010 Analysis</i>			
	-0.147	0.008	*
<i>1995-2005 Training/ 2006-2015 Analysis</i>			
	0.010	-0.398	*
<i>2000-2010 Training/ 2011-2020 Analysis</i>			
	0.567	-0.113	**

Note: * = $p\text{-val} < 0.1$, ** = $p\text{-val} < 0.05$, *** = $p\text{-val} < 0.01$

Table 9: Heterogeneities in Persistence (TPU)

Data	Residuals		
	Structural	TPU	Difference
<i>1990-2000 Training/ 2001-2010 Analysis</i>			
	0.399	-0.033	*
<i>1995-2005 Training/ 2006-2015 Analysis</i>			
	0.051	0.217	
<i>2000-2010 Training/ 2011-2020 Analysis</i>			
	-0.473	0.648	***

Note: * = $p\text{-val} < 0.1$, ** = $p\text{-val} < 0.05$, *** = $p\text{-val} < 0.01$

V. Discussion

That uncertainty can affect international trade is well-understood, in light of the theoretical and empirical contributions made by Bernanke (1983)[1], Dixit (1989)[27] and several subsequent papers discussed above. However, determining the size of the direct and indirect effects is not straightforward. As seen in Figure 6, uncertainty, including policy uncertainty, can impact trade via a number of channels. First, there are the direct effects of policy uncertainty on trade, as presented in Handley (2014)[11], and Handley and Limao (2017)[12], wherein changes to policy uncertainty can directly result in shifts in international trade levels. An earlier literature also discusses how uncertainty leads producers to rethink acreage decisions, ultimately influencing international trade via the production channel. In addition, storage units also act as a crucial buffer between production and supply, with outflows from reserves being used to mitigate immediate needs in response to severe supply shocks. Finally, there are albatross events such as the recent US- China tariff wars that can result in unanticipated jumps in policy uncertainty, and whose effects are seen both directly- in terms of direct changes in trade levels- as well as indirectly- via the aforementioned channels due to the increase in policy uncertainty. A few case studies will help to illustrate these effects in context.

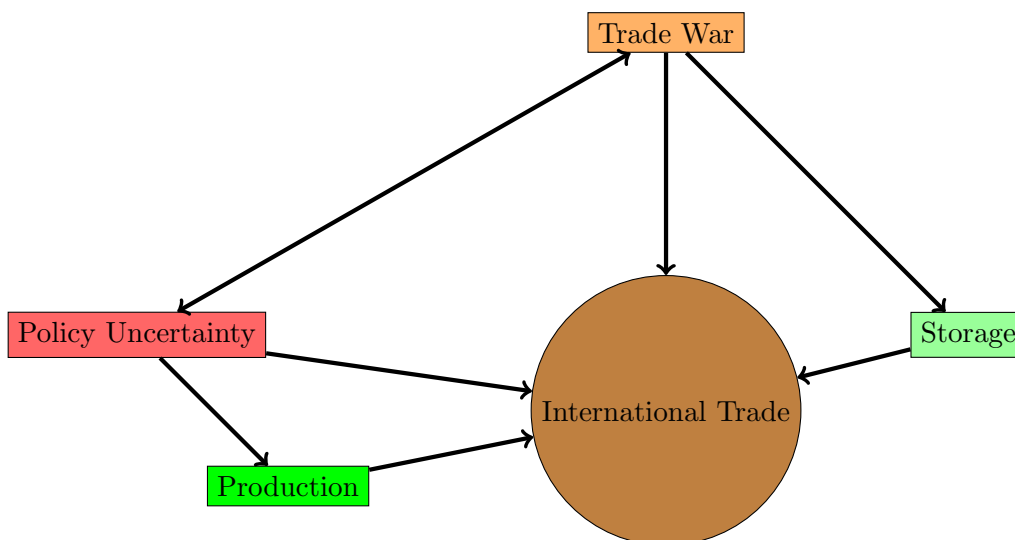


Figure 6: Causal relationships

V.1 The 2008/09 Global Financial Crisis

In early September 2008, two premier government-sponsored lending agencies in the U.S., Fannie Mae and Freddie Mac, were put on a “conservatorship” owing to their unsustainable losses. This

was followed by the Lehman Brothers’ bankruptcy in the middle of the month, and, later in the same month, by the nationalization of American International Group (AIG)- the world’s largest insurance company. The consequences of these events, compounded by various spillovers affecting the “real economy” such as collapsing exports, commodity prices, and remittance payments (Heleneir, 2011)[40] led to widespread effects across the world. Boorman (2009)[41] states that the highly-integrated global trading and financial system magnified and accelerated the transmission of the collapse, aided by inadequate regulation and uncoordinated policy responses to early signs of trouble in the global financial system. An underlying sentiment shared by economists and policy-makers with regards to the causes and consequences of the crisis is that “trust and confidence (singularly or in tandem)” played significant roles in driving the crisis and would be “central to any effective plan for recovery” (Earle, 2009)[42]. This idea is also a key component to understanding how policy uncertainty, in particular, is of prime importance in preventing global collapses of a similar nature.

Novy and Taylor (2020)[14] attempts to answer the puzzle of the asymmetric response of international trade to the drop in output (20 percent fall in trade in the 12 months following April 2008 compared to a 12 percent decline in industrial production). They conclude that up to half of the trade decline in 2008-09 can be explained as a response to the increase in uncertainty. Despite their claims that this effect is only prevalent in manufactures or durable goods, the data suggest that this magnification effect is also observed in agricultural trade. For instance, consider the month of October 2008. Due to the financial crisis, EPU more than tripled in value compared to the same month in the previous year (217.32 then vs. 69.60 in October 2007). For the same months, there was a 12.5 percent decrease in global soybean trade. Interestingly, there was a slight increase in the total supply of soybeans for the same period (by 7000 metric tonnes). Thus, when financial markets were put under severe strain leading to an increase in EPU, trade in agricultural commodities also shrank as a result. The NBC classifier identifies four out of the five anomalies in 2008 as being EPU-related, including the month of October. It is evident that most of the decline in trade is driven by changes to the EPU, as shown by the increase in total supply which eliminates the possibility of trade declining as a result of supply-side changes.

V.2 U.S.-China Tariff wars

Unlike the previous case where EPU was the metric of interest, this section will focus on TPU. Following the end of the previously agreed-upon “100 days of talks” on July 2017 and with no agreements on the reduction of the U.S. trade deficit with China, the then U.S. president Donald Trump ordered a “Section 301” probe into alleged intellectual property theft by China, based on a 1974 trade law that outlines how the U.S. should respond to violations of trade agreements. On January 22, 2018, the U.S. imposed tariffs on all imported washing machines and solar panels, followed by 25 percent tariffs on steel imports and 10 percent tariffs on aluminum. In retaliation, China imposed tariffs of up to 25 percent on 128 U.S. products on April 2, 2018. The following day, the U.S. announced another 25 percent tariff on around \$50 billion of Chinese imports to which

China responded by unveiling plans for retaliatory tariffs on about \$50 billion of U.S. imports. These announcements were followed, over several months, by a series of escalatory tariffs and threats of further trade measures from both sides. After yet another round of failed negotiations, August 2018 witnessed a trade war in full effect as both parties engaged in court battles and public condemnation on multiple fronts including steel and aluminum trade, intellectual property disputes, automotive parts, and superconductor supremacy.

For illustration purposes, consider the month of June 2018 where the TPU reached 688.4 points, one of its highest levels recorded thus far and a massive increment from June 2017 when it stood at 86.85 points. International soybean trade increased by around 7 percent during this time with respect to quantity traded and by around 22.6 percent in terms of dollar value. Thus, TPU, unlike EPU, may actually help in increasing agricultural trade. While in the case of EPU, firms will seek to reduce demand as a response to uncertain outlook about the future, theory predicts that TPU can encourage trade due to anticipatory effects. That is, firms- fearing that business conditions are about to get worse- rush to fulfill their demand specifically as a response to uncertainty shocks. Besides the surge in trade, the total supply of soybean (including stock levels) also rose by 16.7 percent, which is clearly indicative of the anticipatory effects of TPU. Furthermore, we also see year-to-year increases in both the quantity as well as value of soybean trade in August, September, and October 2018, for which the levels of TPU remained consistently high, which highlights the persistent effects of TPU in boosting trade. Not surprisingly, total trade during calendar 2019 was 6.4 percent lower than that in 2018 given the anticipatory stockpiling during 2018. As expected, the NBC classifier identified five out of the ten anomalies in 2018 as being TPU-related.

VI. Takeaways

Increasing globalization has led to unprecedented levels of international agricultural trade over the past three decades. However, the volatility associated with agricultural trade has also amplified considerably in recent years owing to significant shifts in the global political landscape along with the usual idiosyncrasies associated with agricultural production. In light of these political shifts, it is important to understand the effects of such uncertainties on trade since the future path of trade policy is filled with puddles and potholes. While a large body of literature has explored the relationship between uncertainty and economic activity, that between uncertainty and international trade has received limited attention. Trade in nondurables is of particular interest given the recent spillovers of trade war in manufacturing to agriculture and food industries. This study is an initial attempt to rectify this gap and aims to link volatility in agricultural imports with policy-related uncertainty.

This study drew upon recent theoretical advancements to show that a link between uncertainty and trade can arise in the case of nondurables. To test that relationship, Naive Bayes Classifier- a supervised ML technique- is used on monthly trade data at HS-4 digit level. Data on production levels and recent text-mining based uncertainty measures are taken from other sources. Findings

from this study show that structural (production) and policy-uncertainty shocks are fundamentally different and soybean imports react differently to the two classes of shocks. The Naive Bayes approach, preferred based on assurance indicators over other methods, showed that anomalies related to economic policy uncertainty are associated with a statistically significant decline in imports of soybean compared to structural anomalies. This complements previous results on the contractionary effects of uncertainty on trade, and other economic indicators. Imports response to trade policy uncertainty, on the other hand, is positive which may be likely due to an anticipatory stockpiling effect observed in other studies using monthly data. Further analysis shows that the adverse effects of PU-related shocks persist beyond the period of incidence of the shock, and may lead to prolonged decreases in imports relative to production shocks.

The key motivation behind this work is to highlight the often overlooked relationship between policy-uncertainty and the trade of agricultural goods. Future work on other nondurables as well as additional classification of uncertainties (both production and policy-related) and their interdependence might aid in decision-making as the future trade policy path of major economies remains uncertain. An important channel emphasized by scholars as well as the WTO is for nations to commit to predictability and transparency in future policy, which may prove fruitful in assuaging the growing concerns related to policy uncertainties.

References

- [1] Ben S Bernanke. “Irreversibility, uncertainty, and cyclical investment”. In: *The Quarterly Journal of Economics* 98.1 (1983), pp. 85–106.
- [2] Robert McDonald and Daniel Siegel. “The value of waiting to invest”. In: *The Quarterly Journal of Economics* 101.4 (1986), pp. 707–727.
- [3] Robert S Pindyck. “Irreversibility, uncertainty, and investment”. In: *Journal of Economic Literature* 29.3 (1991), pp. 139–162.
- [4] Valerie A Ramey and Matthew D Shapiro. “Displaced capital: A study of aerospace plant closings”. In: *Journal of Political Economy* 109.5 (2001), pp. 958–992.
- [5] Nicholas Bloom. “The impact of uncertainty shocks”. In: *econometrica* 77.3 (2009), pp. 623–685.
- [6] Ryan Kellogg. “The effect of uncertainty on investment: Evidence from Texas oil drilling”. In: *American Economic Review* 104.6 (2014), pp. 1698–1734.
- [7] Hans P Binswanger. “Attitudes toward risk: Theoretical implications of an experiment in rural India”. In: *The Economic Journal* 91.364 (1981), pp. 867–890.
- [8] Jean-Paul Chavas. “Role of risk and uncertainty in agriculture”. In: *The Routledge Handbook of Agricultural Economics*. Routledge, 2018, pp. 603–615.
- [9] Jean-Paul Chavas and Matthew T Holt. “Acreage decisions under risk: the case of corn and soybeans”. In: *American Journal of Agricultural Economics* 72.3 (1990), pp. 529–538.
- [10] Jean-Paul Chavas and Matthew T Holt. “Economic behavior under uncertainty: A joint analysis of risk preferences and technology”. In: *The Review of Economics and Statistics* (1996), pp. 329–335.
- [11] Kyle Handley. “Exporting under trade policy uncertainty: Theory and evidence”. In: *Journal of international Economics* 94.1 (2014), pp. 50–66.
- [12] Kyle Handley and Nuno Limão. “Policy uncertainty, trade, and welfare: Theory and evidence for China and the United States”. In: *American Economic Review* 107.9 (2017), pp. 2731–83.
- [13] George A Alessandria, Shafaat Y Khan, and Armen Khederlarian. *Taking stock of trade policy uncertainty: evidence from china’s Pre-WTO accession*. Tech. rep. National Bureau of Economic Research, 2019.
- [14] Dennis Novy and Alan M Taylor. “Trade and uncertainty”. In: *Review of Economics and Statistics* 102.4 (2020), pp. 749–765.
- [15] Tom M Mitchell. “Generative and discriminative classifiers: Naive bayes and logistic regression”. In: *Machine Learning* 1.2 (2010), pp. 1–17.
- [16] Peter Clark et al. “Exchange rate volatility and trade flows-some new evidence”. In: *IMF Occasional Paper* 235 (2004).

- [17] Benjamin Born and Johannes Pfeifer. “Policy risk and the business cycle”. In: *Journal of Monetary Economics* 68 (2014), pp. 68–85.
- [18] Jesús Fernández-Villaverde et al. “Fiscal volatility shocks and economic activity”. In: *American Economic Review* 105.11 (2015), pp. 3352–84.
- [19] Scott R Baker, Nicholas Bloom, and Steven J Davis. “Measuring economic policy uncertainty”. In: *The Quarterly Journal of Economics* 131.4 (2016), pp. 1593–1636.
- [20] L’uboš Pástor and Pietro Veronesi. “Political uncertainty and risk premia”. In: *Journal of financial Economics* 110.3 (2013), pp. 520–545.
- [21] Xiao-lin Li et al. “The causal relationship between economic policy uncertainty and stock returns in China and India: Evidence from a bootstrap rolling window approach”. In: *Emerging Markets Finance and Trade* 52.3 (2016), pp. 674–689.
- [22] Nikolaos Antonakakis, Ioannis Chatziantoniou, and George Filis. “Dynamic spillovers of oil price shocks and economic policy uncertainty”. In: *Energy Economics* 44 (2014), pp. 433–447.
- [23] Pierre Andreasson et al. “Impact of speculation and economic uncertainty on commodity markets”. In: *International Review of Financial Analysis* 43 (2016), pp. 115–127.
- [24] Yudong Wang et al. “Commodity price changes and the predictability of economic policy uncertainty”. In: *Economics Letters* 127 (2015), pp. 39–42.
- [25] Andrew K Rose. “Do we really know that the WTO increases trade?” In: *American Economic Review* 94.1 (2004), pp. 98–114.
- [26] Arvind Subramanian and Shang-Jin Wei. “The WTO promotes trade, strongly but unevenly”. In: *Journal of International Economics* 72.1 (2007), pp. 151–175.
- [27] Avinash Dixit. “Entry and exit decisions under uncertainty”. In: *Journal of Political Economy* 97.3 (1989), pp. 620–638.
- [28] Dario Caldara et al. “The economic effects of trade policy uncertainty”. In: *Journal of Monetary Economics* 109 (2020), pp. 38–59.
- [29] Joseph B Steinberg. “Brexit and the macroeconomic impact of trade policy uncertainty”. In: *Journal of International Economics* 117 (2019), pp. 175–195.
- [30] Scott Baker, Nicholas Bloom, and Steven Davis. “The extraordinary rise in trade policy uncertainty”. In: *Reading* 19 (2019), p. 21.
- [31] Fei Tony Liu, Kai Ming Ting, and Zhi-Hua Zhou. “Isolation forest”. In: *2008 eighth IEEE international conference on data mining*. IEEE. 2008, pp. 413–422.
- [32] José E Chacón and Tarn Duong. *Multivariate kernel smoothing and its applications*. CRC Press, 2018.
- [33] Michael Hahsler, Matthew Piekenbrock, and Derek Doran. “dbscan: Fast density-based clustering with R”. In: *Journal of Statistical Software* 91.1 (2019), pp. 1–30.

- [34] Chih-Chung Chang and Chih-Jen Lin. “LIBSVM: a library for support vector machines”. In: *ACM Transactions on Intelligent Systems and Technology (TIST)* 2.3 (2011), pp. 1–27.
- [35] Pedro Domingos and Michael Pazzani. “On the optimality of the simple Bayesian classifier under zero-one loss”. In: *Machine Learning* 29.2 (1997), pp. 103–130.
- [36] Harry Zhang. “Exploring conditions for the optimality of Naive Bayes”. In: *International Journal of Pattern Recognition and Artificial Intelligence* 19.02 (2005), pp. 183–198. DOI: [10.1142/S0218001405003983](https://doi.org/10.1142/S0218001405003983). URL: <https://doi.org/10.1142/S0218001405003983>.
- [37] Erpeng Wang et al. “Consumer food stockpiling behavior and willingness to pay for food reserves in COVID-19”. In: *Food Security* 12.4 (2020), pp. 739–747.
- [38] Farm Equipment. *Precautionary Stockpiling of Supplies Creates False Picture of Demand*. <https://www.farm-equipment.com/articles/19888-precautionary-stockpiling-of-supplies-creates-false-picture-of-demand>. Accessed: 2021 January 19. 2021.
- [39] Mike Verdin. *Farm machinery manufacturers stockpile tractors due to Brexit fears*. <https://www.fginsight.com/news/news/farm-machinery-manufacturers-stockpile-tractors-due-to-brexite-fears-79532>. Accessed: 2021 January 19. 2019.
- [40] Eric Helleiner. “Understanding the 2007–2008 global financial crisis: Lessons for scholars of international political economy”. In: *Annual Review of Political Science* 14 (2011), pp. 67–87.
- [41] Jack Boorman. “Remarks for the South Asia Forum on the Global Economic and Financial Crisis”. In: *Manila, March 2* (2009).
- [42] Timothy C Earle. “Trust, confidence, and the 2008 global financial crisis”. In: *Risk Analysis: An International Journal* 29.6 (2009), pp. 785–792.

Appendix

Table A1: Anomalies from other methods

KDE		one-classSVM		DBSCAN	
Year	Month	Year	Month	Year	Month
2019	11	2001	3	2020	4
2007	7	2003	3	2020	10
2003	4	2003	4	2020	8
2020	10	2001	11	2020	5
2006	11	2007	7	2020	6
2002	5	2009	2	2020	7
2005	11	2009	3		
2005	4	2012	8		
2006	12	2014	2		
2009	3	2015	2		
2006	5	2015	11		
2007	11	2018	12		
2001	3	2019	8		
2008	3	2020	4		
2011	2	2020	5		
2015	2	2020	6		
2012	9	2020	7		
2013	2	2020	10		
2019	3				
2018	5				
2004	5				
2004	9				
2002	2				
2015	5				
2010	11				
2002	3				
2005	2				
2004	3				
2017	4				
2006	9				

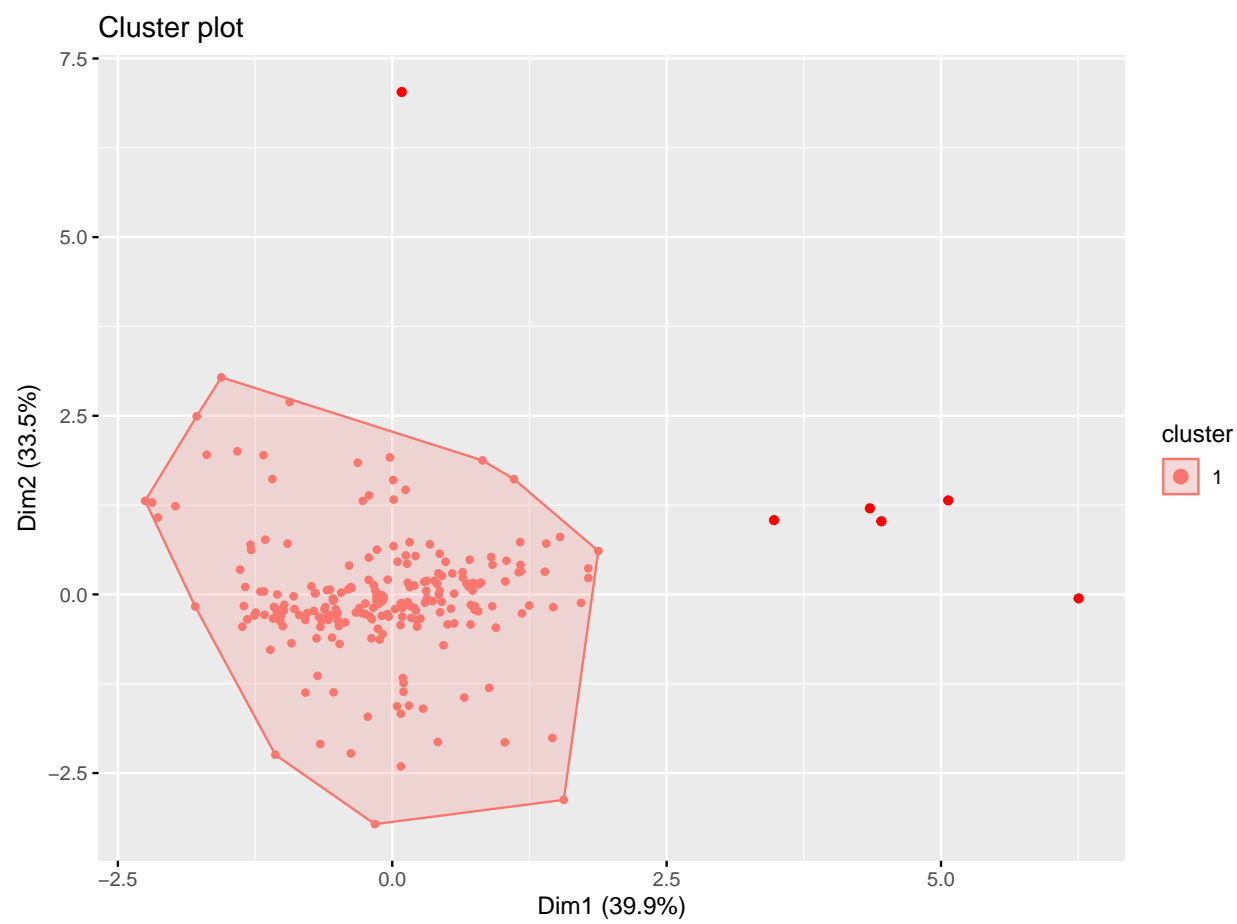


Figure A1: DBSCAN cluster

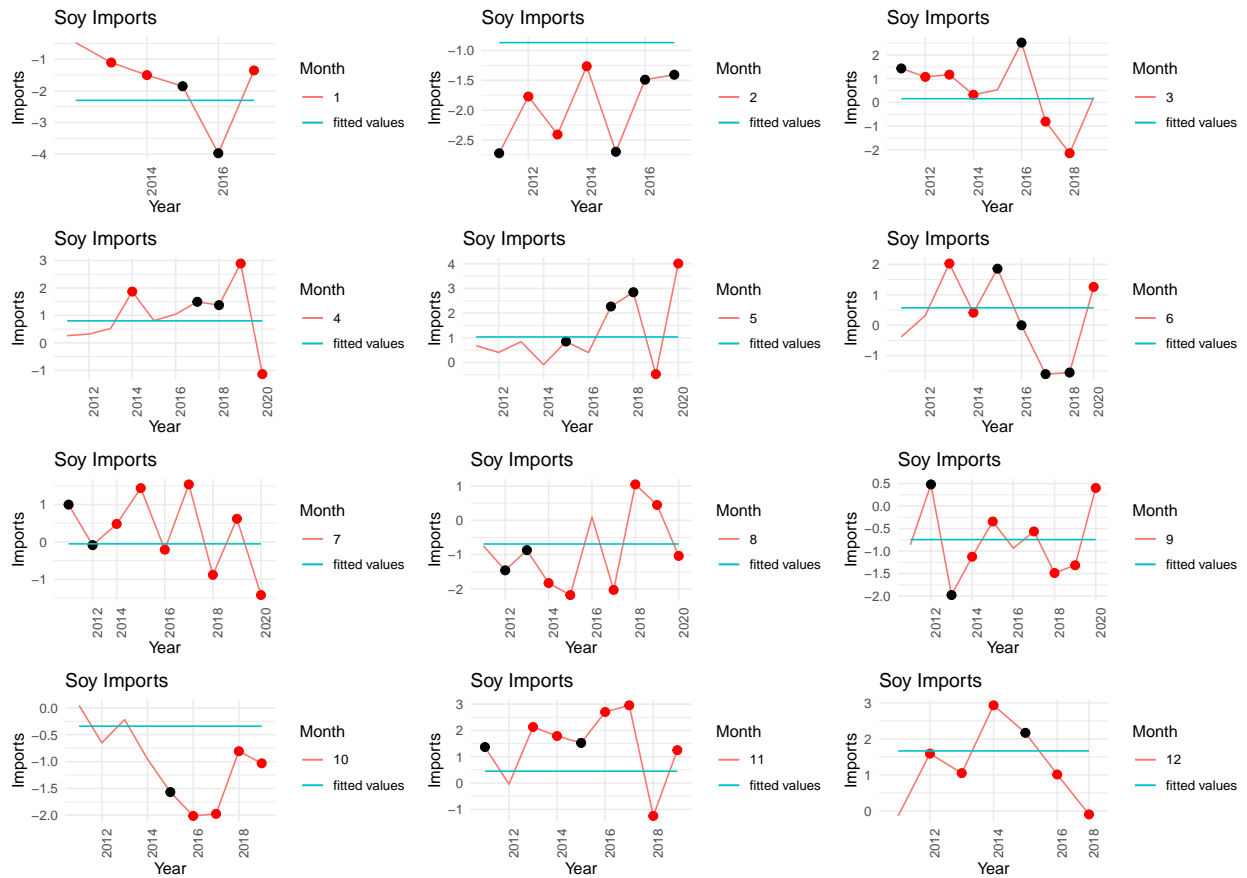


Figure A2: Monthly Trends

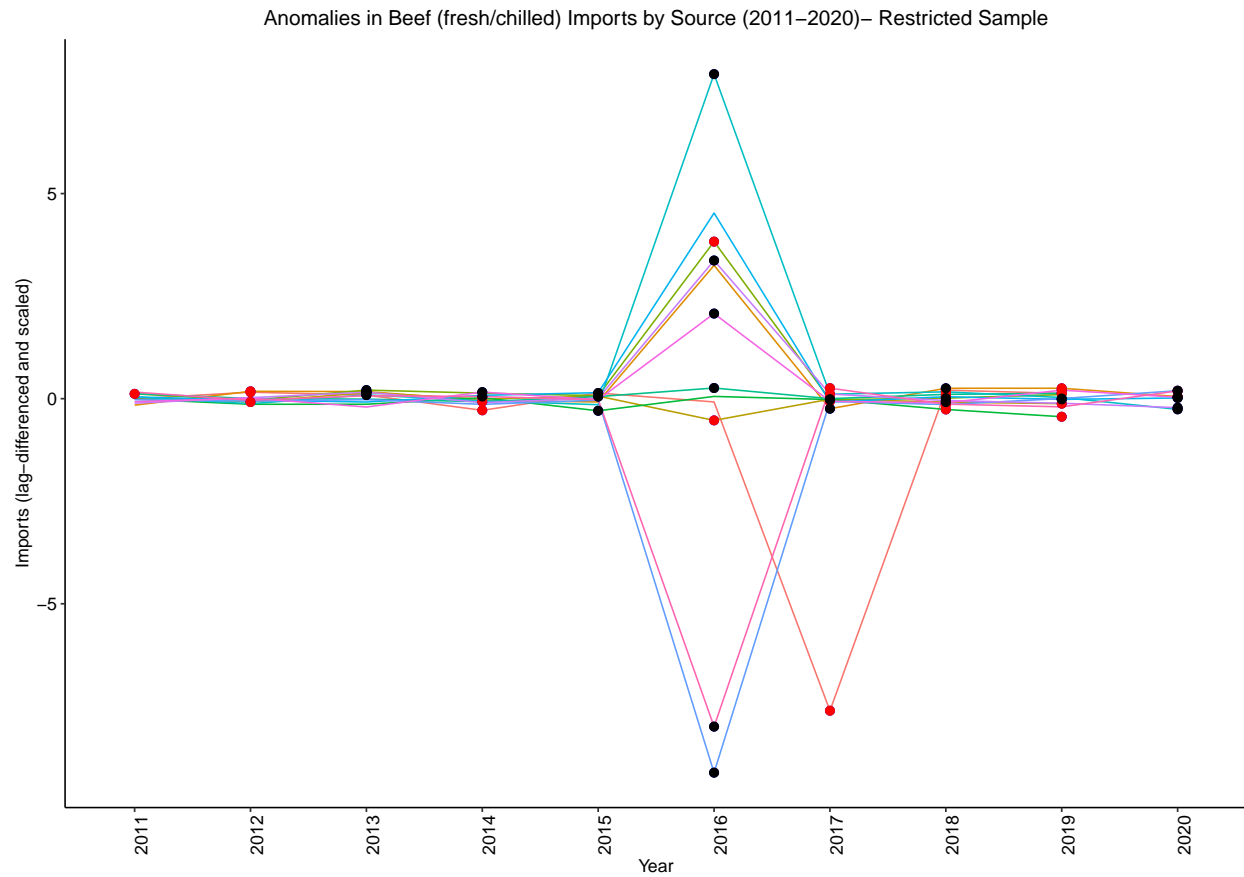


Figure A4: Corn anomalies

Table A3: Anomalies detected for other commodities (2011-2020)

Commodity	Structural	PU-related
Corn	31	30
Beef (fresh/chilled)	0	15
Beef (frozen)	0	25

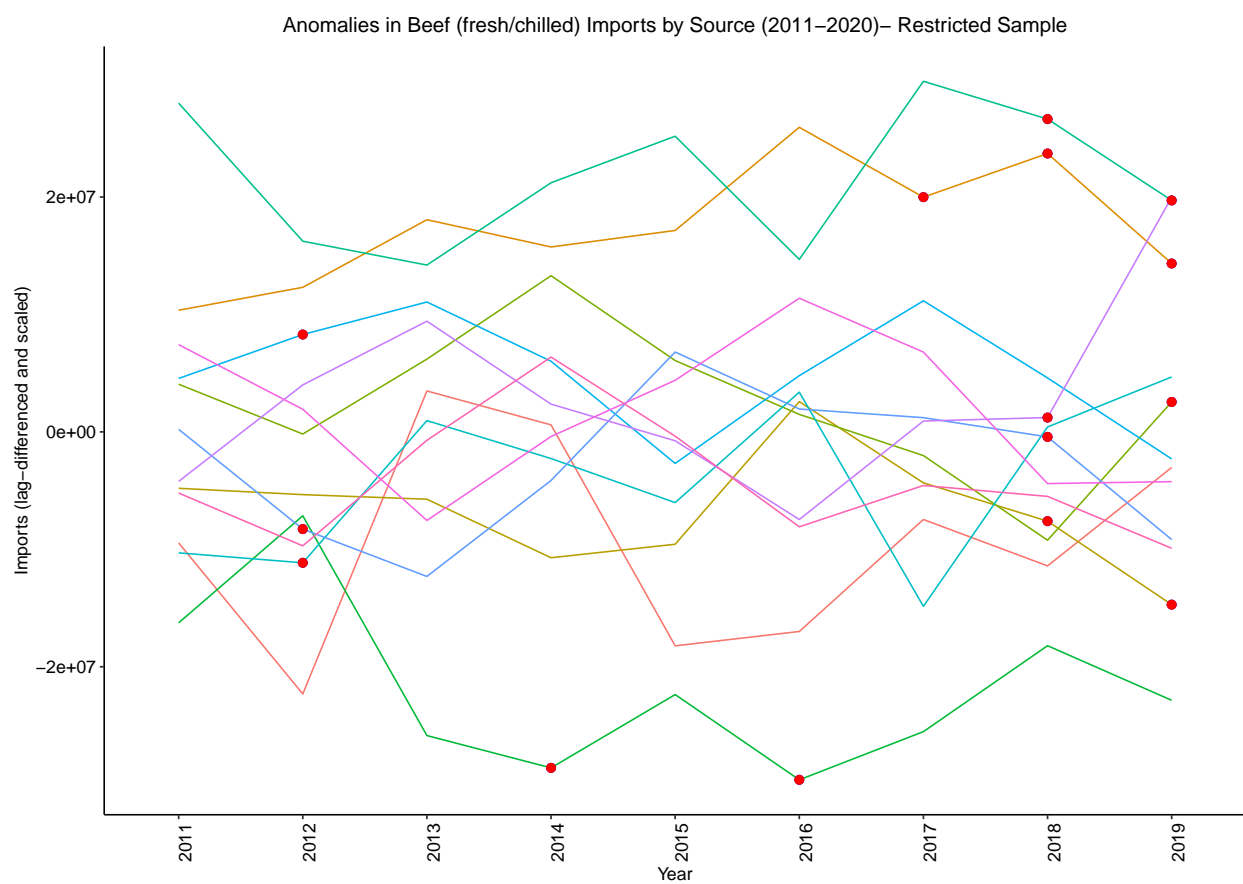


Figure A5:Beef (fresh) anomalies



Figure A6: Beef (frozen) anomalies