Three essays on international trade and policy

by

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B.A., Beijing University of Chemical Technology, China, 2012

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AN ABSTRACT OF A DISSERTATION

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Abstract

International trade in agricultural and food commodities has grown rapidly during the past five decades, with increasingly more countries participating in the international markets either as food importers or as food exporters. Despite the fast growth, international agricultural trade, however, is still largely affected by various policy distortions. This is especially the case in developing countries, in which opening to the international market is often perceived to be in conflict with their policy objectives of ensuring food security. In this context, this dissertation constitutes three essays toward better understanding of how international trade is affected by policy and how it can affect food security in developing countries.

The first essay conducts a case study with quantitative analysis regarding the trade policy for grain commodities in China. Specifically, China emerged as a grain importing country in mid 2000s. In 2016, the U.S., a major grain exporter, launched a trade dispute against China at the World Trade Organization, arguing that China has been restricting its grain imports via tariff quota administration. Despite the criticism of the U.S., little do we know about the extent to which the grain imports in China were actually restricted by its trade policy, mainly because China's grain import behaviors have not been sufficiently studied. For instance, even the import demand elasticity, a key input into policy assessment, is unknown. To fill this gap in the literature, this article investigates impacts of the tariff quota administration on China's grain imports from its trading partners. We estimate import demand elasticity for each grain commodity using a source differentiated import demand model and then use the elasticity estimates to quantify the policy impacts on trade. In particular, the tariff quota administration is treated as a non tariff barrier and measured by ad valorem tariff equivalents in the model. We find that the tariff quota administration might have reduced the quota fill rates for the grain commodities by 10-35% during 2013-2017 in China, and that the wheat

imports from the U.S. were largely negatively affected. We also find that the tariff quota administration acts like an import variable levy – its import restrictiveness varies negatively with world prices, leading to lower import demand elasticities.

The second essay concerns the trade impacts on food price variability in developing countries. In particular, we are interested in this question: do food imports increase the variability of domestic food prices? The question matters because if imports destabilize domestic prices, storing crops for future consumption may prove an appealing strategy to cope with the adverse supply effects of a more unstable climate. Unfortunately, public storage has proven to be unsustainable due to the high costs of carrying crop inventories over time and the inability of policy planners to correctly forecast changes in domestic supply. In this context, it is important to understand the roles of both imports and stocks in affecting domestic food price variability. Using maize prices observed in 76 maize markets of 27 maize net importers across Africa, Asia and Latin America during 2000-2015, we find that, on average, a 1% increase in the ratio of imports to total consumption is correlated with a 0.29% reduction of the intra-annual coefficient of variation of maize prices; likewise a 1% increase in the amount of maize available in stocks at the beginning of the season is correlated with a 0.22% reduction in the said coefficient. We also find that climate-induced supply shocks toward mid-century may increase maize price variability in the focus countries by around 10%. These increases, however, could be offset with similar increases in the ratio of imports to total consumption or in the stock-to-use ratio at the beginning of the crop marketing year.

The third essay also concerns the trade impacts on food price variability in developing countries. Rather than focusing on the roles of imports and stocks, we look into the effects of foreign yield shocks on domestic food price variability in this essay. Around two thirds of developing countries are now net food importers. While enjoying economical food in the international market, these countries have become increasingly more concerned that their food price stability is now vulnerable to foreign yield shocks, which are expected to grow in frequency and intensity in the future due to the climate change. Yet, the extent to which foreign yield shocks could affect food price stability in the food-importing countries have not

been explicitly quantified in previous studies. This article aims to fill the gap by estimating the effects of foreign maize yield shocks on domestic maize price variability. We perform the analysis using price data of 74 maize markets in 24 net food-importing countries during 2000-2016. We find that positive foreign yield shocks have negative effects on domestic price variability, meaning that domestic prices become more stable under positive foreign yield shocks. Negative foreign yield shocks, however, do not have significant effects on domestic price variability, except for causing higher price variability in a few landlocked countries. We also find that domestic maize price variability could increase in the coming decades due to the increasing variability of maize yields under climate change. Yet, most focus countries seem to have accumulated stocks sufficient enough to maintain stable prices. We conclude that food-importing countries benefit from the international market in domestic price stability, and that storage could be an effective policy tool to complement international trade for price stabilization.

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Acknowledgments

Up to now, I have been away from my family in China for more than three years, as I pursue the PhD degree in the United States. Being separated from family was meant to be hard and sorrowful. Yet, thanks to the people to be mentioned below, I have felt my life spent in the United States adventurous and joyful. For this particular reason, I would like to thank these people here as I present my dissertation work.

My sincere and deep gratitude goes first and foremost to my grandpa, who passed away when I entered the third year in my PhD program. The story of my grandpa can best be summarized in the saying of the Nobel Laureate Theodore W. Schultz, "Starting from widespread illiteracy, as more schooling per child is achieved, the older adults continue through life with little or no schooling, whereas the children on entering into adulthood are the beneficiaries" (Schultz, 1980, p.648). Indeed, my grandpa was a farmer endowed with only a few acres of land, and then became a small businessman. He did not make a fortune in his business, because he devoted his earnings and even his life to the education of the youths in the family, including me. He placed trust and great confidence in my ability to achieve success in the academic arena, for which I will be forever grateful. His greatness lies in his wisdom, and sacrifice.

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Last but not the least, I would like to acknowledge my parents, who have always been my source of courage, persistence, and optimism.

Dedication

In dedication to my parents, and to the memory of my grandpa.

Chapter 1

Tariff Quota Administration in China's Grain Markets: An Empirical Assessment

1.1 Introduction

In December 2016, the U.S. launched a dispute request against China at the World Trade Organization (WTO) over China's tariff quota administration for imports of maize, rice and wheat. In the request statement, the U.S. claimed that "China has failed to ensure that the administration of tariff rate quotas would not inhibit the filling of quotas" (USTR, 2016). This trade dispute has been recognized as a major agricultural trade policy issue for the U.S. 115^{th} congress (McMinimy et al., 2017). China, however, insisted on that it abides by the WTO rules when administering the grain quotas (MOA, 2017). Many other grain exporting countries, such as Australia and Canada, have requested to join proceedings of the dispute as third parties. The WTO Dispute Settlement Body has established a panel to look into the dispute in September 2017, and the panel will likely issue its final report in the second quarter of 2019 (WTO, 2018a). To date, the dispute has not yet been resolved.

Given the sheer size of the Chinese economy, some observers indicated that import restrictions of China could have significant adverse impacts on the grain exporting countries. For instance, the U.S. Department of Agriculture projected that China's unused grain quotas in 2015 worth 3.5 billion dollars (USTR, 2016). Yet, trade impacts of the tariff quota administration remain largely unknown because China's grain import behaviors have not been sufficiently studied in the agricultural trade literature – even the import demand elasticity needed for the policy assessment is unavailable. Despite that the U.S. is a major grain exporter in the world, the present impacts of China's grain trade policy on the U.S. could actually be minor, because China has diversified its grain imports to lessen its import dependence on the U.S. (Gale et al., 2015). Thus, the U.S. might actually gain little by pressing China into promoting trade liberalization. In this context, this paper aims to investigate impacts of the tariff quota administration on China's grain imports from its trading partners, with a focus on the U.S.. Going beyond the investigation, we explore rationales behind China's discretionary administration of the grain quotas through evidence revealed in their import behavior. Understanding the rationales is essential to our modeling strategies; and importantly, it could inform policy endeavors to facilitate the grain market liberalization in China.

As China emerges as a consistent grain importer (Gale et al., 2015), many scholars are now paying increasingly more attentions to the global impacts of China's domestic and trade policy. Marchant (2017) introduced a collection of four articles that analyzed recent changes in China's agricultural policies and their impacts on global commodity markets, while focusing on impacts on the U.S.. Orden and Brink (2018) provided a comprehensive analysis of China price support policy and its compliance with the WTO rules. Our paper complements these articles by focusing on the Tariff Rate Quota (TRQ) policy for grain commodities, a topic not yet studied despite its policy relevance. Zhou and Kang (2007) provided detailed background information regarding the quota management in China, but they did not attempt to quantify impacts of the quota policies on trade.

Our paper contributes to the economics literature by providing new estimates of China's import demand elasticities for three grain commodities, including maize, rice and wheat. These elasticities are key inputs into the analysis of China's grain trade policy. Kee et al.

(2008) estimated import demand elasticities at six-digit harmonized system level for a large number of countries including China. Yet, their estimates for grain commodities in China have large standard errors relative to the point estimates, which will lead to high imprecision when projecting the policy impacts on trade.[1] In addition, their estimates might not reflect the current market situation, because they used annual trade data nearly two decades ago (from 1988 to 2001). The TRQ policy was not even implemented in China at the time. In contrast, we use the monthly trade data during 2013-2017, a time period that China consistently imported grains under the TRQ system after acceding to the WTO in 2001 (Gale et al., 2015).

Our paper is related to studies about TRQs. A TRQ is a policy instrument introduced to agriculture in the Uruguay Round Agreement on Agriculture in early 1990s, intended to improve market access (Abbott, 2002). Yet, TRQ as a policy instrument has attracted considerable criticism in the trade policy literature. For instance, Abbott (2002); Abbott and Morse (2000) argued that the way that countries administer the quotas is often cumbersome, weakening the import demand. Skully (2001) analyzed impacts of alternative quota administration methods on market efficiency and the distribution of trade. An empirical study by Mönnich (2003) found that the choice of quota administration methods significantly affects quota fill rates. Despite the criticism, the literature, however, has not yet provided direct empirical evidence showing that the tariff quota administration restricts trade. Our article helps fill the gap by documenting a country case (i.e., China) that the tariff quota administration significantly reduced imports. In addition, we showed that tariff quota administration can actually reduce the import demand elasticity. As noted by Deardorff and Stern (1997), this elasticity effect, through often neglected, has important implications such as to the policy impact assessment and to the competitive structure of the domestic industry.

Tariff quota administration is treated as a non-tariff barrier in this paper. To start with, we develop a simple partial equilibrium model of tariff quota administration to guide our empirical analysis. Followingly, we calculate ad valorem tariff equivalents of the tariff

[1] The import demand elasticities of China estimated by Kee et al. (2008) are -3.2 (std = 3.2) for wheat (HS code: 100190), -5 (std = 35.4) for maize (HS code: 100590) and -11.1 (std = 45.7) for rice (HS code: 100640). None of the estimates are significant at 90% confidence levels.

quota administration in China's grain markets using data on domestic prices and world prices at the border that are directly comparable with each other. Then we specify and estimate a flexible source differentiated import demand model, while accounting for tariff and expenditure endogeneity, to derive import demand elasticities of China for each grain commodity by source country. Lastly, we use the estimated elasticities to simulate for grain imports of China from 2013 to 2017 in a hypothetical scenario that the tariff equivalents were zero, meaning that imports were not restricted by the tariff quota administration. We compare the simulated imports with observed imports to infer trade impacts of the tariff quota administration.

Our results suggest that, in the hypothetical scenario, the quota fill rates for the three grain commodities, i.e., wheat, rice and maize, are 10-35% higher than the observed, but not as high as 100% except for maize in 2015. Besides, China's total grain imports in 2017 could have been 1.4 billion dollars or 40% higher than the observed and, in particular, the wheat imports from the U.S. could have been 324 million dollars or 83% higher. This result indicates that the U.S. wheat industry could still largely benefit from China's grain trade liberalization, despite that China has diversified its import sources to lower import reliance on the U.S..In addition, we find evidence that import restrictiveness of the quota administration varies negatively with import prices, resulting in lower import demand elasticities. With these findings, we conclude that China has used the tariff quota administration as a flexible trade policy instrument to stabilize domestic prices while restricting imports, at least during 2013-2017. Lastly, we argue that grain trade liberalization could hardly be desirable to China as long as it holds large grain stocks and strives to stabilize domestic prices.

In the following section, we provide background information mainly on policies in China's grain markets. We develop a theoretical model under a partial equilibrium framework to explore the trade effects of tariff quota administration in section 3. Section 4 presents the empirical models. Section 5 describes the data and section 6 discusses the results. The final section concludes and discusses the policy implications.

1.2 Policy background

Tariff rate quota is a two-tiered trade tariff system: the first-tier tariff rate is applied to in-quota imports and the second-tier tariff, which is often prohibitive, is applied to out-of-quota imports. Currently, 43 countries have a combined total of 1425 tariff quotas for various agricultural commodities (WTO, 2017). The tariff quota administration involves allocating the quotas among importing agents, and it determines who has the quota and how many quotas can be used for importing at the in-quota tariff rate (Abbott, 2002; de Gorter and Kliauga, 2006). Many studies (e.g. Abbott, 2002) have expressed their concerns that the administration mechanism is cumbersome and induces additional transaction costs, resulting in lower imports and causing quota under-fill. The issue is still under debate in the current WTO Doha negotiation (WTO, 2018b).

China introduced the TRQ schedule into its grain markets when joining the WTO in 2001 (Ianchovichina and Martin, 2001)[2]. The in-quota tariff rate for most grain products is 1%, and the out-of-quota tariff rate is 65%.[3] Initially, the quota limits were set at 8.47 million tonnes for wheat, 5.85 million tonnes for maize and 3.99 million tonnes for rice. In 2004, the quota limits were raised to 9.6 million tonnes, 7.2 million tonnes and 5.3 million tonnes accordingly (Zhou and Kang, 2007). The rice quota is divided equally between long grain rice and short & medium grain rice. The new limits have not been changed since then.

National Development and Reform Commission (NDRC), a government agency, manages the grain quotas in China and distributes them to the quota applicants every calender year. The majorities of quotas – 90% for wheat, 60% for maize and 50% for rice – are reserved to state trading enterprises. The remaining quotas are allocated among private firms mainly based on the "historical performance" and "first-come, first-serve" principles. All private firms have to apply for the quotas to be used in the next year between October 15^{th} and October 30^{th}. NDRC then determines the amount to be granted after receiving applications

[2]Unless explicitly noted, the information regarding the TRQ policy in China are from the official website of the National Development and Reform Commission of China. The website address is: `http://www.ndrc.gov.cn/`

[3]Table A.1 in the appendix provides the tariff rates by products of Harmonized System at eight digits. All section, table or figure references labeled with prefix "A" are contained in the appendix.

and issues the quota limits by the end of December. In 2016, 511 firms, some of which are subsidiaries of the state trading firms, applied for wheat quotas; meanwhile, 920 and 1001 firms applied for maize and rice quotas respectively. We are not aware of any public information about the quota allocations among the applicants or the quota utilization.

NDRC requires all firms, including the state trading enterprises, to fully utilize their quotas within a calendar year. Meanwhile, firms are allowed to return the unused quotas by mid-September without penalty. The NDRC then distributes the returned quotas among the new applicants by October 1^{st}. If a firm does not return its unused quotas, the quota allocated to it in the next year will be reduced proportionally as penalties. We are unable to find information about the amount of quotas that have been reallocated or the usage of reallocated quotas. The U.S. has argued that China is not appropriately administering the reallocation process, resulting in under-utilization of the quotas, especially those reserved for the state trading enterprises (USTR, 2018).

The quotas for maize, rice and wheat have never been filled in China. This is shown in figure 1.1, in which we plot the annual quota fill rates, which equal to import volumes divided by the quota limits, since 2004. The highest level of quota fill rates was around 80% for maize in 2012. Before 2012, the quota fill rates were constantly low, except for wheat in 2004 and 2005, even lower than the quota shares allocated to private firms in the first place. It is probable that China's import demand for grains was weak before 2012, since the domestic prices were constantly lower than the world prices during the time (see figure 1.3). From 2013 to 2017, the quota fill rates for rice constantly increase from 45% to 75%, while the quota fill rates for maize and wheat fluctuate between 30% and 60% during the time.

The TRQ policy is operated against the background that China has implemented price support policy for grain commodities for about two decades since early 2000s. The policy aims to increase farmers' income and promote domestic production (Huang and Yang, 2017). Under the policy, the government purchases grains from farmers with support prices when market prices fall below support price levels and then retains them for public storage (Gale, 2013; Huang and Yang, 2017). A striking consequence of the policy is massive grain stocks. According to USDA (2018) data, China's stocks-to-use ratios are 43% for maize, 61% for

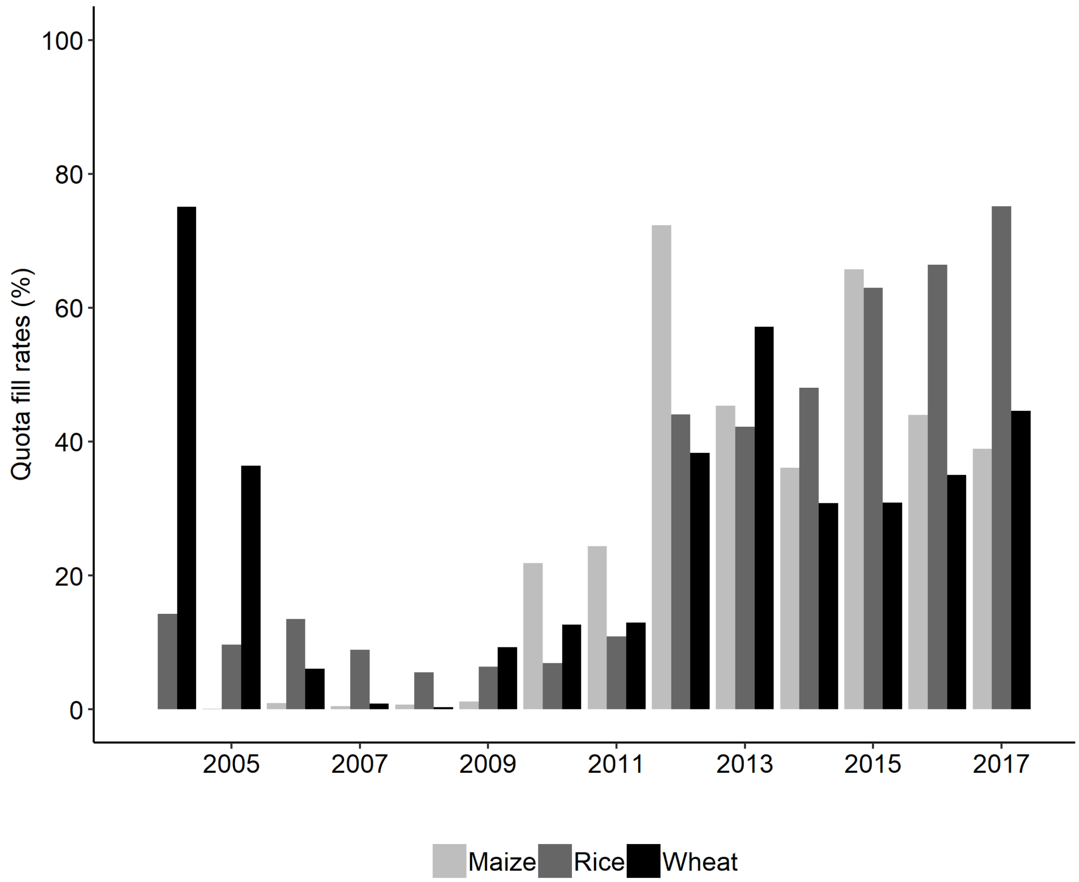

Figure 1.1: Quota fill rates in China's grain markets from 2004 to 2017.

Notes: Quota fill rate is the ratio of annual import quantities to quota limits. The quota limits are 9.636, 7.2 and 5.32 million tonnes for wheat, maize and rice respectively. Data source: UN Comtrade database for trade data before 2016; Ministry of Commerce of China for trade data in 2017.

rice and 94% for wheat in 2016. The large stocks induced high fiscal costs, motivating the government to adjust and reform its price support policy (Huang and Yang, 2017). In 2016, China replaced the price support program with a pilot subsidy program for maize (Huang and Yang, 2017) and began to gradually reduce the rice and wheat support prices (see figure 1.3).

1.3 Theoretical framework

In this section, we explore the conceptual trade effects of tariff quota administration under a simple partial equilibrium framework. We consider a *small* or price-taking importer in the theoretical model. Despite the large economy size of China, the small country assumption is valid here because China remains a small buyer in the global grain markets – it imported less than 5% of wheat, rice and maize traded globally during the sample period (2013-2017) according to the UN Comtrade database. A more direct evidence is provided by Zhong et al. (2015), who found that world prices of grain commodities, i.e., wheat, rice and maize, increase by only 0.0074% when the grain imports by China increase by 1% using the monthly data during 2010-2014. [4]

Consider a tariff rate quota regime, in which the tariff quota administration is a non-tariff barrier that restricts the in-quota imports. We assume that the import market is under perfect competition and that consumer preference does not shift. Without losing generality, we write the import demand function in the following double log form:

$$\log q = \gamma \log \left[\big(\tau + 1 \big) p^w \right] + \beta \log I. \tag{1.1}$$

where import quantity (q) depends on import price (or world price, p^w) and income (I). The terms $\gamma < 0$ and $\beta > 0$ are parameters determining the price and income effects on imports respectively. The term τ represents ad valorem tariff equivalent (abbreviated as tariff equivalents below) of the tariff quota administration. The ED^3 curve in the supply-demand diagram (figure 1.2) illustrates the import demand characterized by equation (1.1), whereas the ED^1 curve in the diagram illustrates the import demand without the influence of the tariff quota administration (or $\tau = 0$). In other words, the presence of τ shifts the import demand curve from ED^1 to ED^3.

We assume that the tariff equivalent contains a fixed component (τ_f) and a variable component (τ_v). The fixed component captures the transaction costs associated with the tariff quota administration that would shift the import demand curve downwards in parallel (Ab-

[4] As one referee points out, the small country assumption could be violated in the absence of TRQs. This is more likely in the case of rice because, in the global rice market, volumes traded are small relative to world production (Liapis, 2012). If the small country assumption is violated, international grain prices will increase instead of being static as China increases its grain imports. Given negative import demand elasticity, the increases in international grain prices would reduce the amount of the increase in China's grain imports. Thus, the projected increases in China's grain imports would be smaller if the small country assumption is violated.

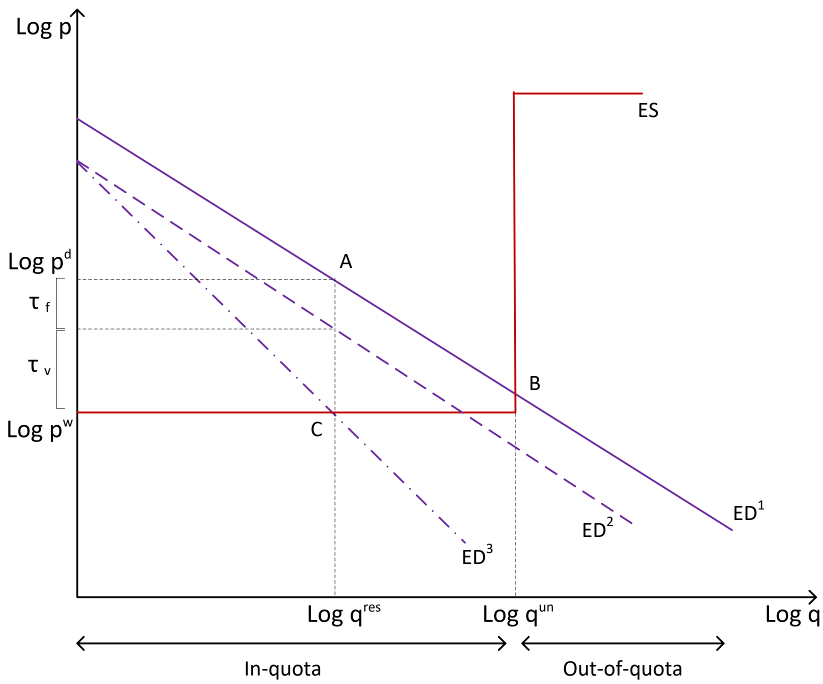

Figure 1.2: Trade effects of tariff quota administration under a partial equilibrium framework.

Notes: The ED curves represent the import demand, and the ES curve represents the excess supply. The terms p^d and p^w represent domestic and world prices respectively.

bott, 2002; Abbott and Morse, 2000), i.e., from ED^1 to ED^2 in figure 1.2. We also consider the situation that the regime might flexibly adjust the tariff equivalent of tariff quota administration as world price changes (Abbott, 2002). This is captured by the variable component that is negatively correlated with world prices, filtering part of the fluctuations in the world prices before they are transmitted to the domestic market. The variable component would reduce the responsiveness of imports to import price changes and rotate the import demand curve inwards, i.e., from ED^2 to ED^3 in figure 1.2. When the world price declines, the gap between ED^2 and ED^3 enlarges, leading to increases in the variable component (τ_v).

The tariff quota administration has two notable impacts on trade in our theoretical setting. Firstly, it reduces the size of the import demand elasticity. To see this, we derive for the import demand elasticity by taking the first-order derivative of equation (1.1) with respect to $\log p^w$. It gives:

$$\gamma^* = \gamma\left(1 + \frac{\partial \log(1+\tau)}{\partial \log p^w}\right). \tag{1.2}$$

where the term $\frac{\partial \log(1+\tau)}{\partial \log p^w}$ is negative when the tariff equivalent is negatively correlated with the world price. We further assume that $\frac{\partial \log(1+\tau)}{\partial \log p^w} > -1$, meaning that the degree of adjustment in the tariff equivalent is smaller than the magnitude of changes in the world price. Under the two conditions, the import demand elasticity is smaller in its absolute value in the presence of τ, i.e., $|\gamma^*| < |\gamma|$. Note that this trade effect is solely attributed to the variable component rather than the fixed component since the latter is invariant to world price changes. One can also see this directly from figure 1.2, in which τ_v makes the import demand curve steeper.

Secondly, the tariff quota administration reduces the import quantity. One can see from figure 1.2 that the import quantity declines from q^{un} to q^{res} as the import demand curve shifts from ED^1 to ED^3. The size of reduction depends on the parameter γ, which can be interpreted as import demand elasticity unaffected by the tariff quota administration, and the tariff equivalent. Specifically, the reduction in the log of import quantity is:

$$\begin{aligned}\Delta \log q &= \{\gamma \log p^w + \beta \log I\} - \{\gamma \log\left[(\tau+1)p^w\right] + \beta \log I\} \\ &= -\gamma \log\left(1+\tau\right). \end{aligned} \tag{1.3}$$

where the first bracket term is obtained from equation (1.1) with $\tau = 0$.

1.4 Empirical framework

In this section, we present an empirical framework to estimate the effects of the tariff quota administration on import demand elasticity and import quantity.

1.4.1 The import demand model

We estimate import demand elasticities for each grain commodity by source country using a source differentiated Almost Ideal Demand System model, a model that was frequently used in the literature to analyze the import demand (Carew et al., 2004; Henneberry and Hwang, 2007; Wan et al., 2010; Yang and Koo, 1994). The model specification is [5]:

$$w_{i_h,t} = \alpha_{i_h} + \sum_j \sum_k \gamma_{i_h j_k} \log\left[\big(\tau_{j,t} + 1\big) p_{j_k,t}\right] + \beta_{i_h} \log\big(E_t / P_t\big) + \boldsymbol{\delta_{i_h} D_t} + \epsilon_{i_h,t}. \tag{1.4}$$

where the subscript i_h denotes the commodity i imported from country h. Similarly, the subscript j_k denotes the commodity j imported from country k. The subscript t denotes month from January 2013 to December 2017, our study period. The import demand model specified by equation (4) is jointly estimated as a complete demand system.

The dependent variable is the budget or import share, calculated as the import value of a particular product divided by total grain import value (E_t). The independent variables include import price ($p_{i_h,t}$), total expenditure or total import value (E_t), and a price index (P_t). The notation $\boldsymbol{D}_t$ represents a vector of dummy variables that capture effects

[5] As one referee points out, one might have to accommodate regime switching when estimating the import demand that is under TRQ regulation, if all three regimes (i.e., within-quota importing, at-quota importing, and over-quota importing) are relevant. For instance, Cioffi et al. (2011); Santeramo and Cioffi (2012) applied a threshold vector autoregressive econometric model to assess the stabilization effects of the entry price system for fresh fruit and vegetables in Europe. Kaabia and Gil (2011) estimated Italian import demand for virgin olive oil using a threshold almost ideal demand system. Both models account for import regime switching and thus could be used to analyze imports under TRQ policy. We do not use these models in this study because, as discussed in the "Results" section, only the within-quota importing regime is relevant in our case.

of seasonality and policy on imports. The term $\epsilon_{i_h,t}$ denotes residuals. The parameters to be estimated are α_{i_h}, β_{i_h}, $\gamma_{i_h j_k}$ and $\boldsymbol{\delta}_{i_h}$ (a vector of parameters). We impose three theoretical restrictions on the parameters (Deaton and Muellbauer, 1980, p. 68), which are adding-up ($\sum_i \sum_h \alpha_{i_h} = 1,\ \sum_i \sum_h \gamma_{i_h j_k} = 0,\ \sum_i \sum_h \beta_{i_h} = 0,\ \sum_i \sum_h \boldsymbol{\delta}_{i_h} = \mathbf{0}$), homogeneity ($\sum_j \gamma_{i_h j_k} = 0$) and symmetry ($\gamma_{i_h j_k} = \gamma_{j_k i_h}$). The term $\tau_{j,t}$ denotes tariff equivalents of tariff quota administration that are commodity-specific. For notation simplicity, we let $\tau^*_{j,t} = \tau_{j,t} + 1$.

The price index is proxied by a simplified loglinear analogue of the Laspeyres price index (Moschini, 1995):

$$\log P_t = \sum_i \sum_h w^0_{i_h} \log \left(\tau^*_{i,t} p_{i_h,t}\right). \tag{1.5}$$

where $w^0_{i_h}$ is the base share, measured by average import shares over the study period. Although Moschini (1995) suggested several other proxies of the price index, we choose this one for two major reasons. First, this index does not include the independent variable w_{i_h}, so that simultaneity issue can be avoided (Moschini, 1995). Second, the index has a simple structure that allows us to derive a tractable expression for price elasticity of import demand.

The equation below is the formula for calculating the own price elasticity of import demand (or import demand elasticity).The derivations are shown in section A.1.

$$\eta^*_{i_h i_h,t} = \left[-1 + \frac{1}{w_{i_h,t}} \left(\gamma_{i_h i_h} + \beta_{i_h} w^0_{i_h} \left(\frac{d \log E_t}{d \log P_t} - 1 \right) \right) + \frac{d \log E_t}{d \log P_t} w^0_{i_h} \right] \left(1 + \frac{d \log \tau^*_{i,t}}{d \log p_{i_h,t}} \right). \tag{1.6}$$

We call the term $\eta^*_{i_h i_h,t}$ restricted import demand elasticity because it is affected by the tariff equivalent. The restricted import demand elasticity is smaller in size when the term is $\frac{d \log \tau^*_{i,t}}{d \log p_{i_h,t}}$ is negative, similar to the discussions in section 1.3. The term in the square bracket is called unrestricted import demand elasticity and is labelled by $\eta_{i_h i_h,t}$.

We need to estimate two other terms to obtain the restricted import demand elasticity. One is $\frac{d \log \tau^*_{i,t}}{d \log p_{i_h,t}}$, and it measures the sensitivity of the tariff equivalents of tariff quota administration to import prices. The term would be negative if China flexibly adjusts the import restrictiveness of the tariff quota administration to stabilize domestic prices. Another one is $\frac{d \log E_t}{d \log P_t}$, and it measures the sensitivity of total expenditure to import prices. The literature has highlighted the importance of considering the endogeneity of expenditure as it directly affects the import demand elasticity (Davis and Jensen, 1994; Thompson, 2004). The following sections describe strategies for estimating the two terms in turn.

1.4.2 Sensitivity of tariff equivalents to import prices

We specify the following equation to estimate the sensitivity of the tariff equivalents of tariff quota administration to import prices:

$$\log \tau^*_{i,t} = a^0_i + a^1_i \log PI_{i,t} + \epsilon^{'}_{i,t}. \tag{1.7}$$

where $PI_{i,t}$ is a commodity-specific Laspeyres price index, defined to be $\log PI_{i,t} = \sum_h w^1_{i_h} \log p_{i_h,t}$. The term $w^1_{i_h}$ is average budget share within a commodity group. The term $\epsilon^{'}_{i_h,t}$ denotes residuals. Then we have:

$$\frac{d \log \tau^*_{i,t}}{d \log p_{i_h,t}} = \frac{d \log \tau^*_{i,t}}{d \log PI_{i,t}} \frac{d \log PI_{i,t}}{d \log p_{i_h,t}} = \tilde{a}^1_i w^1_{i_h}. \tag{1.8}$$

where $\tilde{a}^1_i$ is the estimated value of a^1_i.

Parameter estimates using equation (1.7) might suffer from simultaneity bias. Specifically, the import prices ($p_{i_h,t}$) used to calculate $PI_{i,t}$ could be correlated with the international prices that are used to calculate $\tau^*_{i,t}$, since both of them measure the prices of imported goods. One empirical strategy for addressing this simultaneity issue is to use an instrumental variable (IV) for $\log PI_{i,t}$, i.e., a variable that is correlated with import prices (known as relevance condition) but orthogonal to tariff shocks (known as exclusion condition).

In this paper, we use log of international crude oil prices – data are from the World Bank Pink Sheet – as the instrument. The instrumental variable will likely satisfy the relevance condition, because crude oil price affects food import prices through international transportation cost (Dillon and Barrett, 2016). In terms of the exclusion restriction, the crude oil price might directly affect the tariff equivalents, because an increase in the crude oil price might lead to higher transportation cost of domestic goods, higher domestic price and then higher tariff equivalent. However, this effect would be much smaller than the effect of the crude oil price on import prices because the shipping distances within borders are much shorter than the shipping distances across borders. Later we show that our estimates are robust to a possible violation of the exclusion restriction.

1.4.3 Sensitivity of expenditure to import prices

To model the sensitivity of expenditure to import prices, we need to consider the first-stage allocation problem, i.e., the economic decision of the amount of expenditure spent on grain imports. The empirical literature has proposed different control variables, such as per capita income and consumer price index from the consumer theory perspective (Thompson, 2004), as well as output and input prices (e.g. wage and capital rental rate) from the production theory perspective (Muhammad et al., 2007, 2012). We do not have monthly data for these variables, so we utilize the panel structure of the data to control these variables. The objective is to minimize the risk of omitting important variables while using the least number of extra variables.

We specify the following equation to estimate the sensitivity of the commodity-specific expenditure to a commodity-specific import price index:

$$E_{i,t} = b_0 + b_1 \log P^X_{i,t} + b_2 \log P^O_{i,t} + \mu_i + \nu_t + \epsilon''_{i,t}. \tag{1.9}$$

where $E_{i,t}$ denotes the expenditure spent on commodity i at time t, and $\sum_i E_{i,t} = E_t$. The term $P^X_{i,t}$ is a commodity-specific import price index, and $\log P^X_{i,t} = \sum_h w^0_{i_h,t} \log\left(\tau^*_{i,t} p_{i_h,t}\right)$. We define the price index in this way to obtain a closed form for the derivation of the expenditure elasticity. The term $P^O_{i,t}$ denotes output price, which is measured by retail prices of corresponding commodities in China. The output price for maize is the pork price, because the imported maize in China is mainly used as livestock feed (Gale, 2015). We rely on the commodity dummy (μ_i) to control for market specific characteristics. The time dummy (ν_t)

can control for per capita income and consumer price index, because these variables vary by time but are commodity invariant.

The parameter b_1 determines the sensitivity of total expenditure to import prices (see section A.2 for derivations). Specifically,

$$\frac{d \log E_t}{d \log P_t} = \frac{b_1}{E_t}. \tag{1.10}$$

1.4.4 Simulating the import quantity

Once obtaining the import demand elasticities, we simulate import quantities for grain commodities in China during 2013-2017 in a hypothetical scenario that the tariff equivalents of the tariff quota administration are zero, i.e., $\tau_{i,t} = 0$. The differences between the simulated and observed imports can be used to infer trade impacts of the tariff quota administration (Deardorff and Stern, 1997).

With reference to Kastens and Brester (1996) (equation 8 on p. 304), the formula to obtain the simulated import quantity is:

$$q^*_{i_h,y} = \left[\sum_j \sum_k \eta_{i_h j_k} \left(\frac{1}{1 + \bar{\tau}_{i,y}} - 1 \right) + 1 \right] q_{i_h,y}, \; y \in \{2013, ..., 2017\}. \tag{1.11}$$

where $\eta_{i_h j_k}$ is *unrestricted* own or cross price elasticity of import demand. The terms $q_{i_h,y}$ and $q^*_{i_h,y}$ denote observed and simulated import quantity in year y, respectively. We use the subscript y instead of t here, because we are interested in the annual trade impact. The term $\bar{\tau}_{i,y}$ denotes average tariff equivalents in year y. This formula is analogous to equation (1.3) except for that the substitution effects, captured by the cross price elasticity of import demand, are considered here.

1.5 Data and descriptive analysis

1.5.1 Price data and the tariff equivalents

We obtain monthly prices of maize, rice and wheat in China during 2013-2017 from "Monthly Bulletin of Agricultural Demand and Supply Statistics" (unofficial translation), an economic report regularly released by Ministry of Agriculture of China. The report provides monthly domestic and world wholesale prices of grain products – data are collected at a port in southern China – that share similar qualities. For instance, both domestic and world maize prices are prices of No.2 yellow maize. In addition, the world prices account for transportation costs, tariffs and taxes (see table A.2 for details). Given these data attributes, the reported domestic and world prices can be directly compared (Ferrantino, 2006). We calculate percentage differences between the observed domestic and world prices and refer them to as tariff equivalents of tariff quota administration, a typical way of measuring price effects of non-tariff barriers (Deardorff and Stern, 1997; Ferrantino, 2006). We attribute the price differentials to the tariff quota administration, because, to our best knowledge, it is the primary border measure for regulating grain imports in China (Huang and Yang, 2017). The price data during 2009-2013 are from the China Grain website (see section A.3 for details). Figure 1.3 displays the obtained price data.

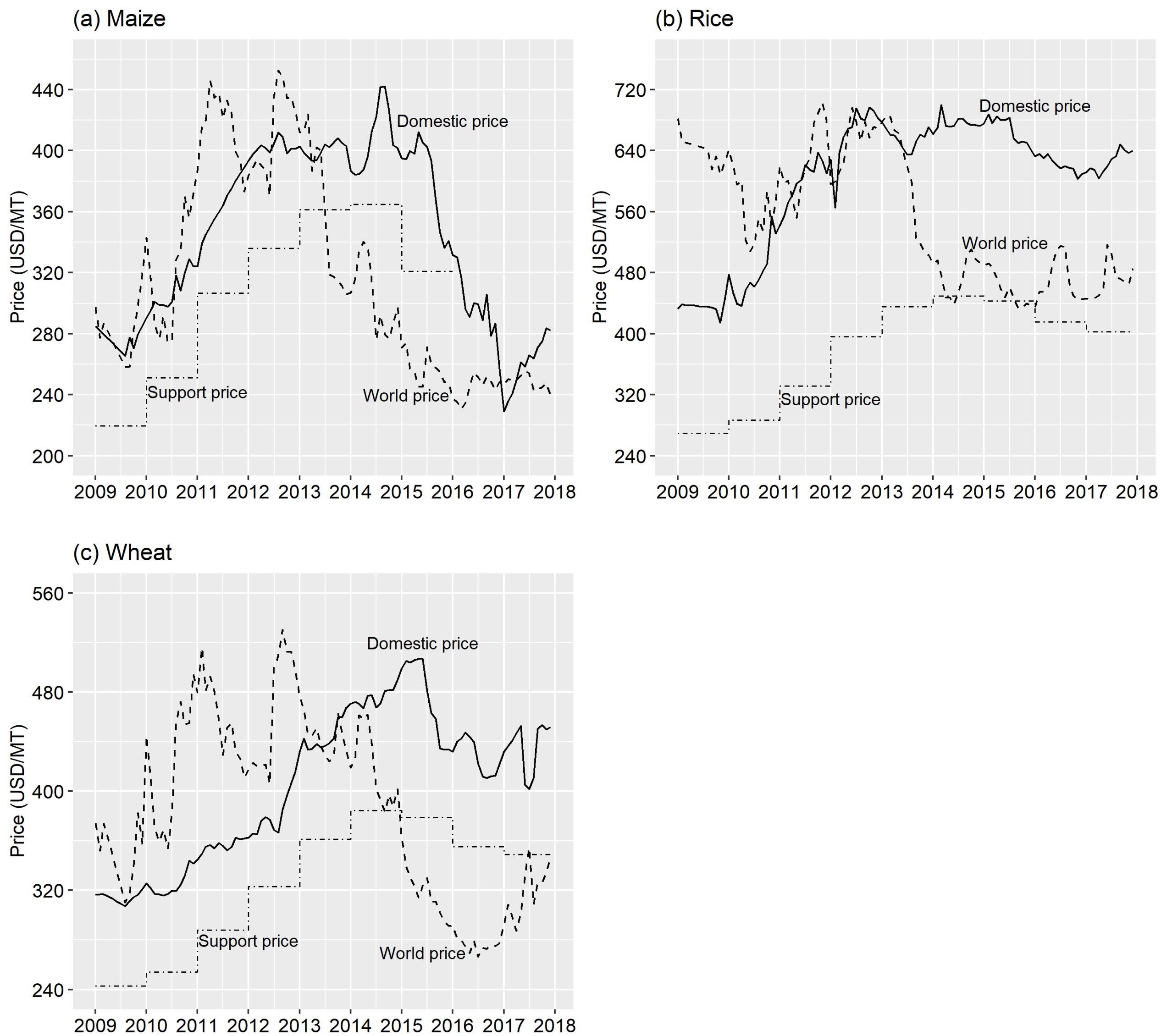

Figure 1.3: Monthly domestic prices and world prices of maize, rice and wheat in China.

Notes: The support price series (*dotdashed*) stop in 2016 in panel (a) because the price support program for maize was terminated in 2016. Data source: Data on domestic and world prices are from Ministry of Agriculture of China. Data on support prices are from the official website of National Development and Reform Commission of China. The raw prices are in Chinese RMB, and they are converted to US dollars by using the average annual exchange rates that are sourced from the International Monetary Fund (IMF) exchange rate archive.

Figure 1.4 plots the annual tariff equivalents (monthly averages) for each grain commodity from 2009 to 2017. We see that the tariff equivalents for all three grains were constantly negative prior to 2013 and became positive thereafter (2013-2017). This means that the tariff quota administration was not import-restrictive until 2013. The figure also shows that the tariff equivalents for maize and rice reached their historic maximum values in 2015 and began to decline afterwards. In particular, the tariff equivalent for maize slumped to less than 10% in 2017. The change was mainly driven by the plummet in domestic maize prices since 2016 (see figure 1.3).

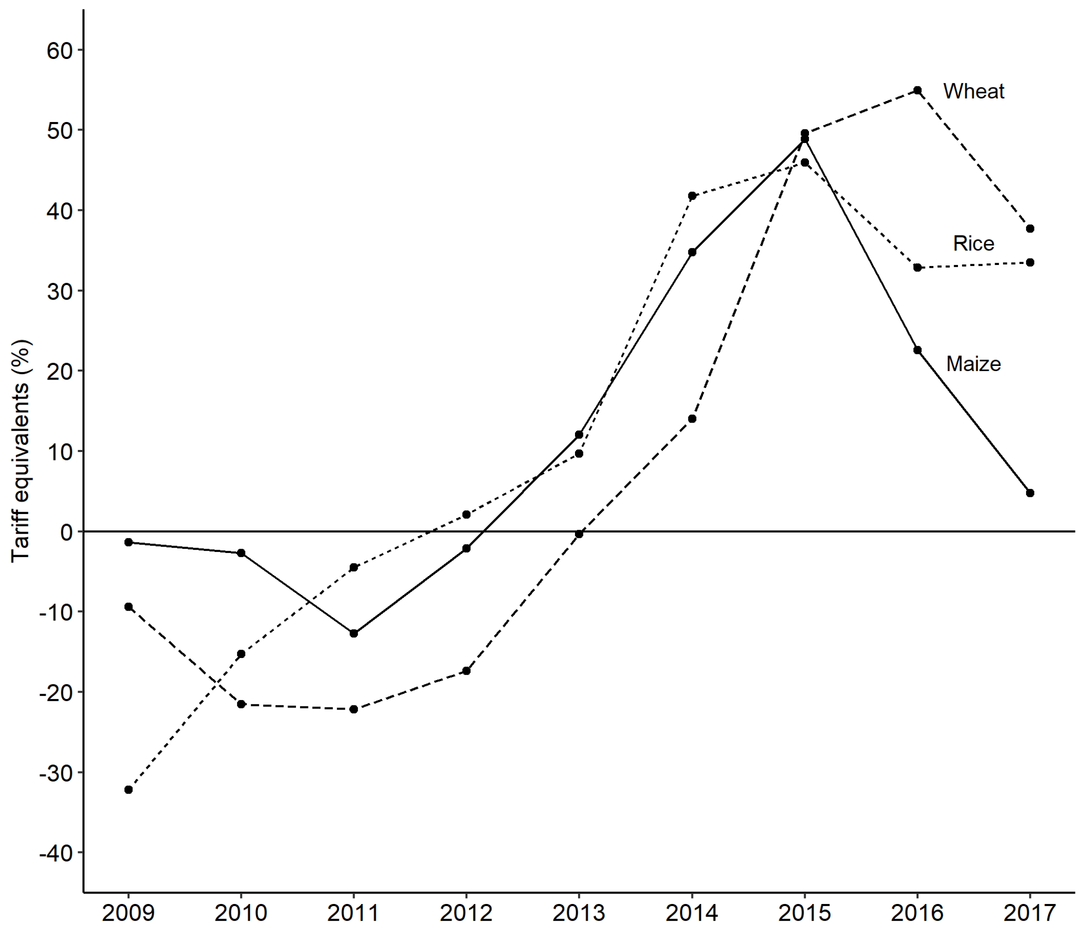

Figure 1.4: Tariff equivalents of tariff quota administration for grain commodities in China. Data source: Ministry of Agriculture of China and the China Grain website.

1.5.2 Trade data and import shares

We obtain monthly trade data during 2013-2017 from the "Monthly Bulletin of Agricultural Trade Statistics" (unofficial translation), a statistical report that is regularly released by Ministry of Commerce of China. The report provides monthly data on China's imports from the top three exporters and total imports in quantities and in values. Following Muhammad et al. (2007), we use the ratio of import value to import quantity, also called unit value, to proxy the import prices.

Despite that China imported from a large number of countries across the globe (see table A.3), its import shares for the grain commodities are highly concentrated in two or three countries. As shown in table 1.1, China imported nearly 90% of maize from only two countries: U.S. and Ukraine in 2016. Over 90% of wheat imports are from Australia, Canada and the U.S.; likewise, over 90% of rice imports are from Vietnam, Thailand and Pakistan. The high import concentration has been persistent over time, at least over the study period (see figure A.1). When estimating the import demand model characterized by equation (1.4), we consider imports from the major exporters listed in table 1.1 and imports from other countries. The other countries are treated as a single region, called Rest of the World (ROW).

Table 1.1: Import shares of major exporters in China's grain markets in 2016.

Commodity	Country	Import value (million USD)	Import share (%)
Maize	Ukraine	501.9	79.5
	U.S.	55.9	8.8
	Subtotal	557.8	88.3
Wheat	Australia	326.3	40.2
	Canada	214.6	26.4
	U.S.	205.1	25.3
	Subtotal	811.5	91.9
Rice	Vietnam	733.9	45.5
	Thailand	490.3	30.4
	Pakistan	249.6	15.5
	Subtotal	1613.1	91.4

Data source: Ministry of Commerce of China.

1.6 Results

In this section, we report estimated results of equation (1.4), (1.7) and (1.9). We also report the estimated impacts of the tariff quota administration on imports and import demand elasticities.

1.6.1 Model estimates

We estimate equation (1.4) as a complete demand system using iterative seemingly unrelated regression method. The parameter estimates, reported in table 1.2, are used to calculate the own and cross price of import demand elasticity. We impose the theoretical restrictions of adding up, homogeneity and symmetry on the model following Kastens and Brester (1996); Muhammad et al. (2007). Ukraine, a current major maize exporter, did not export maize to China in 2013, because China did not allow maize imports from it until 2013 (Joshua and Jiang, 2012, 2013). Due to this, we do not observe import prices of Ukrainian maize in 2013; then we impute for them by multiplying export prices of Ukrainian maize – data sourced from the FAO GIEWS database (FAO, 2018) – by 1.65, an average markup ratio. Meanwhile, we add a year dummy of 2013 to the maize equations to capture the quantity effects of the limited market access. This dummy, as expected, is significantly negative in the Ukraine maize equation and significantly positive in the U.S. maize equation, meaning that China prefers the U.S. to Ukraine as a maize supplier in 2013.

The tariff equivalents of tariff quota administration in China's grain markets stopped increasing in 2015 (figure 1.4). We then include dummies that are 0 before 2015 and 1 afterwards to see if there is any associated change in the import structure in all equations. Interestingly, the dummies in U.S. maize and U.S. wheat equations are significantly negative, while the dummies in other equations are either positive or insignificant. This result suggests that China has largely reduced its import dependence on the U.S. after 2015, possibly for promoting import diversification (Gale et al., 2015). The diagonal terms in table 1.2 measure responses of import shares to changes in own prices, which are large in size in the U.S. maize and Australian wheat equations, underlying the large import demand elascitities (to

Table 1.2: Regression results of the source differentiated import demand model.

	Maize			Rice				Wheat			
	USA	UKR	ROW	THI	VIN	PAK	ROW	USA	AUS	CAN	ROW
Log price of	-0.06**	0.03	-0.01	0.02	-0.03	0.02	0	0.07**	-0.02	-0.02**	0
USA maize	(0.02)	(0.03)	(0.01)	(0.02)	(0.02)	(0.01)	(0.01)	(0.03)	(0.02)	(0.01)	(0.01)
Log price of	0.03	0.02	-0.06*	-0.1	-0.05	-0.02	-0.01	-0.11	0.2***	0.07	0.03*
UKR maize	(0.03)	(0.1)	(0.03)	(0.05)	(0.06)	(0.04)	(0.02)	(0.07)	(0.06)	(0.04)	(0.01)
Log price of	-0.01	-0.06*	-0.01	0	0.02	0.01	0	-0.01	0.03	0.02	0
ROW maize	(0.01)	(0.03)	(0.01)	(0.02)	(0.02)	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)	(0.01)
Log price of	0.02	-0.1	0	-0.07	0.11**	0	0.05***	-0.03	0.07	-0.04	-0.01
THI rice	(0.02)	(0.05)	(0.02)	(0.06)	(0.05)	(0.04)	(0.02)	(0.04)	(0.05)	(0.03)	(0.02)
Log price of	-0.03	-0.05	0.02	0.11**	0.11	-0.07	-0.01	-0.05	0.07	-0.14***	0.04
VIN rice	(0.02)	(0.06)	(0.02)	(0.05)	(0.08)	(0.04)	(0.02)	(0.05)	(0.05)	(0.04)	(0.02)
Log price of	0.02	-0.02	0.01	0	-0.07	0.04	0.02	0.01	0.02	-0.04	0
PAK rice	(0.01)	(0.04)	(0.01)	(0.04)	(0.04)	(0.05)	(0.02)	(0.03)	(0.04)	(0.03)	(0.02)
Log price of	0	-0.01	0	0.05***	-0.01	0.02	0.02	-0.03	-0.03	0	0.01
ROW rice	(0.01)	(0.02)	(0.01)	(0.02)	(0.02)	(0.02)	(0.01)	(0.02)	(0.02)	(0.01)	(0.01)
Log price of	0.07**	-0.11	-0.01	-0.03	-0.05	0.01	-0.03	-0.06	0.06	0.13***	0.01
USA wheat	(0.03)	(0.07)	(0.02)	(0.04)	(0.05)	(0.03)	(0.02)	(0.09)	(0.04)	(0.03)	(0.01)
Log price of	-0.02	0.2***	0.03	0.07	0.07	0.02	-0.03	0.06	-0.36***	0.02	-0.06
AUS wheat	(0.02)	(0.06)	(0.02)	(0.05)	(0.05)	(0.04)	(0.02)	(0.04)	(0.08)	(0.04)	(0.02)
Log price of	-0.02	0.07	0.02	-0.04	-0.14***	-0.04	0	0.13***	0.02	-0.02	0.02
CAN wheat	(0.01)	(0.04)	(0.02)	(0.03)	(0.04)	(0.03)	(0.01)	(0.03)	(0.04)	(0.04)	(0.01)
Log price of	0	0.03	0	-0.01	0.04	0	-0.01	0.01	-0.06***	0.02	-0.01
ROW wheat	(0.01)	(0.02)	(0.01)	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)
Log of real	0.1***	0.11**	-0.02	-0.08***	-0.15***	0	-0.03**	0.14**	-0.04	-0.02	0
expenditure	(0.03)	(0.05)	(0.01)	(0.02)	(0.03)	(0.02)	(0.01)	(0.05)	(0.03)	(0.02)	(0.01)
Y2013	0.07***	-0.08***	0.01	–	–	–	–	–	–	–	–
dummy	(0.02)	(0.02)	(0.01)	–	–	–	–	–	–	–	–
Y2015	-0.06**	0.04	-0.04**	-0.01	0.04	0.01	0.05***	-0.18**	0.09***	0.05*	0.01
dummy	(0.03)	(0.05)	(0.02)	(0.03)	(0.04)	(0.02)	(0.01)	(0.05)	(0.03)	(0.02)	(0.01)
Quarterly dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	–
Obs.	60	60	60	60	60	60	60	60	60	60	–
R^2	0.52	0.41	0.41	0.6	0.4	0.31	0.63	0.38	0.34	0.43	–
D.W.	1.51	1.27	1.61	1.39	1.37	1.17	1.6	1.25	1.3	2.1	–

Notes: The dependent variable is the import share. The country correspondences are: USA – United States, UKR – Ukraine, THI – Thailand, VIN – Vietnam, PAK – Pakistan, AUS – Australia, CAN – Canada, ROW – Rest of the World. Parameters in the ROW-Wheat equation are not directly estimated due to singularity and recovered based on the restriction equations. *p<0.1; **p<0.05; ***p<0.01

be discussed below). The parameter estimates with real expenditure are positive in maize equations and negative in rice equations, indicating that the growth in grain imports in China has mainly been driven by the higher import demand for maize.

Table 1.3 reports parameter estimates for the variable of log of import price index in equation (1.7). The parameter estimates are larger in size after using the instrument, i.e., crude oil price, to account for the simultaneity issue. Specifically, the IV estimates for rice and wheat are -0.79 and -1.01 respectively. These estimates are negative, meaning that the tariff equivalents of the tariff quota administration are negatively associated with import prices in China's rice and wheat markets. In other words, the tariff quota administration is more (or less) import restrictive when the import prices are lower (or higher), acting like an import variable levy. Quantitatively, based on the IV estimates and equation (1.8), the tariff equivalents of wheat would increase by 0.29% if the U.S. wheat price is to decrease by 1%.[6]

The first-stage F tests reject the null hypothesis that the instrument is weak, meaning that crude oil price is significantly correlated with import prices, satisfying the relevance condition for a valid instrument. What if the crude oil price directly affect the tariff equivalent, violating the exclusion condition? This is possible because crude oil price could positively affect domestic grain prices through effects on domestic transportation costs and then positively affect the tariff equivalents. Regarding this, we follow Conley et al. (2010) to derive for consistent parameter estimates in cases that the crude oil price directly affect the tariff equivalent positively. We find that the bounds on the strength of the parameter estimate are actually further away from zero (i.e., a larger effect) relative to the IV estimates (figure A.5). In other words, our finding that the tariff equivalents are negatively correlated with the import prices holds even when the exclusion restriction is violated.

The IV estimate in the maize equation is negative but statistically insignificant. This is not surprising. As aforementioned, China terminated the price support program for maize in 2016 and might be no longer interested in stabilizing domestic maize prices. Otherwise, we would not have seen the slump of domestic maize price after 2016 (figure 1.3). To put this into perspective, we run the instrumental variable regression using the data prior to 2016. We detect a negative parameter estimate (-1.09) in the maize equation (part 3 of table 1.3), and the size of the estimate is as large as the size of estimates in the rice and wheat equations. Hence, we can conclude that China altered the way to administer the maize import quotas once it terminated the price support policy.

Table 1.4 reports the regression results for equation (1.9). The parameter estimate for the

[6] The elasticities of tariff equivalents in wheat with respect to import prices of Australian, Canadian and ROW wheat are -0.42, -0.22, -0.08 respectively. The elasticities of tariff equivalents in rice with respect to import prices of Thai, Vietnamese, Pakistani and ROW rice are -0.25, -0.4, -0.08 and -0.06 respectively.

Table 1.3: Regression of the tariff equivalents of tariff quota administration on import price indices.

Part 1.	Ordinary least squares regression [Year $\in \{2013, ..., 2017\}$]		
	Maize	Rice	Wheat
Log import price index	0.08	-0.69	-0.76^{***}
	(0.12)	(0.47)	(0.17)
R^2	0.01	0.35	0.58
Obs.	60	60	60
Part 2.	Instrumental variable regression [Year $\in \{2013, ..., 2017\}$]		
	Maize	Rice	Wheat
Log import price index	-0.16	-0.79^{**}	-1.01^{***}
	(0.23)	(0.39)	(0.09)
Obs.	60	60	60
Weak instrument	22.78^{***}	50.38^{**}	111.28^{***}
Wu-Hausman	1.9	0.22	49.09^{***}
Part 3.	Instrumental variable regression [Year $\in \{2013, ..., 2015\}$]		
	Maize	Rice	Wheat
Log import price index	-1.09^{***}	-1.19^{***}	-1.6^{***}
	(0.32)	(0.42)	(0.13)
Obs.	36	36	36
Weak instrument	11.03^{***}	26.72^{***}	41.68^{***}
Wu-Hausman	13.24^{***}	0.01	49.44^{***}

Notes: The dependent variable is log of commodity-specific tariff equivalents of tariff quota administration. The instrumental variable is monthly crude oil price. All three equations in each part are estimated jointly as a single system. Estimates for intercepts are ommited here. Numbers in parentheses are heteroskedasticity and autocorrelation consistent standard errors. *p<0.1; **p<0.05; ***p<0.01

import price index significantly changes once the market and time fixed effects are included in the model. We prefer model (3) with the fixed effect variables, since these variables control the market-specific and time-specific variables that we do not observe. Based on the fixed effect estimates of model (3) and equation (1.10), we find that the elasticity of expenditure with respect to import prices is -0.92, meaning that the expenditure spent on imported grains increases by 0.92% when the import price index declines by 1% in China.

Table 1.4: Regression of commodity-specific import expenditures on commodity-specific import price index.

	(1)	(2)	(3)
Import price index	28.9^{***}	-183.6^{*}	-257.8^{**}
	(0.8)	(104.3)	(129.2)
Log of retail price	2.9^{***}	22.8	-59.1
	(0.7)	(81.2)	(69)
Month fixed effect	No	No	Yes
Commodity fixed effect	No	Yes	Yes
R^2	0.11	0.14	0.45
F statistics	11.2^{***}	6.9^{***}	1.5^{**}
	(df = 2, 177)	(df = 4, 175)	(df = 63, 116)
Obs.	180	180	180

Notes: The import expenditures are measured in million dollars. Numbers in parentheses are clustered standard errors by commodity. *p<0.1; **p<0.05; ***p<0.01.

1.6.2 Policy impacts on trade

The estimated results of equation (1.4), (1.7) and (1.9), combined with equation (1.6), are used to calculate import demand elasticity. With regards to equation (1.7), the results presented in part 2 of table 1.3 (IV estimations) are used for the calculation. Figure 1.5 shows restricted and unrestricted import demand elasticities that are evaluated at sample means for each grain commodity by source country. The error bars represent 90% confidence intervals, with the underlying standard errors generated by multivariate Monte Carlo simulations with 5000 iterations. The figure shows that the import demand elasticities for wheat from the U.S. and Australia are largely reduced by the tariff quota administration and, consequently, imports of the two products are less sensitive to their price changes. For instance, given 1% decrease in U.S. wheat prices, China's wheat imports from the U.S. should have increased by 1.9%; but under the influence of the tariff quota administration, the imports would only increase by 1.3% instead. In other words, nearly 37% of the import growth following the price decreases was counteracted by the flexible adjustments in quota allocations.

We simulate China's import quantities for each grain commodity by source country in every year ($q_{ih,y}$) during 2013-2017 in a hypothetical scenario that the tariff equivalents of tariff quota administration were zero based on equation (1.11). We obtain import quantities for each commodity i by summing over the source countries ($q_{i,y} = \sum_h q_{ih,y}$). These simulated import quantities are then divided by the commodity-specific quota limits to generate simulated quota fill rates. Figure 1.6 showed the simulated results; we also show the observed quota fill rates in the figure for comparisons.

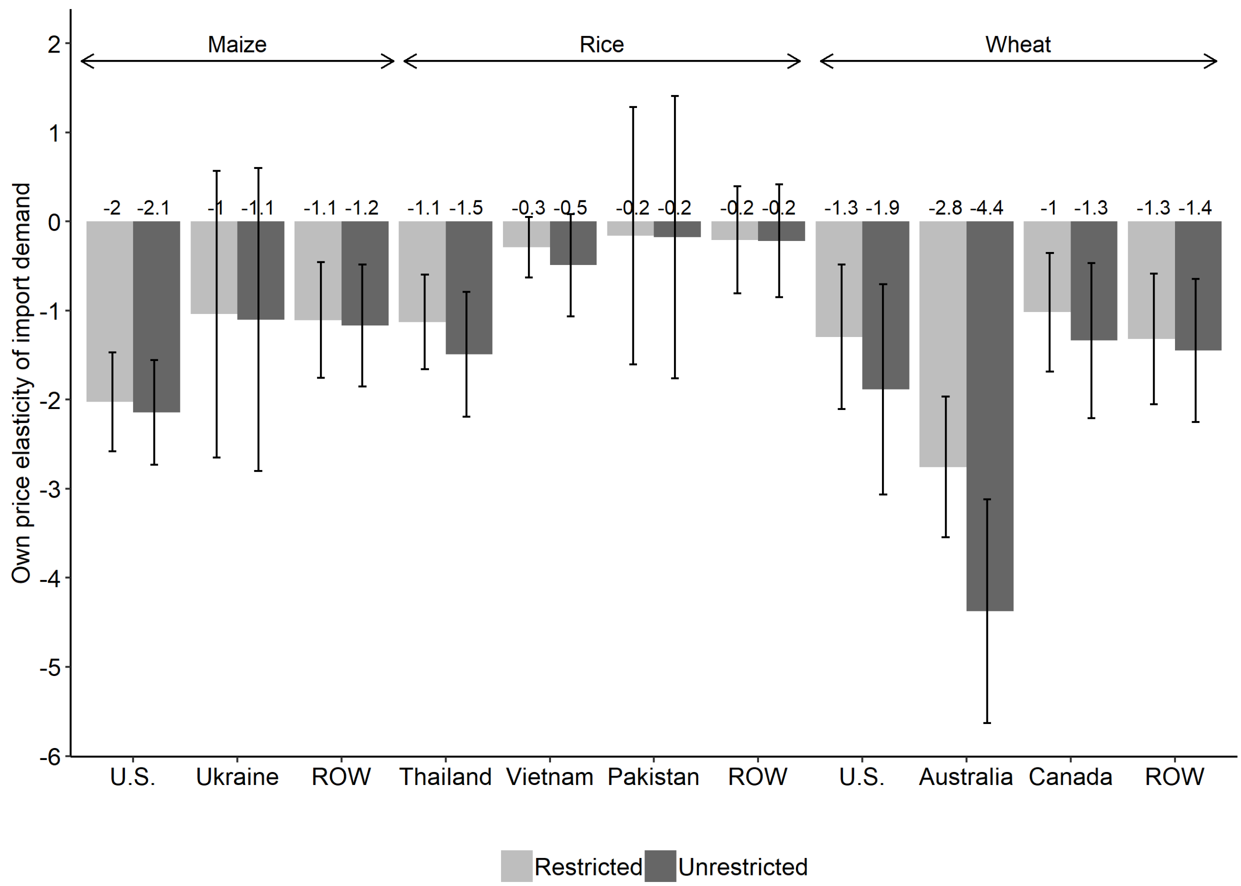

Figure 1.5: Estimates of restricted and unrestricted own price elasticity of import demand for grain commodities by source country in China.

Notes: The error bars represent 90% confidence intervals.

As shown in figure 1.6, the simulated quota fill rates are 10-35% higher than the observed

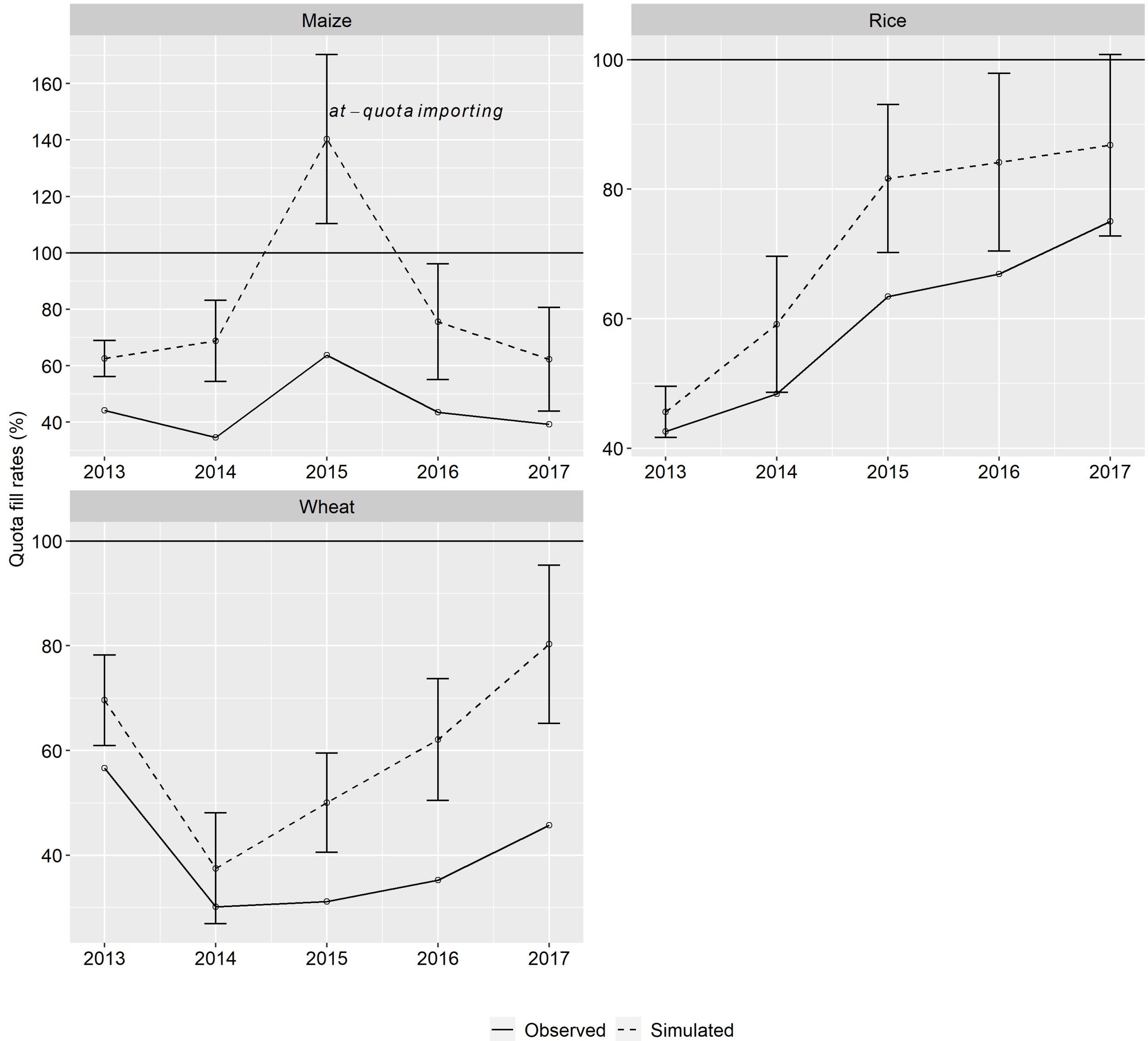

Figure 1.6: Simulated and observed quota fill rates for grain commodities from 2013 to 2017.

Notes: The error bars represent the 90% confidence intervals.

during 2013-2017 in China's grain markets; and they are lower than 100% at most times even at the upper bound of 90% confidence intervals. Exceptionally, the simulated quota fill rate for maize in 2015 is larger than 100%. But this does not mean that the over-quota imports would occur but that the quotas would be filled (at-quota importing). Over-quota importing is unlikely in any year during 2013-2017, because the tariff equivalents have always been lower than the over-quota tariff rates (65%) during the time (see figure 1.4). In this case, importing while paying for out-of-quota tariff rate leads to negative profits. Figure 1.6 also shows that the wheat imports have became more restricted in China over time – the gap between the simulated quota fill rates and the observed gradually enlarge since 2014 and reached 35% in 2017. In contrast, the import restrictions in the rice market have been stable, with the simulated quota fill rates constantly higher than the observed by about 10%. The quota fill rates in maize market is now least affected by the tariff quota administration.

The fact that wheat imports are being more restricted is possibly due to the growing wheat stocks in China. From 2013 to 2017, the stock-to-use ratio was more than doubled to 95% in China (USDA, 2018), inducing high fiscal costs (Huang and Yang, 2017). In contrast, the stock-to-use ratio for rice only increased by 22% to 61%, and the stock-to-use ratio for maize only increased by 10% to 42% during the same time (USDA, 2018). Higher imports would increase domestic wheat supply and then make it harder to dispose the already accumulated large stocks. Hence, it would be desirable to the policymakers in China to restrict imports through the quota administration.

Lastly, we report simulated import values (products of simulated import quantities and observed import prices) by source country to shed light on the economic interests of different grain exporters. We use the year of 2017 as an example and show the results in figure 1.7. We find that the U.S. wheat industry was one of those that were affected by the tariff quota administration in China's grain market. In particular, the simulated import value for U.S. wheat is 324 million dollars or 83% larger than the observed. In total, the simulated value of grain imports from all source countries in 2017 is 1.4 billion dollars or 40% higher than the observed (see figure A.3).

1.7 Conclusions

In 2016, the U.S. launched a trade dispute against China at the WTO over China's tariff quota administration for the imports of three grain commodities. In this context, this paper investigated the extent to which the tariff quota administration restricted imports in China's grain markets, with a focus on imports from the U.S.. To do this, we calculate ad valorem

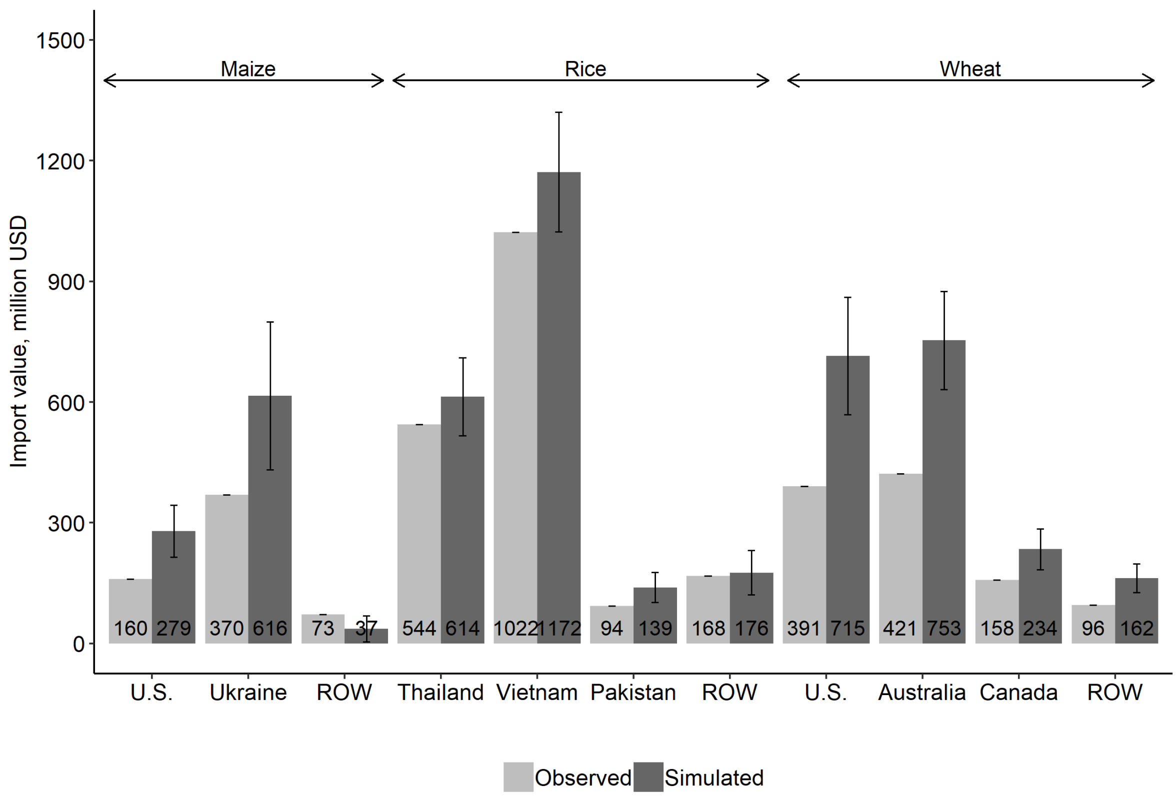

Figure 1.7: Simulated and observed grain import values of China by commodity and by source country in 2017.

Notes: Import values are products of import quantities and average import prices in 2017. The error bars represent 90% confidence interval of the estimates.

tariff equivalents of the tariff quota administration and estimate import demand elasticities for grain commodities of China based on a source differentiated import demand model. We account for tariff and expenditure endogeneity in the estimation. A main finding is that the quota fill rates could have been 10-35% higher than the observed 2013-2017 in a hypothetical scenario that the tariff equivalents were zero. With more quotas to be used, the U.S. wheat exports to China could largely increase, such as by 83% in 2017. But we do not find evidence that the quotas would have been filled except for maize in 2015. Another interesting finding is that the tariff quota administration for the grain commodities seems to act as an import variable levy in China – its restrictiveness varies with import prices, leading to lower import demand elascitities.

Our results about simulated quota fill rates shall be interpreted with caution. In the hypothetical scenario, the tariff equivalents are zero, meaning that the domestic prices are equal to the world prices. This scenario cannot happen if the domestic support prices are higher than the world prices. This was the case for maize in 2015 and in 2016, and for wheat from 2015 to 2017 (see figure 1.3). Hence, the underlying assumption of our simulation is that price support programs for maize and wheat were discarded. If China maintains support prices higher than the world prices while not restricting imports, all quotas would be fully utilized due to the presence of arbitrage profits, resulting in 100% quota fill rates. It depends on the policymakers in China to choose among the different policy options. However, in our view, it is unlikely that China leaves domestic policies intact while liberalizing the import sector only. In fact, the heavy fiscal burden associated with traditional farm policy has prompted Chinese government to undertake multiple market-oriented reforms on domestic farm policy recently, such as lowering domestic support prices, decoupling producer subsidy from production, and improving stock management. At the meantime, these market-oriented policy reforms would likely help China alleviate the pressure from its trading partners regarding its domestic support commitments (Huang and Yang, 2017; Yu, 2017). Therefore, liberalization reforms in both domestic and trade sector are quite possible in China. Nevertheless, in any case, over-quota importing during 2013-2017 is unlikely because domestic prices have always been higher than the world prices by less than the over-quota tariff rate, as shown in figure 1.4.

Our empirical analyses face several caveats. First, we ignore possible rice smuggling from Myanmar and Vietnam to China, which are probably large based on an analysis of discrepancies in trade statistics presented in section A.4. Consequently, the import demand elasticities for rice could be biased. [7] We also ignore imports of the maize substitutes

[7] One can think of smuggling (or illegal imports) as an omitted variable in the import demand equation for rice. For instance, many studies on smuggling (Buehn and Eichler, 2011; Martin and Panagariya, 1984; Pitt, 1981; Thursby et al., 1991) noted that the illegal imports are possibly positively correlated with legal imports that are likely used to cloak or camouflage the illegal imports. Meanwhile, these studies also argued that illegal imports are positively correlated with the disparity between domestic price and import price, and thus are negatively correlated with import prices when holding domestic prices unchanged (this is likely the case in China's rice market as discussed in the Results section). In this case, failing to control the illegal imports would cause negative bias or an overestimation of import demand elasticity for rice that is expected

such as sorghum (Hansen et al., 2018), which might lead to an underestimation of import demand elasticities for maize and then an underestimation of impacts of the tariff quota administration on maize imports. Second, our policy simulations do not consider the case that China might release stocks to lower domestic prices. Grain imports would be lower if stocks were to be released.

With the limitations in mind, our results implies that the massive stocks that China has accumulated could prevent it from being fully open to the international market. This is especially the case for wheat, of which the stock-to-use ratio has now reached around 100% (USDA, 2018). Besides, like many regimes in the world that strive to maintain stable domestic food prices, China could use trade restrictions to insulate domestic markets from international price variability (Anderson and Nelgen, 2012; Yu and Jensen, 2014). In this context, China's willingness to liberalize grain trade likely depends on its progress in disposing the excess grain stocks, reforms on domestic floor price policy, and its tolerance for transmission of world food price variability to domestic markets.

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to be negative. By the same logic, omitting the sorghum imports in the import demand equation for maize would cause an underestimation of import demand elasticity for maize, because sorghum imports are likely negatively correlated with maize imports as well as maize import prices (Hansen et al., 2018).

Chapter 2

Climate Shocks, Food Price Stability and International Trade: Evidence from 76 Maize Markets in 27 Net-importing Countries*

2.1 Introduction

International trade in agricultural products has grown rapidly since the early 1980s, with many developing countries becoming net importers of cereals and other staples (OECD/FAO, 2018; Porkka et al., 2013; Rakotoarisoa et al., 2012; Valdes and Foster, 2012). By spreading the sources of supply of a given market over a larger group of suppliers, trade can serve as a risk sharing mechanism (Bigman, 1986). Therefore, imports could help to reduce domestic price instability by supplementing domestic markets at times of adverse domestic supply shocks. However, imports also increase the vulnerability of domestic markets to supply shocks originated overseas (Ceballos et al., 2016; d'Amour et al., 2016; Gephart et al., 2016;

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Marchand et al., 2016; Puma et al., 2015; Seekell et al., 2017), a possibility exacerbated by the fact that agricultural exports of main staples are concentrated in a handful of countries like the U.S. (Brooks et al., 2013; Challinor et al., 2017a; d'Amour et al., 2016).

Regardless of export concentration, whether imports reduce or increase domestic price instability depends on whether international markets are more volatile than domestic markets (Díaz-Bonilla, 2015). Deaton and Laroque (1992)'s seminal characterization of commodity prices indicates "rare but violent explosions in prices, coupled with a high degree of price autocorrelation in more normal times." In world agricultural markets, this behavior takes the form of long periods of relatively stable prices interrupted by sudden price spikes, such as those in the second half of the 2000s (Abbott, 2012). In contrast to world markets — where supplies of many countries are pooled — domestic markets are subject to the localized vagaries of weather every single season; therefore, prices determined in isolation from world markets and absent any other price stabilization policy [e.g, floor prices in India (Villoria and Mghenyi, 2016)] are more likely to show greater levels of instability than those in world markets. Empirical evidence from Brown and Kshirsagar (2015), for instance, shows that food price variations in the developing world were mainly attributable to local weather-induced crop yield shocks, rather than to international price shocks.

An alternative way to stabilize domestic markets is to use public buffer stocks, whereby, a government agency intervenes by buying domestic excess supplies in years of good crops in order to increase domestic prices; likewise, the release of stocks in years of bad crops helps to mitigate price spikes (Williams and Wright, 1991). Most countries use a mix of buffer stocks and variable trade policies to stabilize markets (Demeke et al., 2009; Williams and Wright, 1991). Stocks, however, are costly and inefficient (Díaz-Bonilla, 2017), often leading to spoilage and high costs of keeping inventories. Advocates of international trade point out to these costs as a main argument to use international markets as a way to stabilize prices (Bigman and Reutlinger, 1979).

Previous studies have used model simulations to examine the impacts of trade and buffer stocks on the stability of domestic food prices (Bigman and Reutlinger, 1979; Makki et al., 2001; Miranda and Glauber, 1995; Williams and Wright, 1991). Some used case studies in Bangladesh, Mexico, Malawi and Zambia (Dorosh, 2001; World Bank, 2005) and cross-sectional comparisons (Chapoto and Jayne, 2009; Minot, 2014) with a focus on trade. Yet, none of them has estimated the functional relationship of imports on domestic food price stability. To fill this gap, the objective of this letter is to estimate the effects of imports and buffer stocks on the intra-annual coefficient of variation (CV) of real monthly prices of maize in a group of net food-importing countries in Africa, Asia, and Latin America. We focus on maize, because it is a major staple that is widely produced, consumed and traded around the world (Ranum et al., 2014), and its domestic prices are highly variable in many developing countries (Minot, 2014).

Crop yields will likely become more variable under climate change (Challinor et al., 2014; IPCC, 2014; Villoria and Chen, 2018), with some authors documenting the potential for more variable domestic prices (Haile et al., 2017). In light of this, we explore the roles of international trade and buffer stock in mitigating the potential greater price variability associated with a more unstable climate.

2.2 Methods and Data

We proceed in two steps. First, we use regression analysis to estimate the effects of domestic yield shocks, imports, and buffer stocks on the intra-annual CV of real monthly prices of maize in 27 countries, most of them low- or middle-income. Second, we use the parameter estimates from the regression to examine future scenarios of maize price variability under alternative projections of maize yields toward mid-century. We also explore the potential of increasing maize imports and maize buffer stocks to counteract the price effects of more variable yields stemming from a more variable climate.

2.2.1 Estimating the effects of domestic supply shocks, import dependence, and buffer stocks on price variability

The data used for estimation, described below, have a panel structure with 76 sub-national markets (denoted by k) in 27 countries (denoted by i) observed during the 2000-2015 marketing years, denoted by t. With these data, we estimate the following regression:

$$CV_{ik,t} = \alpha_1 I_{i,t} + \alpha_2 Y_{i,t} + \alpha_3 M_{i,t} + \boldsymbol{\beta} \boldsymbol{Z}_{i,t} + \mu_i + \delta_k + \phi_t + \epsilon_{ik,t}, \tag{2.1}$$

where $CV_{ik,t}$ is intra-annual CV of real monthly prices of maize in kth market of country i at year t.

Our main interests are the parameter estimates of α_1, α_2, and α_3. The data used to estimate these parameters are: the national annual ratios of net imports (i.e., imports minus exports) to domestic consumption, $I_{i,t}$; the annual absolute yield deviations from historical trends[1] in each country i, $Y_{i,t}$, which captures the effects of both positive and negative domestic supply shocks on domestic maize price instability; and the country-level stock-to-use ratio at the beginning of the marketing year t, $M_{i,t}$. The $\boldsymbol{Z}_{i,t}$ and $\boldsymbol{\beta}$ are vectors of control variables and their corresponding parameter estimates that have direct effects on domestic price stability, namely, exchange rate variability (Cho et al., 2002), food aid (Barrett et al., 1999; Lentz et al., 2005) and social conflict (Bellemare, 2015). In addition, as discussed below, the robustness of our results is explored by controlling for other variables that could be correlated with both price variability and import ratios, including physical trading distance, degree of import diversification, and per-capita income (Jeon and Ahn, 2017; Luan et al., 2013).

We also exploit the panel nature of our data to control for unobservables. Specifically,

[1] We use the Hodrick-Prescott (HP) filter (Hodrick and Prescott, 1997) and quadratic trends. The HP filter is used to decompose a time series into cyclical fluctuations and its more stable trends; the filtered series are smooth representations of the underlying data, and as such they are less sensitive to short-run fluctuations. The HP filter has been used by Gollin (2006) to detrend crop yields, and in our case, offers a smoother approximation in countries such as Rwanda, which have markedly non-linear trend trajectories (appendix figure B.1). The smoothing parameter is set to be 100, a usual choice for annual data (Ravn and Uhlig, 2002).

the terms μ_i and δ_k denote country and market fixed effects, which control for time-invariant, unobserved country and market heterogeneity. The term ϕ_t is a year fixed effect that controls for the unobserved shocks affecting all the markets within a given marketing year. These account, for instance, for the excessive volatility that characterized the period 2005-2012 (Abbott, 2012). The term $\epsilon_{ik,t}$ denotes residuals, assumed to be normally and independently distributed, as well as uncorrelated with the independent variables. Equation (2.1) is estimated using a fixed effects, panel data regression estimator—also known as Least Squares Dummy Variable—as described in Greene (2011, p.287).

Table 2.1 describes data sources and definitions of the regression variables in equation (2.1). Table 2.2 reports their descriptive statistics. The dependent variable is annual CV of real monthly prices of maize (in 1982-1984 US dollars) obtained from the FAO GIEWS database (FAO, 2017). We focus on 76 retail or wholesale markets in 27 countries in the FAO GIEWS database that are net importers of maize. These countries are in Asia, Africa, and Latin America. The data are available from 2000 to 2015 (see appendix tables B.1-B.2, figure B.2). Cumulative maize imports during 2011-2015 of these countries accounted for nearly one third of maize global imports. Figure 2.1 shows the 2000-2015 averages of intra-annual CV of real monthly maize prices, net import ratios, and stock-to-use ratios at the beginning of the marketing year for all the focus countries. At a glance, this map suggests that, generally speaking, countries with relatively low imports (e.g. those in Africa and Asia) tend to display more variable prices.

Table 2.1: Definitions of regression variables and data sources.

Variable name	Definition	Data source
Domestic price variability (dependent variable)	Intra-annual coefficient of variation of real monthly prices (in 1982-1984 US dollars) within a country-specific marketing year.	Prices: FAO Global Information and Early Warning System (FAO, 2017); Marketing year: PS&D online database (USDA, 2017).
Net import ratio	Net imports (imports - exports) divided by consumption.	PS&D online database (USDA, 2017).
Beginning stock-to-use ratio	Stocks available at the beginning of marketing year divided by consumption.	PS&D online database (USDA, 2017).
Absolute yield deviations	Absolute yield deviations from historic trends divided by trend values. Trends are fitted by HP filter (Hodrick and Prescott, 1997) with smoothing parameter of 100.	FAOSTAT (FAO, 2018).
Variability of real exchange rate	Intra-annual coefficient of variation of real exchange rate within a country-specific marketing year. Calculations of real exchange rates follow Villoria and Hertel (2011, p. 921).	Exchange rates: exchange rate archives of International Monetary Fund and OANDA website.[2] Consumer price index: FAOSTAT (FAO, 2018).
Food aid ratio	Food aid divided by consumption.	Food Aid Information System of the World Food Programme (WFP, 2018).
Social conflict	A dummy variable that is 1 if the use of armed force results in at least 25 battle deaths in a year and 0 otherwise.	Social Conflict in Africa Database (Salehyan et al., 2012).
Import distance	Import share weighted distance between the importing country and its trading partners.	Trade data: Global Agricultural Trade System (USDA, 2017); Distance data: CEPII (Mayer and Zignago, 2011).
Herfindahl index of import shares	Sum of squared bilateral import shares.	Global Agricultural Trade System (USDA, 2017).
Per capita GDP	GDP divided by the population.	World Bank open data system.[3]

[2] The website link is https://www.oanda.com/currency/average

[3] The website link is https://data.worldbank.org/

Table 2.2: Summary statistics of regression variables.

	Number of Obs.	Mean	Median	Standard deviation	Min.	Max.
Domestic price variability	851	0.13	0.11	0.08	0	0.52
Net import ratio	851	0.25	0.11	0.3	-0.19	1.06
Beginning stock-to-use ratio	851	0.09	0.09	0.06	0	0.5
Absolute yield deviation (HP filter)	851	0.09	0.05	0.1	0	0.56
Absolute yield deviation (Quadratic)	851	0.11	0.07	0.11	0	0.61
Social conflict	851	0.17	0	0.37	0	1
Variability of real exchange rate	851	0.03	0.02	0.02	0	0.11
Food aid ratio	631	0.01	0	0.03	0	0.34
Import distance	808	0.41	0.35	0.24	0.02	1.56
Herfindahl index of import share	808	0.72	0.75	0.25	0.19	1
Per capita GDP	808	3.72	1.93	4.42	0.22	32.99

Notes: There are much fewer observations for "food aid ratio" because data on food aids during 2013-2015 are not included in the source database. The units for import distance and per capita GDP are thousand kilometers and thousand U.S. dollars, respectively. Other variables do not have units.

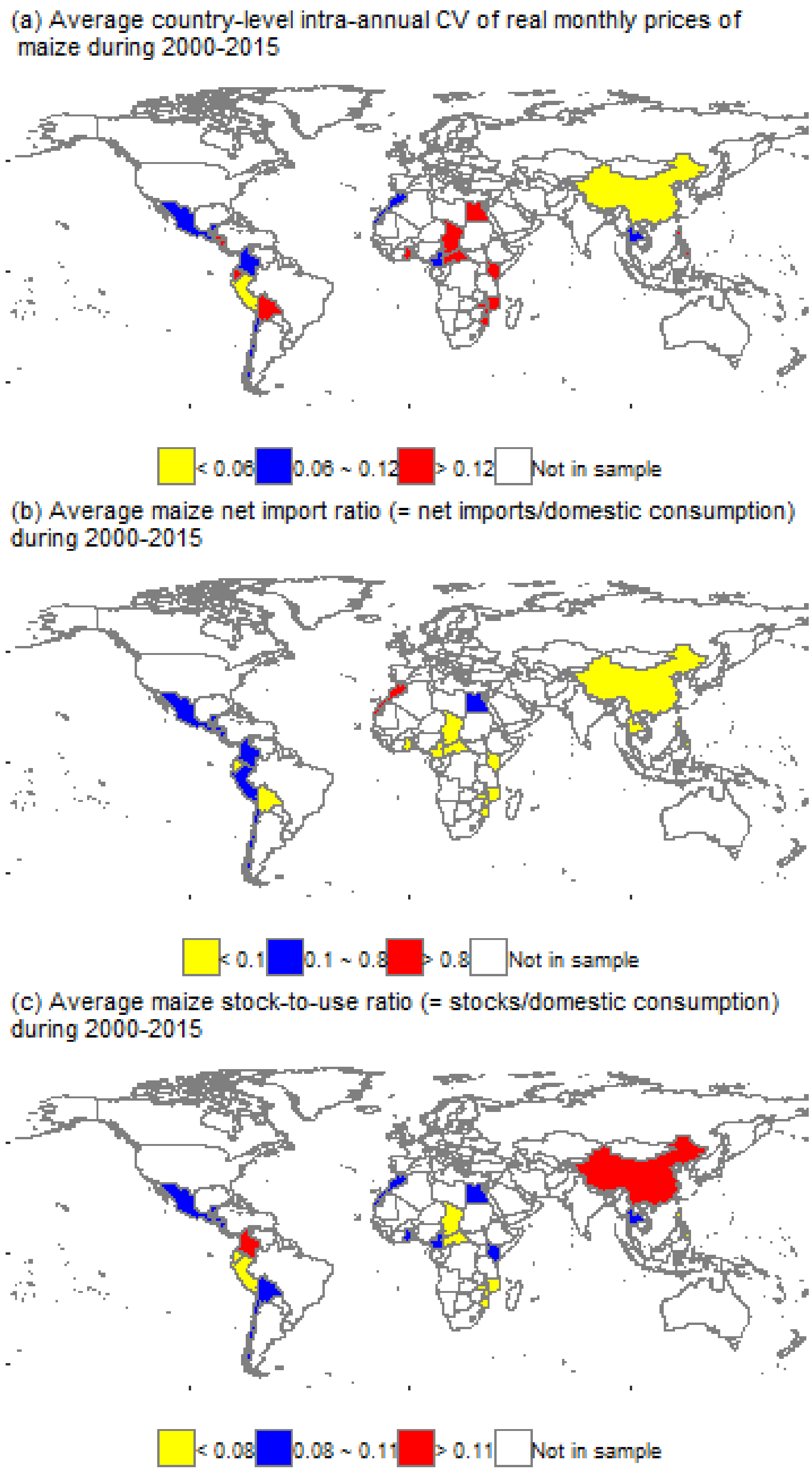

Figure 2.1: Maize price variability, imports and buffer stocks across focus countries.

Data source: PS&D online database (USDA, 2017).

A different perspective on these data is in figure 2.2, which plots the 2000-2015 average intra-annual CV of real monthly maize prices against import ratios in all the focus countries[4]. This figure shows that African and Asian countries have low import ratios (less than 0.1) and highly variable maize prices (Morocco is an exception). China, on the other hand, has a low import ratio and also the lowest levels of price variability among the focus countries, probably reflecting the effects of price stabilization policies (Chen et al., 2018; Pieters and Swinnen, 2016). Compared with the countries in Asia and Africa, the countries in Americas have higher import ratios and lower intra-annual CVs of their maize real prices.

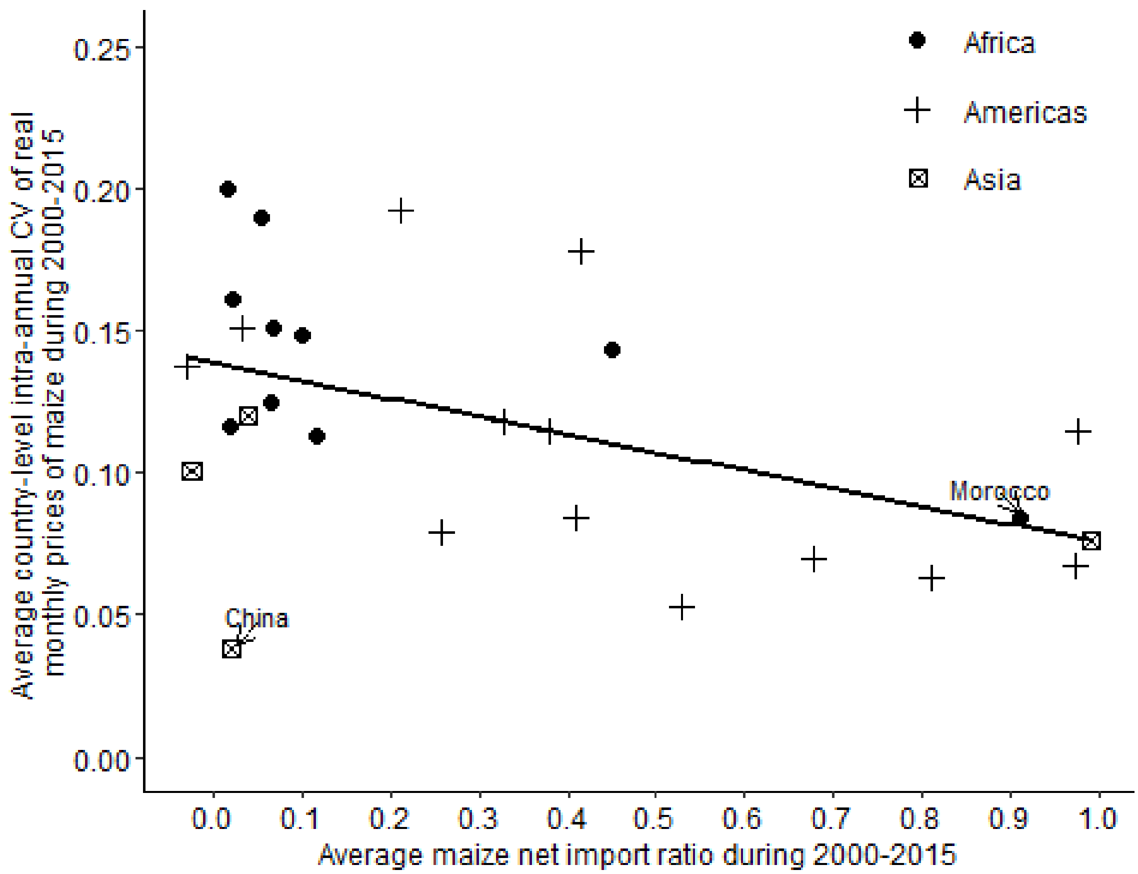

Figure 2.2: Relationship between maize price variability and maize import ratio across focus countries.

[4]The import ratio for maize varies across countries but is relatively stable over time (appendix figure B.3), reflecting the fact that imports and domestic productions have increased together (FAO, 2003; Konandreas, 2012). A notable exception is Ecuador, whose import ratio declined from around 0.6 in early 2000s to almost none in 2015.

2.2.2 Predicting future price variability

To predict the variability of future maize prices in each market, we proceed as follows. First, we obtain times series of maize yields (in tonnes per hectare) for the period 2006-2050 from two alternative sources: the yield-climate response function estimated by Moore et al. (2017) and two of the global crop models from the GGCMI-AgMIP archive (Elliott et al., 2014a; Rosenzweig et al., 2014)[5].

Moore et al. (2017)'s function is a meta-analysis regression of a large database on crop yield changes compiled by Challinor et al. (2014). This function relates changes in temperature, precipitation, CO_2 concentration, and on-farm management to changes in crop yields of several crops. The parameter estimates of this response function are global (see appendix section B.1); therefore, variability in yield responses at any resolution other than global (e.g. gridcell or country) comes solely from regional variability in climate and the other explanatory variables. Moore et al. (2017) used this function, jointly with data of future climate, to estimate high-resolution yields for the entire world. In an analogous manner, we use the their parameter estimates to predict country-level maize yields for each year in 2006-2050.

For this, we use data on temperature and precipitation from the ensemble of five global circulation models included in the GGCMI-AgMIP archive (Hempel et al., 2013; Warszawski et al., 2014), aggregated to the growing season of each focus country by Villoria et al. (2018). Moreover, we obtain predictions with and without the effects of CO_2 fertilization, using the data on temperature to infer CO_2 concentrations as indicated in Moore et al. (2017) (see appendix section B.1 for details)[6]. We also obtain projected yields with and without CO_2 from the GGCMI-AgMIP archive (Elliott et al., 2014a; Rosenzweig et al., 2014), aggregated both to the country-level and to the growing season of each country using the GGCMI-

[5]We only use two crop models, LPJmL and pDSSAT, because only these two models provide uninterrupted time-series of projected yields from 2006 to 2050, under both representative concentration pathways (RCP) 2.6 and RCP 8.5, with and without CO_2 (see table S6 in Rosenzweig et al., 2014, for details), for all the focus countries. We chose RCP 2.6 and RCP 8.5 because they represent the most benign and extreme potential pathways of of emissions during the projection period (Riahi et al., 2011; van Vuuren et al., 2011). This allows us to understand whether potential scenarios of price variability are conditional on the chosen emissions pathway.

[6]The authors thank Frances Moore for graciously sharing the actual parameter estimates as well as the codes and data necessary for replicating the results. However, the empirical choices made here are our responsibility.

AgMIP interface by Villoria et al. (2016). To be consistent with the treatment of the maize yield shocks used to estimate equation (2.1), we calculate absolute projected maize yield deviations from their trends (see footnote 1). We denote these absolute deviations as $Y^*_{i,t}$, for t in 2006-2050.

Second, we combine these future yield deviations with the parameter estimates of equation (2.1); this procedure yields the corresponding predicted intra-annual CV of real monthly prices of maize in each focus market for each year in 2006-2050. In the analysis below, we will contrast our predicted scenarios of price variability against historical price variability. The most obvious measure of historical price variability in our study are the observed intra-annual CV of real monthly maize prices used to estimate equation (2.1). However, historical maize yield variability explains only some of the observed variance of past real maize prices while our predictions are solely driven by yield fluctuations. In order to circumvent this difficulty, we use absolute deviations from trend (see footnote 1) of observed maize yields during 1961-2014, denoted by $Y^{FAO}_{i,t}$, to predict the historical intra-annual CV of real monthly prices of maize in each focus market. These are directly comparable with the future predictions.

Formally, we get the historical ($\widehat{CV}^{FAO}_{ik,t}$) and future ($\widehat{CV}^{*}_{ik,t}$) predictions using:

$$\widehat{CV}^{FAO}_{ik,t} = \widehat{\alpha}_1 \bar{I}_i + \widehat{\alpha}_2 Y^{FAO}_{i,t} + \widehat{\alpha}_3 \bar{M}_i + \widehat{\boldsymbol{\beta}} \bar{\boldsymbol{Z}}_i + \widehat{\mu}_i + \widehat{\delta}_k + \widehat{\phi}_{t=2015},\ t \in \{1961, ..., 2014\}, \tag{2.2}$$

and

$$\widehat{CV}^{*}_{ik,t} = \widehat{\alpha}_1 \bar{I}_i + \widehat{\alpha}_2 Y^{*}_{i,t} + \widehat{\alpha}_3 \bar{M}_i + \widehat{\boldsymbol{\beta}} \bar{\boldsymbol{Z}}_i + \widehat{\mu}_i + \widehat{\delta}_k + \widehat{\phi}_{t=2015},\ t \in \{2006, ..., 2050\}, \tag{2.3}$$

where *hat* indicates that these are the parameters estimated in equation (2.1), or their predicted values. The rest of the variables are set to their means over 2000-2015. For example, $\bar{I}_i$ is the average import ratio of country i during 2000-2015. In addition, $\widehat{\mu}_i$ and $\widehat{\delta}_k$ are intercept estimates specific to each country i and market k, and $\widehat{\phi}_{2015}$ is the estimated value of the fixed effect for year 2015. In other words, our predictions of both historical and projected CV of maize prices assume that the rest of the variables remain constant, and therefore, they exclusively capture the effect of historical and projected yield variability on price variability.

2.3 Results

2.3.1 Import dependency reduces domestic price variability

To aid with interpretation, figure 2.3 reports our regression results as elasticities evaluated at their sample means, with 95% confidence intervals generated by the Delta method (appendix section B.3). The underlying parameter estimates are reported under column "Model 4" in appendix table B.3. These elasticities measure percentage changes in the intra-annual CV of monthly real maize prices given one percentage change in a given independent variable.

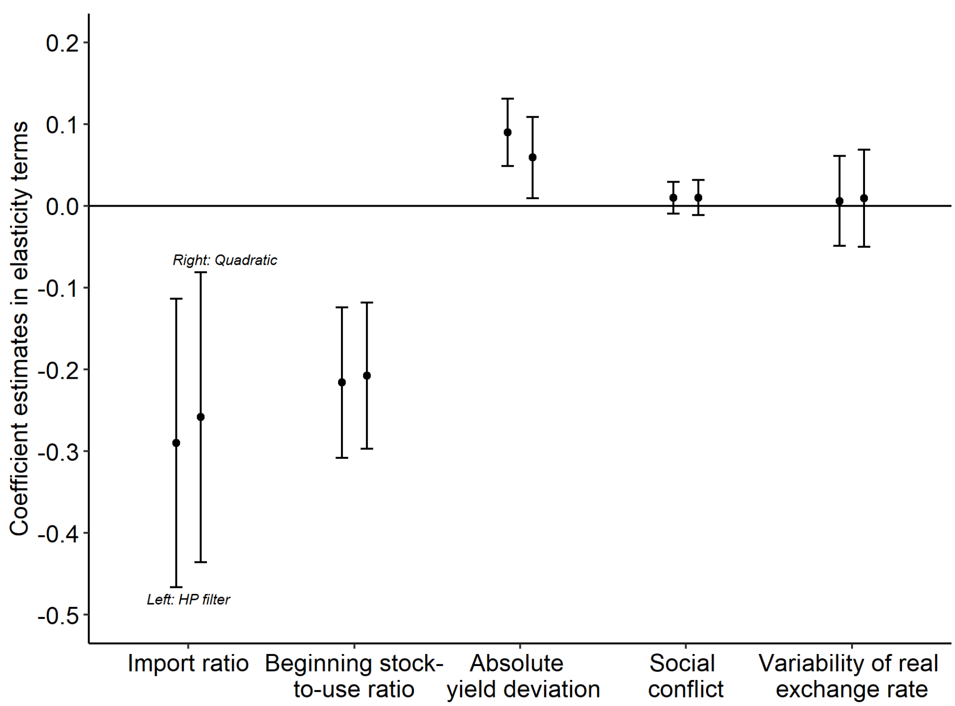

Figure 2.3: Elasticities of the intra-annual CV of real monthly maize prices to changes in the determinants of price volatility.

Notes: The error bars represent 95% confidence intervals. An elasticity is defined as the percentage changes in the intra-annual CV of real monthly maize prices, given one percentage change in a given independent variable.

Starting with the effects of yield shocks, our estimates suggest that a 1% increase in the absolute deviation of annual maize yields from their historical trend, is associated with a statistically significant increase of 0.09% in the intra-annual CV of real monthly maize prices. Also, a 1% increase in maize stocks relative to maize consumption at the beginning of the marketing year, is associated with a reduction of the intra-annual CV of real monthly maize prices of 0.22%. Regarding imports, an increase of 1% in the ratio of maize imports to total consumption is associated with a decrease in the intra-annual CV of real monthly maize prices of 0.29%. In short, our findings are aligned with the expectation that domestic maize supply shocks are a source of maize price fluctuations. They also confirm that larger import ratios and stock inventories at the beginning of the year are associated with lower price instability in the focus countries.

In appendix table B.4, we show that these findings are robust to estimations using different time periods, to the omission of years with either high or low international prices, to alternative calculations of domestic supply shocks and to additional controls such as physical import distances, import diversification and per capita income. In appendix table B.5, we show that these results are robust to estimation focused on different geographic regions, to the inclusion of countries with high or low import ratios, and to the inclusion of countries with large or short distances to their trading partners.

2.3.2 Future maize prices are expected to become more unstable

Figure 2.4 displays, for each focus country[7], the density distributions of market-average intra-annual CV of real monthly prices of maize in the historical period (1961-2014), $\widehat{CV}_{ik,t}^{FAO}$ from equation (2.2), and in the projected period until mid-century (2006-2050), $\widehat{CV}_{ik,t}^{*}$ from equation (2.3). The price projections in this figure were obtained using projected yields assuming no effects of increased CO_2 fertilization under RCP 2.6 and 8.5 [8]. The most

[7]In the analysis that follows, we omit Ecuador, Honduras and Israel because of lack of observed crop calendar data to aggregate the projections of temperature and precipitation (Sacks et al., 2010).

[8]As shown in appendix figure B.4, the inclusion of CO_2 fertilization makes no significant difference to the price variability projections. The underlying reason is that the projections on future maize yield variability do not change after including the CO_2 fertilization under both RCP scenarios (see appendix figure B.10-B.11).

consequential finding in this figure is that the two sources of projected maize yields produce conflicting views of future scenarios of price instability. In particular, the GGCMI-AgMIP crop models predict that, in 17 out of 24 focus countries, maize prices will become more variable over the coming decades, which is evidenced by the more right-skewed density curves over the projection period 2006-2050. In contrast, the yield response function from Moore et al. (2017) predicts that maize prices will become less variable in almost every focus country, relative to the historical densities (appendix figure B.8 shows a case for Kenya).

The conflicting views on prices are rooted in very different projections on future yield variability from the two modeling frameworks. Specifically, visual inspection of figure 2.5 reveals that the GGCMI-AgMIP crop models predict increases in maize yield variability in most countries. In contrast, the meta-analysis yield response function from Moore et al. (2017) predicts density functions that are less spread than the density of historical yields.

We surmise that this reduction in maize yield variability owes to the fact that nearly 70% of the data points in the underlying database used by Moore et al. (2017), are for the U.S. and China (supplementary table 1 in Challinor et al., 2014). Countries in tropical regions, which are more sensitive to warming (Challinor et al., 2014; Porter et al., 2014), are much less represented. As noted by Moore et al. (2017, p.3), "our meta-analysis results are more optimistic in tropical areas" than the GGCMI-AgMIP crop models — in fact, their projected yield losses are 5 to 50% lower than those projected by the GGCMI-AgMIP crop models within the tropical regions [see supplementary figure 6 in Moore et al. (2017)]. Such a reduction in yield variability is at odds with the expectation that future yields will become more variable because of more variable temperature and precipitation[9] (Chen et al., 2004; Haile et al., 2017; McCarl et al., 2008; Müller and Robertson, 2014a; Porter et al., 2014). In light of this discussion, we will use the prices projected using GGCMI-AgMIP yields in the discussion that follows. We notice, however, that these data have some well known caveats. For instance, the GGCMI-AgMIP crop models use simplistic assumptions about

[9]Our own analysis of the data used to elicit these yields indicates substantive increases in the variance of temperature and precipitation in most of the focus countries (appendix figure B.5 - B.6), which is consistent with increases in variance of detrended maize yields projected by GGCMI-AgMIP crop models (appendix figure B.7).

the distribution of soils, sowing dates, varieties and fertilizers, which can affect the temporal dynamics in the yield projections (Müller et al., 2017). Nor do these models capture weather-related pest or disease outbreaks that could constitute short-term yield shocks (Müller et al., 2017; Rosenzweig et al., 2014).

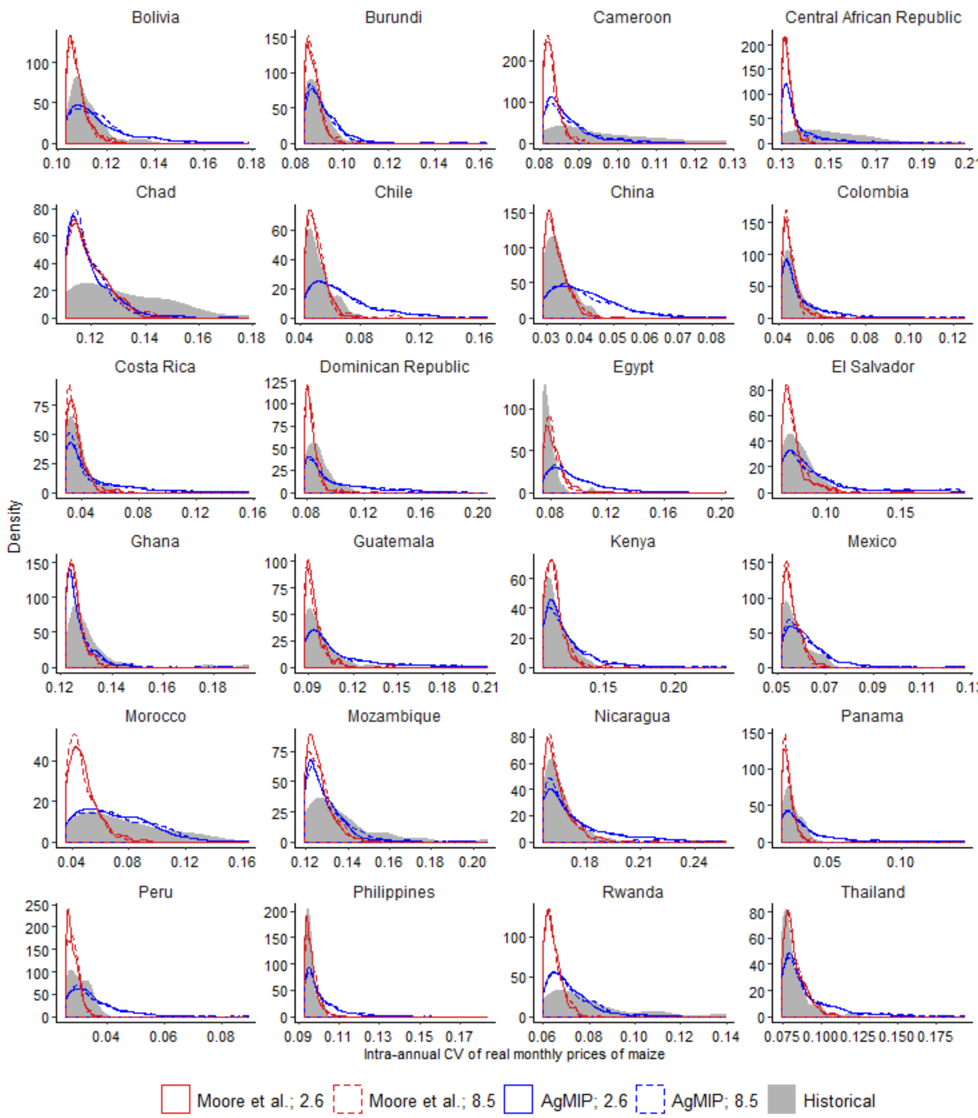

Figure 2.4: Distributions of projected intra-annual CV of real monthly prices of maize during 2006-2050 without CO_2 fertilization and during 1961-2014.

Notes: Results for Ecuador, Honduras and Israel are not shown due to lack of observed crop calendar data to aggregate the projections of temperature and precipitation (Sacks et al., 2010). The results with CO_2 fertilization are shown in appendix figure B.4.

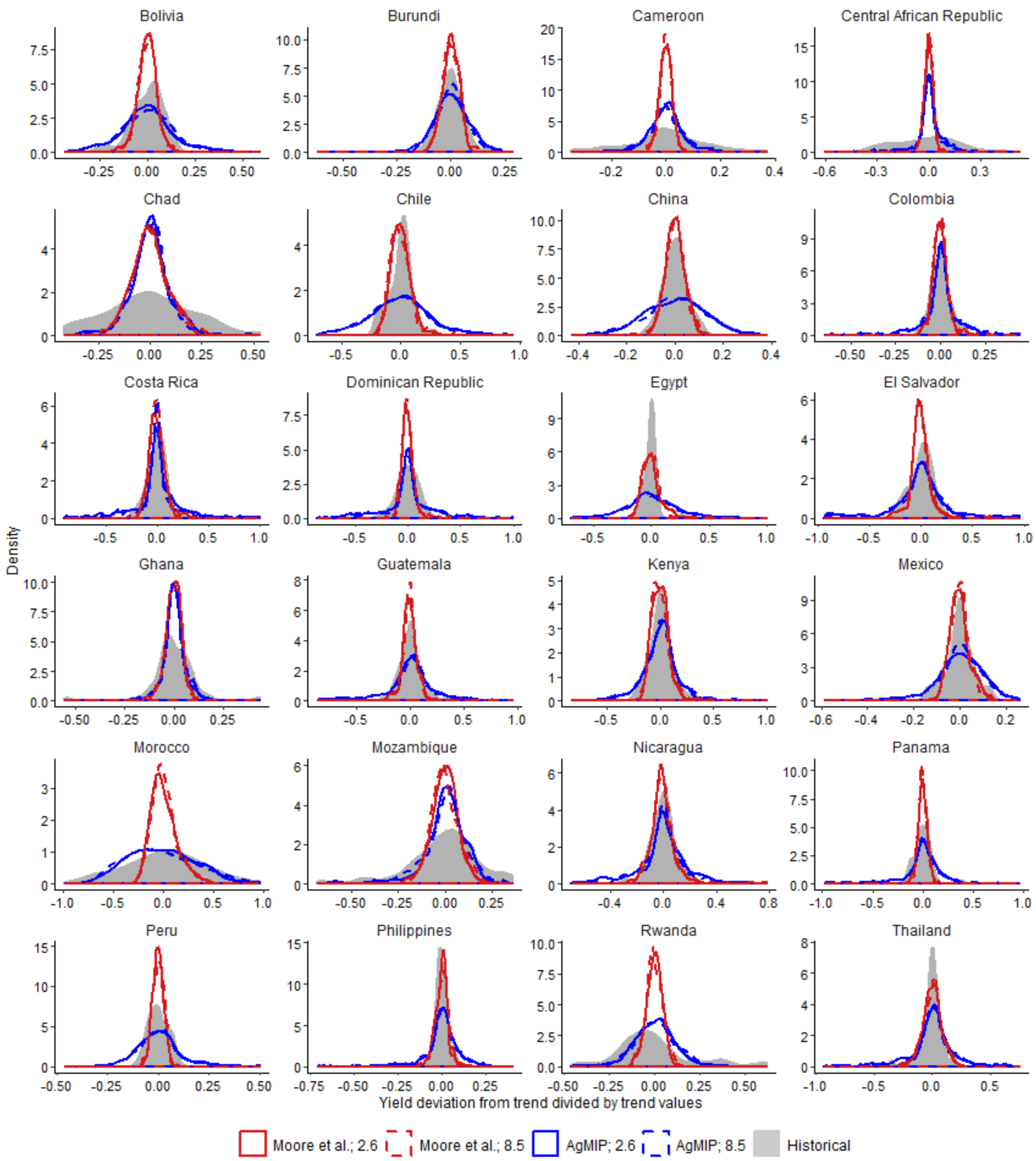

Figure 2.5: Distributions of detrended maize yields during 2006-2050 without CO_2 fertilization and during 1961-2014.

Notes: Maize yields are detrended by the HP filter (Hodrick and Prescott, 1997) with a smoothing parameter of 100. Historical yields are from FAOSTAT (FAO, 2018), and future yields are projected by GGCMI-AgMIP crop models (Elliott et al., 2014a; Rosenzweig et al., 2014) and Moore et al. (2017)'s yield-climate response function in combination with five global climate model ensembles used by the Inter-Sectoral Impact Model Intercomparison Project (Hempel et al., 2013; Warszawski et al., 2014). Results for Ecuador, Honduras and Israel are not shown due to lack of observed crop calendar data to aggregate the projections of temperature and precipitation (Sacks et al., 2010). The results with CO_2 fertilization are shown in appendix figure B.9.

2.4 Discussion and Limitations

To discuss the implications of our results, we investigate by how much could countries increase either their maize imports or buffer stocks in order to offset the destabilizing effects of a more variable climate on domestic maize prices.

For this, we first calculate, for each country, the number of intra-annual CV of real monthly maize prices during 2006-2050 that are equal or greater than the lower bound of the upper decile of their historical (1961-2004) distribution. We consider the historical upper decile as containing extreme instances of intra-annual price variability, in the sense that these have been experienced once in a decade, or only around five times during 1961-2014. Therefore, more observations of CV within or beyond this decile indicate potential increases in the incidence of extreme price variability toward mid-century. Figure 2.6 shows that in the median country, the relative frequency of extreme intra-annual maize price CV during 2006-2050 increases to 30%, which is two times higher than in the period 1961-2014 (10%). Incidentally, notice that Moore et al. (2017)'s yield response implies a reduced incidence of extreme instances of price variability toward mid-century. This is a direct consequence of the reduction in the expected variance of prices implicit in Moore et al. (2017)'s yield response. The changes in extreme price variability are largely homogeneous across both RCP and CO_2 fertilization scenarios.

Second, we conduct an ad-hoc search of the increase in either maize imports or stocks (both relative to their 2000-2015 averages) that would keep the median frequency of extreme maize price CV (across all the markets) close to their historical incidence. We find these values to be an increase of imports equivalent to 10% of total consumption or an increase in stocks equivalent to 5% of current use (see figure 2.6a). Also notice that, as shown in figure 2.6b), such increase of maize imports and/or stocks will displace down the entire distribution of intra-annual CV of real monthly prices of maize during 2006-2050, suggesting that, on average, such a modest increase in imports of stocks more than offset the variability embedded in the GGCMI-AgMIP yields.

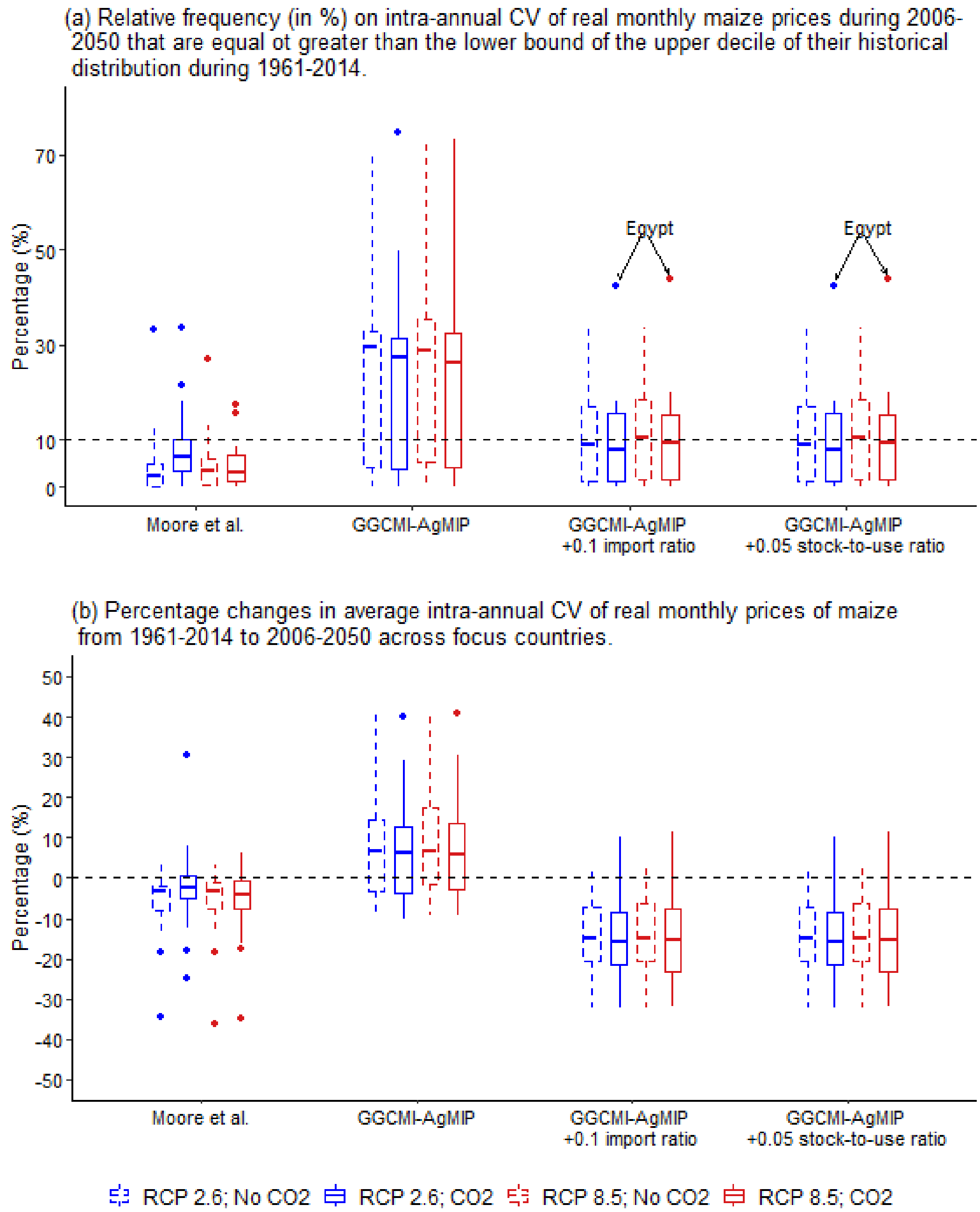

Figure 2.6: Incidence of extreme price variability towards mid-century and changes in average price variability across focus countries under alternative trade and storage policy scenarios.

Notes: The dashed lines in panel (a) and panel (b) represent the baselines values, i.e., 10% and 0%, respectively.

Conversely, reducing maize imports relative to total consumption would amplify the impacts of more variable yields on price stability (appendix figure B.12). For instance, if countries would reduce their import ratio by 10%, the median relative frequency of extreme intra-annual CV of real monthly maize prices during 2006-2050 would largely increase to approximately 70%, meaning that, in the median country, the extremely high intra-annual CV of real monthly prices of maize is to be seen at least 7 years in every 10 years during 2006-2050. This suggests that countries that reduce their imports relative to domestic consumption while holding buffer stocks unchanged could face high price risks in the future as the climate becomes less stable.

Several caveats are in order. The price stabilization effects of imports and stocks captured by equation (2.1) could change in the future. The effects of imports on domestic price stability could increase as the global maize market expands in size (Bigman, 1986) or decrease if maize yields in the major exporting countries become much more variable than in the importing countries. Smaller import growth is needed to offset the negative impacts of more variable yields on domestic price stability if imports have a larger negative effect on price variability, and vice versa.

In addition, our yield projections ignore factors that can either dampen (e.g., better technology) or exacerbate [e.g., pests and disease (Donatelli et al., 2017)] yield variability. Moreover, the climate models that we use do not fully capture climate change influences on short-term temperature extremes, monsoon dynamics, and the frequency and intensity of precipitation (Rosenzweig et al., 2014); therefore, the projected changes in yield and price variability could be biased downward. Another caveat is that we do not consider the simultaneous occurrence of food supply shocks in exporting countries and in importing countries. This is an important issue and a fruitful area for further research, particularly due to persistent high export concentrations.

Despite the uncertainties and limitations, our findings suggest that pursuing food self-sufficiency by restricting international trade may be an ineffective way to increase domestic price stability, at least for maize, under the current world market situation. Food self-sufficient countries could increase buffer stocks to maintain market stability. Yet, the historical experience suggests that public buffer stocks tend to be costly and inefficient (Díaz-Bonilla, 2017; Wright, 2011). The option of supplying the domestic market with foreign supplies is not without perils either. Food and national security concerns, the pressure of domestic interest groups, as well as excessive dependence on one or two exporters are legitimate concerns that often underlie the policy measures for suppressing agricultural trade. Continued efforts to reduce international trade costs and to facilitate the supply diversification of international markets would be cost-effective in mitigating the negative effects of a more unstable climate on food price stability in the years to come.

Lastly, we highlight that more efforts are needed to better understand the sensitivity of maize yields to temperature shocks, especially in the tropical regions. In those regions, lands are less productive and constraints in water availability are more severe, making their yield stability more vulnerable to the climate change. In a foreseeable future, domestic production will remain a main source of domestic consumption in African and Latin American countries (Alexandratos and Bruinsma, 2012; OECD/FAO, 2018). So the question that to what extent that the increase in climate variability is to be translated into higher yield variability is essential to our understanding of the climate change impacts on food price stability.

2.5 Conclusion

Do food imports increase the variability of domestic food prices? In this article, we estimate the effects of imports, stocks and domestic yield shocks on maize price stability in 76 markets distributed across 27 net-importing countries in Africa, Asia, and Latin America. We use standard panel data regression estimator that allows for controlling unobserved heterogeneity through the use of cross-sectional and time varying fixed effects. We also examine the potential effects of a more variable climate on maize price variability using alternative sources of maize yields toward mid-century. We find that maize prices are more stable in countries where imports constitute a larger part of domestic consumption. This suggests that international markets act as a source of stability rather than as a source of risk, even as international food prices have gone through turbulent periods during most of the estimating period. We also find that climate change will likely escalate maize yield variability and thereby increase price variability by around 10% among focus countries. These effects could be offset by increasing maize imports or carrying larger stocks. The fact that both imports and stocks help to stabilize domestic prices suggests that, whether countries decide to use one or the other strategy should hinge on a careful cost-benefit analysis, including the risk of facing world markets more variable than domestic production vis a vis the costs of carrying maize inventories over time.

Chapter 3

The Asymmetric Effects of Foreign Supply Shocks on Domestic Price Stability: An Application to Maize Markets in Developing Countries

3.1 Introduction

In the recent past, growth in domestic food production in developing countries has lagged behind growth in domestic food consumption, resulting in ever-increasing import dependence (Luan et al., 2013; Porkka et al., 2013; Puma et al., 2015; Sadler and Magnan, 2011), with as many as 111 out of 163 countries currently considered net importers of food (Ng and Aksoy, 2008). While food-importing countries enjoy economical food from international markets, some observers have expressed concerns that international trade might not be effective as a global risk-sharing mechanism to stabilize prices; rather, it transmits yield shocks across borders, causing higher food price variability in the importing countries (Challinor et al., 2017b; d'Amour et al., 2016). In particular, we have heard these concerns frequently since the 2007-2008 world food price crisis, when the excess volatility in international food markets was transmitted into domestic markets of many food-importing countries (Demeke et al., 2009; Headey and Fan, 2008). For instance, a series of studies (d'Amour et al., 2016; Gephart et al., 2016; Marchand et al., 2016; Puma et al., 2015) simulated the impacts of supply shocks originating from exporting countries on food consumption in food importing countries, highlighting the vulnerability of food security in the importing countries to foreign supply shocks. The cross-border price impacts of foreign yield shocks are of particular relevance now as there is mounting evidence suggesting that crop yields in major exporters, like the U.S., could become more variable in the coming decades (Müller et al., 2018; Schlenker and Roberts, 2009; Urban et al., 2012; Villoria and Chen, 2018).

Historical experience suggests that, in developing countries, the desire for stable food prices often draws nationwide government interventions aimed at price stabilization (Anderson and Nelgen, 2012; Cummings, 2012; Dawe and Timmer, 2012). For this reason, concern about the vulnerability of domestic food price stability to foreign yield shocks has policy consequences — in fact, it has already become a policy motive to adopt trade-distorting policies (e.g., import tariffs) to protect domestic markets from international price volatility (Anderson and Nelgen, 2012; Clapp, 2017; Staatz et al., 2008; van Oort et al., 2015). These trade-distorting policies could induce high social costs, especially for countries (e.g., in North Africa and the Middle East) where the natural resources for producing food are scarce and, thus, food imports play an important role in food supply (Fader et al., 2013; OECD/FAO, 2018). In light of this, some scholars have recommended that, although it is also costly, countries hold larger stocks instead to maintain stable domestic prices in the presence of uncertain domestic and foreign crop yields (Dorosh, 2009; Larson et al., 2014; Wright and Cafiero, 2011). Yet, the amount of stocks to be held by the importing countries for price stabilization under yield uncertainty remains unexplored.

As the price impacts of foreign yield shocks gain more attention, we are interested in the following question – to what extent is domestic price variability in food importing countries affected by yield shocks in the food exporting countries? This question matters because, if it is to a great extent, the international market would serve as a price transmission mechanism, rather than a risk-sharing mechanism as desired. In this case, food stocks, another policy tool for price stabilization in addition to international trade (Williams and Wright, 1991), would become crucially important to the developing countries that desire stable food prices.

In this context, this article aims to estimate the extent to which domestic food price variability in net-importing and developing countries is affected by yield shocks originating from their trading partners. Price variability is measured by the Coefficient of Variation (CV) of real monthly prices within a crop marketing year; yield shocks are measured by the deviations of yields from their historical trends relative to the trend values. We focus on maize, because it is a major staple that is widely produced, consumed and traded around the world (Ranum et al., 2014), and its prices have been highly variable in many developing countries (Minot, 2014). Our price data cover 74 markets in 24 countries across Africa, Latin America, and Asia in the years 2000-2016. Further, we combine the estimation results with global maize yield projections from the AgMIP-GGCMI archive (Elliott et al., 2014b; Rosenzweig et al., 2014) to project the climate change impacts on maize price variability in focus countries toward mid-century. We also calculate the amount of stocks needed by the selected countries to fully offset such price impacts.

Our article makes two contributions to the literature. First, it provides direct estimates of the effects of foreign yield shocks on food price variability in importing countries. So far, a large number of empirical studies (e.g., Bekkers et al., 2017; Ceballos et al., 2016; Kalkuhl et al., 2016; Kornher and Kalkuhl, 2017) have estimated the price transmissions from international to domestic markets. These estimates, however, are at their best imperfect indicators of the effects of foreign supply shocks on domestic price variability for two reasons. On one hand, the incidence of yield shocks in exporting countries is only one of many factors (e.g., global food stocks (Schewe et al., 2017), prices of non-food commodities such as ethanol and oil, and financial speculation (Tadesse et al., 2014)) that determine international food prices. Even if yield shocks in exporting countries are the most relevant driver, it would be reasonable to expect that the variability of global prices is lower than the volatility in any particular supplier (Bigman and Reutlinger, 1979), especially because the major producers are located in different continents or hemispheres and are uncorrelated in their yields (Villoria and Chen, 2018). On the other hand, international prices might not be the relevant source of risk for all the importing countries, particularly in the short run when trade patterns are fixed and thus what matters are the supply shocks of individual suppliers (Villoria and Hertel, 2011).

Second, this article contributes to a policy-relevant question regarding stock management – how much stock countries should hold while facing uncertain food supply. This question has recently been gaining more attention in international food policy debates (Díaz-Bonilla, 2017; World Bank, 2012). In fact, this question has been extensively studied in the storage literature since the pioneering work by Gustafson (1958). Most previous studies (e.g. Williams and Wright, 1991) derive for the optimal stocks under the competitive storage framework, in which profit-maximizing agents make storage decisions primarily based on the expected yield uncertainty in the next year, current stock level, and storage cost. Differently, we calculate for the amount of stocks that countries should hold based on the marginal effects of stock release on domestic food price variability, projected yield uncertainty, and the targeted level of price stability, and the calculation is not targeted at for obtaining maximum social welfare. Our article is also different to other studies for directly relating stock management to yield uncertainty under climate change for multiple developing countries at a time.[1]

The following section discusses methods applied in this study. Then we introduce data sources and provide a data description in section 3. Section 4 presents the empirical results. Section 5 discusses implications of the results, and section 6 concludes.

3.2 Methods

We proceed in two steps. First, we construct a multi-year panel dataset for 24 net-importing and developing countries to estimate the effects of domestic and foreign yield shocks, as

[1] In the past two decades, the storage literature has focused on improving the accuracy of solving for the competitive storage model (Gouel, 2013; Gouel and Legrand, 2017; Makki et al., 2001; Miranda and Glauber, 1995) and on exploring the relevance of the model in explaining commodity price behavior (Cafiero et al., 2011; Deaton and Laroque, 1992; Schewe et al., 2017). Most of these studies constrained their analyses to a two-country context (domestic market versus world market) for model tractability, and it remains technically challenging to model storage for multiple countries at once, especially for food importing countries (Larson et al., 2014; Williams and Wright, 1991).

well as domestic buffer stocks on intra-annual CV of real monthly prices of maize. Second, we combine the estimated model with the global crop models that provide maize yield projections to project intra-annual CV of real monthly prices in focus countries toward mid-century.

3.2.1 Model specification and parameter identification

We specify the following equation to estimate the effects of domestic and foreign yield shocks, as well as domestic buffer stocks, on maize price variability in importing countries:

$$CV_{ik,t} = \beta_1 Y_{i,t} + \beta_2 D_{i,t} Y_{i,t} + \beta_3 EY_{i,t} + \beta_4 E_{i,t} EY_{i,t} + \beta_5 S_{i,t} + \boldsymbol{\gamma} \boldsymbol{Z}_{ik,t} + \mu_i + \theta_k + \phi_t + \epsilon_{ik,t}. \quad (3.1)$$

where $CV_{ik,t}$ denotes domestic maize price variability in k^{th} market of country i in marketing year t, and it is measured by intra-annual CV of real monthly prices of maize within a crop marketing year. The variables $Y_{i,t}$ and $EY_{i,t}$ denote domestic and foreign yield shocks, respectively. Yield shocks are measured by deviations from historical yield trends relative to the trend values. Following Chen and Villoria (2019), maize yield trends are modeled by the Hodrick-Prescott filter with a smoothing parameter of 100 (Hodrick and Prescott, 1997). The variables $D_{i,t}$ and $E_{i,t}$ are dummies, which take the value of one when $Y_{i,t}$ and $EY_{i,t}$ are negative and zero otherwise, respectively. We interact the dummies with the yield shocks, including $D_{i,t}Y_{i,t}$ and $E_{i,t}EY_{i,t}$, to allow for different impacts of positive and negative yield shocks on domestic price variability. For instance, the marginal effect of a positive domestic yield shock on intra-annual CV of real monthly prices is captured by β_1, while the marginal effect of a negative domestic yield shock is captured by $(\beta_1 + \beta_2)$ instead.

We construct the variable of foreign yield shocks ($EY_{i,t}$) as the weighted average of yield shocks in country i's trading partners (also exporters). The weight, denoted by $\omega_{ji,t}$, is average import values between year $t-k$ and year $t-1$. The lagged structure of the import variable helps to alleviate concerns about the exogeneity of the weights (Calì and Mulabdic, 2017). We attempt different values for k, i.e., from 2 to 5, when constructing $EY_{i,t}$ to assess robustness of results. Mathematically, the variable $EY_{i,t}$ is defined as follows:

$$EY_{i,t} = \sum_{j \neq i}^{N_t} \omega_{ji,t} Y_{j,t}. \tag{3.2}$$

where $\omega_{ji,t}$ is the share of country i's average maize import values from country j to total average import values from year $t-k$ to year $t-1$. The variable $Y_{j,t}$ denotes yield shocks in country i's trading partner j. The notation N_t denotes the number of exporters that country i has at years from $t-k$ to $t-1$. For instance, $N_{2016} = 3$ if there were three exporting countries that had ever exported maize to the focus country in the period 2011-2015 for $k = 5$. Yield shocks in countries other than the three exporting countries are not used to calculate $EY_{i,t}$.

We assume that domestic and foreign yield shocks are exogenous to domestic price variability, because yield shocks are mostly caused by exogenous weather shocks (Ray et al., 2015; Schlenker and Roberts, 2009). In addition, we control for variables that are possibly correlated with domestic or foreign yield shocks and domestic price variability by including in the set $\boldsymbol{Z}_{ik,t}$. Specifically, we control social conflict, because it is arguably correlated with yield shocks (Koren, 2018) and food prices (Bellemare, 2015). Interestingly, Koren (2018) recently found, using data in Africa, that conflict is more likely when countries are in food abundance followed by crop yield increases, not when they are in food scarcity followed by yield decreases as conventionally expected. We also control exchange rate variability, which would affect food import prices and then domestic food prices; in addition, exchange rates might also be correlated with crop yields, especially in agriculture-centered countries where crop production matters to economic performance. Further, we control per capita GDP shocks, which act as a proxy of demand shocks, which might be dependent on crop yields and, in the meantime, affect food prices.

In addition to the observable variables, we control for unobservables by exploiting the panel nature of our data. Specifically, the terms μ_i and θ_k are the country and market fixed effects to control for time-invariant, unobserved country and market heterogeneity, respectively. The term ϕ_t is a marketing year fixed effect that controls for the unobserved shocks, e.g., changes in international food market volatility (Díaz-Bonilla, 2016), that affect all the markets within a given marketing year. The objective of adding these controls is to minimize the risk of omitting variables that are correlated with both yield shocks and domestic price variability, a risk that would lead to estimation bias (Greene, 2005).

The variable $S_{i,t}$ is the ratio of stock released (beginning stocks minus ending stocks) in year t relative to domestic consumption. Theoretically, prices are more stable when countries release stocks (Williams and Wright, 1991); thus, we expect the parameter associated with $S_{i,t}$, i.e., β_5, to be negative. We are interested in the parameter β_5, because it informs the amount of stocks to be released when countries seek to lower price variability. In this equation, the estimation of β_5 could be biased towards zero, because countries likely release more stocks when domestic price become more variable. Due to this reverse causality, the variable $S_{i,t}$ would be negatively correlated with the error term $\epsilon_{ik,t}$ and, thus, cause underestimation of β_5 when it is negative (Greene, 2011). Consequently, we would overestimate the amount of stocks to be released for achieving stable prices. We address this concern by using beginning stock-to-use ratio, calculated as the ratio of beginning stocks to domestic consumption, as an instrument of $S_{i,t}$.

An instrument is valid when it satisfies two conditions: relevance and exogeneity (Greene, 2011). First, an instrument is relevant when it is correlated with the variable of interest (Greene, 2011, p.223). In our case, the beginning stock-to-use ratio is likely positively correlated with the stock released relative to domestic consumption, meaning that countries likely release more stocks in the year if larger stocks have been accumulated to reduce associated storage costs (World Bank, 2012). As discussed below, our regression confirms the positive correlation – for instance, stock released relative to domestic consumption increases by 6.4% when the beginning stock-to-use ratio increases by 10%. Second, an instrument is exogenous when it does not affect the dependent variable other than through the included independent variables (Greene, 2011, p.223). This condition is likely satisfied, because the price stabilization effect of stocks is very likely materialized through the stock release. In other words, the variable of interest $S_{i,t}$ would likely be the only channel through which beginning stocks reduce domestic price variability (Chen et al., 2018; Kornher et al., 2017).

Equation (3.1) is estimated in two stages, with each stage estimated by the Least Squares Dummy Variable estimator (Greene, 2011, p.287).

3.2.2 Projecting domestic maize price variability into the future

We project the intra-annual CV of domestic real monthly maize prices for each focus country using the estimated equation (3.1) below:

$$CV^m_{ik,t} = \hat{\beta}_1 Y^m_{i,t} + \hat{\beta}_2 D^m_{i,t} Y^m_{i,t} + \hat{\beta}_3 EY^m_{i,t} + \hat{\beta}_4 E^m_{i,t} EY^m_{i,t} + \hat{\beta}_5 \bar{S}_{i,t} + \hat{\boldsymbol{\gamma}} \bar{\boldsymbol{Z}}_{ik,t} + \hat{\mu}_i + \hat{\theta}_k + \hat{\phi}_{t=2014} \quad (3.3)$$

where *hat* indicates the parameter estimates. We add a superscript m to yield variables (i.e., domestic and foreign yield shocks) as well as the dependent variable for labeling the data source where we have obtained the future maize yields ($m \in \{\text{AgMIP}, \text{FAO}\}$). One source is the GGCMI-AgMIP archive ($m = \text{AgMIP}$) that produces maize yield projections during 2006-2050 ($t \in \{2006, \cdots, 2050\}$) from 10 different model combinations (2 crop model $\times$ 5 climate models). These projected maize yields are used to predict the intra-annual CV of real monthly prices of maize during 2006-2050 for each focus country. To be clear, these yields are detrended by the HP filter with smoothing parameter of 100 when calculating the yield shocks. We let the 2009-2013 average import values be the weight when calculating future foreign yield shocks during 2006-2050 based on equation (3.2), because it was also used for calculating historical foreign yield shocks in the base year 2014 in the case of $k = 5$.

Another source is the FAOSTAT database ($m = \text{FAO}$), from which we obtain historical maize yields during 1961-2016 to "project" historical intra-annual CV of real monthly prices of maize during 1961-2016. These historical "projections" of intra-annual CV of real monthly prices of maize are used as a benchmark to be compared with those in the projection period (during 2006-2050). We perform the comparison to understand the impacts of climate-induced maize yield changes on domestic maize price variability. Meanwhile, we hold the values of the variables other than domestic and foreign yield shocks constant when doing the projections, so that changes in the domestic maize price variability can be solely attributed to changes in maize yields. Specifically, we let the values of the variable conflict and the variable per capita GDP be zero. We let the value of the variable exchange rate variability be the country-specific historical means.

Regarding the stocks, we let the stock changes relative to domestic consumption ($\bar{S}_{i,t}$) be zero at first when comparing the projected intra-annual CV of real monthly prices of maize during 1961-2015 and during 2006-2050. Later, we discuss scenarios in which countries could release stocks to maintain stable prices against higher yield variability in the future.

3.3 Data sources and description

We use monthly maize prices, in U.S. dollars, from the FAO GIEWS database (FAO, 2018) to calculate intra-annual CV of domestic real monthly prices of maize. The marketing year information is from the PS&D online database (USDA, 2018). The maize prices are divided by the US Consumer Price Index (base year: 1982-1984) retrieved from FRED online database (https://fred.stlouisfed.org) to obtain real maize monthly prices. We focus on 74 markets (retail or wholesale) in 24 net maize importing countries, in which the average net maize imports during 2000-2016 are greater than zero. Among them, 11 countries are in Africa, 11 countries are in Latin America, and 2 countries are in Asia (see table C.1 for country names). The data are unbalanced, mainly due to the fact that the beginning years of the price data differ across countries. Cumulative maize imports of the focus countries during 2005-2016 accounted for 18.6% of global maize imports, according to the UN Comtrade database.

Figure 3.1 displays the intra-annual CV of domestic real monthly prices of maize, a measure of domestic maize price variability, over time and across focus country. The figure shows that the degree of domestic maize price variability varies greatly over time and across countries. Notably, as shown in figure 3.1(a), maize prices in focus countries have become less variable in recent years – the mean intra-annual CV of domestic real monthly prices was around 0.15 during 2000-2010 and then reduced to around 0.1 during 2011-2016. Figure 3.1(b) shows that maize prices are relatively more variable in countries like Mozambique, Kenya, Nicaragua, and Honduras than in others. In contrast, the intra-annual CV of domestic real monthly prices of maize has been constantly low in Angola, Cabo Verbe, China and Uruguay, which could be a consequence of stable yields, or the price stabilization policy (Chen et al., 2018; Pieters and Swinnen, 2016).

Data on historical maize yields during 1961-2016 are from the FAOSTAT database (FAO, 2018). We obtain maize yields in the projection period (during 2006-2050) with CO_2 fertilization from a combination of 2 crop models (i.e., LPJmL and pDSSAT) and 5 climate models (i.e., HadGEM2-ES, IPSL-CMSA-LR, MIROC-EXM-CHEM, GFDL-ESM2M, NorESM1-M) in the GGCMI-AgMIP archive (Elliott et al., 2014b; Rosenzweig et al., 2014). The projected maize yields are at grid cell level and are then aggregated to the country-level for the growing season using the GGCMI-AgMIP interface by Villoria et al. (2016). To understand whether potential scenarios of price variability are conditional on the choice of emissions pathway, we choose two representative concentration pathways, i.e., RCP 2.6 and RCP 8.5, as they represent the most benign and extreme potential pathways of emissions during the projection period (Riahi et al., 2011; van Vuuren et al., 2011).

Data on stocks and domestic consumption of maize are from the PS&D online database (USDA, 2018). We use real effective exchange rate from Darvas (2012), a measure of real value of a country's currency against a basket of the trading partners of the country, to calculate exchange rate variability. Similar to the measure of domestic price variability, the exchange rate variability is measured by the coefficient of variation of monthly real effective exchange rates within a crop marketing year. We use data from Gleditsch et al. (2002) for the variable conflict. By definition, the variable takes the value of 1 if there were 25 annual battle-deaths in the country and 0 otherwise. Data on per capita GDP are from the World Bank open data system (`https://data.worldbank.org/`). Bilateral trade data are from the UN Comtrade database (`https://comtrade.un.org/`).

Table 3.1 presents the summary statistics of the regression variables. We find that the magnitude of domestic yield shock is higher than the magnitude of foreign yield shock. For instance, the largest negative domestic yield shock is -0.79 (or 79% below the historic trend), which is almost three times larger than the largest negative foreign yield shock (-

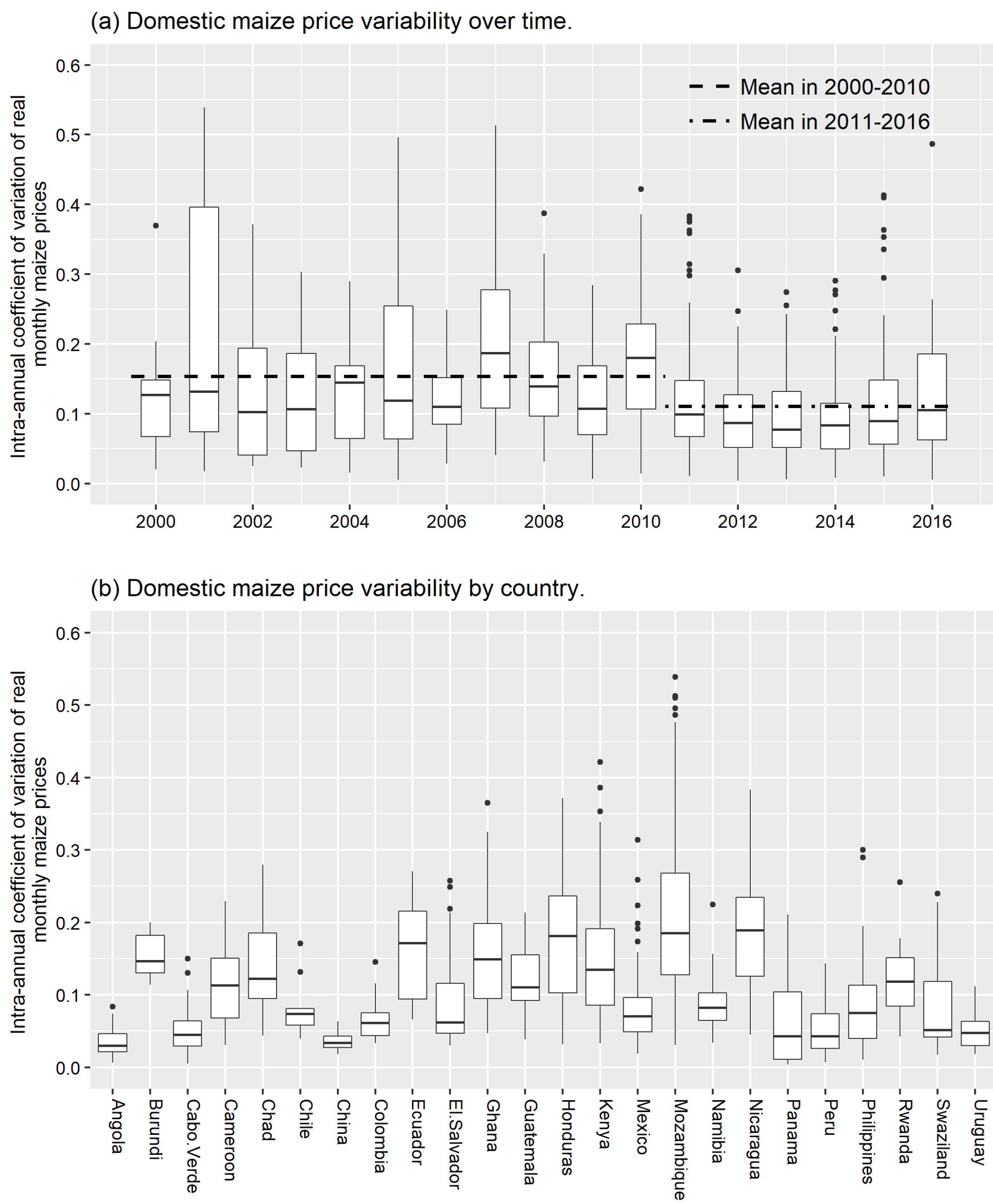

Figure 3.1: Variation in domestic maize price variability over time and across countries.

Note: Maize price variability is measured by intra-annual coefficient of variation of real maize monthly prices.

0.21). The reasons are twofold. First, maize yields in exporting countries, especially in the U.S., Argentina and Brazil, have been relatively more stable than those in the focus importing countries (figure C.1). Second, by definition, foreign yield shock is the weighted average of yield shocks in exporting countries. This averaging procedure would wash away parts of the yield variability associated with individual countries.

Table 3.1: Summary statistics of regression variables.

Variables	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
Intra-annual CV of domestic real monthly maize prices	926	0.13	0.09	0.003	0.06	0.18	0.54
Domestic yield shock	926	−0.01	0.15	−0.79	−0.05	0.05	0.75
Foreign yield shock	926	0.004	0.07	−0.21	−0.04	0.04	0.21
Stock released relative to domestic consumption	926	−0.004	0.04	−0	−0.03	0.02	0
Exchange rate variability	926	0.03	0.02	0.002	0.01	0.04	0.11
Conflict	926	0.17	0.37	0	0	0	1
Per capita GDP shock	926	0.002	0.03	−0.11	−0.01	0.01	0.16

Note: Five-year average imports (i.e., $k = 5$) are used as weights to construct the foreign yield shock.

Now we examine the import structure of the focus countries, because it matters to the calculation of foreign yield shocks, as expressed by equation (3.2). Figure 3.2 displays the top three exporting countries from which the focus countries imported maize during 2005-2016 in a network graph. We focus on the top three exporting countries only because they constitute majority shares of the imports (82% on average) of the focus countries. In fact, maize imports of focus countries are at most times concentrated on the top exporting countries (see figure C.2 and figure C.3), which take nearly half of the maize import share on average. Nevertheless, this graph indicates an interesting geographical pattern of trade — countries mainly import from those that are physically close to them. Specifically, African countries mainly import from the regional major exporters, such as South Africa, Zambia and Uganda; Latin American countries also mainly import from the major regional exporters, which include the U.S., Argentina and Brazil.

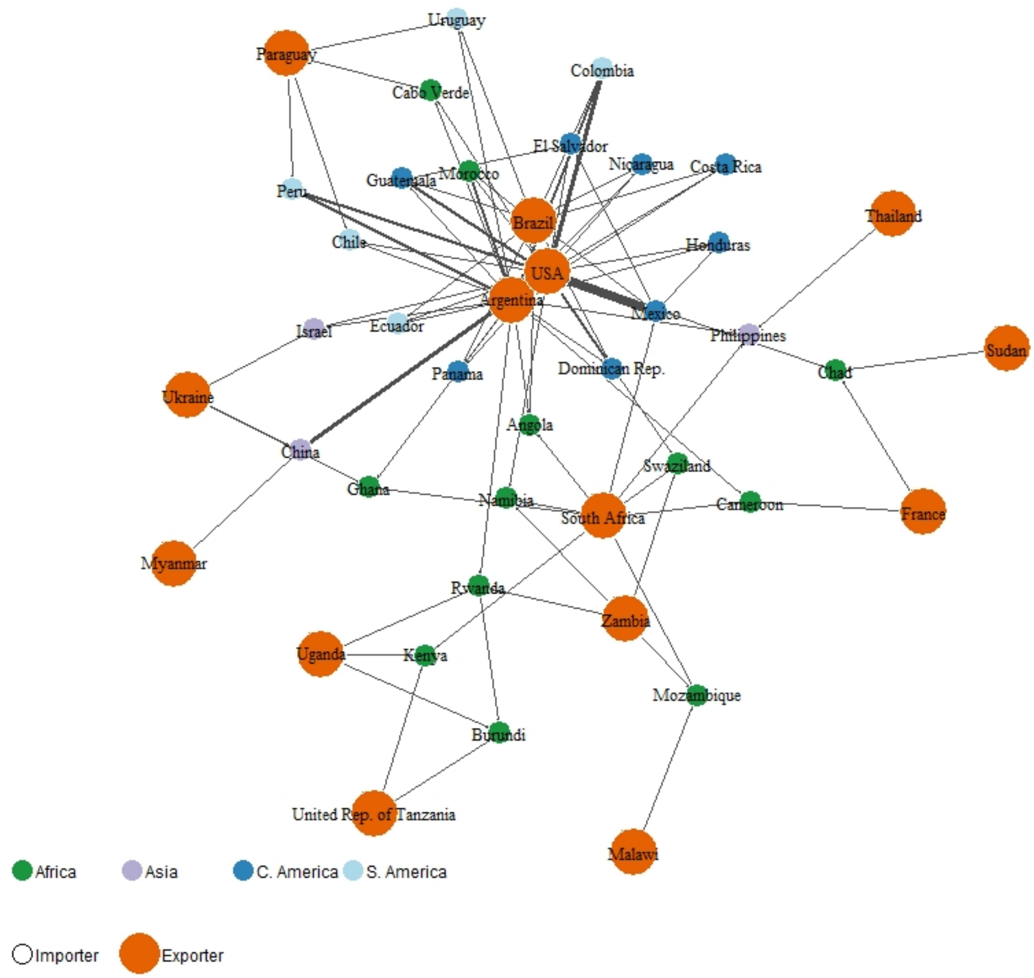

Figure 3.2: Network of accumulated maize imports from 2005 to 2016 of focus countries.

Notes: Only the top three maize exporters are included in the figure. The thickness of vertices is in proportion to the size of cumulative import values.

3.4 Results

3.4.1 Foreign yield shocks have asymmetric effects on domestic price variability in importing countries

The second column in table 3.2 reports the regression results for equation (3.1) using Ordinary Least Squares (OLS). The results indicate that positive foreign yield shocks are associated with lower maize price variability in focus importing countries. Specifically, the intra-annual CV of domestic real monthly maize prices decreases by 0.0034 in year t when foreign maize yields increase by 1% of the historical trend value in year t. The marginal effect, though small, is economically important, because foreign maize yields experience positive shocks regularly. In particular, the likelihood of the focus countries experiencing foreign yield shocks of 5% or higher is 20% (figure C.4). In other words, once every five years, the foreign countries would have at least 5% shocks on their maize yields, which would lead to a decrease in the intra-annual CV of domestic real monthly maize prices by at least 0.017 $(= 0.0034 * 5)$. Such a decrease is nontrivial because the average intra-annual CV of domestic real monthly maize prices across all focus countries in the sampling period is just 0.13 (table 3.1).

As shown in table 3.2, the parameter associated with negative foreign yield shocks is negative, meaning that domestic maize prices in importing countries become more variable when maize yields in exporting countries fall below the historical trends. The parameter associated with negative foreign yield shocks (-0.11) is smaller than the parameter associated with positive foreign yield shocks (-0.34) in magnitude. This indicates that, overall, the importing countries likely benefit from exposing themselves to foreign yield shocks in domestic price stability, even though their prices become more variable in times of negative foreign yield shocks. For sure, this argument is not true if negative shocks are much more frequent than positive shocks in foreign yields; yet, this is not the case shown in the historical data (figure C.4).

We performed alternative regressions to assess robustness of our results. In table C.3 and C.4, we show that our results are robust to alternative choices of k ($k \in \{2, 3, 4, 5\}$) that affect the calculation of foreign yield shocks defined by equation (3.2), to alternative methods (quadratic or HP filter with different smoothing parameters) for detrending the maize yields, to alternative choices of weights (static as opposed to dynamic) for constructing foreign yield shocks, to the yield shocks in top exporters, and to inclusion of food aid as a control variable.

Further, we explore heterogeneity in parameters associated with foreign yield shocks among country groups. The goal is to empirically assess the arguments or perceptions

Table 3.2: Regressing intra-annual CV of real monthly prices of maize on foreign yield shocks.

Independent variables	OLS	IV	IV + Hetero. effects
Positive foreign yield shock	-0.34^{***}	-0.34^{***}	–
	(0.12)	(0.13)	
Negative foreign yield shock	-0.11^{*}	-0.09	–
	(0.06)	(0.06)	
Positive foreign yield shock,	–	–	-0.08
landlocked countries			(0.1)
Positive foreign yield shock,	–	–	-0.4^{***}
coastal countries			(0.14)
Negative foreign yield shock,	–	–	-0.47^{***}
landlocked countries			(0.27)
Negative foreign yield shock,	–	–	-0.07
coastal countries			(0.06)
Positive domestic yield shock	0.05	0.05	0.06
	(0.04)	(0.04)	(0.04)
Negative domestic yield shock	-0.19^{*}	-0.19^{*}	-0.18^{*}
	(0.10)	(0.10)	(0.1)
Stock released relative to	-0.13	-0.27^{*}	-0.28^{*}
domestic consumption	(0.09)	(0.16)	(0.16)
Exchange rate variability	0.05	0.04	0.05
	(0.11)	(0.11)	(0.11)
Conflict	-0.03^{**}	-0.03^{**}	-0.03^{**}
	(0.01)	(0.01)	(0.01)
Per capita GDP shock	0.00	-0.01	0.04
	(0.16)	(0.17)	(0.18)
Country fixed effect	Yes	Yes	Yes
Market fixed effect	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes
Num. obs.	926	926	926
R^2	0.57	–	–
Adj. R^2	0.52	–	–

Notes: The weight for constructing foreign yields shocks is lagged 5-year average imports ($k = 5$). The IV regression uses the beginning stock-to-use ratio as an instrument of the variable: stock released relative to domestic consumption. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

that countries are more susceptible to foreign yield shocks when they are more import-dependent (Ceballos et al., 2016; Gephart et al., 2016; Marchand et al., 2016; Myers and Jayne, 2012), closer to trading partners (Mengel and von Carmon-Taubadel, 2014), more connected to the trade network (Coleman, 2009; Myers and Jayne, 2012), or poorer in terms of per capita income (Bekkers et al., 2017; Distefano et al., 2018). We also examine the following two possibilities: African countries might be more susceptible to foreign yield shocks than others because they are less open to maize trade (Minot, 2014). Besides, countries relying on regional exporters in Africa, like South Africa, Zambia and Uganda, might be more susceptible to foreign yield shocks because maize yields in these countries have been more variable than in other exporters such as the U.S. (see figure C.1).

To be specific, we create binary dummy variables with regards to import dependence, trading distance and so on (see table C.2) to categorize the countries into different groups. Then we interact the dummy variables one after another with the parameters associated with foreign yield shocks, which are β_3 and β_4, when estimating equation (3.1). The interaction terms allow us to obtain the marginal effects of positive and negative foreign yield shocks for countries in different groups. The statistical F test is performed to test the null hypothesis that the marginal effects associated with different country groups are equal.

Figure 3.3 displays the parameter estimates associated with the key variables of interest, i.e., positive and negative foreign yield shocks, with the OLS estimator. Parameter estimates for variables other than the foreign yield shocks are not of interest to us and thus are reported in the appendix (table C.5). The main finding from the figure is that the parameters associated with foreign yield shocks differ significantly between landlocked and coastal countries. Specifically, price variability in the landlocked countries, which are Burundi, Chad, Rwanda and Swaziland, are affected by negative foreign yield shocks, yet not by positive foreign yield shocks. In contrast, price variability in the coastal countries are affected by positive foreign yield shocks, yet not by the negative foreign yield shocks. Thus, the beneficial effects of positive yield shocks in foreign countries on domestic price variability are not enjoyed by the landlocked countries, but only the coastal countries. Compared with coastal countries, landlocked countries are much less connected with the international market, and thus have to always rely on regional exporters such as South Africa, Uganda and Zambia for importing maize. Given the limited freedom to choose trading partners, the landlocked countries could be more prone to absorb the price destabilization effect of negative foreign yield shocks.

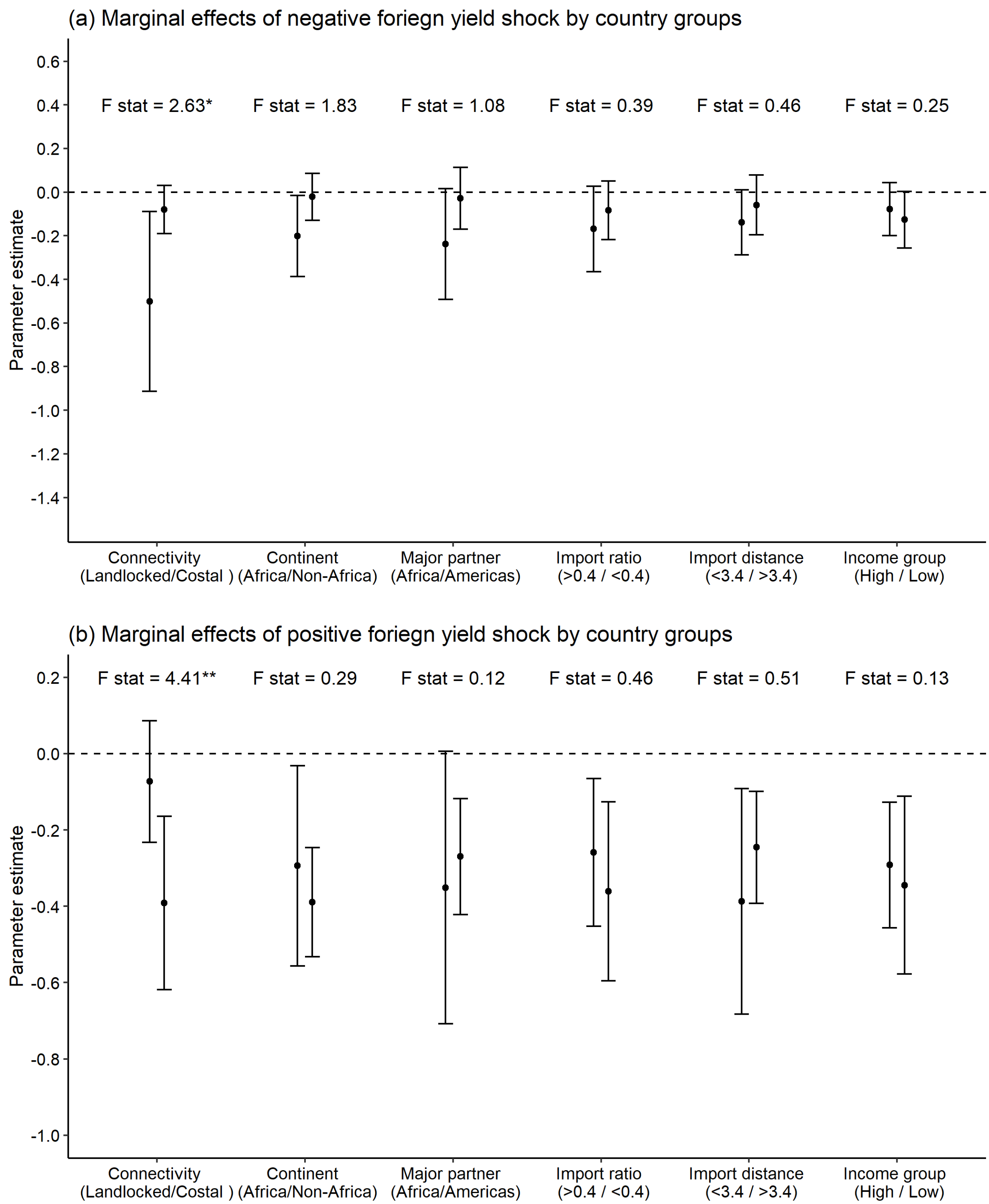

Figure 3.3: Parameter estimates for the variable exporter yield shocks with different country groups.

Note: Details regarding the country groups are presented in table C.2.

3.4.2 Stock release can maintain stable prices against domestic yield shortfalls

The OLS regression results reported in table 3.2 indicate that domestic maize prices are more variable when domestic maize yields fall below historical trends. Specifically, the intra-annual CV of domestic real monthly maize prices increases by 0.0019 when domestic maize yields fall 1% below the historical trends. Interestingly, the parameter associated with positive domestic yield shock is not statistically significant at a 90% confidence level, meaning that domestic price variability does not respond to positive domestic yield shocks.

Regarding stocks, table 3.2 shows that, with the OLS estimator, the parameter associated with stock released relative to domestic consumption is -0.14 and insignificant. As discussed in section 2.1, the parameter associated with stock released relative to domestic consumption is likely biased towards zero due to the reverse causality — countries release more stocks when domestic price become more variable. Besides, food stocks are usually not measured accurately (Abbott, 2014) and thus contain measurement error. The existing measurement error would result in low precision, though not bias, in the parameter estimates (or higher standard errors).

We address the potential estimation bias caused by reverse causality by using beginning stocks relative to domestic consumption (also known as beginning stock-to-use ratio) as the instrument of stock released relative to domestic consumption. The first stage regression results (see table C.6) show that beginning stock-to-use ratio has significant positive effects on stock released relative to domestic consumption, meaning that more stocks relative to consumption would be released when they are available at the beginning of the year. For this reason, we are able to reject the null hypothesis that the instrument is weak, and the F statistics is 489 ($p < 0.01$). As shown in table 3.2, the marginal effect of stock released relative to domestic consumption changes from -0.13 with the OLS estimator to -0.27 with the IV estimator.

The IV estimates indicate that releasing stocks is an effective way of maintaining stable prices against negative domestic yield shocks. Specifically, given the IV estimates, we find that countries could release stocks amounting to 0.8% of domestic consumption to keep the intra-annual CV of domestic real monthly maize prices unchanged when domestic yields fall by 1% of historical trends.

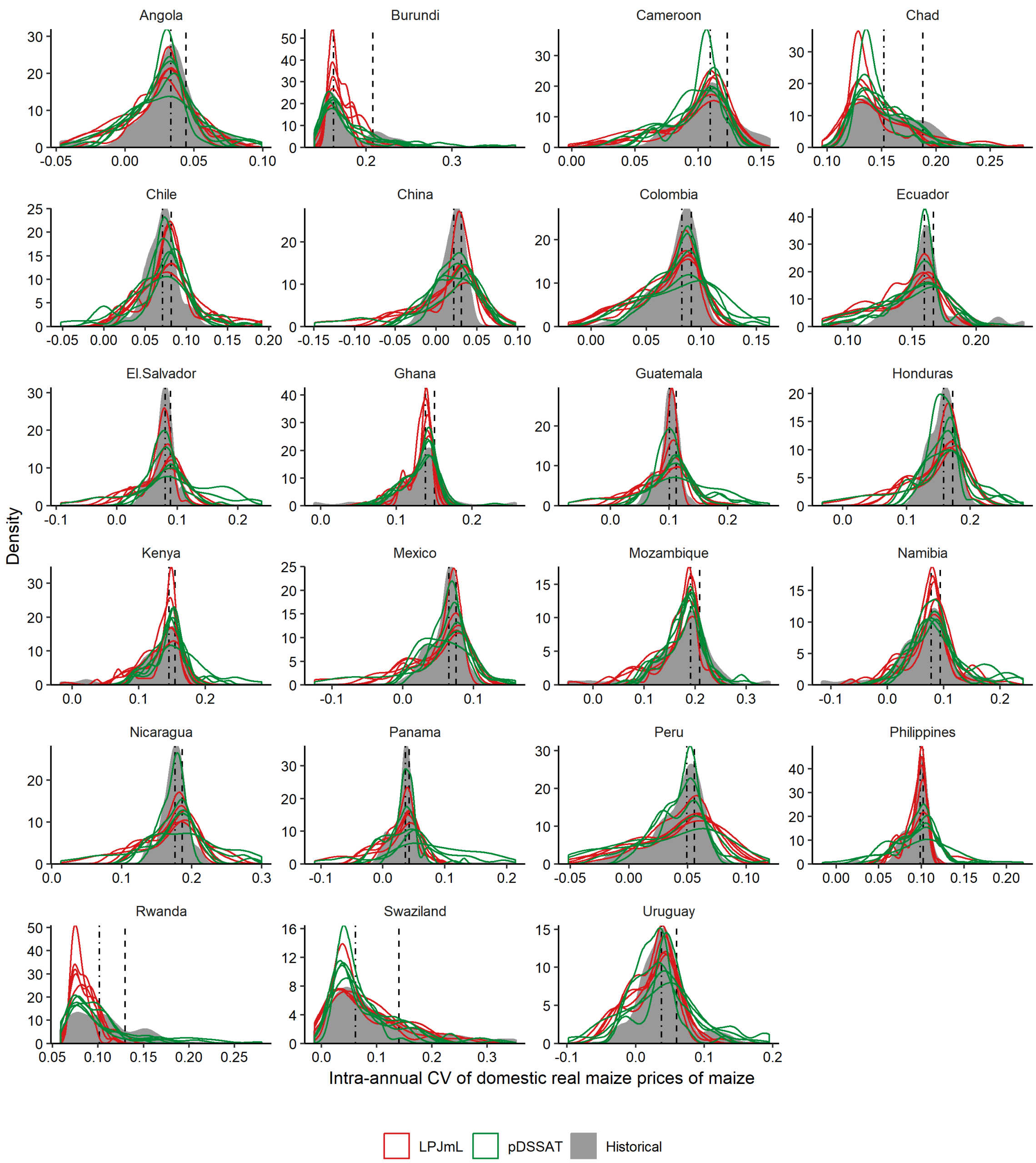

Figure 3.4: Distribution of projected intra-annual CV of real monthly prices of maize during 2006-2050 with CO2 fertilization under RCP 2.6 and during 1961-2014.

Note: Results for Cape Verde is not shown for missing its yield projection in the AgMIP-GGCMI archive.

3.4.3 High maize price variability likely become more frequent in the future

Figure 3.4 displays the density distributions of market-average intra-annual CV of real monthly prices of maize in the historical period (1961-2014) and projection period (2006-2050) under RCP 2.6. The figure for RCP 8.5 is not shown in the main text because it resembles figure 3.4 (see figure C.5), suggesting that RCP scenarios have minor impacts on projections of maize price variability. All these projections are obtained from equation (3.3) in combination with the IV regression estimates, reported in the rightmost column of table 3.2, for equation (3.1). This figure shows that distributions of the market-average intra-annual CV of real monthly prices of maize become more divergent during 2006-2050 than during 1961-2014 in more than half of 23 focus countries. Note that one focus country, Cape Verde, is excluded from the projection because its maize yield projection is missing from the AgMIP-GGCMI archive. In countries where the distributions become more divergent, high domestic price variability becomes more frequent. To put this into perspective, we calculate the ratio of frequency to total number of years, which is relative frequency, in the projection period of the projected intra-annual CV of real monthly prices during 2006-2050 being greater than the $80th$ percentiles of the historical distribution of intra-annual CV of real monthly prices, a level considered abnormally high since it only occur once every five years. The $80th$ percentiles are denoted by the dashed vertical lines in figure 3.4.

Figure 3.5 displays the relative frequency of abnormally high price variability (i.e., intra-annual CV of real monthly prices greater than the $80th$ percentiles) for each country for each climate-crop model combination under RCP 2.6 and RCP 8.5. A consequential finding is that, regardless of the RCP scenarios, almost all models agree that the relative frequency of abnormally high price variability during 2006-2050 would increase to the range of 20% – 50% in 11 out of 23 focus countries. Note that, by definition, the relative frequency of years with abnormally high price variability is only 20% in the historical period (1961-2014). Thus, our finding can be interpreted in this way – the abnormally high intra-annual CV of real monthly prices of maize could be seen up to every 2 years during 2006-2050, rather than every 5 years during 1961-2014. In seven focus countries, i.e., Burundi, Cameroon, Chad, Ghana, Mozambique, Rwanda, and Swaziland, the abnormally high price variability is projected to become less frequent. This change can be attributed to lower yield variability, because yield change is the only source of changes in the projections of price variability.

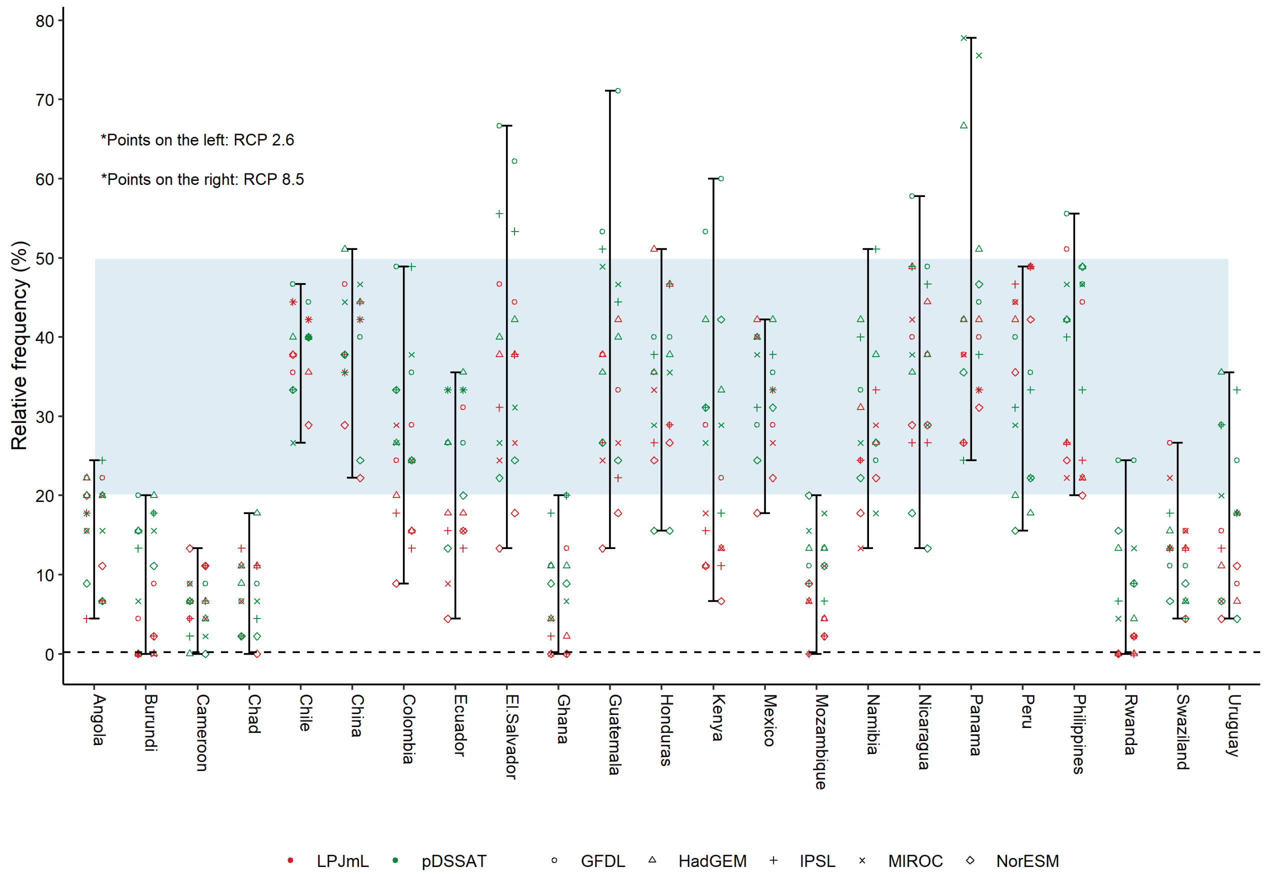

Figure 3.5: Relative frequency of focus countries experiencing abnormally high maize price variability during 2006-2050.

Notes: A country experiences abnormally high maize price variability when its intra-annual CV of real monthly maize prices is equal or greater than the 80*th* percentile of its historical distribution during 1961-2014. The benchmark value of the relative frequency is 20%.

3.5 Implications

Our analytical results yield two important implications. The first implication is that the focus importing countries, except for the landlocked countries, have benefited from being exposed to foreign yield shocks in their domestic maize price stability. This is because, as discussed above, neither positive nor negative foreign yield shocks are positively associated with maize price variability in focus importing countries. To put this into perspective, we compare the "projected" intra-annual CV of real monthly prices of maize in the historical period (1961-2014) with and without incorporating the historical foreign yield shocks. The projections considering the historical foreign yield shocks are already shown by the grey density curves in figure 3.4. To obtain the projections without incorporating the historical foreign yield shocks, we simply let the foreign yield shocks ($EY_{it}^{\mathrm{FAO}} = 0$) in equation 3.3 be zero when performing the projection of maize price variability.

Figure 3.6 displays percentage changes in the mean values of intra-annual CV of real monthly prices of maize during 1961-2014 for each focus country once we ignore foreign yield shocks in the projections. We see that the mean historical intra-annual CV of real monthly prices of maize increases in all focus countries except for the landlocked countries. The magnitude of increase is the highest (51%) in China, and for other countries, the increases fall in the range between 10% and 30%. The results imply that domestic maize prices would be much more variable if the focus countries isolate themselves from the international market. Figure 3.6 also indicates that ignoring the effects of foreign yield shocks could result in an overestimation of price variability in the food-importing countries.

The second implication is related to storage policy. Specifically, we utilize our analytical results to shed light on such a question: how many stocks should be held to maintain stable maize prices, as maize yields are expected to become more unstable under climate change (Bathiany et al., 2018; Müller and Robertson, 2014b; Rosenzweig et al., 2014)? Indeed, the relationship between food stocks and prices has been extensively studied in previous literature (e.g. Deaton and Laroque, 1992; Gouel and Jean, 2015; Williams and Wright, 1991); few of them, however, infer the amounts of food stocks required for offsetting the impacts of increasing crop yield variability induced by climate change on price variability. We tackle the question by firstly assuming that the focus countries set an upper bound, which can be understood as the tolerance level, for its domestic maize price variability. In cases that price variability exceeds the upper band following yield shocks during 2006-2050,

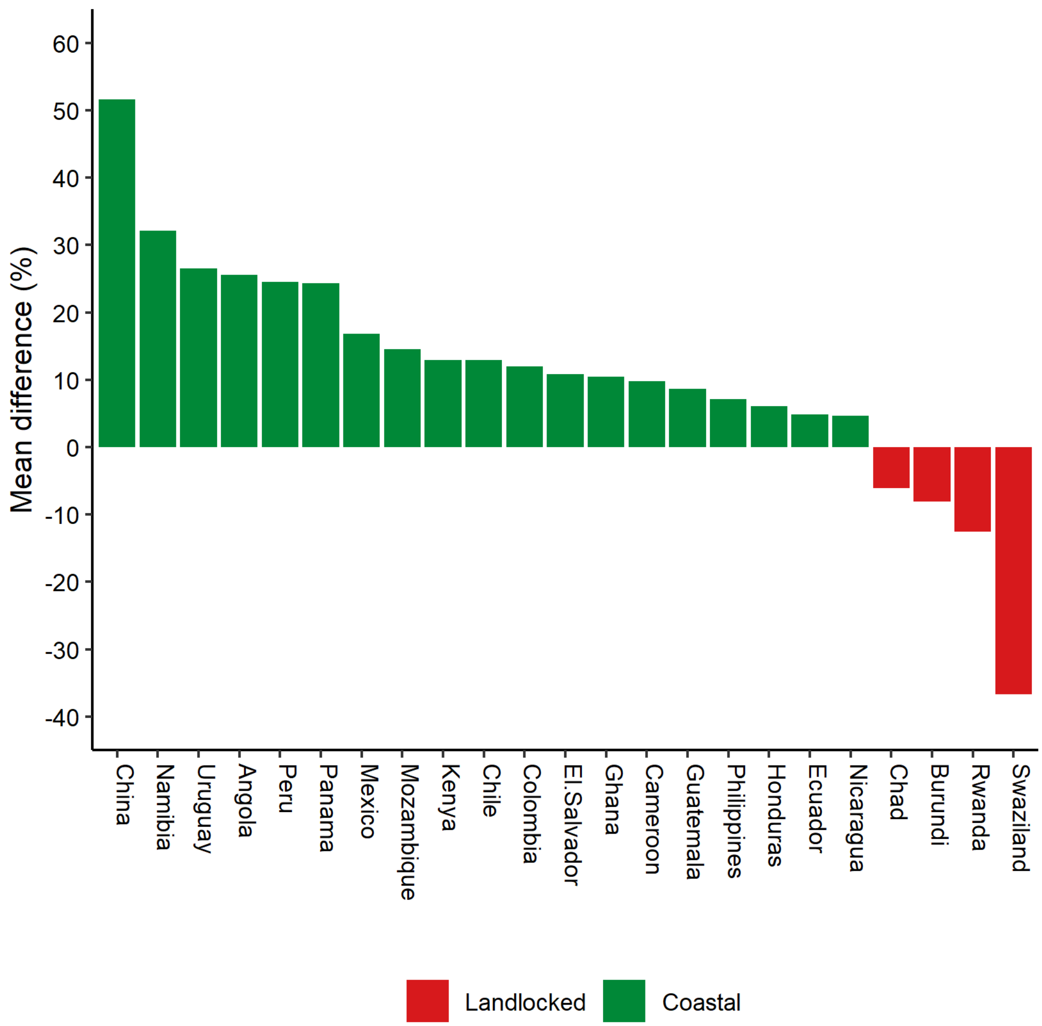

Figure 3.6: Percentage changes in mean value of calculated maize price variability in historical times once ignoring foreign yield shocks.

Note: Positive changes indicate that the country benefit in its price stability from exposing to foreign yield shocks; negative changes indicate that the country are worse off in its price stability from exposing to foreign yield shocks.

countries release stocks until the price variability is reduced to the upper bound level.

In our case, we assume that the upper bound is the median value of the projected intra-annual CV of real monthly prices of maize during 1961-2014. The rationale behind making such an assumption is that countries likely desire normal levels of price variability, which can be represented by the median values. For the sake of clarity, we label the median value for country i as $\bar{CV}_i^{\text{FAO}}$ and have shown their values using the dot dashed vertical lines in figure 3.4. The amount of stocks to be released, denoted by $SS_{i,t}$, is then equal to $-\frac{CV_{i,t}^{\text{AgMIP}} - \bar{CV}_i^{\text{FAO}}}{\hat{\beta}_5}$ $(t \in \{2006, \cdots, 2050\})$, in which $CV_{i,t}^{\text{AgMIP}}$ denotes the projected intra-annual CV of real monthly prices of maize during 2006-2050, and $\hat{\beta}_5$ is the parameter estimate for the variable stock released relative to domestic consumption in equation (3.1). The estimated value of $\hat{\beta}_5$ is -0.28 as reported by the rightmost column in table 3.2.

The values of $SS_{i,t}$ vary across countries and by time; they also differ by crop models that produce different yield projections. We discard the negatives values of $SS_{i,t}$ because these correspond to cases that the projected intra-annual CV of real monthly prices of maize are lower than the upper bounds. Figure 3.7 displays the empirical cumulative density of positive values of $SS_{i,t}$ from all 10 different climate-crop models under scenarios RCP 2.6 and RCP 8.5. This figure shows that, for instance, the empirical cumulative density for the stock release relative to domestic consumption of 0.1 is approximately 0.75 in Angola. This can be interpreted as that the probability that Angola could keep its intra-annual CV of real monthly maize prices below the upper bound (i.e., historical median) during 2006-2050 is 0.75, if it holds maize stocks amounting to 0.1 of its domestic maize consumption. In fact, as shown in figure 3.7, Angola has actually accumulated maize stocks equivalent to 0.3 of domestic maize consumption, meaning that it could likely prevent unstable maize prices through releasing the existing stocks. In general, the probability of experiencing high price variability would decreases as countries hold larger stocks, and more stocks would be required if countries desire more stable food prices.

Another interesting finding from figure 3.7 is that the empirical cumulative densities corresponding to the average stock-to-use ratios during 2013-2017, as denoted by the vertical dashed lines, are approximately 0.75 in most focus countries. This means that most focus countries are likely (75% chance) able to keep domestic maize price variability lower than the assumed upper bounds during 2006-2050 through stock release. Indeed, food stocks have caught the interests of many food-importing countries, especially since the global food price spikes in mid 2000's (Díaz-Bonilla, 2017; Wright and Cafiero, 2011). For the focus countries, the stock-to-use ratio has increased from 3% in 2001 to around 10% in 2017 (figure C.6). There are a few exceptions. Burundi and Swaziland have no recorded maize stocks, which could expose themselves to unstable food prices. In contrast, Angola, China and Ghana seem have accumulated too many stocks that are higher than required for price stabilization.

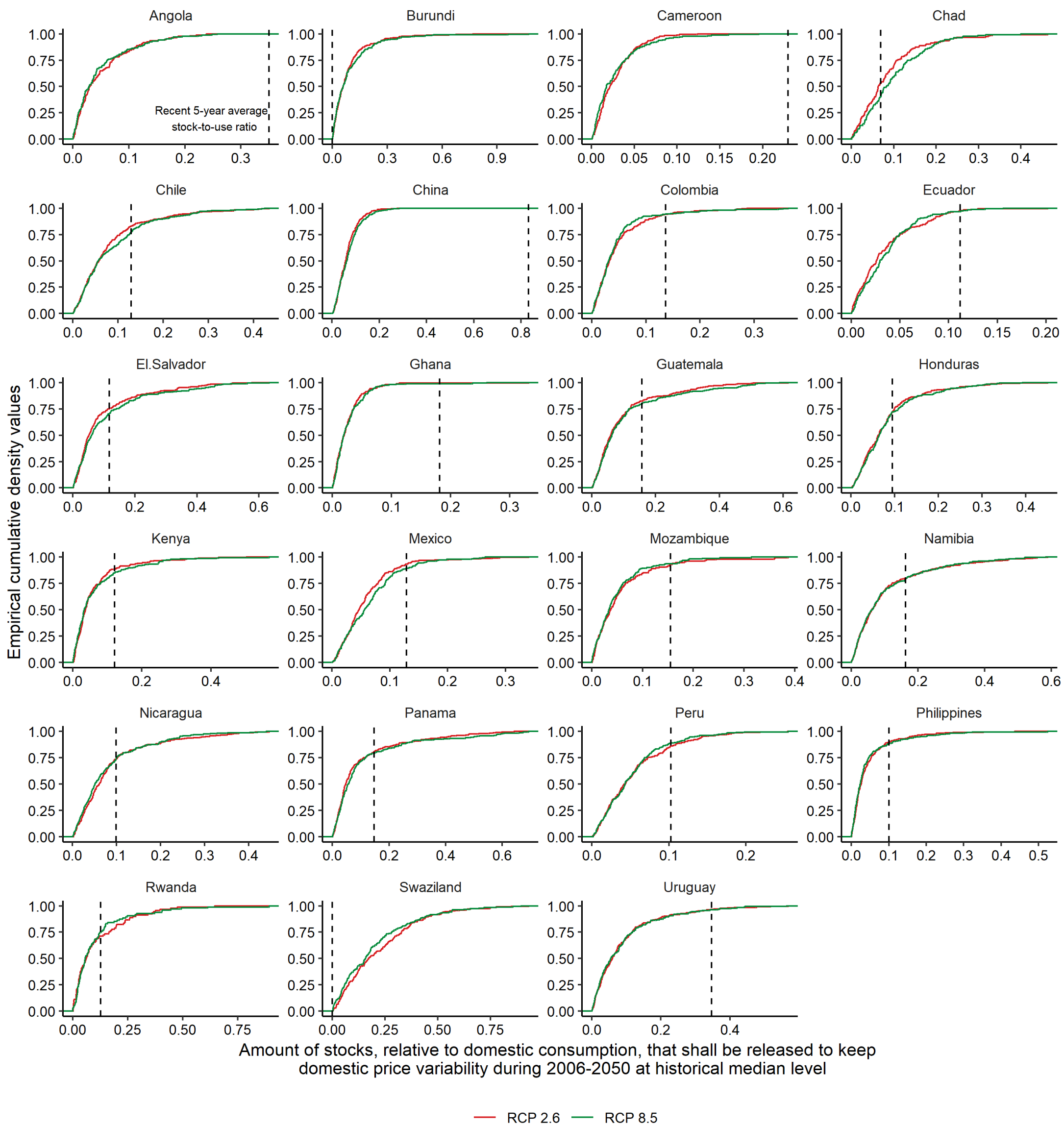

Figure 3.7: Empirical cumulative density of stocks to be released, relative to domestic consumption, to keep domestic price variability lower than the historic median level during 2006-2050.

3.6 Conclusion

To what extent is domestic maize price variability affected by foreign yield shocks? The question caught our attention because increasingly more scholars and policymakers are concerned that crop yield variability in exporting countries may be translated into food price variability in importing countries. We, in this article, explore answers to the question by estimating the marginal effects of foreign maize yield shocks on domestic maize price variability in 24 net-importing and developing countries across Africa, Asia and Latin America. We apply a linear panel data regression model to do the estimation, while using fixed effects to control unobserved heterogeneity that varies across different countries, markets and years. Motivated by our interest in storage policy, we also estimate to what extent the domestic maize price variability can be reduced by releasing maize stocks. We address an endogeneity issue caused by reverse causality associated with the estimation by using an instrumental variable regression. Lastly, we utilize the estimation results and the AgMIP crop models to assess climate change impacts on domestic maize price variability toward mid-century and to discuss roles of the storage policy.

Our analyses face a caveat. That is, the yield projections by the AgMIP crop models ignore factors such as technology, pests, and diseases, as well as short-term climate extremes that are important factors of crop yield variability (Donatelli et al., 2017; Elliott et al., 2014b; Rosenzweig et al., 2014). Consequently, our projection of maize price variability based on the crop model outputs could be biased. We remain uncertain about the direction and size of the potential biasedness, because there exists only a limited number of studies evaluating performance of the AgMIP crop models in capturing the crop yield variability at the national level (Chen and Villoria, 2019; Müller et al., 2017; Villoria and Chen, 2018). Yet, despite the limitation, the AgMIP crop models are possibly better than alternative sources (e.g., Moore et al., 2017) in analyzing countries' future crop yield variability (Chen and Villoria, 2019).

With the limitation in mind, we find no evidence that foreign yield shocks lead to higher price variability in the food-importing countries, except for in a few landlocked countries (Burundi, Chad, Rwanda, Swaziland). Rather, we find that positive foreign maize yield shocks are associated with lower maize price variability in the importing countries. This finding supports the argument that "international markets act as a source of stability rather than a source of risk" (Chen and Villoria, 2019, p.12). In addition, we find that at least half of the focus countries will likely experience higher maize price variability toward mid-century under increasing climate and yield variability. Most of them, however, seem to have accumulated sufficient maize stocks to combat with potential increases in their domestic maize price variability. In light of this, we conclude that combined use of international trade and storage could best serve a nation's interest in tackling food price variability.

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Appendix A

Supplementary material for Chapter 1

A.1 Elasticities in the import demand model

To derive for the price elasticity of import demand, we first consider the definition of the budget share. The time subscript is omitted here for notational simplicity.

$$w_{i_h} = \frac{\tau_i^* p_{i_h} q_{i_h}}{E}. \tag{A.1}$$

Taking log on both sides and then taking derivatives with respect to $\log p_{j_k}$ returns

$$\frac{d \log w_{i_h}}{d \log p_{j_k}} = \frac{d \log \tau_i^*}{d \log p_{j_k}} + \delta_{i_h j_k} + \frac{d \log q_{i_h}}{d \log p_{j_k}} - \frac{d \log E}{d \log p_{j_k}}. \tag{A.2}$$

where $\delta_{i_h j_k}$ is the Kronecker delta. It equals 1 when $i = j$ and $h = k$ and 0 otherwise. Our goal is to calculate the price elasticity of demand, which is the third term on the right-hand side. So we rearrange the terms to get

$$\frac{d \log q_{i_h}}{d \log p_{j_k}} = -\delta_{i_h j_k} - \frac{d \log \tau_i^*}{d \log p_{j_k}} + \frac{d \log w_{i_h}}{d \log p_{j_k}} + \frac{d \log E}{d \log p_{j_k}}. \tag{A.3}$$

Next, we evaluate the first term on the right-hand side. We shall refer to equation (1.4) in the main text to get its value. We expand the log terms in equation (1.4) first,

$$w_{i_h} = \alpha_{i_h} + \sum_j \sum_k \gamma_{i_h j_k} \Big(\log \tau_j^* + \log p_{j_k} \Big) + \beta_{i_h} \Big(\log E - \log P \Big) + \boldsymbol{\delta_{i_h} D_t} + \epsilon_{i_h}. \tag{A.4}$$

Taking the derivative of the above equation with respect to $\log p_{j_k}$ returns,

$$\begin{aligned}
\frac{dw_{i_h}}{d\log p_{j_k}} &= \gamma_{i_h j_k} \Big(\frac{d\log \tau_j^*}{d\log p_{j_k}} + 1 \Big) + \beta_{i_h} \Big(\frac{d\log E}{d\log P} - 1 \Big) \frac{d\log P}{d\log p_{j_k}} \\
&= \gamma_{i_h j_k} \Big(\frac{d\log \tau_j^*}{d\log p_{j_k}} + 1 \Big) + \beta_{i_h} \Big(\frac{d\log E}{d\log P} - 1 \Big) w_{j_k}^0 \Big(\frac{d\log \tau_j^*}{d\log p_{j_k}} + 1 \Big) \\
&= \Big[\gamma_{i_h j_k} + \beta_{i_h} w_{j_k}^0 \Big(\frac{d\log E}{d\log P} - 1 \Big) \Big] \Big(\frac{d\log \tau_j^*}{d\log p_{j_k}} + 1 \Big).
\end{aligned} \tag{A.5}$$

From the first step to the second step, we incorporate the fact that $\frac{d\log P}{d\log p_{j_k}} = w_{j_k}^0 \Big(\frac{d\log \tau_{j_k}^*}{d\log p_{j_k}} + 1 \Big)$ based on the specification of P, i.e. $\log P = \sum_i \sum_h w_{i_h}^0 \log \big(\tau_i^* p_{i_h} \big)$. Plugging equation (A.5) into equation (A.3),

$$\begin{aligned}
\eta_{i_h j_k}^* &= \frac{d\log q_{i_h}}{d\log p_{j_k}} \\
&= -\delta_{i_h j_k} - \frac{d\log \tau_i^*}{d\log p_{j_k}} + \frac{d\log w_{i_h}}{d\log p_{j_k}} + \frac{d\log E}{d\log p_{j_k}} \\
&= -\delta_{i_h j_k} - \frac{d\log \tau_i^*}{d\log p_{j_k}} + \frac{dw_{i_h}}{d\log p_{j_k}} \frac{1}{w_{i_h}} + \frac{d\log E}{d\log P} \frac{d\log P}{d\log p_{j_k}} \\
&= -\delta_{i_h j_k} - \frac{d\log \tau_i^*}{d\log p_{j_k}} + \frac{1}{w_{i_h}} \Big[\gamma_{i_h j_k} + \beta_{i_h} w_{j_k}^0 \Big(\frac{d\log E}{d\log P} - 1 \Big) \Big] \Big(1 + \frac{d\log \tau_{i_h}^*}{d\log p_{j_k}} \Big) + \frac{d\log E}{d\log P} w_{j_k}^0 \Big(1 + \frac{d\log \tau_j^*}{d\log p_{j_k}} \Big) \\
&= -\delta_{i_h j_k} - \frac{d\log \tau_i^*}{d\log p_{j_k}} + \Big[\frac{1}{w_{i_h}} \Big(\gamma_{i_h j_k} + \beta_{i_h} w_{j_k}^0 \Big(\frac{d\log E}{d\log P} - 1 \Big) \Big) + \frac{d\log E}{d\log P} w_{j_k}^0 \Big] \Big(1 + \frac{d\log \tau_j^*}{d\log p_{j_k}} \Big).
\end{aligned} \tag{A.6}$$

The above equation gives the formula for calculating own and cross price elasticity of import demand with the Laspeyres price index. In particular, the own price elasticity is ($i =$

j and $h = k$),

$$\eta^*_{i_h i_h} = \left[-1 + \frac{1}{w_{i_h}} \left(\gamma_{i_h i_h} + \beta_{i_h} w^0_{i_h} \left(\frac{d \log E}{d \log P} - 1 \right) \right) + \frac{d \log E}{d \log P} w^0_{i_h} \right] \left(1 + \frac{d \log \tau^*_i}{d \log p_{i_h}} \right). \quad \text{(A.7)}$$

The above equation is the same as to equation (1.6) in the main text, except for that the time subscript is omitted here.

A.2 Deriving the elasticity of aggregate expenditure to price index

The elasticity of aggregate expenditure to price index is $\frac{d\log E_t}{d\log P_t} = \frac{a_1}{E_t}$. Define $E_{i,t}$ as the group expenditure, so we have $E_t = \sum_i E_{i,t}$. Also, define $\log P_{i,t} = \sum_h w^0_{i_h,t} \log \tau^*_{i,t} p_{i_h,t}$ and then $\log P_t = \sum_i \sum_h w^0_{i_h,t} \log \tau^*_{i,t} p_{i_h,t} = \sum_i \log P_{i,t}$. Then, we have

$$\begin{aligned} \frac{d\log E_t}{d\log P_t} &= \frac{1}{E_t}\frac{dE_t}{d\log P_t} \\ &= \frac{1}{E_t}\frac{d\sum_i E_{i,t}}{d\sum_i \log P_{i,t}} \\ &= \frac{1}{E_t}\frac{\sum_i dE_{i,t}}{\sum_i d\log P_{i,t}}. \end{aligned} \tag{A.8}$$

As specified by equation (1.9), $\frac{dE_{i,t}}{d\log P_{i,t}} = b_1$ for $\forall i$. Alternatively, $dE_{i,t} = b_1 d\log P_{i,t}$. Plugging this into the above equation,

$$\frac{1}{E_t}\frac{\sum_i dE_{i,t}}{\sum_i d\log P_{i,t}} = \frac{1}{E_t}\frac{\sum_i a_1 d\log P_{i,t}}{\sum_i d\log P_{i,t}} = \frac{b_1}{E_t}. \tag{A.9}$$

Hence,

$$\frac{d\log E_t}{d\log P_t} = \frac{b_1}{E_t}. \tag{A.10}$$

A.3 Price data management

The monthly data on domestic prices and world prices after January 2013 are from Ministry of Agriculture of China. The data before 2013 are from the China Grain website (http://datacenter.cngrain.com). We compare the price data in the overlapping period, i.e., from March 2013 to December 2014, from the two sources and detect high correlations between them. However, the wheat prices from the two sources differ in levels, as they report prices of wheat that have different qualities. We treat the data from Ministry of Agriculture of China as benchmark and then shift the data from the China Grain website, either by adding a constant or multiplying a constant to them, depending on which method produces the lowest sum of squared. We use the Kalman filter based on the state space representation of the ARIMA model (Harvey and Pierse, 1984), an efficient and consistent method for time series data imputation to impute for less than 10 missing price data that are from the China Grain website. Figure 1.3 shows the finally obtained price data, with the data after January 2013 from Ministry of Agriculture of China and the data before from the China Grain website.

A.4 Rice smuggling in China

There is no authentic database that records the smuggling across country borders. The previous studies in the trade literature have been using the trade discrepancy as an indicator of trade smuggling (Buehn and Eichler, 2011; Fisman and Wei, 2001; Javorcik and Narciso, 2008; Kubo and Lwin, 2010). The trade discrepancy is also called trade misinvoicing and is calculated as difference in the trade data that are reported by a country and its trading partners. We follow this approach to detect the smuggling from the trade data.

We collect data on grain imports that are reported by China as importer and by China's trading partners as exporters from the UN Comtrade database. Then we take difference between the import data reported by China and the export data reported by the exporters. We find notable discrepancies in the trade statistics for rice but not for wheat or maize. Specifically, as shown in figure A.4, Vietnam and Myanmar consistently reported higher export values than the import values that were reported by China since 2011. The difference peaked at around 700 million dollars in 2014. The large discrepancy could be an indicator that rice was smuggled into China from Vietnam and Myanmar, two countries that share land borders with China. This finding is consistent with news that were reported by Chinese media. Specifically, as one of our referees points out, in 2016, a Chinese media reported that the Chinese custom department detected rice smuggling activities in cities that are close to Vietnam and Myanmar. The link to the media report is: http://www.legaldaily.com.cn/index/content/2016-12/04/content_6904330.htm?node=30348.

The section explains how we use the crop yield-climate response function estimated by Moore et al. (2017) to predict future maize yields. The estimated equation for maize by Moore et al. (2017, p.7) is:

$$\Delta Y_{i,t} = 3.7\Delta T_{i,t} - 0.9\Delta T_{i,t}^2 - 0.4\Delta T_{i,t}\cdot\bar{T}_i + 0.04\Delta T_{i,t}^2\cdot\bar{T}_i + 0.2\Delta P_{i,t} + 10.8 f(\Delta CO_{2i,t}) + 0.2\Delta T_{i,t}\cdot D. \tag{A.11}$$

where $\Delta T_{i,t}$ denotes changes in growing season temperature (in Celsius degree) relative to its historic averages (denoted by $\bar{T}_i$) reported by the Climate Research Unit (Harris et al.,

2014) during the benchmark period (1979-2013). Changes in temperature interact with the baseline growing-season temperature, denoted by the term $0.04\Delta T_{i,t}^2 \cdot \bar{T}_i$, for capturing "the intuition that the impacts of a 1°C warming should be different in a cold location than a hot location" (Moore et al., 2017, p.7).

The variables $\Delta P_{i,t}$ and $\Delta Y_{i,t}$ denote percentage changes (in %) in growing season precipitation and crop yield relative to their historic averages during the benchmark period, respectively. The f denotes a function of changes in CO_2 concentrations ($\Delta CO_{2i,t}$), i.e., $f = \frac{\Delta CO_{2i,t}}{\Delta CO_{2i,t}+50}$. The variable D is a dummy for adaptation. Moore et al. (2017) also includes an intercept variable in their equation, but it is omitted here because it does not affect the variance of detrended yields. The effect of adaptation, captured by the term $0.2\Delta T_{i,t} \cdot D$, is ignored because the parameter estimated is too small (also statistically insignificant) to make a difference to the projected yield changes (appendix figure B.13)

We construct data on climate and CO_2 variables following Moore et al. (2017)'s definitions and use them to predict maize yields for each year during 2006-2050 in each focus country. Specifically, we calculate the growing season temperature ($\bar{T}_i$) and growing season precipitation ($\bar{P}_i$) in country i using their averages during 1979-2013 based on the climate data from the Climatic Research Unit monthly time-series Version 3.23 (Harris et al., 2014; Mitchell and Jones, 2005). Then we calculate changes in the two climate variables at each year t during 2006-2050 relative to their baseline values in country i: $\Delta T_{i,t} = T_{i,t} - \bar{T}_i$ and $\Delta P_{i,t} = 100 \cdot \frac{P_{i,t} - \bar{P}_i}{\bar{P}_i}$. We construct data on $CO_{2i,t}$ concentrations following Moore et al. (2017), with the details explained in appendix section B.2. Next, we use the data on changes in temperature ($\Delta T_{i,t}$), precipitation ($\Delta P_{i,t}$), CO_2 concentrations ($\Delta CO_{2i,t}$) and equation (B.1) to predict future yield changes ($\Delta Y_{i,t}$) at each year t from 2006 to 2050 in country i. Lastly, we re-express the predicted yield changes ($\Delta Y_{i,t}$) in yield levels ($Y_{i,t}$, in tonnes per hectare) based on the relationship $\Delta Y_{i,t} = 100 \cdot \frac{Y_{i,t} - \bar{Y}_i}{\bar{Y}_i}$, where $\bar{Y}_i$ is average observed yields during 1979-2013 from the FAOSTAT (FAO, 2018).

Note that the choice of baseline period matters to the projected yield levels, but it does not affect the projected yield deviations from trend; while the latter is what we use for predicting price variability. Appendix figure B.14 illustrates the procedures for projecting maize yields from 2006-2050 in China using the selected baseline period (1979-2013). Appendix figure B.15 displays the histograms of projected yield changes for all focus countries during 2006-2050 using climate projections by all 5 climate models with and without CO_2. Among all the projected yield changes, 82% of them are negative because the temperature increases in most focus countries, and the number is reduced to 58% with CO_2 concentrations. Appendix figure B.16 visualizes the relationship between projected yield changes using temperature data only (not including precipitation or CO_2 concentration) and projected temperature changes across focus countries during 2006-2050. This figure is similar to the one shown in Moore et al. (2017) (fig. 1), suggesting that we have correctly practiced their estimated model.

A.5 Additional tables and figures

Table A.1: Import tariff rates for wheat, maize and rice products by harmonized schedule eight-digits in China.

Commodity	HS code	Common tariff(%)	Most-Favored-Nation tariff(%)	In-quota tariff (%)
Wheat	10011100	180	65	1
	10011900	180	65	1
	10019100	180	65	1
	10019900	180	65	1
	11010000	130	65	6
	11031100	130	65	9
	11032010	180	65	10
Maize	10051000	180	20	1
	10059000	180	65	1
	11022000	130	40	9
	11031300	130	65	9
	11042300	180	65	10
Rice	10061011	180	20	1
	10061019	180	65	1
	10061091	180	65	1
	10061099	180	65	1
	10062010	180	65	1
	10062090	180	65	1
	10063010	180	65	1
	10063090	180	65	1
	10064010	180	65	1
	10064090	180	65	1
	11029011	130	40	9
	11029019	130	40	9
	11031921	70	10	9
	11031929	70	10	9

Notes: The Most-Favored-Nation tariff is the over-quota tariff rate for member countries of the WTO, and the common tariff is the over-quota tariff rate for non-member countries of the WTO. The Most-Favored-Nation tariff rate for 10064010 and 10064090 products are reduced from 65% to 10% in December 2017. Data source: http://www.qgtong.com/hgsz/ShowArticle.asp?ArticleID=44121

Table A.2: Definition of the grain price series.

	Domestic prices	International prices
Maize	Exit price at *Huangpu* port in Guangzhou of No.2 yellow maize shipped from northeastern China	Price of U.S. No.2 yellow maize shipped from the gulf of Mexico at *Huangpu* port in Guangzhou after duties and taxes
Wheat	Price of high quality wheat at *Huangpu* port in Guangzhou	Price of U.S hard red winter wheat from the gulf of Mexico at *Huangpu* port in Guangzhou after duties and taxes
Rice	Average wholesale price of No.1 late Indica rice	Price of Thai white long grain rice (25% broken) at *Huangpu* port in Guangzhou after duties and taxes

Note: *Huangpu* port is one of the biggest marine transportation centers in southern China.

Table A.3: Countries exported grains to China during 2013-2017.

Commodity	Country
Maize	**U.S., Ukraine**, Argentina, Austria, Bolivia, Brazil, Bulgaria, Myanmar, Canada, Chile, Czechia, France, Germany, Greece, Guyana, Hungary, Israel, Italy, South Korea, Lao's, Mexico, Neverlands, New Zealand, Pakistan, Peru, Philippines, Russia, India, South Africa, Thailand, Turkey, United Kingdom, Japan. (Number = 33)
Rice	**Vietnam, Pakistan, Thailand**, U.S., Myanmar, Cambodia, Canada, Costa Rica, Ethiopia, France, Greece, Italy, Japan, North Korea, South Korea, Malaysia, New Zealand, Philippines, Russia, India, Spain. (Number = 21)
Wheat	**U.S., Australia, Canada**, Denmark, France, Hungary, Isreal, Kazakhstan, Mexico, Mongolia, Netherlands, Pakistan, Russia, Slovenia, Turkey, United Kingdom, Uruguay (Number = 17).

Notes: Countries in bold are major exporters, and the rest of countries are considered Rest of the World (ROW). Data source: UN Comtrade database.

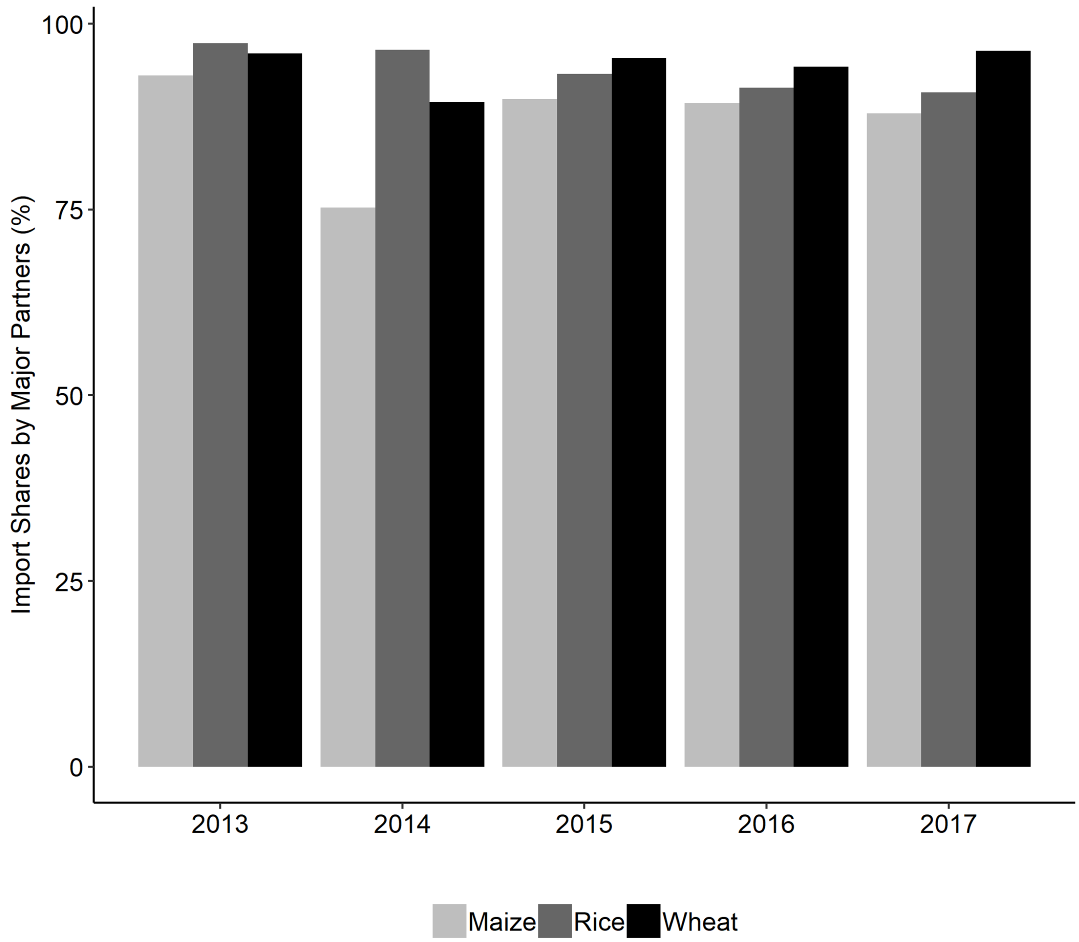

Figure A.1: China's share of imports from its major trading partners by grain commodity during 2013-2017.

Notes: The major trading partners are the U.S. and Ukraine for maize; Vietnam, Thailand and Pakistan for rice; Australia, Canada and the U.S. for wheat. The data are from Ministry of Commerce of China.

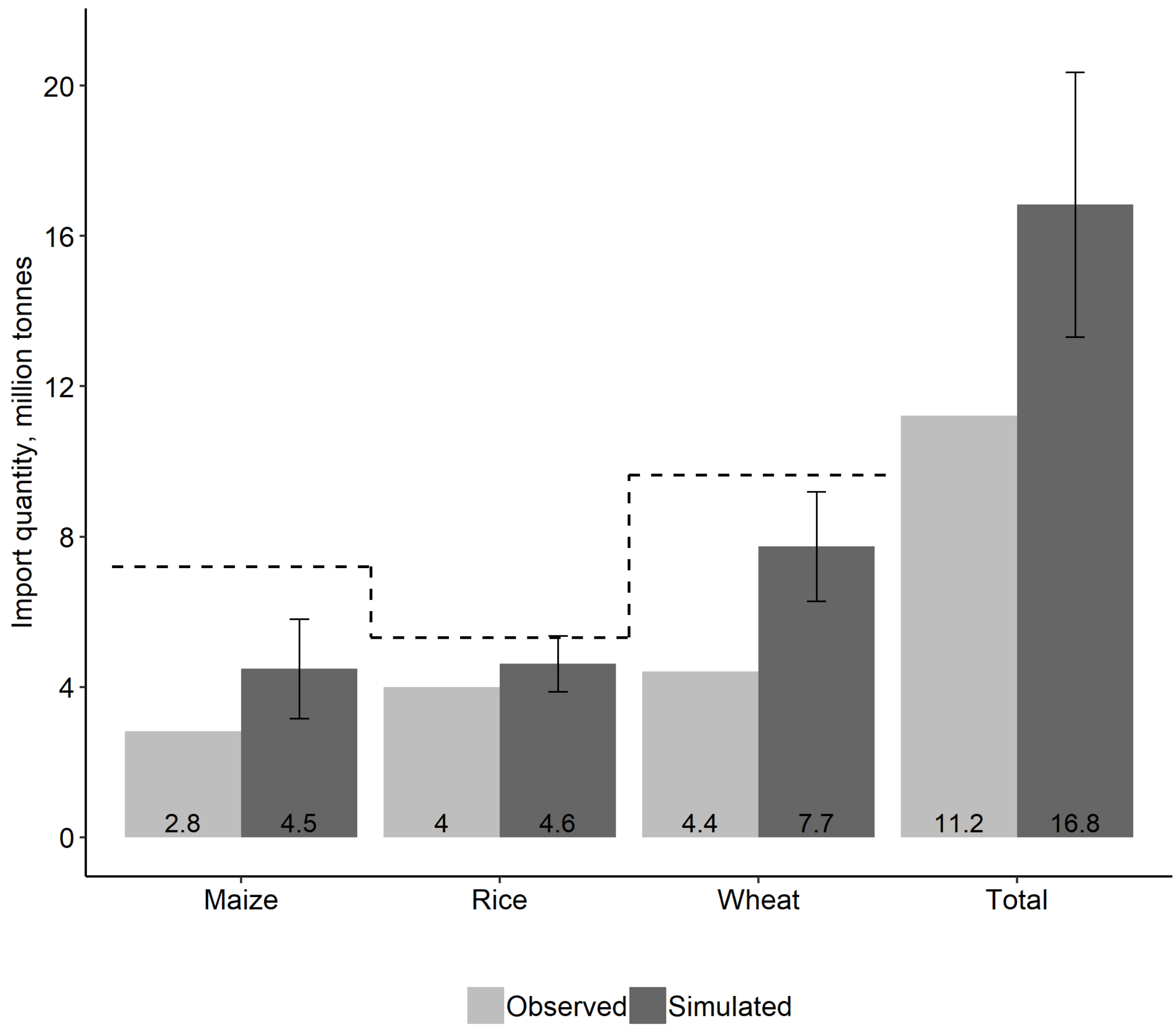

Figure A.2: Simulated and observed grain import quantities of China by commodity and by source country in 2017.

Notes: The dashed lines represent the quota limits. The error bars represent 90% confidence interval of the estimates.

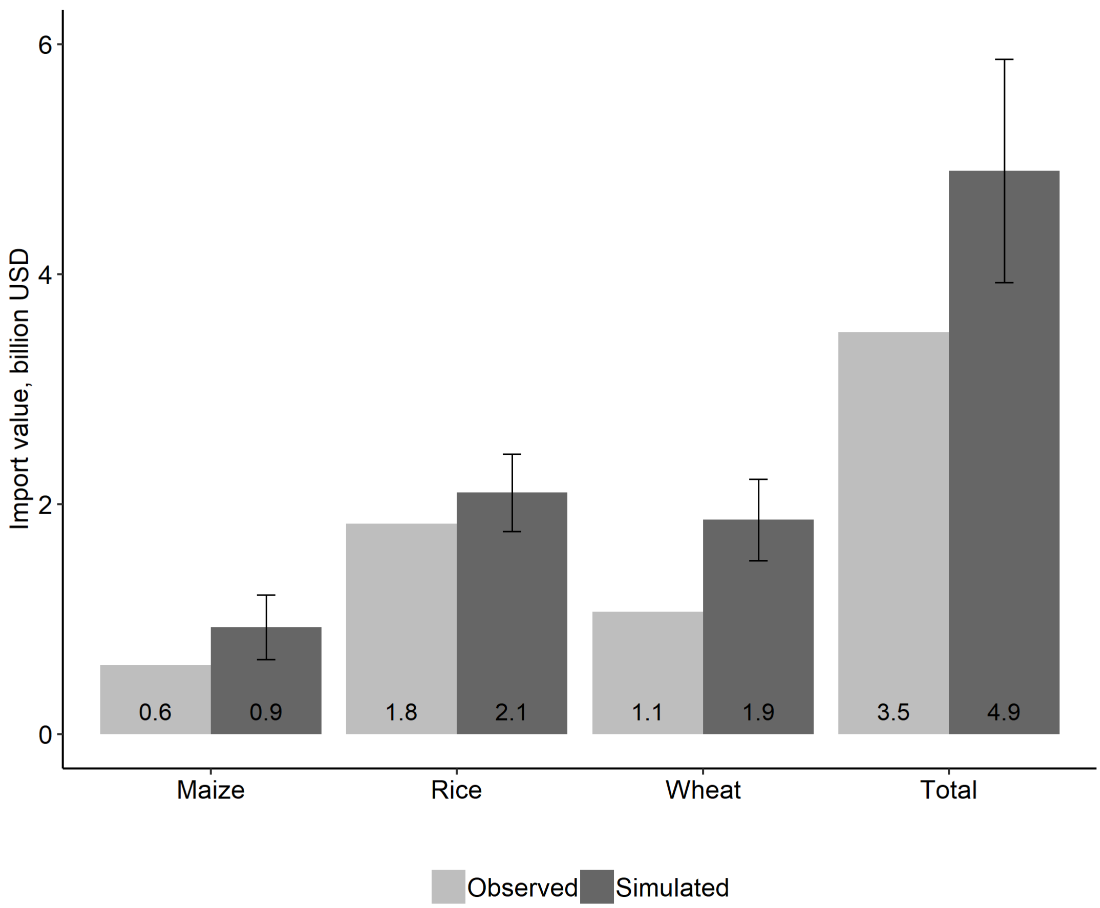

Figure A.3: Simulated and observed grain import values of China by commodity in 2017.

Notes: Import values are products of import quantities and average import prices in 2017. The error bars represent 90% confidence interval of the estimates.

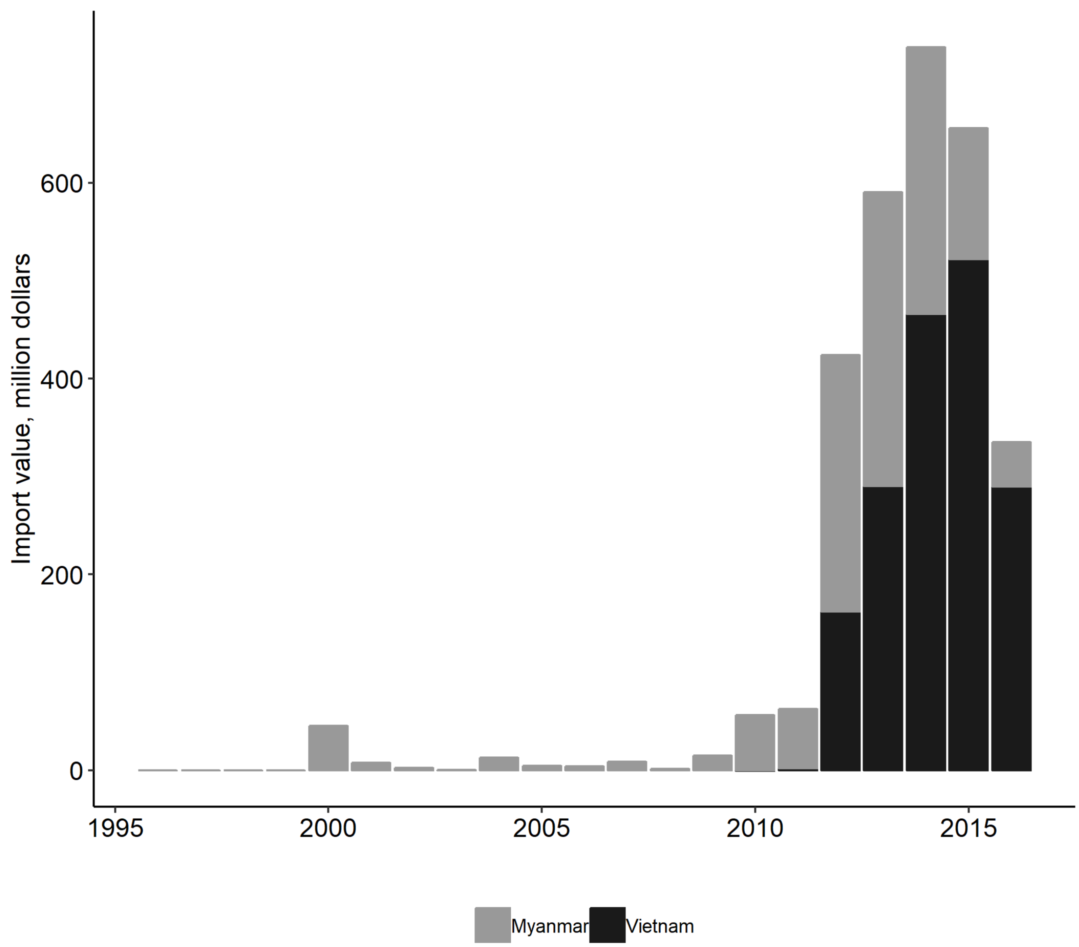

Figure A.4: Differences in the export values reported by Vietnam and Myanmar and the import values reported by China for rice during 1996-2016.

Data source: UN Comtrade database.

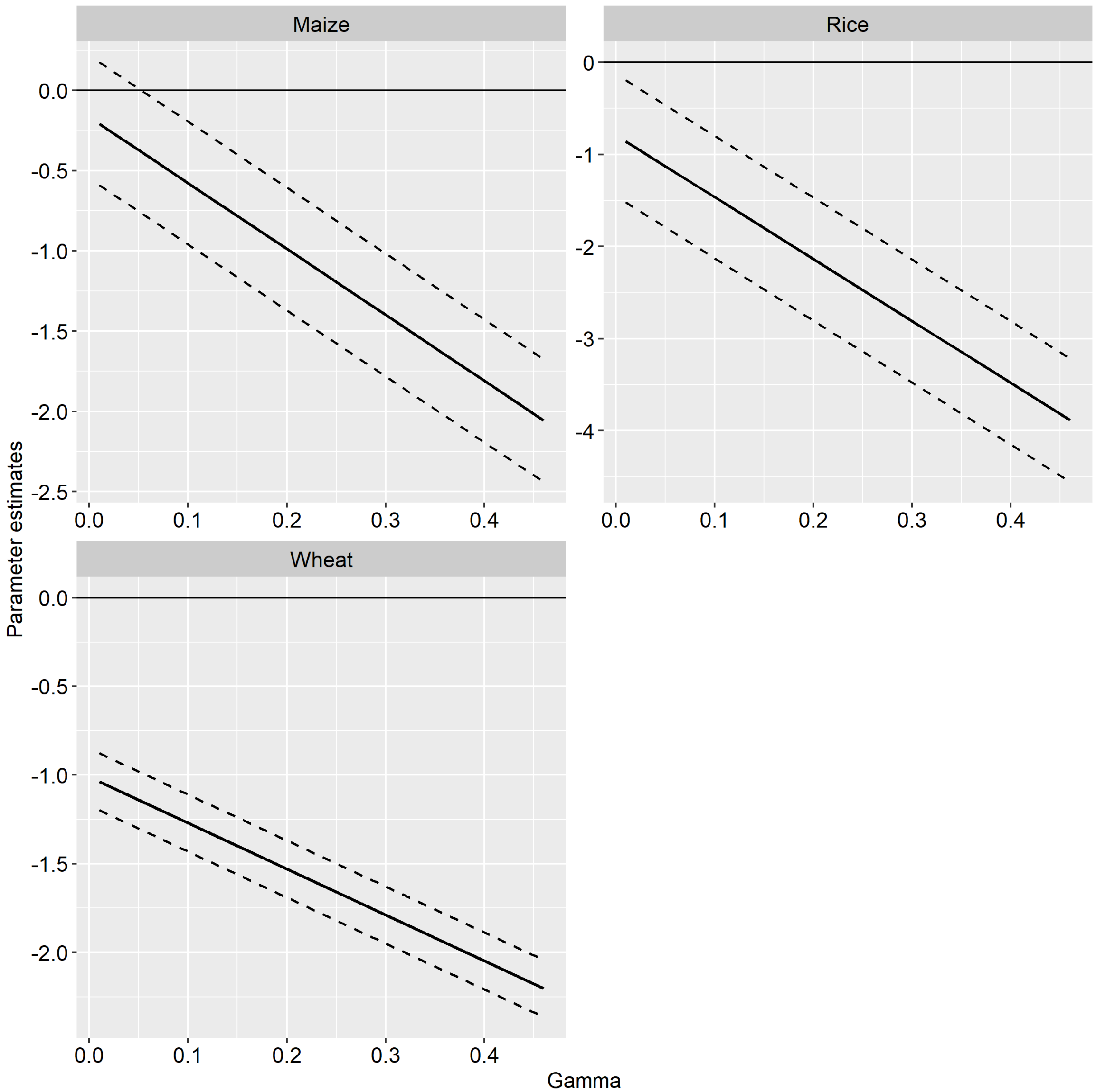

Figure A.5: Parameter estimates of import prices in equation (1.8) using instrumental variable regression given positive direct effects of the instrument on the dependent variable.

Notes: The instrument is the crude oil price. The dependent variable is the tariff equivalent. Gamma represents the marginal effect of the instrument on the tariff equivalent. The dashed lines represent 90% confidence interval. The estimates are derived based on Conley et al. (2010).

Appendix B

Supplementary material for Chapter 2

B.1 Yield prediction based on an alternative yield-climate response function

The section explains how we use the crop yield-climate response function estimated by Moore et al. (2017) to predict future maize yields. The estimated equation for maize by Moore et al. (2017, p.7) is:

$$\Delta Y_{i,t} = 3.7\Delta T_{i,t} - 0.9\Delta T_{i,t}^2 - 0.4\Delta T_{i,t}\cdot\bar{T}_i + 0.04\Delta T_{i,t}^2\cdot\bar{T}_i + 0.2\Delta P_{i,t} + 10.8f(\Delta CO_{2i,t}) + 0.2\Delta T_{i,t}\cdot D. \tag{B.1}$$

where $\Delta T_{i,t}$ denotes changes in growing season temperature (in Celsius degree) relative to its historic averages (denoted by $\bar{T}_i$) reported by the Climate Research Unit (Harris et al., 2014) during the benchmark period (1979-2013). Changes in temperature interact with the baseline growing-season temperature, denoted by the term $0.04\Delta T_{i,t}^2 \cdot \bar{T}_i$, for capturing “the intuition that the impacts of a 1°C warming should be different in a cold location than a hot location” (Moore et al., 2017, p.7).

The variables $\Delta P_{i,t}$ and $\Delta Y_{i,t}$ denote percentage changes (in %) in growing season precipitation and crop yield relative to their historic averages during the benchmark period, respectively. The f denotes a function of changes in CO_2 concentrations ($\Delta CO_{2i,t}$), i.e.,

$f = \frac{\Delta CO_{2i,t}}{\Delta CO_{2i,t}+50}$. The variable D is a dummy for adaptation. Moore et al. (2017) also includes an intercept variable in their equation, but it is omitted here because it does not affect the variance of detrended yields. The effect of adaptation, captured by the term $0.2\Delta T_{i,t} \cdot D$, is ignored because the parameter estimated is too small (also statistically insignificant) to make a difference to the projected yield changes (appendix figure B.13)

We construct data on climate and CO_2 variables following Moore et al. (2017)'s definitions and use them to predict maize yields for each year during 2006-2050 in each focus country. Specifically, we calculate the growing season temperature ($\bar{T}_i$) and growing season precipitation ($\bar{P}_i$) in country i using their averages during 1979-2013 based on the climate data from the Climatic Research Unit monthly time-series Version 3.23 (Harris et al., 2014; Mitchell and Jones, 2005). Then we calculate changes in the two climate variables at each year t during 2006-2050 relative to their baseline values in country i: $\Delta T_{i,t} = T_{i,t} - \bar{T}_i$ and $\Delta P_{i,t} = 100 \cdot \frac{P_{i,t} - \bar{P}_i}{\bar{P}_i}$. We construct data on $CO_{2i,t}$ concentrations following Moore et al. (2017), with the details explained in appendix section B.2. Next, we use the data on changes in temperature ($\Delta T_{i,t}$), precipitation ($\Delta P_{i,t}$), CO_2 concentrations ($\Delta CO_{2i,t}$) and equation (B.1) to predict future yield changes ($\Delta Y_{i,t}$) at each year t from 2006 to 2050 in country i. Lastly, we re-express the predicted yield changes ($\Delta Y_{i,t}$) in yield levels ($Y_{i,t}$, in tonnes per hectare) based on the relationship $\Delta Y_{i,t} = 100 \cdot \frac{Y_{i,t} - \bar{Y}_i}{\bar{Y}_i}$, where $\bar{Y}_i$ is average observed yields during 1979-2013 from the FAOSTAT (FAO, 2018).

Note that the choice of baseline period matters to the projected yield levels, but it does not affect the projected yield deviations from trend; while the latter is what we use for predicting price variability. Appendix figure B.14 illustrates the procedures for projecting maize yields from 2006-2050 in China using the selected baseline period (1979-2013). Appendix figure B.15 displays the histograms of projected yield changes for all focus countries during 2006-2050 using climate projections by all 5 climate models with and without CO_2. Among all the projected yield changes, 82% of them are negative because the temperature increases in most focus countries, and the number is reduced to 58% with CO_2 concentrations. Appendix figure B.16 visualizes the relationship between projected yield changes using temperature data only (not including precipitation or CO_2 concentration) and projected temperature changes across focus countries during 2006-2050. This figure is similar to the one shown in Moore et al. (2017) (fig. 1), suggesting that we have correctly practiced their estimated model.

B.2 Data on CO_2 concentrations by countries

Moore et al. (2017, p.7) documented that "CO_2 concentrations for a given level of global temperature change are determined based on a fitted quadratic relationship between global temperature change and CO_2 concentrations from the RCP 8.5 CMIP5 multi-model ensemble mean".

We obtain the data on global temperature change and CO_2 concentrations from Moore et al. (2017) and then fit two quadratic equations between global CO_2 concentrations (CO_2) and global temperature change (ΔT) for two different RCP scenarios. The fitted equations are:

$$\text{RCP 8.5} : CO_2 = 358 + 78\Delta T + 15\Delta T^2 \tag{B.2}$$

$$\text{RCP 2.6} : CO_2 = 337 + 167\Delta T - 68\Delta T^2 \tag{B.3}$$

The adjusted R-squared for equation (B.2) is 0.999, with 98 degrees of freedom. These are consistent with what are reported by Moore et al. (2017). The adjusted R-squared for equation (B.3) is 0.907, and the degree of freedoms is also 98. All right-hand side variables in the two equations are significant at 99% confidence level.

We fit for the CO_2 concentrations, denoted by $\widehat{CO}_{2it}$, for country i at year t using the growing season temperature for country i at year t. Changes in CO_{2it} concentrations, denoted by ΔCO_{2it} in the main text, is set to be $\widehat{CO}_{2it} - 360$, where 360 is a baseline value (Moore et al., 2017, p.7).

B.3 Elatsicities and their standard errors

Equation (2.1) after estimation is:

$$CV_{ik,t} = \widehat{\alpha}_1 I_{it} + \widehat{\alpha}_2 Y_{i,t} + \widehat{\alpha}_3 M_{it} + \widehat{\boldsymbol{\beta}} \boldsymbol{Z}_{it} + \widehat{\mu}_i + \widehat{\delta}_k + \widehat{\phi}_t \tag{B.4}$$

where *hat* indicates that the parameters have been estimated.

All the estimated parameters including $\widehat{\alpha}_1$, $\widehat{\alpha}_2$, $\widehat{\alpha}_3$ and $\widehat{\boldsymbol{\beta}}$ capture the marginal effects of the independent variables on the dependent variable. We then transform the estimated parameters into elasticties, which measure the percentage changes in the intra-annual CV of monthly real maize prices given one percentage change in a given independent variable. To do this, we use the formula below (using the variable I_{it} as an example):

$$\frac{d \log CV_{ik,t}}{d \log I_{i,t}} = \frac{dCV_{ik,t}}{dI_{i,t}} \frac{I_{i,t}}{CV_{ik,t}} = \widehat{\alpha}_1 \frac{I_{i,t}}{CV_{ik,t}}. \tag{B.5}$$

where $I_{i,t}$ and $CV_{ik,t}$ are evaluated at their sample means (reported in table 2.2). Based on Greene (2011, p.68), the standard deviation of the estimated parameter in elasticity form is: $s.d.(\widehat{\alpha}_1)\frac{I_{i,t}}{CV_{ik,t}}$, where $s.d.$ refers to standard deviation.

Table B.1: List of focus countries and sample markets for this study.

No.	Country	Markets by city or region	Period
1	Bolivia	Cochabamba, La Paz, Oruro, Santa Cruz, Trinidad	2008/15
2	Burundi*	Bujumbura	2012/15
3	Cameroon	Bafoussam, Bamenda, Douala, Garoua, Yaoundé	2004/15
4	Central AfricanRepublic	Bangui	2007/15
5	Chad	Bol, N'Djamena	2003/15
6	Chile	National Average	2007/15
7	China	Heilongjiang, Jilin, Shandong	2011/15
8	Colombia	Bogotá, Cartagena, Medellín	2000/15
9	Costa Rica*	National Average	2000/15
10	Dominican Republic	Santo Domingo	2005/15
11	Ecuador	Ambato, Cuenca, Guayaquil, Portoviejo, Quito, Riobamba	2000/15
12	Egypt	Lower Egypt, Upper Egypt	2007/15
13	El Salvador*	San Salvador	2005/15
14	Ghana	Accra, Bolgatanga, Kumasi, Tamale, Techiman, Wa	2007/15
15	Guatemala	Guatemala City, National Average	2000/15
16	Honduras	National Average, San Pedro Sula, Tegucigalpa	2000/15
17	Israel	National Average	2005/15
18	Kenya	Eldoret, Kisumu, Mombasa, Nairobi, Nakuru	2005/15
19	Mexico	Culiacàn, Guadalajara, Mexico City, Puebla, Xalapa	2000/15
20	Morocco	National Average	2009/15
21	Mozambique*	Angonia, Chokwe, Gorongosa, Manica, Maputo, Maxixe, Milange, Montepuez, Nampula, Ribaue	2006/15
22	Nicaragua	Granada, Leon, Managua, Managua (oriental), National Average	2000/15
23	Panama	Panama City	2005/15
24	Peru*	Lima	2005/15
25	Philippines	South Cotabato	2000/15
26	Rwanda	Kigali	2006/15
27	Thailand	Bangkok	2000/15

Notes: The data source is the FAO GIEWS database (FAO, 2017). The countries labelled with stars have both wholesale and retail prices. We exclude 22 countries that have local maizr price data in the FAO GIEWS database (FAO, 2017) (See appendix table B.2 for details).

Table B.2: List of countries with maize price data in the FAO GIEWS database (FAO, 2017) excluded from the study.

No.	Country	Reasons for exclusion
1	Togo	a, b
2	Benin	a, b
3	Ethiopia	a, b
4	Nigeria	a, b
5	Paraguay	b
6	Argentina	b
7	Brazil	b
8	Uganda	b
9	Ukraine	b
10	Zambia	b
11	South Africa	b
12	Zimbabwe	c
13	South Sudan	c
14	Democratic Republic of Congo	c
15	Somalia	c
16	Republic of Moldova	d
17	Russian Federation	d
18	Tanzania	d
19	Cape Verde	d
20	Niger	e
21	Timor-Leste	e
22	Italy	e

Notes: The reasons for excluding the countries are: no variation in net import ratio (a), not net maize importers (b), no data on monthly exchange rate (c), no data on consumption (d), no information on the marketing year (e).

B.4 Additional tables and figures

Table B.3: Regression results.

Variables	Model 1	Model 2	Model 3	Model 4	Model 5
Net import ratio	-0.08*** (0.01)	-0.07*** (0.01)	-0.07*** (0.01)	-0.15*** (0.05)	-0.18*** (0.06)
Beginning stock--to-use ratio	–	-0.27*** (0.04)	-0.25*** (0.03)	-0.3*** (0.07)	-0.43*** (0.09)
Absolute yield deviation	–	0.13*** (0.03)	0.13*** (0.03)	0.13*** (0.03)	0.19*** (0.03)
Social conflict	–	-0.01 (0.01)	-0.002 (0.01)	0.01 (0.01)	-0.001 (0.01)
Variability of real exchange rate	–	0.33*** (0.13)	-0.11 (0.12)	0.03 (0.13)	-0.19 (0.19)
Food aid ratio	–	–	–	–	0.01 (0.19)
Observations	851	851	851	851	631
Country fixed effect	No	No	No	Yes	Yes
Market fixed effect	No	No	No	Yes	Yes
Retail/Wholesale fixed effect	No	No	No	Yes	Yes
Year fixed effect	No	No	Yes	Yes	Yes
Adjusted R^2	0.09	0.16	0.32	0.49	0.5
F statistics	82.4*** (d.f.=1, 849)	36.6*** (d.f.=5, 845)	19.9*** (d.f.=21, 829)	9.4*** (d.f.=97, 753)	8*** (d.f.=89, 541)

Notes: The dependent variable is annual CV of real monthly prices. Values in parentheses are standard errors, clustered by countries (MacKinnon and White, 1985). Model 1-5 contains different sets of independent variables, including the fixed effect variables. Model 5 has fewer observations because data on food aid from 2013 to 2015 are not available. The "d.f" under F statistics refers to degree of freedom. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table B.4: Robustness tests to alternative model specifications.

Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Net import ratio	-0.17***	-0.17***	-0.13***	-0.1**	-0.1**	-0.15***	-0.14**
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.08)	(0.05)
Beginning stock-	-0.17***	-0.27***	-0.29***	-0.28***	-0.13**	-0.28***	-0.27***
-to-use ratio	(0.08)	(0.08)	(0.07)	(0.07)	(0.06)	(0.07)	(0.07)
Absolute yield	0.12***	0.09***	0.06**	0.12***	0.04	0.14**	0.14**
deviation	(0.03)	(0.04)	(0.03)	(0.03)	(0.02)	(0.03)	(0.03)
Social conflict	0.01	0.01	0.01	0.01	0.003	0.001	-0.003
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Variability of real	-0.01	-0.05	0.02	0.04	-0.02	0.04	0.03
exchange rate	(0.13)	(0.14)	(0.13)	(0.13)	(0.14)	(0.13)	(0.13)
Import distance	–	–	–	–	–	0.03**	0.03**
						(0.01)	(0.01)
Herfindahl index	–	–	–	–	–	0.03**	0.03**
of import share	–	–	–	–	–	(0.01)	(0.01)
Per capita GDP	–	–	–	–	–	–	-0.004
							(0.005)
Observations	714	655	851	851	850	822	808
Country fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Market fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Retail/Wholesale fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.46	0.5	0.48	0.48	0.43	0.49	0.49
F statistics	7.3*** (d.f.= 95, 618)	8.1*** (d.f.= 89, 565)	9.2*** (d.f.= 97, 753)	9.2*** (d.f.= 97, 753)	7.6*** (d.f.= 97, 752)	8.6 *** (d.f.= 99, 722)	8.8*** (d.f.= 99, 708)

Notes: Model 1 excludes data in 2007 and 2008, which were years of high market turbulence. Model 2 uses data after 2007 only. In model 3, the absolute yield deviation is replaced by absolute production deviation. In model 4, the net import ratio is replaced by import ratio, ignoring exports. In model 5, the dependent variable is measured by standard deviation of log returns of real monthly prices; the variability of real exchange rates is also changed to standard deviation of log returns of real exchange rates. In model 6, we add import-share weighted distances in 10 million kilometers and the Herfindahl index of import share (higher concentration of the import shares, higher the index). In model 7, we add per capita GDP in thousand dollars. Values in parentheses are standard errors, clustered by countries (MacKinnon and White, 1985). The "d.f" under F statistics refers to degree of freedom. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table B.5: Robustness tests to different sample compositions.

Variables	Model 1	Model 2	Model 3
Net import ratio	-0.18*	-0.09	-0.14***
	(0.09)	(0.07)	(0.05)
Net import ratio + (Net import ratio × Group)	-0.18**	-0.18**	-0.31***
	(0.08)	(0.07)	(0.16)
Beginning stock--to-use ratio	-0.43***	-0.28***	-0.3***
	(0.09)	(0.07)	(0.06)
Absolute yield deviation	0.19***	0.13***	0.13***
	(0.09)	(0.07)	(0.05)
Social conflict	-0.001	0.009	0.008
	(0.01)	(0.008)	(0.008)
Variability of real exchange rate	-0.19***	0.006	0.02
	(0.19)	(0.13)	(0.13)
Food aid ratio	0.006	–	–
	(0.19)		
Observations	631	851	851
Country fixed effect	Yes	Yes	Yes
Market fixed effect	Yes	Yes	Yes
Retail/Wholesale fixed effect	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes
Adjusted R^2	0.5	0.49	0.49
F statistics	7.9***(d.f. = 90, 540)	9.3***(d.f. = 98, 752)	9.3*** (d.f. = 98, 752)

Notes: In model 1, the group is non-African countries. In model 2, the group is countries with average net import ratio lower than 10%. In model 3, the group is countries with average import-share weighted distance greater than 4,500 kilometers. Values in parentheses are clustered standard errors by countries (MacKinnon and White, 1985). The "d.f" under F statistics refers to degree of freedom. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table B.6: Comparison of regression estimates of equation (2.1) using Hodrick-Prescott (HP) filter with smoothing parameter of 100 and quadratic for fitting the yield trend.

Variables	HP filter	Quadratic	Difference
Net import ratio	-0.15***	-0.13***	-0.02
	(0.05)	(0.05)	(0.07)
Beginning stock-	-0.3***	-0.3***	0
-to-use ratio	(0.07)	(0.07)	(0.1)
Absolute yield	0.13***	0.07**	0.05
deviation	(0.03)	(0.03)	(0.04)
Social conflict	0.01	0.01	0
	(0.01)	(0.03)	(0.03)
Variability of real	0.03	0.04	-0.01
exchange rate	(0.13)	(0.13)	(0.18)
Observations	851	851	–
Country fixed effect	Yes	Yes	–
Market fixed effect	Yes	Yes	–
Retail/Wholesale fixed effect	Yes	Yes	–
Year fixed effect	Yes	Yes	–
Adjusted R^2	0.49	0.48	–
F statistics	9.4*** (d.f.=97, 753)	9.2*** (d.f.=97, 753)	–

Notes: Values in parentheses are clustered standard errors by countries (MacKinnon and White, 1985). The "d.f" under F statistics refers to degree of freedom. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

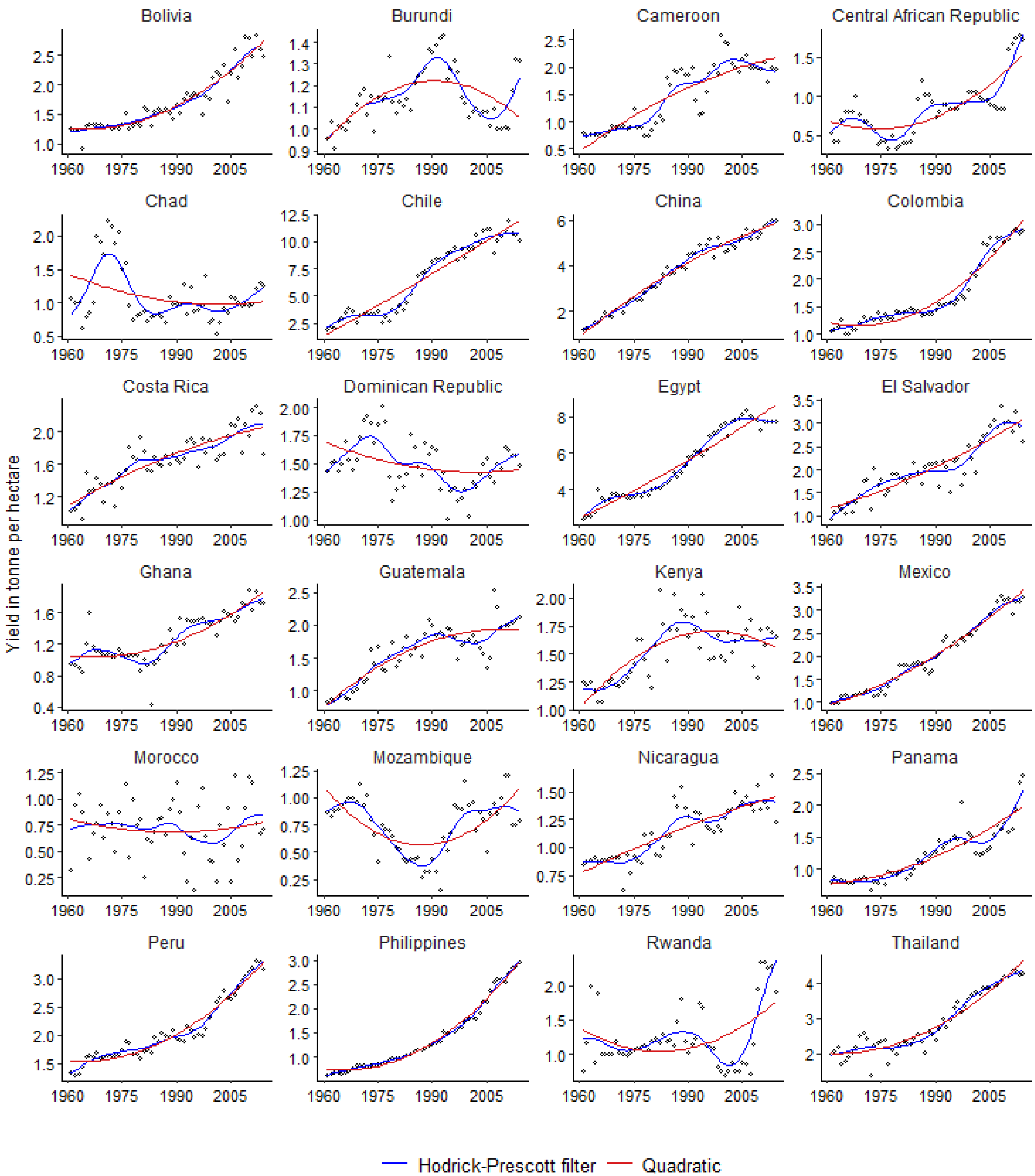

Figure B.1: Historical maize yields of focus countries with trends fitted by HP filter and by quadratic regression.

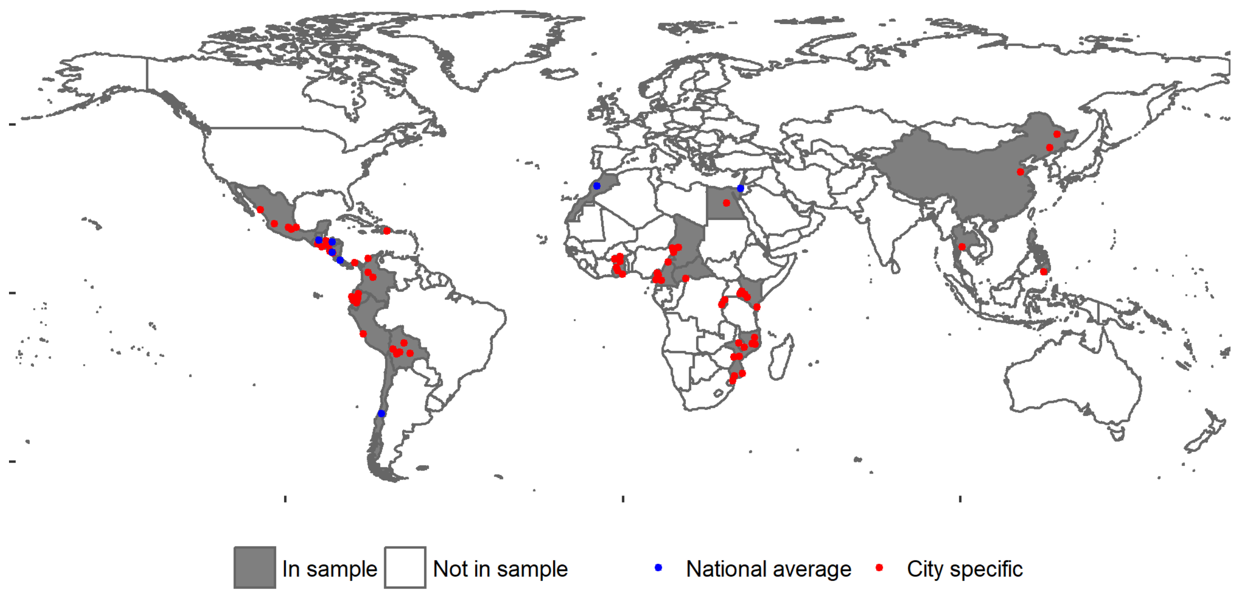

Figure B.2: Geographical location of sample countries and sample markets.

Notes: The point for "National average" are approximately located at the geographical center of the country.

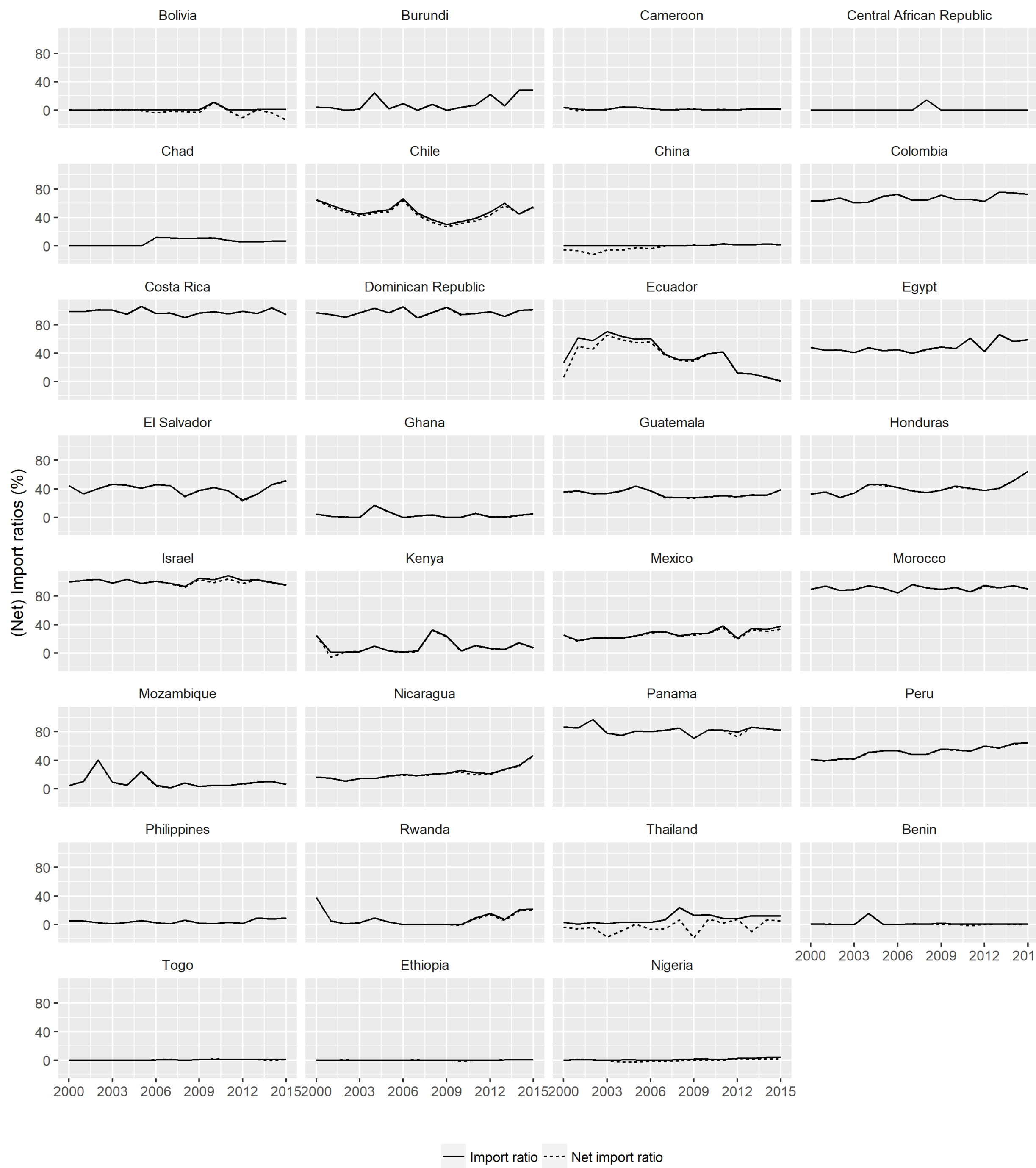

Figure B.3: Import ratios and net import ratios of maize among focus countries during 2000-2015.

Notes: Import ratio equals to the ratio of imports to domestic consumption. Net import ratio equals to the ratio of net imports (= imports - exports) to domestic consumption. Data source: PS&D online database (USDA, 2017).

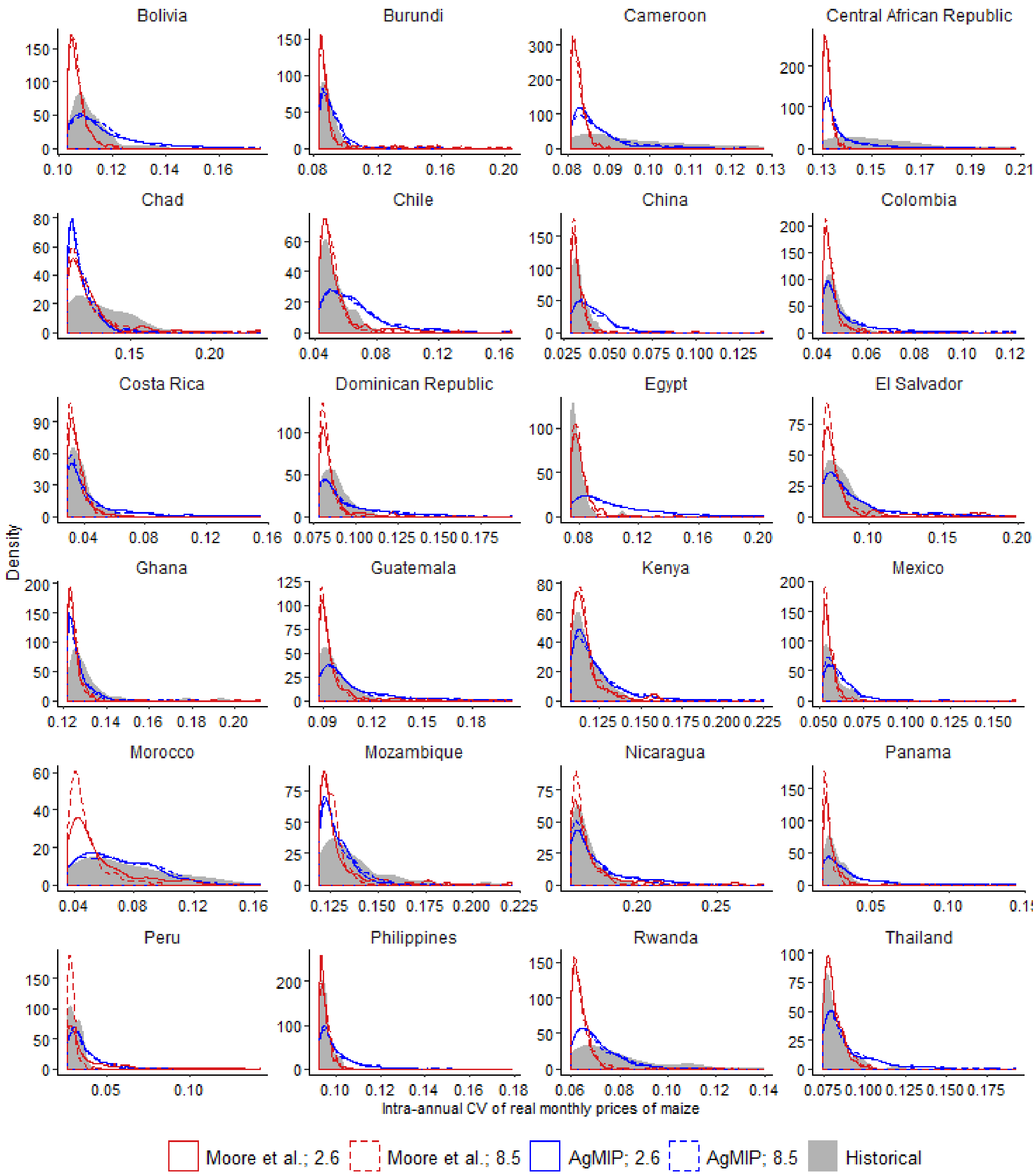

Figure B.4: Distributions of projected intra-annual CV of real monthly prices of maize during 2006-2050 with CO_2 fertilization and during 1961-2014.

Notes: Results for Ecuador, Honduras and Israel, three countries included in the sample, are not shown due to missing climate data.

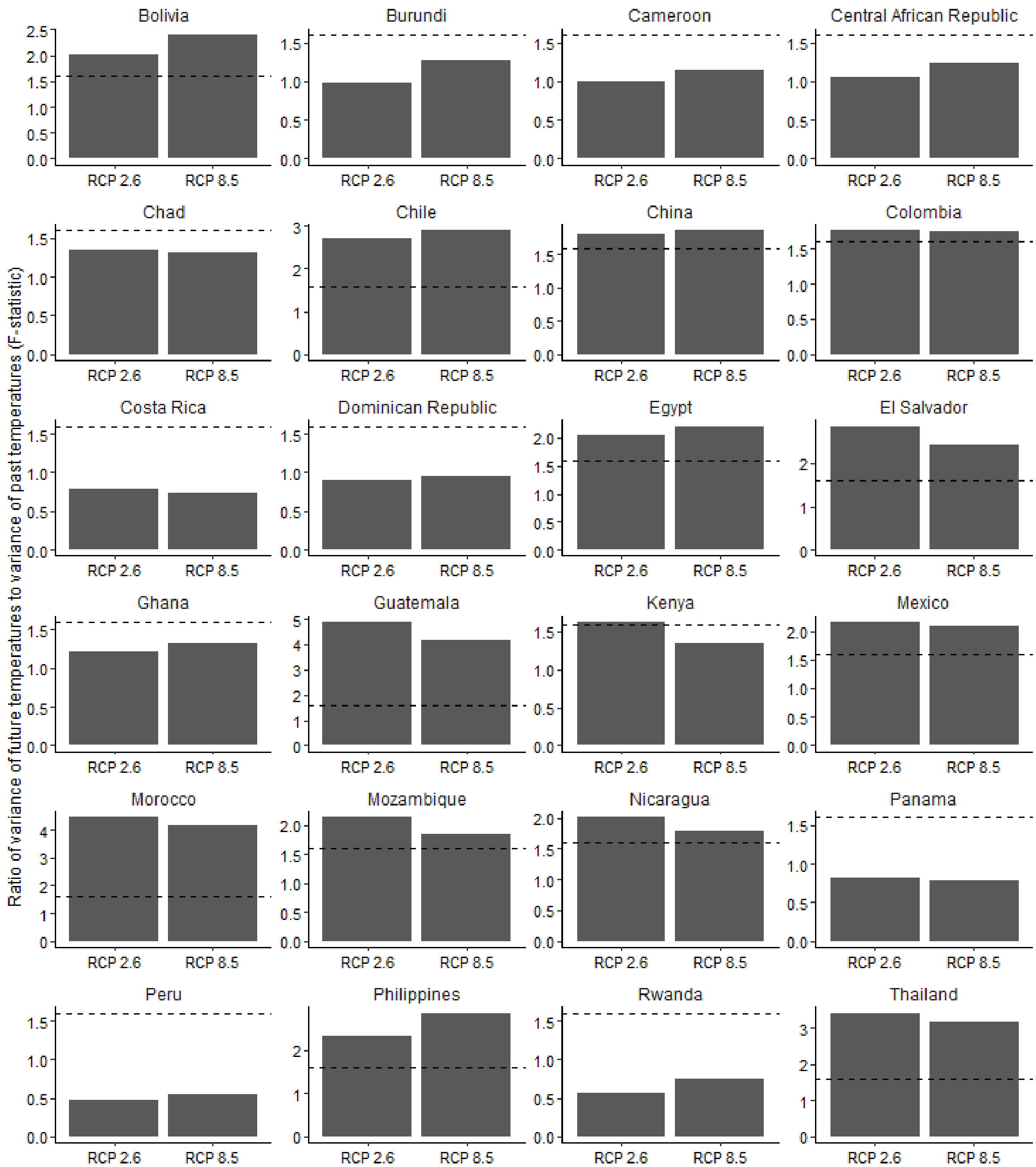

Figure B.5: Historical to future growing season temperature variance ratio.

Note: The ratio is F-statistic and it is significant at 95% confidence level when greater than 1.6 (noted by the dashed lines). Time series growing season temperatures are detrended by the HP filter (Hodrick and Prescott, 1997) with a smoothing parameter of 100. Source: Data on historical temperatures are from the Climatic Research Unit monthly time-series version 3.23 (Harris et al., 2014; Mitchell and Jones, 2005). Data on future temperatures are from five global climate model ensembles used by the Inter-Sectoral Impact Model Intercomparison Project (Hempel et al., 2013; Warszawski et al., 2014)

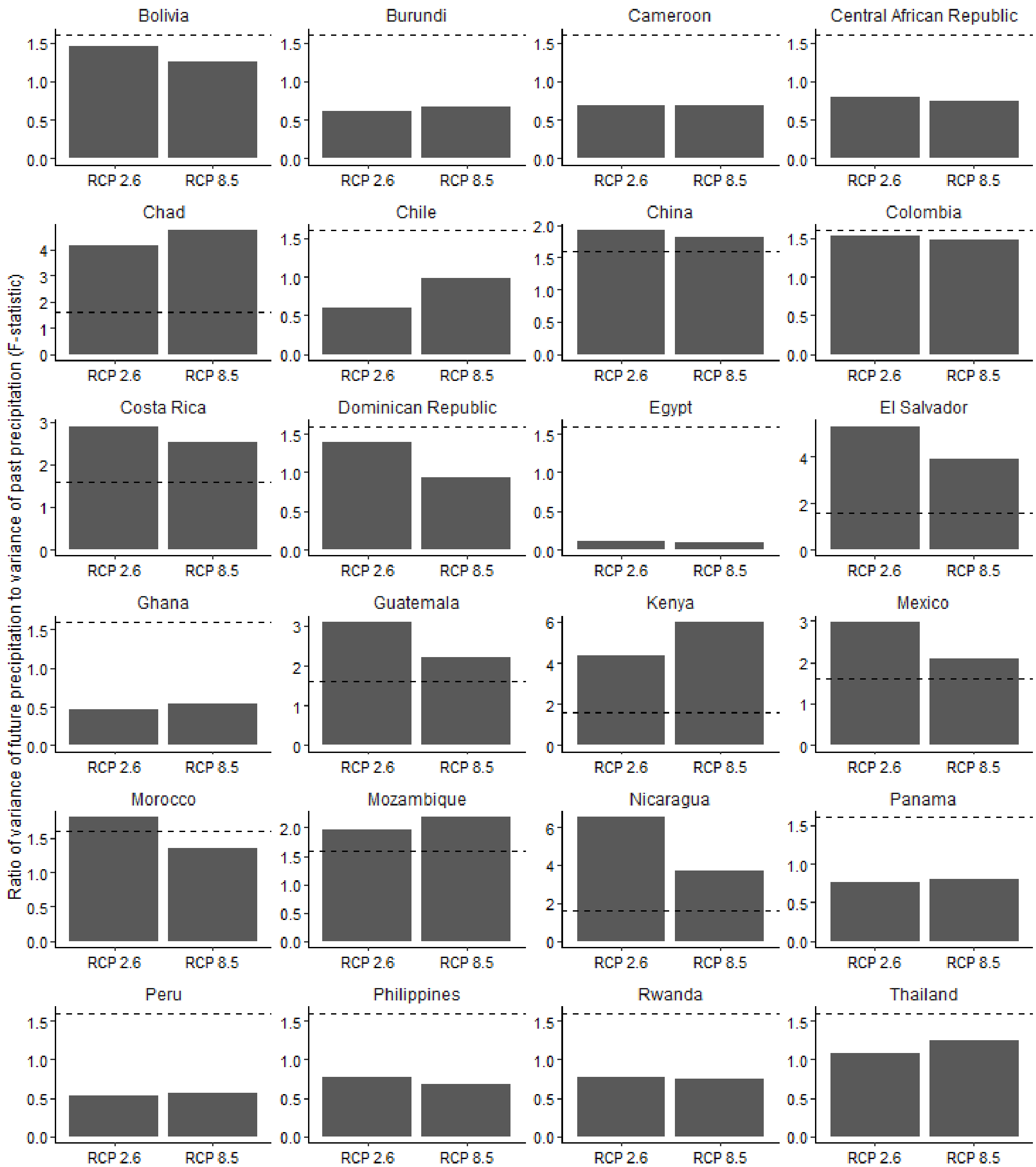

Figure B.6: Historical to future growing season precipitation variance ratio.

Note: The ratio is F-statistic and it is significant at 95% confidence level when greater than 1.6 (noted by the dashed lines). Time series growing season precipitation are detrended by the HP filter (Hodrick and Prescott, 1997) with a smoothing parameter of 100. Source: Data on historical precipitation are from the Climatic Research Unit monthly time-series version 3.23 (Harris et al., 2014; Mitchell and Jones, 2005). Data on future precipitation are from five global climate model ensembles used by the Inter-Sectoral Impact Model Intercomparison Project (Hempel et al., 2013; Warszawski et al., 2014)

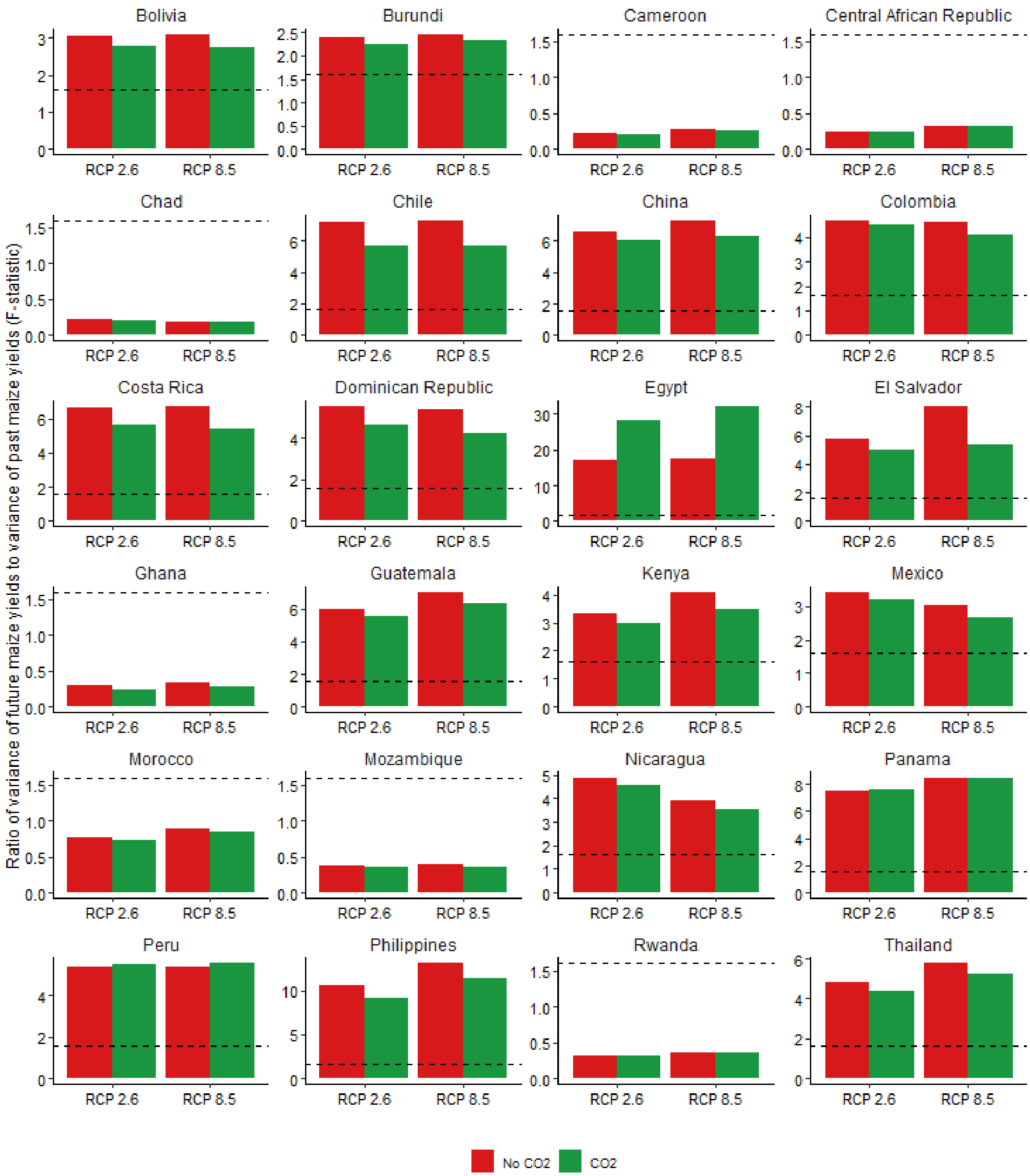

Figure B.7: Historical to future maize yield variance ratio.

Note: The ratio is F-statistic and it is significant at 95% confidence level when greater than 1.6 (noted by the dashed lines). Time series maize yields are detrended by the HP filter (Hodrick and Prescott, 1997) with a smoothing parameter of 100. Source: Data on historic maize yields are from FAOSTAT (FAO, 2018). Future maize yields are projected by a combination of two GGCMI-AgMIP crop models (Elliott et al., 2014a; Rosenzweig et al., 2014) and five global climate model ensembles used by the Inter-Sectoral Impact Model Intercomparison Project (Hempel et al., 2013; Warszawski et al., 2014) without CO_2 fertilization (density curves are shown in figure 2.5).

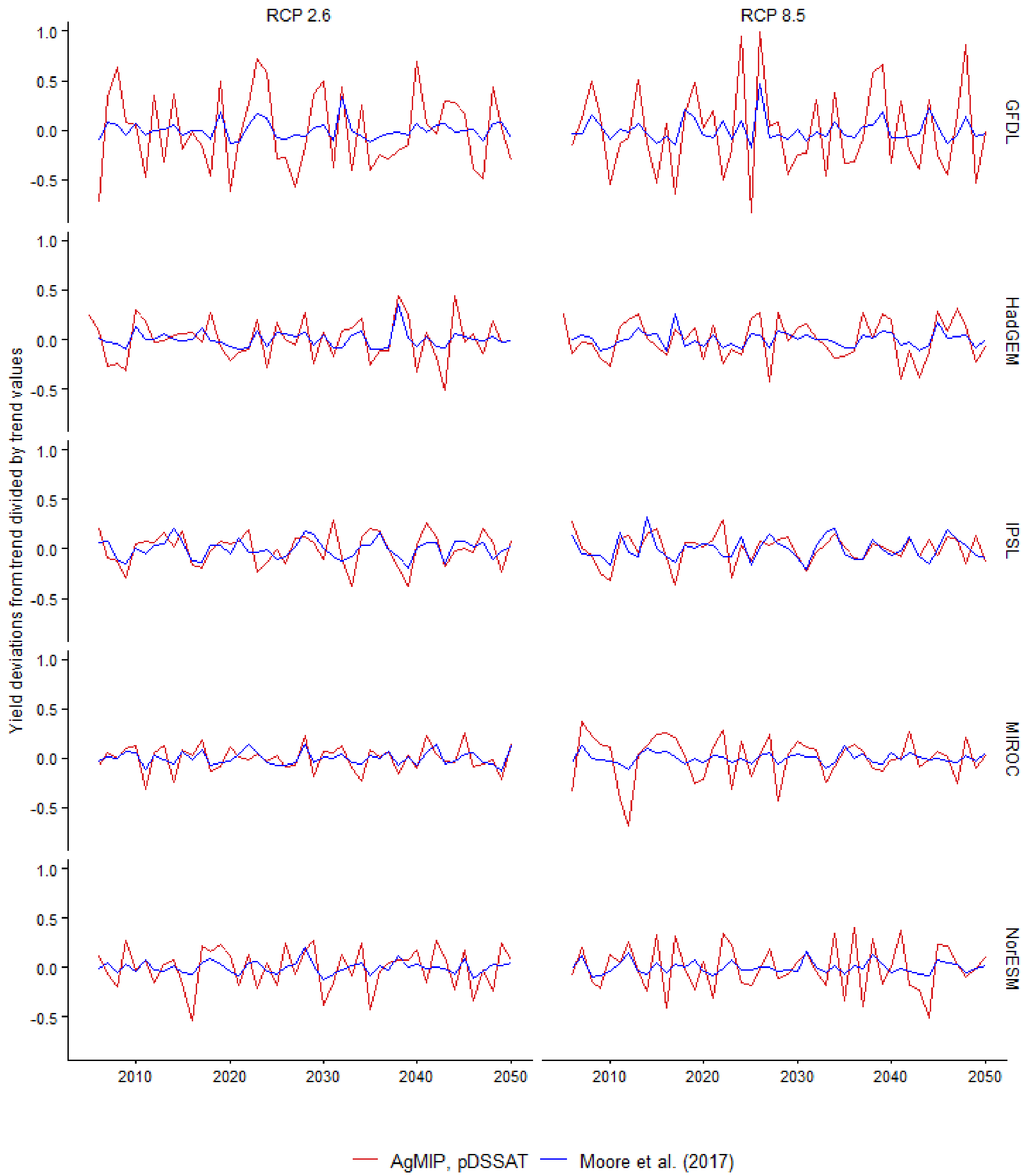

Figure B.8: Maize yields of Kenya during 2006-2050 projected by alternative sources under RCP 2.6 and RCP 8.5 without CO_2 fertilization.

Notes: One source is the pDSSAT crop model under the GGCMI-AgMIP project, and another source is Moore et al. (2017)'s yield-climate response function combined with five global climate models used by the Inter-Sectoral Impact Model Intercomparison Project (Hempel et al., 2013; Warszawski et al., 2014). Maize yields are detrended by the HP filter (Hodrick and Prescott, 1997) with a smoothing parameter of 100. All two maize yield series in each are significantly correlated, with correlation coefficients ranging from 0.58 to 0.74.

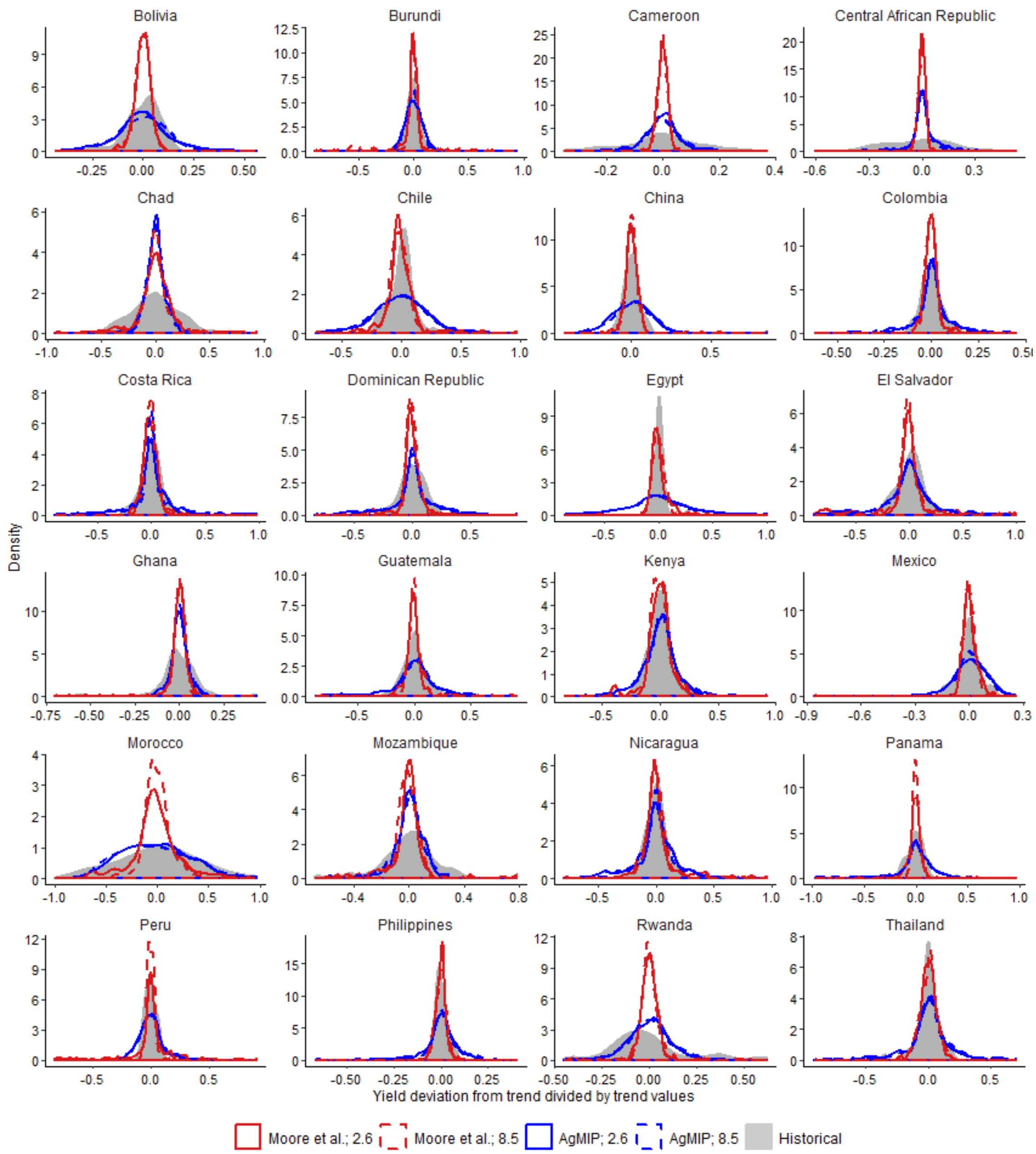

Figure B.9: Distributions of maize yield deviations during 2006-2050 with CO_2 fertilization and during 1961-2014.

Notes: The future yields are from GGCMI-AgMIP crop models and Moore et al. (2017)'s yield-climate response function in combination with 5 global climate models used by the Inter-Sectoral Impact Model Intercomparison Project (Hempel et al., 2013; Warszawski et al., 2014). The historic yields are from FAOSTAT (FAO, 2018). Results for Ecuador, Honduras and Israel are not shown due to missing climate data.

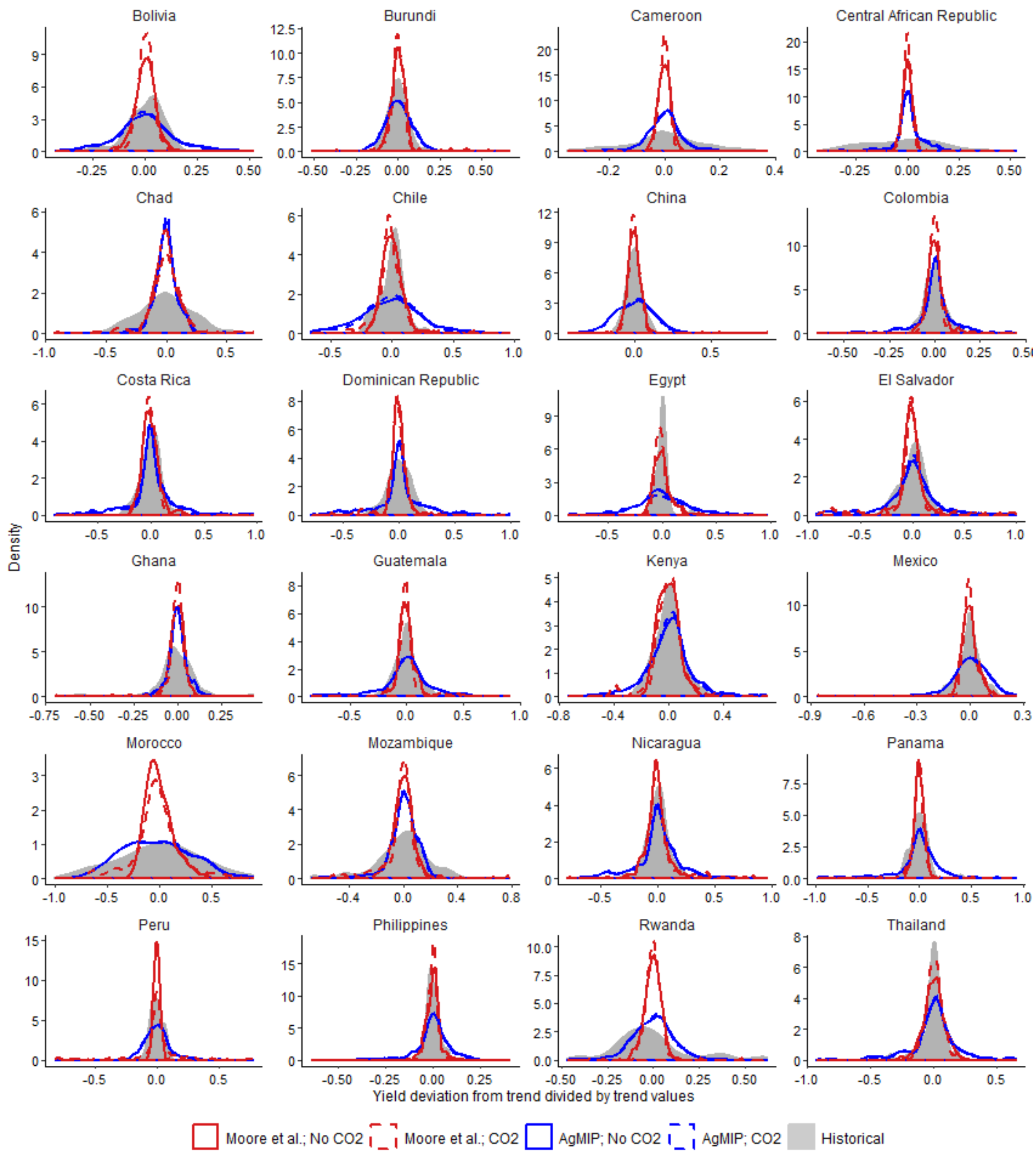

Figure B.10: Distributions of projected intra-annual CV of real monthly prices of maize during 2006-2050 under RCP 2.6 and during 1961-2014.

Notes: The future yields are from GGCMI-AgMIP crop models and Moore et al. (2017)'s yield-climate response function in combination with 5 global climate models used by the Inter-Sectoral Impact Model Intercomparison Project (Hempel et al., 2013; Warszawski et al., 2014). The historic yields are from FAOSTAT (FAO, 2018). Results for Ecuador, Honduras and Israel are not shown due to missing climate data. Results for Ecuador, Honduras and Israel, three countries included in the sample, are not shown due to missing climate data.

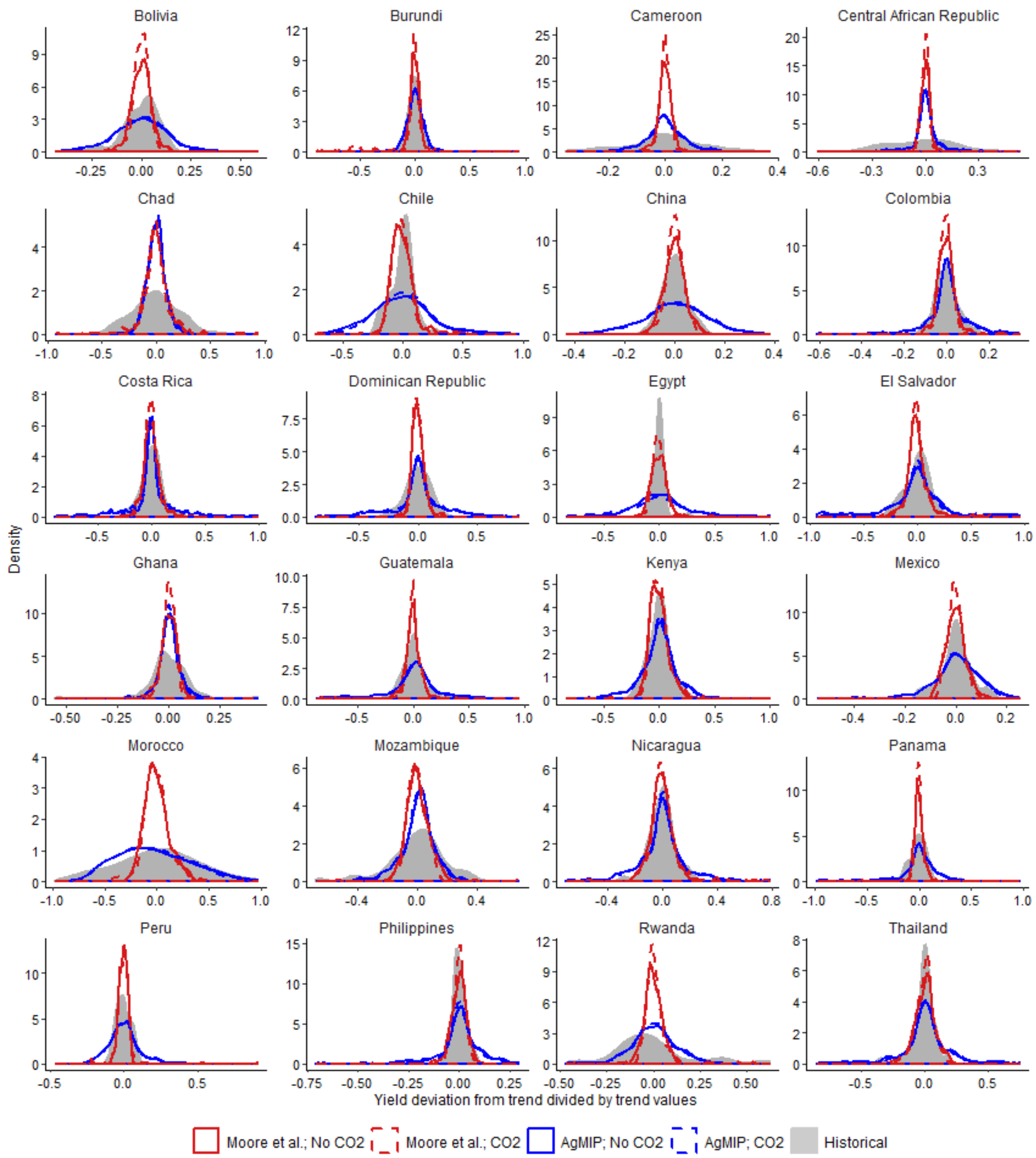

Figure B.11: Distributions of projected intra-annual CV of real monthly prices of maize during 2006-2050 under RCP 8.5 and during 1961-2014.

Notes: The future yields are from GGCMI-AgMIP crop models and Moore et al. (2017)'s yield-climate response function in combination with 5 global climate models used by the Inter-Sectoral Impact Model Intercomparison Project (Hempel et al., 2013; Warszawski et al., 2014). The historic yields are from FAOSTAT (FAO, 2018). Results for Ecuador, Honduras and Israel are not shown due to missing climate data. Results for Ecuador, Honduras and Israel, three countries included in the sample, are not shown due to missing climate data.

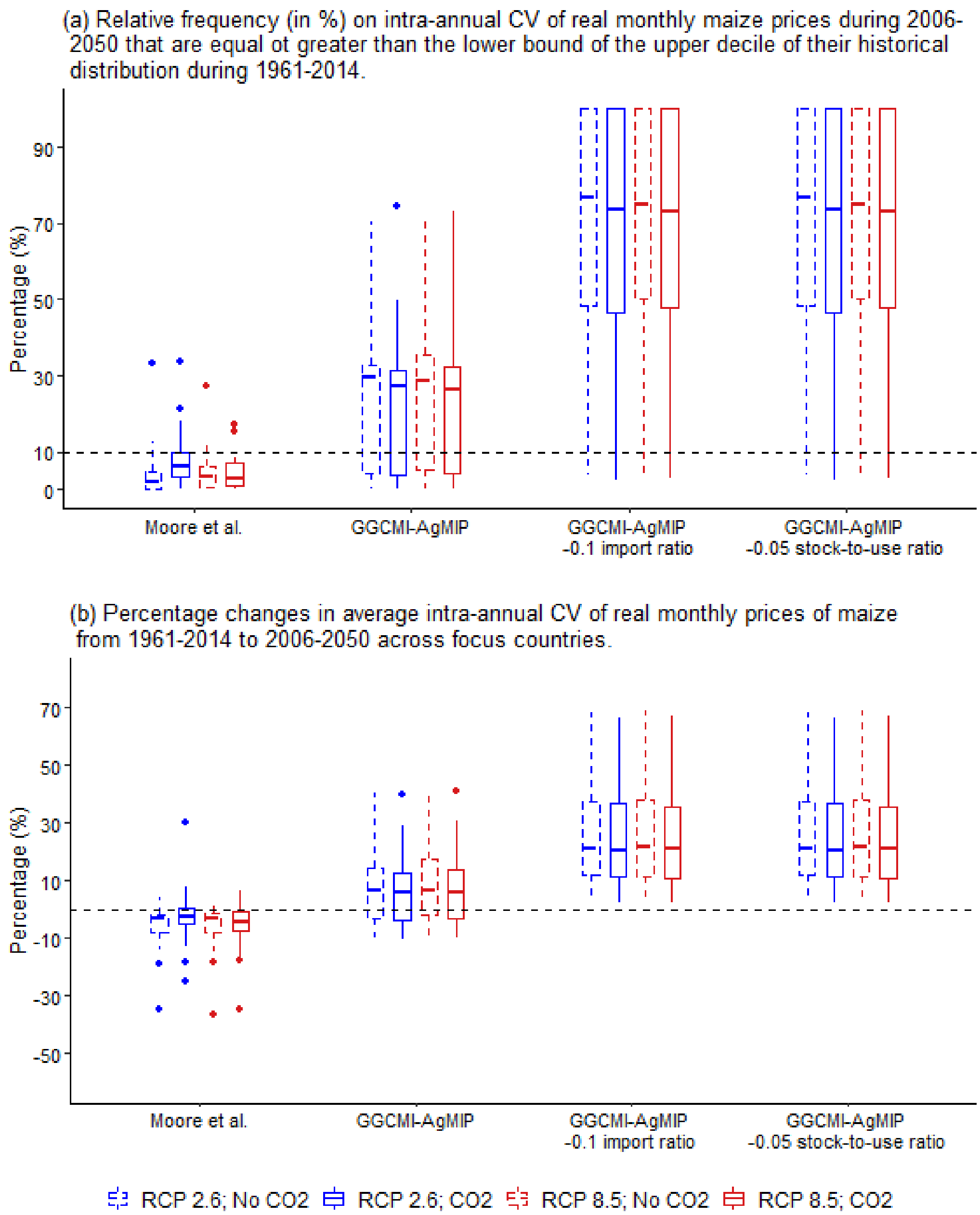

Figure B.12: Incidence of extreme price variability towards mid-century and changes in average price variability across focus countries under alternative trade and storage policy scenarios.

Notes: The dashed lines in panel (a) and panel (b) represent the baselines values, i.e., 10% and 0%, respectively.

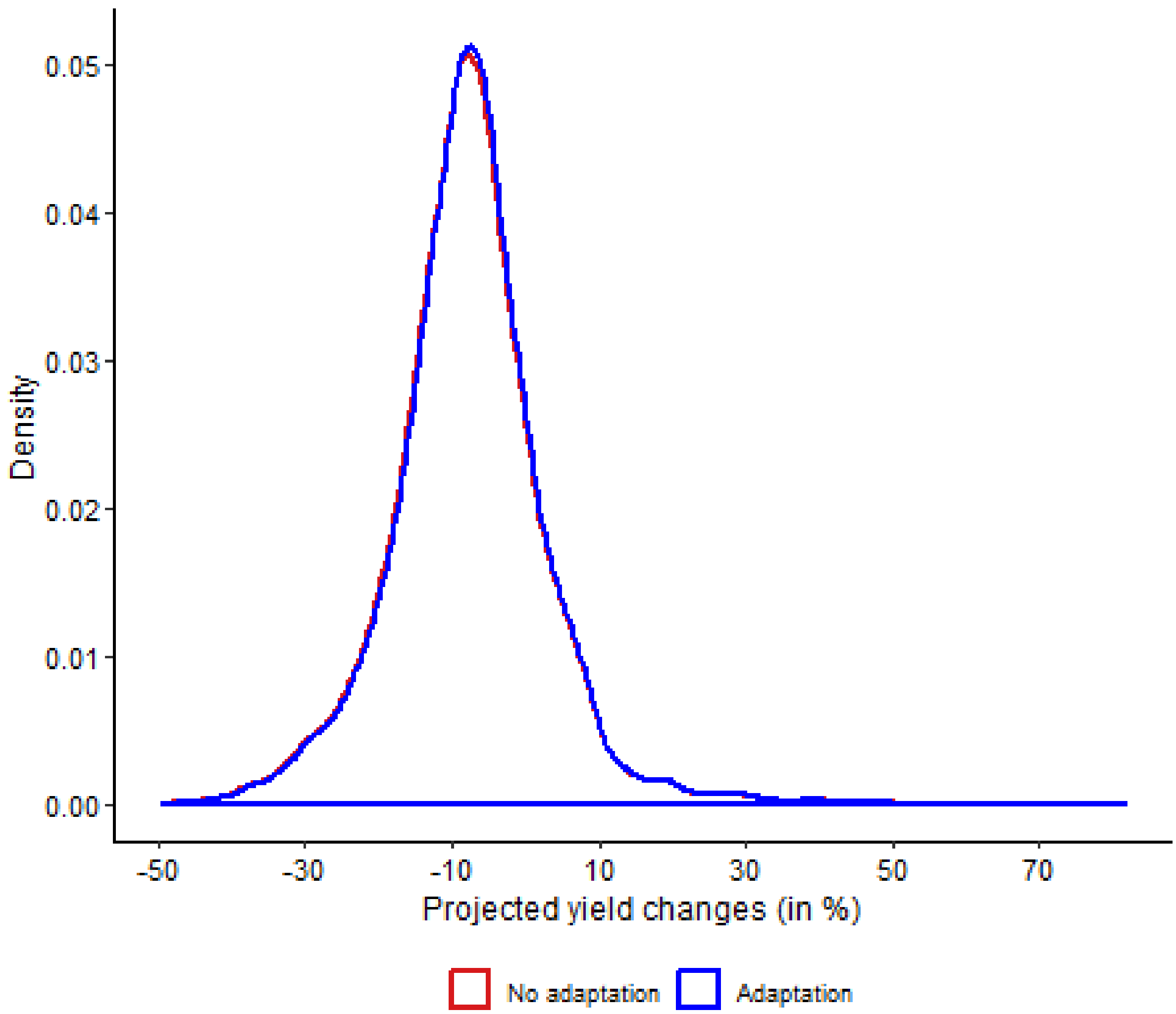

Figure B.13: Density curves of projected yield changes (in %) with and without adaptation.

Notes: Each density curve contains projected yield changes by Moore et al. (2017)'s yield-climate response function in all years during 2006-2050 in all focus countries with all 5 climate models used by the Inter-Sectoral Impact Model Intercomparison Project (Hempel et al., 2013; Warszawski et al., 2014). The density curve without adaptation corresponds to the histogram shown in panel a) of figure B.15.

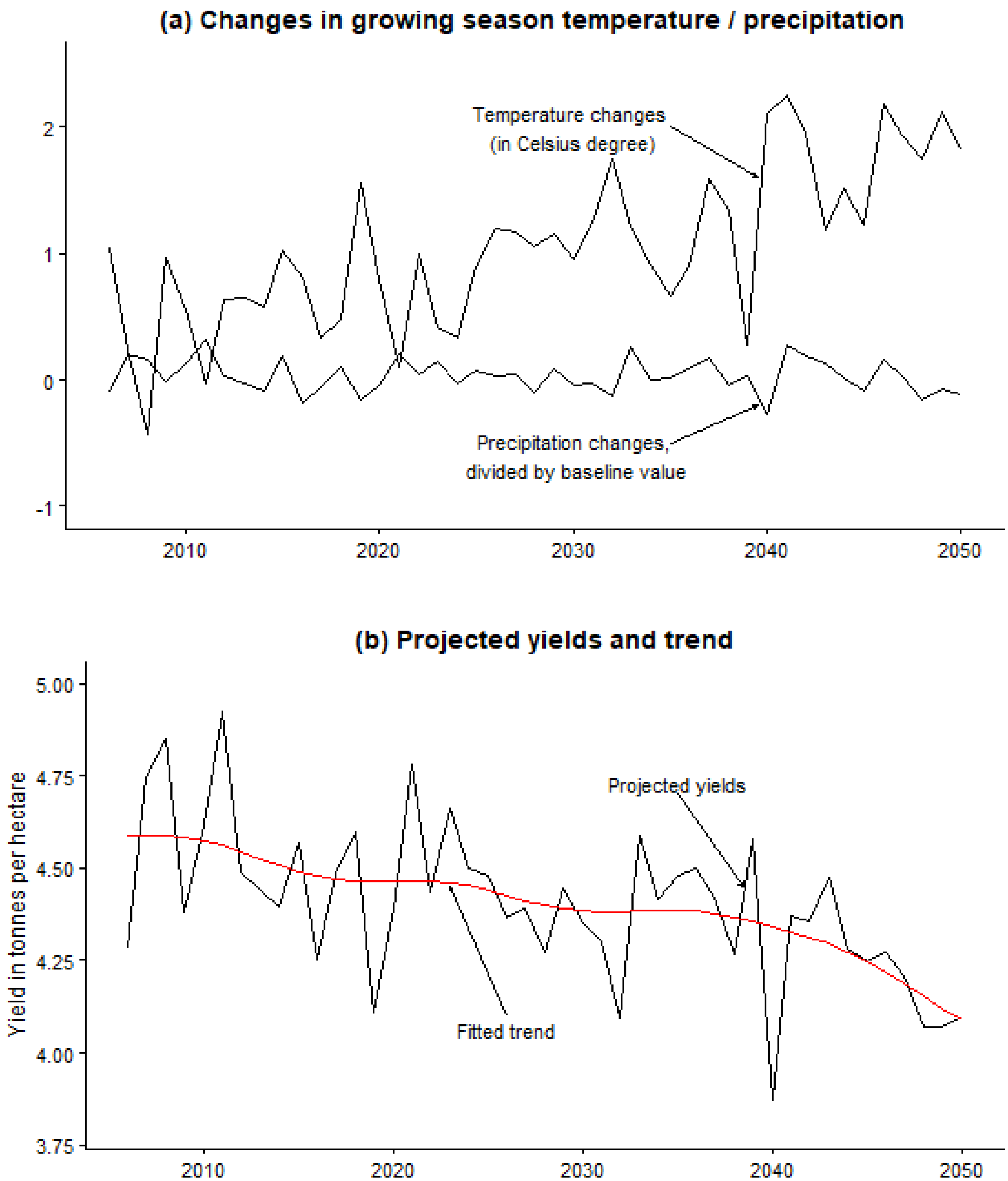

Figure B.14: Projecting maize yields for China based on Moore et al. (2017)'s yield-climate response function.

Notes: The climate data are from the GFDL climate model. The baseline growing season temperature and precipitation are 20.6 Celsius degree and 96.8 millimeters, respectively. The baseline maize yield is 4.6 tonnes per hectare. The yield trend is fitted by HP filter (Hodrick and Prescott, 1997) with a smoothing parameter of 100. CO_2 concentration is not considered in the projection.

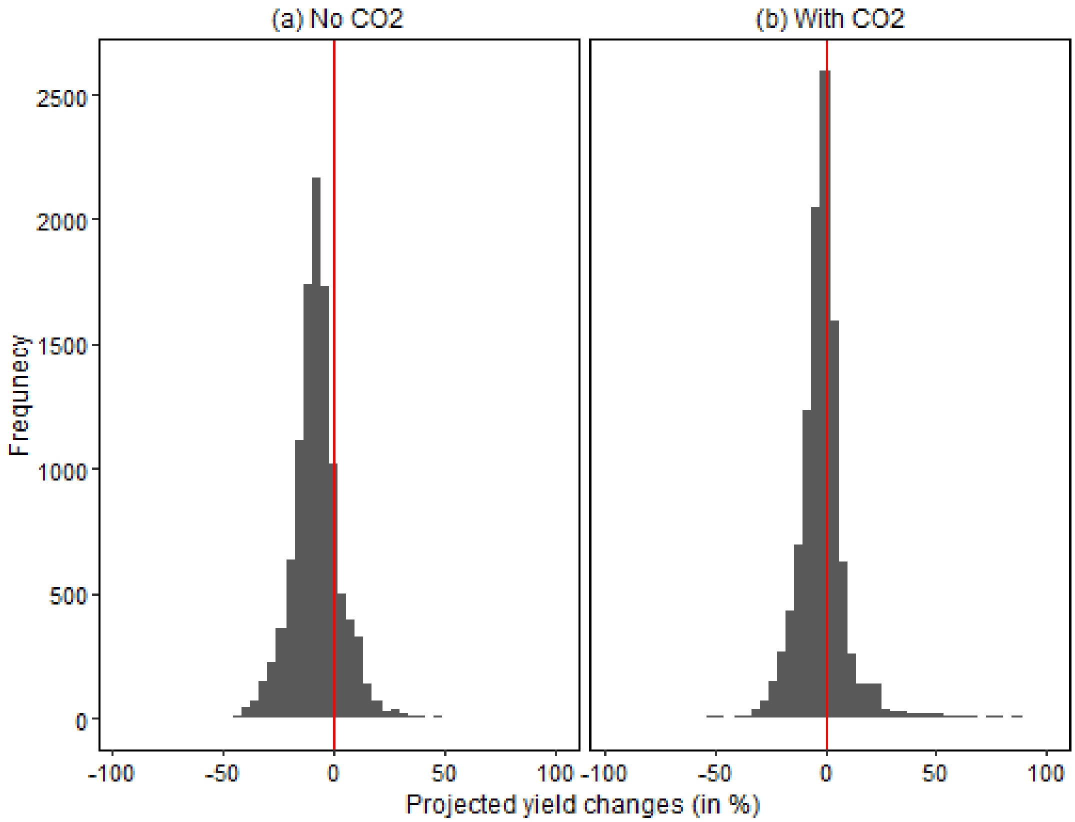

Figure B.15: Histograms of projected yield changes with and without CO_2 fertilization.

Notes: Each histogram contains projected yield changes by Moore et al. (2017)'s yield-climate response function in all years during 2006-2050 in all focus countries with all 5 climate models used by the Inter-Sectoral Impact Model Intercomparison Project (Hempel et al., 2013; Warszawski et al., 2014). The total number of yield projections displayed here is 10800. We remove 56 projected values with CO_2 fertilization, as their absolute values are greater than 100.

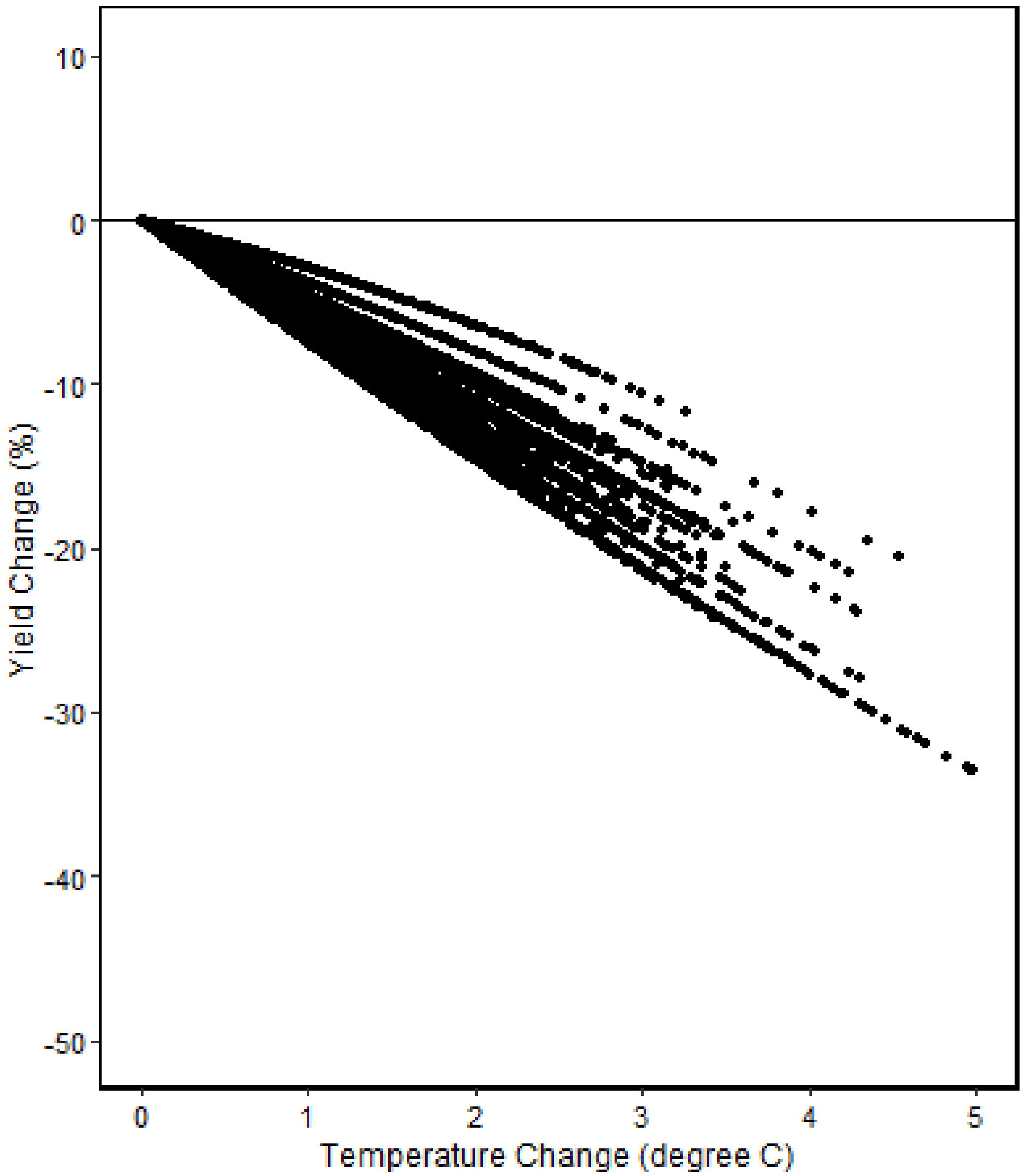

Figure B.16: Relationship between projected yield changes and projected growing season temperature changes during 2006-2050 across all focus countries.

Notes: The yield changes are predicted by using Moore et al. (2017) yield-climate response function and data on growing season temperature only. Yield changes are different given a certain temperature change when the baseline temperature levels are different.

Appendix C

Supplementary material for Chapter 3

C.1 Additional tables and figures

Table C.1: List of focus countries and markets.

Region	Country	Markets	Period
	Angola	Luanda	2008/16
	Burundi	Bujumbura	2012/16
	Cabo Verde	S. Antão, S. Vincente, Santiago	2005/16
	Cameroon	Bafoussam, Bamenda, Douala, Garoua, YaundÃ	2004/16
Africa	Chad	Bol, Moussoro, N'Djamena	2003/16
(No. = 11)	Ghana	Accra, Bolgatanga, Kumasi, Techiman, Wa	2005/16
	Kenya	Eldoret, Kisumu, Mombasa, Nairobi, Nakuru	2005/16
	Mozambique	Angonia, Chokwe, Gorongosa, Manica, Maputo,	2000/16
		Maxixe, Milange, Montepuez, Nampula, Ribaue	
	Namibia	Gobabis, Katima, Keetmanshoop, Mariental, Oshakati	2010/16
	Rwanda	Kigali	2000/16
	Swaziland	Hhohho, Lubombo, Manzini, National ave., Shiselweni	2007/16
	Chile	National average	2008/16
	Colombia	Bogotá, Cartagenaín	2000/16
	Ecuador	Ambato, Riobamba, Portoviejo,	2014/16
	El Salvador	San Salvador	2005/16
Americas	Guatemala	Guatemala City, National Average	2000/16
(No. = 11)	Honduras	National average, San Pedro Sula, Tegucigalpa	2000/16
	Mexico	Culiacàn, Guadalajara, Puebla, Xalapa	2000/16
	Nicaragua	Granada, Leon, Managua, National average.	2000/16
	Panama	Panama City	2005/16
	Peru	Lima	2000/16
	Uruguay	National average	2010/16
Asia	China	Heilongjiang, Jilin, Shandong	2011/16
(No. = 2)	Philippines	Cebu, Metro Manila	2000/16

Table C.2: List of focus countries in different country groups.

Group	Value	Countries
G1: Import dep.	High	Cabo Verde, Chile, Colombia, Honduras, Namibia, Panama
		Peru, Swaziland
	Low	Angola, Burundi, Cameroon, Chad, China, Ecuador, El Salvador
		Ghana, Guatemala, Kenya, Mexico, Mozambique, Nicaragua
		Philippines, Rwanda, Uruguay
G2: Distance	Low	Burundi, Cabo.Verde, Chile, Colombia, Ecuador, El Salvador
		Guatemala, Honduras, Kenya, Mexico, Mozambique, Namibia
		Nicaragua, Panama, Peru, Rwanda, Swaziland, Uruguay
	High	Angola, Cameroon, Chad, China, Ghana, Philippines
G3: Connectivity	Landlocked	Burundi, Chad, Rwanda, Swaziland
	Coastal	Angola, Cabo Verde, Cameroon, Chile, China, Colombia
		Ecuador, El Salvador, Ghana, Guatemala, Haiti, Honduras,
		Kenya, Mexico, Mozambique, Namibia, Nicaragua, Panama,
		Peru, Philippines, Uruguay
G4: Major partner	Africa	Burundi, Kenya, Mozambique, Namibia, Swaziland
	Others	Angola, Cabo Verde, Cameroon, Chad, Chile, China, Colombia
		Ecuador, El.Salvador, Ghana, Guatemala, Honduras, Mexico
		Nicaragua, Panama, Peru, Philippines, Rwanda, Uruguay
G5: Continent	Africa	Angola, Burundi, Cabo Verde, Cameroon, Chad, Ghana, Kenya
		Mozambique, Namibia, Rwanda, Swaziland
	Non-Africa	Chile, China, Colombia, Ecuador, El Salvador, Guatemala
		Honduras, Mexico, Nicaragua, Panama, Peru, Philippines, Uruguay
G6: Income	High	Chile, China, Colombia, Ecuador, Mexico, Namibia, Panama
		Peru, Uruguay
	Low	Angola, Burundi, Cabo Verde, Cameroon, Chad, El Salvador
		Ghana, Guatemala, Honduras, Kenya, Mozambique, Nicaragua
		Philippines, Rwanda, Swaziland

Notes: Countries with major partners in Africa are those relying on South Africa, Uganda, and Zambia as the top exporters during the sample period. Countries with low (high) distance have import value weighted average distance during the sample period lower (higher) than 3,490 kilometers, the historical median level. Countries with high (low) low import dependence have average ratio of imports to domestic consumption greater (lower) than 40%, a threshold level for significant price transmission from world market to local market (Ceballos et al., 2016). Countries with low (high) income are categorized into high or upper middle income (low or lower middle income) according to the World Bank.

Table C.3: Robustness tests on the parameter estimations associated with the variable foreign maize yield shocks with alternative choice of k.

	Model 1 (k=2)	Model 2 (k=3)	Model 3 (k=4)	Model 4 (k=5)
†Positive foreign yield shock	-0.35^{***}	-0.45^{***}	-0.35^{***}	-0.34^{***}
	(0.07)	(0.10)	(0.11)	(0.12)
†Negative foreign yield shock	-0.06	-0.05	-0.13^{*}	-0.11^{*}
	(0.07)	(0.07)	(0.07)	(0.06)
†Positive domestic yield shock	0.04	0.05	0.06	0.05
	(0.04)	(0.04)	(0.04)	(0.04)
†Negative domestic yield shock	-0.20^{*}	-0.19^{*}	-0.20^{*}	-0.19^{*}
	(0.10)	(0.10)	(0.10)	(0.10)
Stock change ratio	-0.14^{*}	-0.15^{*}	-0.13	-0.13
	(0.08)	(0.08)	(0.08)	(0.09)
Exchange rate variability	0.08	0.08	0.05	0.05
	(0.12)	(0.12)	(0.11)	(0.11)
Conflict	-0.03^{*}	-0.03^{*}	-0.03^{**}	-0.03^{**}
	(0.02)	(0.01)	(0.02)	(0.01)
Per capita GDP shock	-0.04	-0.06	-0.00	0.00
	(0.20)	(0.18)	(0.16)	(0.16)
County fixed effect	Yes	Yes	Yes	Yes
Market fixed effect	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes
Num. obs.	914	920	923	926
R^2	0.57	0.58	0.57	0.57
Adj. R^2	0.52	0.53	0.52	0.52

Notes: The variables of our key interests are labelled by †. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table C.4: Robustness tests on the parameter estimations associated with the variable foreign yield shocks.

	Model 1	Model 2	Model 3	Model 4	Model 5
†Negative foreign yield shock	-0.08	-0.13	-0.15^{**}	-0.11^{*}	-0.16^{***}
	(0.05)	(0.09)	(0.07)	(0.07)	(0.06)
†Positive foreign yield shock	-0.25^{**}	-0.31^{***}	-0.38^{***}	-0.22^{***}	-0.37^{***}
	(0.12)	(0.11)	(0.12)	(0.06)	(0.1)
Negative domestic yield shock	-0.17	-0.15	-0.18^{*}	-0.20^{*}	-0.19^{*}
	(0.11)	(0.09)	(0.10)	(0.10)	(0.11)
Positive domestic yield shock	0.06	0.01	0.03	0.05	0.05
	(0.06)	(0.05)	(0.03)	(0.04)	(0.04)
Stock change ratio	-0.14^{*}	-0.15^{*}	-0.13^{*}	-0.14^{*}	-0.11
	(0.08)	(0.09)	(0.07)	(0.07)	(0.09)
Exchange rate variability	0.06	0.02	0.03	0.05	0.21
	(0.11)	(0.10)	(0.11)	(0.11)	(0.14)
Conflict	-0.03^{*}	-0.03^{**}	-0.03^{**}	-0.03^{**}	-0.03^{*}
	(0.02)	(0.02)	(0.01)	(0.01)	(0.02)
Per capita GDP shock	0.02	-0.00	0.01	0.04	-0.02
	(0.17)	(0.16)	(0.13)	(0.13)	(0.02)
Food aid ratio					0.00003
					(0.00002)
County fixed effect	Yes	Yes	Yes	Yes	Yes
Market fixed effect	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes
Num. obs.	926	926	932	932	853
R^2	0.56	0.55	0.57	0.57	0.58
Adj. R^2	0.51	0.50	0.52	0.52	0.53

Notes: The variables of our key interests are labelled by †. Model 1 uses quadratic yield trends ($k = 5$); Model 2 uses HP filter with a smoothing parameter of 6.25, another suitable choice for annual data ($k = 5$); Model 3 uses average imports during the sample period as weights, which are static as opposed to dynamic weights, to construct exporter yield shocks. Model 4 uses yield shocks in top exporters only as exporter yield shocks, without using any weight. Model 5 includes the food aid ratio (maize aid divided by domestic maize consumption) in the control variable set. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table C.5: Ordinary least squares regression of intra-annual CV of real monthly maize prices in focus countries on foreign yield shocks with heterogeneous effects across different country groups.

	G1	G2	G3	G4	G5	G6
† Positive foreign yield shock,	-0.26^{**}	-0.39^{**}	-0.07	-0.35^{*}	-0.29^{*}	-0.29^{***}
group 1	(0.11)	(0.17)	(0.09)	(0.21)	(0.16)	(0.10)
† Positive foreign yield shock,	-0.36^{***}	-0.25^{***}	-0.39^{***}	-0.27^{***}	-0.39^{***}	-0.34^{**}
group 2	(0.14)	(0.09)	(0.13)	(0.09)	(0.08)	(0.14)
† Negative foreign yield shock,	-0.17	-0.14	-0.50^{**}	-0.24	-0.20^{*}	-0.08
group 1	(0.12)	(0.09)	(0.24)	(0.15)	(0.11)	(0.07)
† Negative foreign yield shock,	-0.08	-0.06	-0.08	-0.03	-0.02	-0.13^{*}
group 2	(0.08)	(0.08)	(0.07)	(0.08)	(0.06)	(0.08)
Negative domestic yield shock	-0.19^{*}	-0.19^{*}	-0.19^{*}	-0.20^{*}	-0.19^{*}	-0.19^{*}
	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)
Positive domestic yield shock	0.05	0.05	0.05	0.05	0.05	0.05
	(0.04)	(0.04)	(0.03)	(0.04)	(0.04)	(0.04)
Stock change ratio	-0.14	-0.13	-0.13	-0.13	-0.12	-0.13
	(0.09)	(0.08)	(0.08)	(0.08)	(0.08)	(0.09)
Per capita GDP shock	0.00	0.03	0.06	0.01	-0.01	0.01
	(0.17)	(0.17)	(0.17)	(0.17)	(0.17)	(0.17)
Conflict	-0.03^{**}	-0.03^{**}	-0.03^{**}	-0.03^{*}	-0.03^{*}	-0.03^{**}
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Exchange rate variability	0.06	0.03	0.06	0.02	0.06	0.06
	(0.11)	(0.10)	(0.11)	(0.11)	(0.11)	(0.11)
County fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Market fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Num. obs.	926	926	926	926	926	926
R^2	0.57	0.57	0.57	0.57	0.57	0.57
Adj. R^2	0.52	0.52	0.52	0.52	0.52	0.52

Notes: The country groups for columns from "G1" to "G6" are categorized based on: import dependence (group 1: high / group 2: low), distance (group 1: low / group 2: high), connectivity (group 1: landlocked / group 2: coastal), major partners (group 1: Africa / group 2: Others), continent (group 1: Africa / group 2: Non-Africa), and income (group 1: high / group 2: low). Table C.2 lists the countries by each country group. The notation † labels the variables of interest. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table C.6: First-stage regression results.

	No hetero. effect	Hetero. effect
†Beginning stock-to-use ratio	0.64^{***}	0.64^{***}
	(0.09)	(0.09)
Exchange rate variability	0.01	0.00
	(0.12)	(0.12)
Conflict	0.01	0.01
	(0.01)	(0.01)
Per capita GDP shock	-0.25	-0.26^{*}
	(0.16)	(0.15)
Negative domestic yield shock	-0.01	-0.01
	(0.02)	(0.02)
Positive domestic yield shock	-0.01	-0.01
	(0.02)	(0.02)
Negative foreign yield shock	0.03	
	(0.07)	
Positive foreign yield shock	-0.00	
	(0.05)	
Negative foreign yield shock, group1		0.03
		(0.08)
Negative foreign yield shock, group2		0.17
		(0.23)
Positive foreign yield shock, group1		0.01
		(0.05)
Positive foreign yield shock, group2		-0.08
		(0.11)
County fixed effect	Yes	Yes
Market fixed effect	Yes	Yes
Year fixed effect	Yes	Yes
Num. obs.	926	926
R^2	0.49	0.50
Adj. R^2	0.44	0.44

Notes: The dependent variable is stock released relative to domestic consumption. The notation † labels the variable of interest.$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

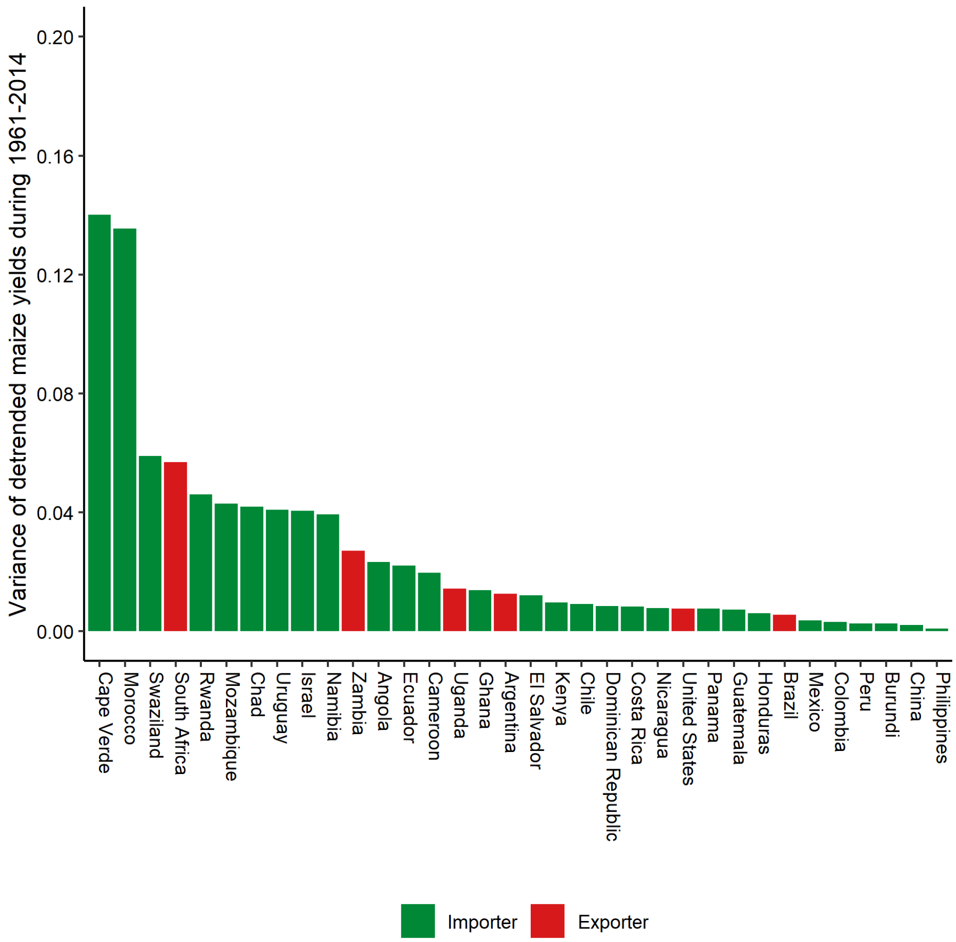

Figure C.1: Comparing maize yield variability between exporters and importers.

Note: Yield variability is measured by variance of maize yield deviation from trends during 1961-2014.

Figure C.2: Distribution of maize imports of focus countries in America and Asia across exporters during 2005-2016.

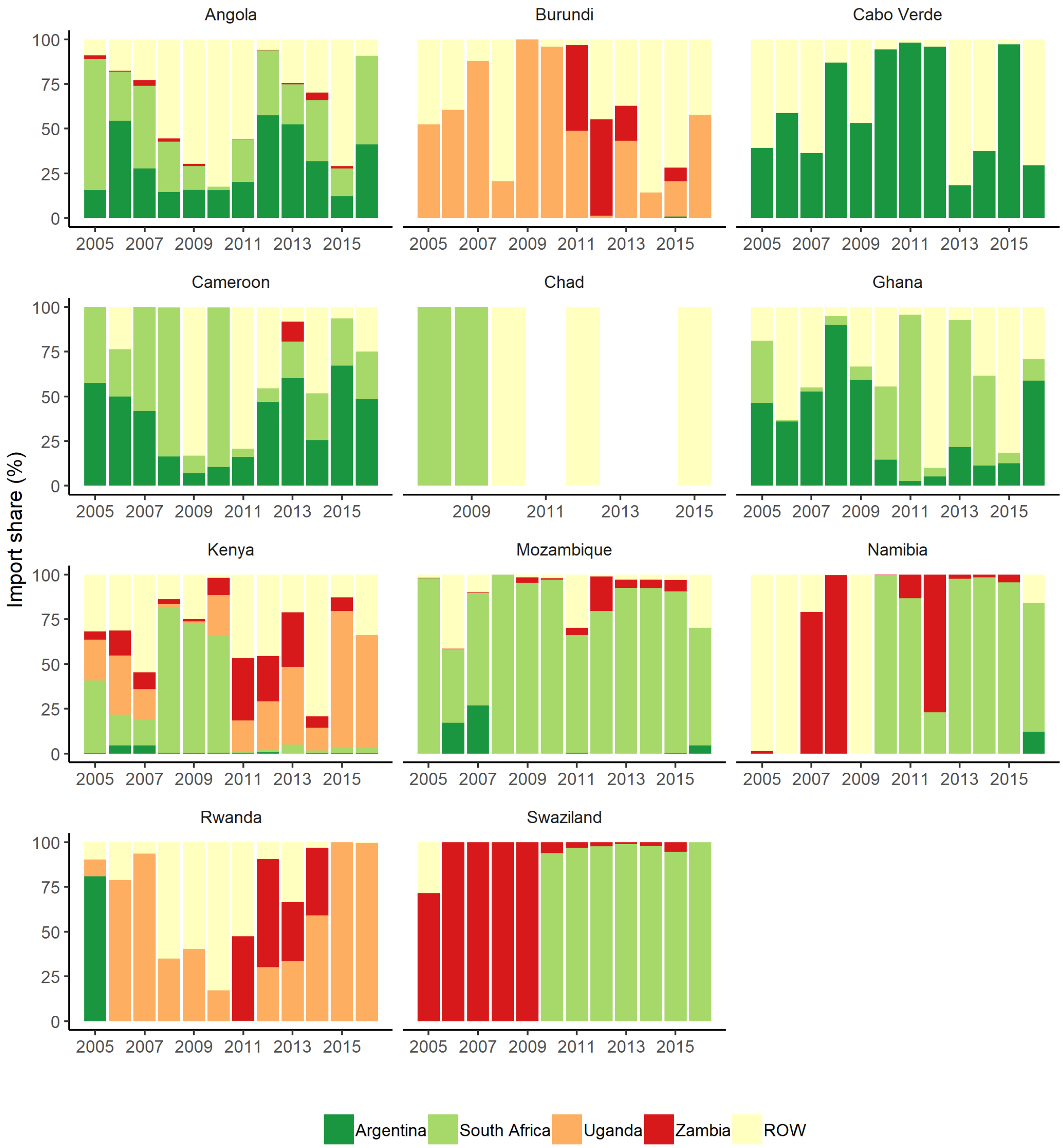

Figure C.3: Distribution of maize imports of focus countries in Africa across exporters during 2005-2016.

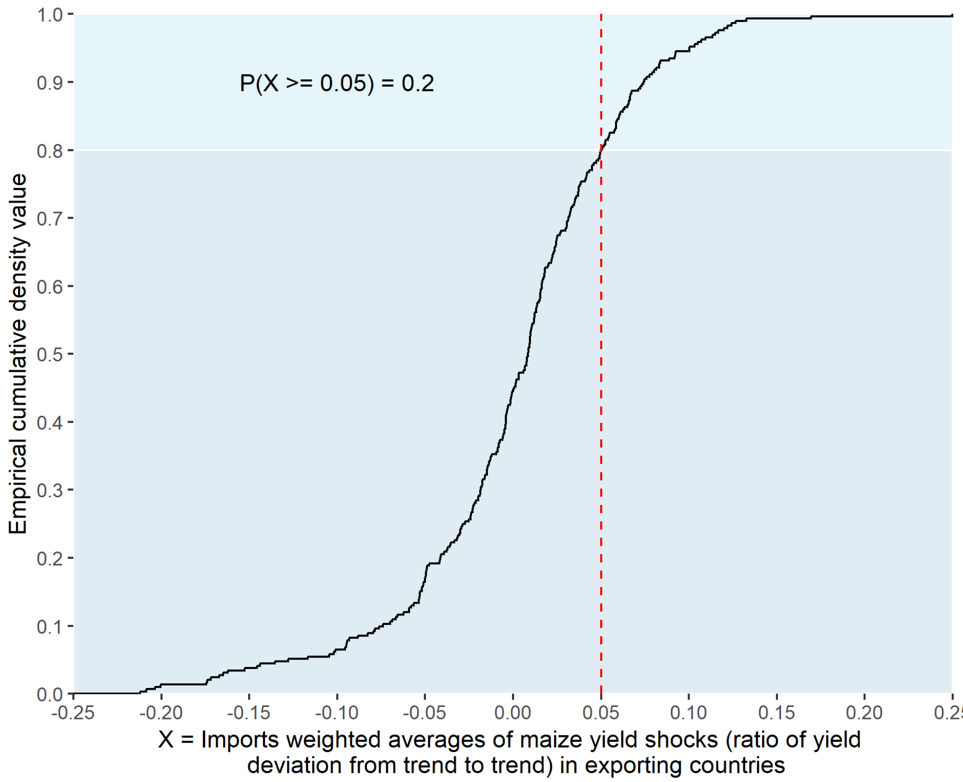

Figure C.4: Empirical cumulative density of foreign maize yield shocks associated with focus countries during 2000-2017.

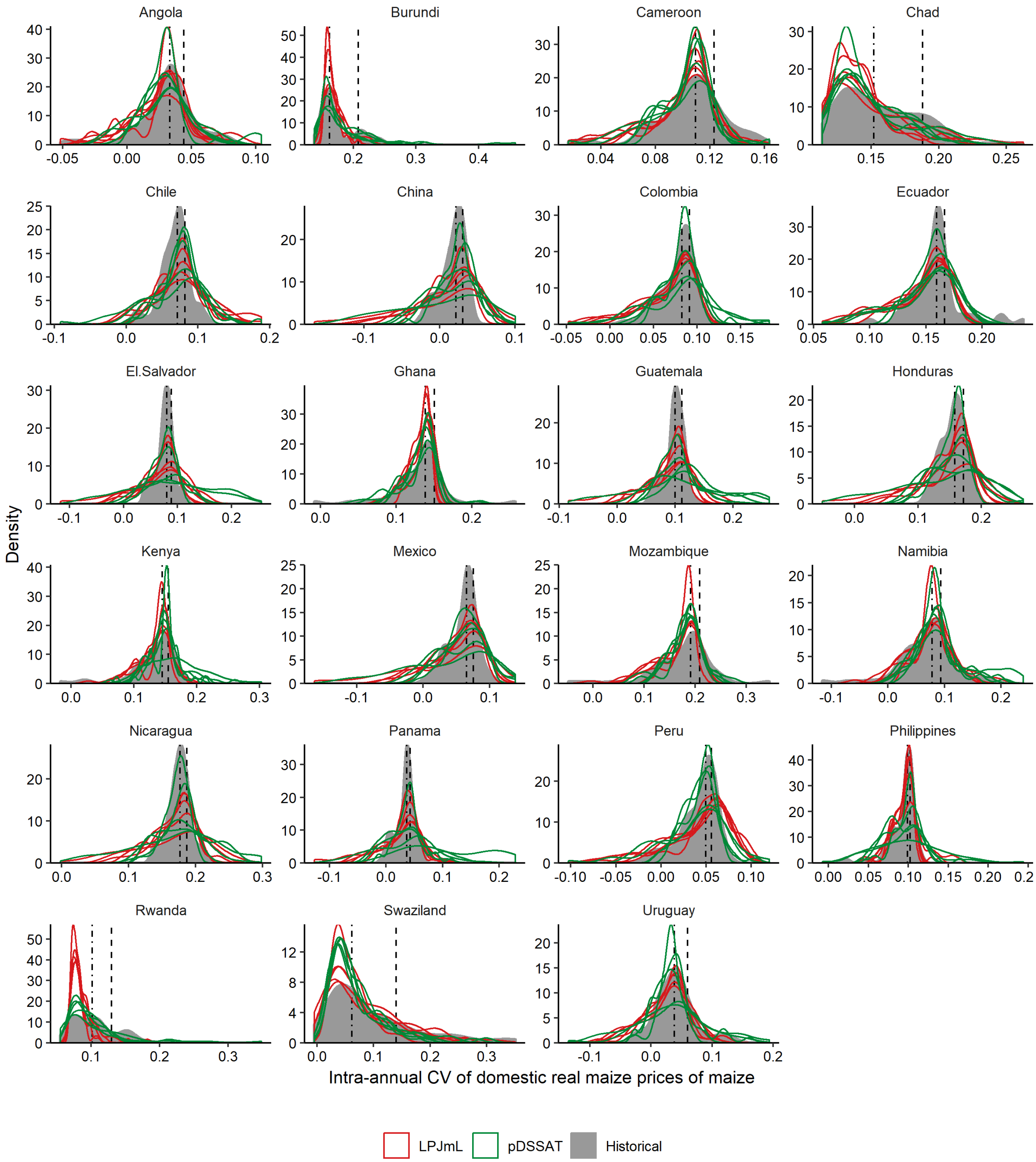

Figure C.5: Distribution of projected intra-annual CV of real monthly prices of maize during 2006-2050 with CO2 fertilization under RCP 8.5 and in historical times.

Note: Results for Cape Verde is not shown for missing its yield projection in the AgMIP-GGCMI archive.

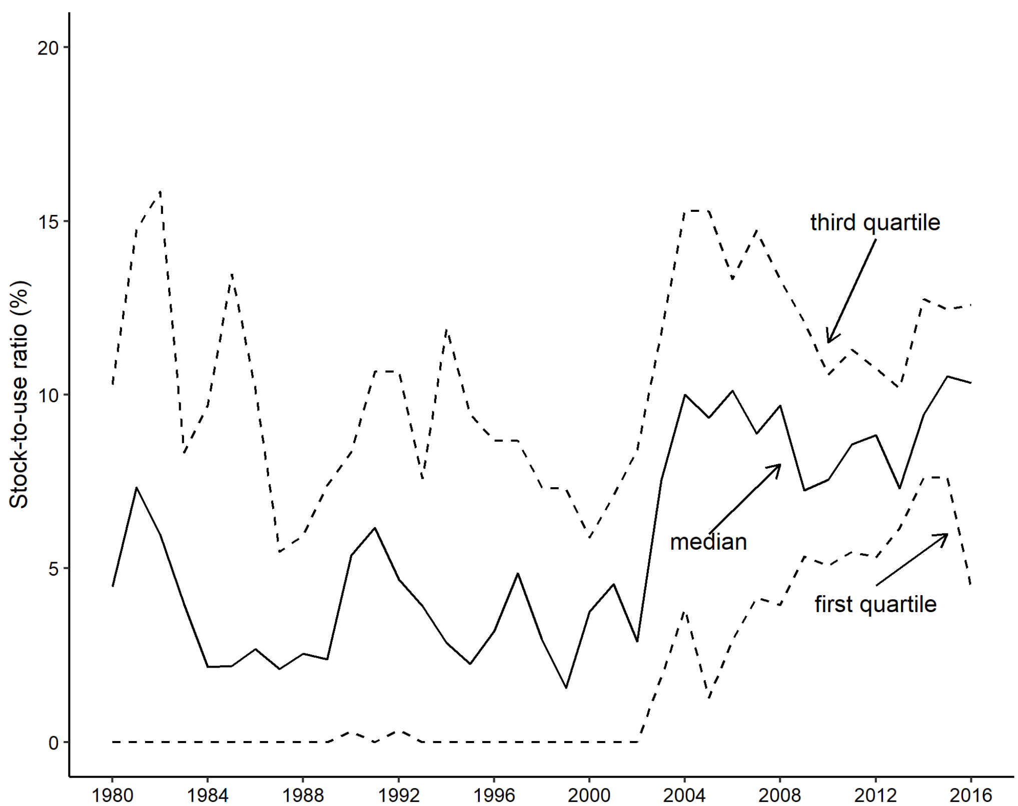

Figure C.6: Historical changes in first quartile, median, and third quartile of maize stock-to-use ratio across focus countries from 1980 to 2016.