Anomalous Weather, Prices and the ‘Missing Middle’

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Abstract

Climate change will increase the frequency of extreme weather events, affecting food systems. How food prices in domestic markets are affected by resulting supply shocks is key to understanding the impacts of climate change on food security. The expectation that supply shocks translate to higher consumer prices may, however, not hold true even for commodities that see minimal processing from farm to plate, and where markets deviate from perfect competition. Focussing on the UK banana market, we show that anomalous weather patterns in exporting countries result in effectively zero price transmission to consumers, while wholesale prices see considerable fluctuation. But anomalous weather in exporting countries affects the spread between wholesale and retail prices suggesting that shocks are absorbed by the supply chain - ‘the missing middle’. Our findings highlight placing equal emphasis on understanding how firms in this ‘missing middle’ will adapt to, and absorb the impact of, climate shocks.

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Climate change will increase the frequency of extreme weather events, affecting food systems. How food prices in domestic markets are affected by resulting supply shocks is key to understanding the impacts of climate change on food security. The expectation that supply shocks translate to higher consumer prices may, however, not hold true even for commodities that see minimal processing from farm to plate, and where markets deviate from perfect competition. Focussing on the UK banana market, we show that anomalous weather patterns in exporting countries result in effectively zero price transmission to consumers, while wholesale prices see considerable fluctuation. But anomalous weather in exporting countries affects the spread between wholesale and retail prices suggesting that shocks are absorbed by the supply chain - ‘the missing middle’. Our findings highlight placing equal emphasis on understanding how firms in this ‘missing middle’ will adapt to, and absorb the impact of, climate shocks. *(150 words)*

Introduction

Climate change and modified weather patterns have widely been shown to impact agricultural production, including that of many globally traded agricultural commodities (Lobell *et al.* 2012; Challinor *et al.* 2014; Rosenzweig *et al.* 2014, Iizumi *et al.* 2014). By extension, commodity prices are also expected to be affected, with direct consequences for food and nutritional security. Empirical evidence on the effect of climatic phenomena on commodity prices has recently emerged with measures of anomalous weather patterns typically being measured by data on the El Niño-Southern Oscillation (ENSO). For example, studies have successfully identified ENSO anomalies as an important driver of world prices for a number of agricultural commodities, though effects often varied by commodity (Brunner 2002; Cashin *et al*. 2017; Ubiliva 2017). These approaches to identifying the responses of commodity prices to climate fluctuations are complemented by Guittarez (2017), who employed an econometric framework that accounts for the effect of ENSO intensity on wheat yields and prices amongst the main exporters of wheat.

The sensitivity of world agricultural prices to climate fluctuations implies that consumer prices in importing countries should, in principle, also respond and reflect the share of the raw commodity in the final retail price. As such, prices can have an important function in communicating information and signalling demand and supply shocks in markets. Prices can therefore play a role in determining how consumers respond to climate change. However, this role for prices may only apply to the fullest extent if domestic value chains are perfectly competitive at all stages of the value chain. Deviation from the textbook framework of competitive markets can result from intermediary and retail firms that link producers and consumers absorbing some of these price shocks, and hence affecting the role of prices as a source of information and resource allocation (Weyl and Fabinger 2013). While previous empirical research has reported less than perfect price transmission in food markets (Lloyd 2017) it has, however, been limited in rationalising these observations and identifying the role of intermediary firms, nor appropriately controlled for explicit exogenous shocks in deriving price transmission effects. Hence, we may term the intermediary firms which link producers to consumers the ‘missing middle’, as their role in price transmission is poorly understood.

Here, we use the UK banana market to investigate the role of the missing middle. Bananas are a globally traded commodity that see very little modification from production to retail; this aids the assessment of the price transmission impact as there is no transformation of the product at the farm through to the retail level. But the banana value chain is complex involving multinationals from production to distribution and highly concentrated food retail sectors (i.e. where the retail stage is dominated by a small number of retail chains). Using an econometric framework to analyse compiled data on banana world, UK wholesale and UK retail prices, we determine the extent to which price transmission occurs across different levels of the value chain, and identify where in the chain price shocks are being absorbed. To understand and quantify how climate change could influence price transmission, we then incorporate weather variation into our analyses. We utilise a global aggregate measure of weather variability, i.e. ENSO anomalies, that is commonly used in economic analyses of climate and agricultural commodity markets and further, compare it to results obtained using more precise exporter country specific weather data. The results presented below therefore offers new perspectives on how food value chains absorb shocks and offers important insights for assessing the impact of climate change events.

UK banana market: world-wholesale-retail price relationship

Globally, bananas are the most traded fruit (FAO, 2016), with exports accounting for 15% of total production (FAO 2020). As a commodity, bananas are essentially unchanged from plantations in exporting countries to retail markets in importing countries. In the UK, bananas are largely sourced from a handful of developing countries, primarily in Latin America and the Caribbean, but also a few nations in Africa and, occasionally, the Philippines. As such, so-called ‘world’ prices (the price of Ecuadorian bananas landing in New York) are not necessarily representative and may not equate directly with import prices in specific national markets that are affected by country-specific trade costs of transportation, distribution, trade policy and the extent of competition between distributors and retailers.

Compiling ‘world’ banana prices, as well as UK wholesale and retail prices between 1998-2016 reveal interesting patterns (figure 1a), with noticeable differences between the three price series for an identical commodity. World commodity prices are generally characterised by volatility (Gilbert and Morgan 2010); the world banana price exhibits this characteristic volatility and also exhibits a general upward trend since 2008. The UK wholesale price shows greater volatility even during periods of relatively stable world prices. However, retail banana prices are very different from both the wholesale and world prices, showing much less volatility. The coefficients of variation for world, UK wholesale and UK retail prices are 0.3654, 0.2069 and 0.0964 respectively, over the time series. Importantly, retail prices have remained more or less unchanged over the last few years of data coverage in the face of variability in both UK wholesale price and world market conditions. Given that bananas undergo minimal transformation, this implies a departure from the textbook model of commodity markets, where price changes for producers and consumers are assumed to be 1:1. In turn, this has an implication for how we consider the impact of production shocks, such as those from climate change and weather events, on consumers.

Economic theory points to issues surrounding competition and characteristics of value chains as the principal potential reason for low price transmission to consumers (McCorriston *et al*., 1998); a low share of the raw commodity in the final retail product will result in low price transmission. Even for commodities with minimal processing between the production and retail stages of value chains, low price transmission can also arise when competition is limited i.e. where there are a relatively small number of competing firms at and or all stages of the value chain. For bananas in the UK, while the commodity itself undergoes minimal modification from production to consumption, its procurement and distribution is complex, and hinges on the roles of multinational (in some cases, vertically integrated) firms and a limited number of firms competing at the retail stage. Although the role of multinationals in world banana trade has reduced in recent years, the UK retail sector is highly concentrated, with five retail chains accounting for the large majority (around 70 per cent) of food sales in the country (Competition Commission, 2000). Retailers have also increasingly played a role in procurement via direct contracting with suppliers in exporting countries. These features characterise the complexity of the banana value chain as we have a retail sector dominated by a few retail chains together with a small number of multinationals at the intermediate stage. In principle, this could lead to 'double marginalisation' with mark-ups, or in other words, prices in excess of marginal cost (i.e. costs that depend on the level of sales) beyond the competitive benchmark (prices equal to marginal cost) at each stage of the value chain.

The significance of this for price transmission is that the mark-ups of firms in the value chain may adjust to absorb the impact of exogenous shocks and, in turn, affecting the extent to which the price impacts of exogenous shocks are passed through to consumers. Specifically, if factors relating to competition matter for price adjustment, then when shocks impact on a specific market, low price transmission to consumers would imply that the 'spread', or difference, between prices at different levels would adjust; if competition prevailed throughout the value chain, the spread between prices at different levels would be constant given perfect price transmission. But the feature of less than perfect competition with low price transmission, firms in the intervening stages in the value chain ameliorate the effect of shocks by adjusting margins, and not pass the full effect of shocks on to consumers. In this context, we note a relatively volatile pattern when examining the change in the spread between UK banana retail and wholesale prices between 1998-2016 (figure 1b). Indeed, given that retail prices do not change that much, the spread is more volatile than either of the price series (also see supplementary figure S1). The data suggests low price transmission to consumers (further demonstrated by econometric methods below) and that changes in wholesale prices are overwhelmingly accommodated by changes in the spread. These results further imply that if we are looking for effects of climate phenomena on banana markets, then changes in price spread should be the focus of investigation, and that the 'missing middle' in the value chain (i.e. firms that account for the links between producers and consumers), to a large extent, absorbs the effects of anomalous weather.

Estimating price transmission

While the casual inspection of the price data in figure 1 already suggests some deviation from the textbook model of food markets (i.e. where price changes are equal at the producer and consumer stages) we nevertheless formally explored the links between prices at different levels using impulse response methods. Further, we characterised the temporal signature of price transmission, i.e. how price transmission may propagate and persist over time in the market, by employing local projection methods (Jordà, 2005, 2009), an efficient way to measure the impact of change in one variable (e.g. world banana prices) on another variable (e.g. UK wholesale banana prices) while accounting for other factors (e.g. costs in the value chain that may impact on the retail price) that may influence the relationship between the focal variables. These methods quantified price transmission from changes in world prices to UK wholesale prices, and from UK wholesale prices to UK retail prices.

Our results show that UK wholesale markets respond relatively strongly, but imperfectly, to changes in world banana prices (figure 2). The econometric model allows for lags in the price adjustment process so that the price transmission effect is traced over time. For example, our analysis reveals that a 10% change in world prices, which captures factors that determine supply and demand in the main producing and consuming countries, translates to a 4.3% (95% confidence intervals = +/- 1.0%) and 2.5% (95% CIs = +/- 1.2%) change in UK wholesale prices six and 12 months from when world prices changed, respectively. On the other hand, the impulse response for the UK wholesale prices on retail prices is almost non-existent (figure 2), indicating very low price transmission from wholesale to retail prices. These latter results are important: consumer prices are not adjusting to price changes occurring at other stages in the banana value chain. As noted above, with the existence of less than perfect competition in value chains, with low price transmission, it is potentially the mark-ups that are changing to absorb price changes that would otherwise occur at the retail stage. This turns attention to the impact of supply shocks on price spreads between stages in the banana value chain.

In summary, the results relating to price transmission between different stages in the value chain quantitatively corroborate patterns observed directly from the price data, that intermediary firms in the banana value chain may be absorbing a substantial portion of price volatility. It re-emphasises that for bananas, changes in price spread between wholesale and retail prices, a proxy for mark-up elasticity (i.e. the responsiveness of firm mark-ups in response to shocks), should be the focal response variable when assessing production shocks. The impulse response method we have applied here provides a suitable quantitative framework within which to assess these effects.

Impact of anomalous weather patterns on the 'missing middle'

Fluctuations in the El Nino Southern Oscillation (ENSO) index is a commonly used proxy that captures weather variability in the econometric modelling of climate impacts on commodity markets (e.g. Cashin *et al*. 2017; Ubiliva 2017). ENSO is an aperiodic cycle of ocean and atmospheric currents across the equatorial Pacific ocean with wide ranging teleconnections to global weather systems and crop production (Iizumi *et al* 2014).Hence, we incorporated ENSO anomalies in our local projection methods to assess the role of the 'missing middle' in ameliorating the effects of anomalous weather on consumers via changes in price spread. Consistent with economic theory, we would expect the change in spread to be negatively related to anomalous weather fluctuations (i.e. as upstream prices change, retail prices change by less); specifically, consistent with low price transmission, the margin between prices absorbs a degree of the supply side shock that would otherwise be reflected in price changes (Weyl and Fabinger 2013). These analyses controlled for extraneous factors that could influence responses, including world prices (reflecting global supply and demand conditions) and other manufacturing costs relevant to the retail and distribution sectors of the food chain.

Our results show that anomalous weather patterns have a substantial influence on the spread between UK banana wholesale and retail prices. A single-period increase in the ENSO anomalies lead to a marked decline in price spread, and this change was sustained over a period of time (figure 3a). As an example, our analyses indicate that a 1 SD or 0.89 increase in ENSO anomaly is associated with a 10.1% (95% CI = +/- 6.1%) and 21% (95% CI = 6.6%) decline in price spread six and 12 months from the event, respectively.

The attraction of using ENSO anomaly data is that it is easily accessible, and therefore, serves as a useful proxy for weather patterns that can be used to gauge effects on commodity markets. However, as an aggregate global metric, it translates to a variety of weather outcomes across the world (Dai and Wigley 2000; Holmgren *et al.* 2001; Larkin and Harrison 2005). Hence, it may not be precise enough when assessing weather effects on specific commodity markets and/or for a subset of countries within a global import-export network of a commodity. Further, specifically for bananas, previous research has shown that changing climate can have a variety of country-specific effects on productivity (Varma and Bebber 2019). The ENSO anomaly data does not capture this phenomenon. Hence, there is a need to incorporate producer country specific weather data in models for a robust assessment.

To address this issue, we use temperature and precipitation data that applies directly to banana growing areas in countries that export to the UK. We constructed measures of anomalous variation in temperature and precipitation for each banana exporter (supplementary figures S2 and S3), which were then averaged across exporter countries. To ensure these weather anomaly data are more pertinent to the UK, the averaging of anomalies was weighted by exporter country share to the UK market. These weighted anomalies for temperature and precipitation substituted ENSO anomaly data in separate local projections.

Consistent with the results from our analysis using measures of ENSO anomalies, exporter country temperature anomalies also reduce price spread (figure 3b). In fact, the price spread is highly elastic and responsive to temperature anomalies, and results show that a 1 SD (0.37°C) increase in temperature leads to a 6.8% (95% CI = +/- 6.84%) and 20.35% (95% CI = +/- 7.05%) reduction in spread six and 12 months from the time of the temperature anomaly, respectively. Again, this suggests that the effect of climatic variation is being absorbed by changes in the spread, and is in line with expectations, given the near constancy of banana retail prices over time. Precipitation anomalies, on the other hand, had very little influence on the spread (figure 3c). This is not an unexpected finding as, compared to changes in temperature, changes in precipitation patterns can be mitigated against to a greater degree during production (e.g. greater use of irrigation during drier than average periods, farm drainage infrastructure to mitigate against minor local flooding, etc.). Indeed, a recent global analysis reported that changes in temperature, rather than precipitation, over the past few decades has been a stronger driver of change in banana yields (Varma and Bebber 2019).

Although our results focus on anomalous weather patterns and the UK banana value chain, there are a number of more general implications that arise from this. First, observing retail banana prices in other major consuming countries suggest prices at the retail level are less volatile than ‘world’ prices indicating that the price dynamics for the UK are not unusual (Supplementary figure S4). Given that concerns about concentration (i.e. competition between a limited number of firms) in retail and intermediary stages of food chains are general (McCorriston 2014), it suggests that the insights we provide will readily extend beyond the UK. Second, the insights will extend to other commodity sectors particularly where there is low, or no processing between the commodity that is produced in the exporting country to what appears on retail shelves. This is particularly relevant to fresh fruit and vegetables, which are key to healthy diets but may be particularly vulnerable to climate change (Springmann *et al*. 2016). The minimal degree of processing that applies in this case, and the control for other factors that may impact on price transmission, allows us to infer that the role of the structure of the value chain is influencing the extent of price transmission. More generally, low price transmission appears to characterise food markets (Lloyd 2017), though what we identify here is the extent to which it affects the ‘missing middle’ where most of the adjustment to climate shocks is being absorbed; this is likely to be an important source of low price transmission in other commodity-food value chains. Finally, given the increasing concerns with climate change and extreme events, our research has shown that measures of anomalous weather patterns in exporting countries will give a more fine-grained characterisation of weather shocks and how they will affect value chains and ultimately consumers. In sum, although our analysis is bespoke to one value chain for a specific importing country, the insights are more general with important policy implications: the role of the 'missing middle' matters in determining how climate change events will be transmitted into price changes facing consumers.

Conclusion

Our analyses point to the importance of firms in value chains that link producers and consumers, or the 'missing middle', in addressing how climate change will affect food markets. Prices of commodities on the so-called 'world' markets can behave quite differently from prices in national markets, particularly at the retail level, even when the product itself is more or less physically identical between the production and retail stages of the supply chain. With reference to the UK banana market, we have shown that retail prices are more or less unrelated to prices in wholesale markets. In this setting, the impact of anomalous weather fluctuations is manifested as adjustments in mark-ups, or the spread between wholesale and retail prices. This is consistent with the main mechanism underlying low price transmission that arises from theoretical approaches to price transmission in imperfectly competitive markets, and will likely generalise to other commodities and national markets which share similar characteristics (i.e. where competition at stages of value chains is limited to a small number of competing firms).

Using data specific to the countries that export to the UK, we have shown that climate phenomena can significantly affect price spreads. We infer three key insights from our results. First, it is not just that price spread adjusts in response to weather anomalies, but the extent of this adjustment. Mark-ups are potentially highly responsive in the face of exogenous shocks such as anomalous weather patterns and are tied directly to the lack of price transmission in the value chain. Second, adjustments in price spread are more strongly driven by temperature anomalies, rather than precipitation anomalies. Third, there are considerable benefits of using more accurate and geographically targeted temperature and precipitation data for such assessments. Depending on global aggregate indicators, such as ENSO anomalies, though of qualitative use, are likely to overestimate (or in some cases, underestimate) the impact of anomalous weather fluctuations on firms in the value chain.

Intermediary firms play a role in ameliorating the impacts of price effects on consumers due to weather variability and climate phenomena. This also implies a substantially dampened signal to consumers of climate risks to their everyday food needs. But this points to another issue: if consumers are being shielded from the price impacts of climate shocks, how resilient are supply chains given the expected extents of climate modification weather variability that will occur over time (Hoegh-Guldberg *et al.* 2018). If intermediary firms are absorbing shocks, this will have implications for the structure and, by extension, competition in the value chain in the longer run. Resilience in value chains relates not only to producers and consumers at either end but also how firms can sustainably cope with these shocks if not being shared with consumers. Therefore, formulating effective policy for food security relies on gauging the full spectrum of climate impacts on food commodity value chains, and relies on understanding the role of the 'missing middle'.

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Figures

Figure 1. Time series of banana prices: (a) World (black), UK wholesale (yellow) and UK retail prices (blue) for bananas recorded between 1998 and 2016. World and UK wholesale prices show a consistent upward trend over time, with greater volatility in the UK wholesale price. Retail prices show a declining trend, relatively lower volatility, and remain relatively constant from 2012. This has resulted in declining retail-wholesale price spread (b) along with high volatility.

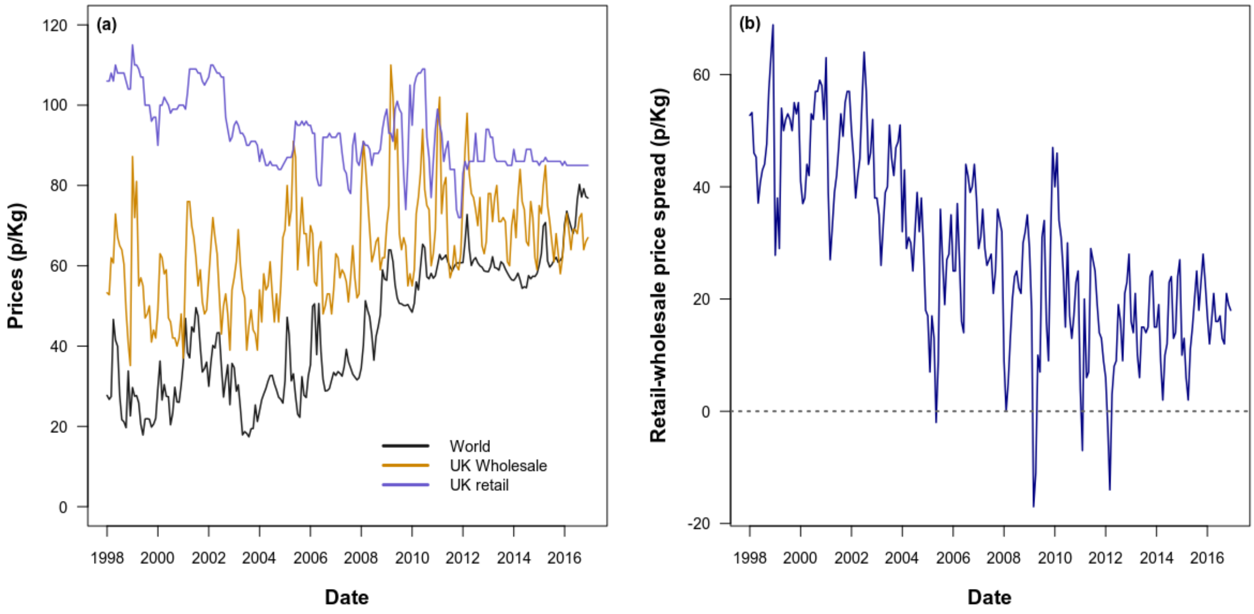


Figure 2. Magnitude of price transmission at different levels of the UK banana market: estimates from local projection models show relatively large price transmission of changes in banana world prices on UK wholesale banana prices (blue) compared to price transmission from changes in UK wholesale prices to UK retail prices. Bands around solid lines represent 95% confidence intervals.

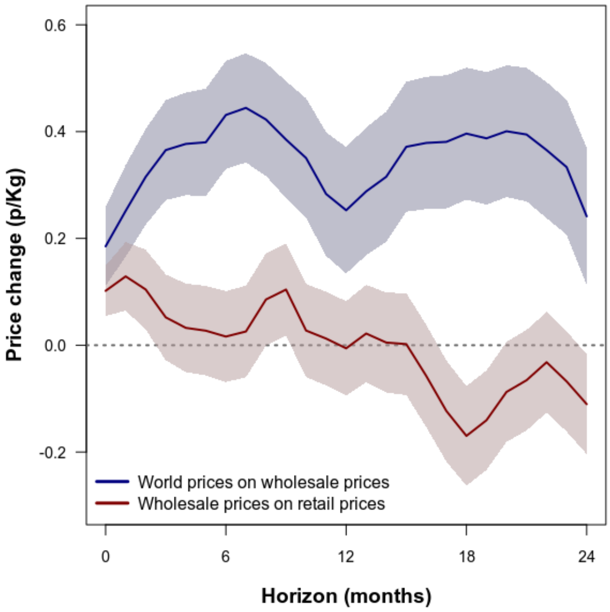
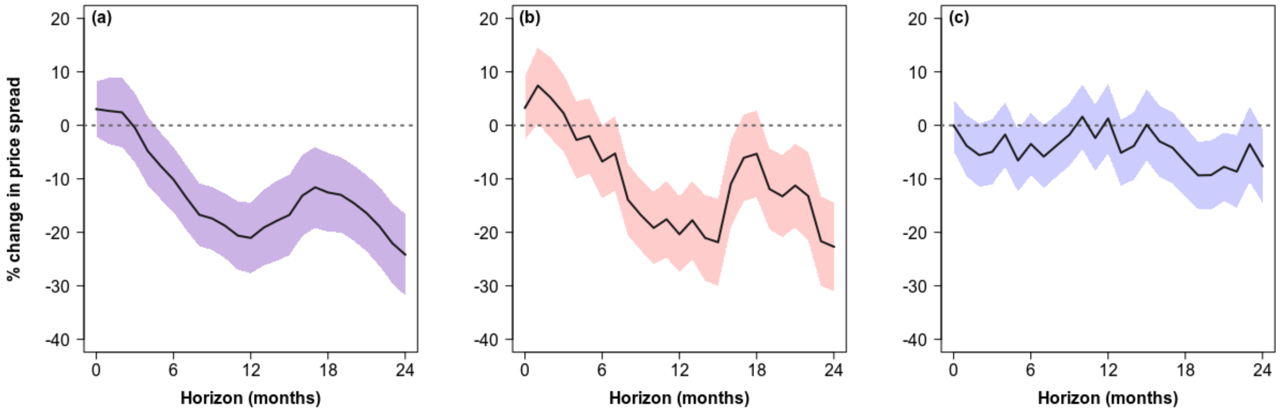


Figure 3. Impact of weather anomalies on banana retail-wholesale price spread in the UK: percent change in the difference between retail and wholesale prices as a result of a 1 standard deviation change in ENSO anomaly index (a; 0.89), temperature anomaly (b; 0.37°C) and precipitation anomaly (c; 37.5 mm). Anomalies for temperature (b) and precipitation (c) are aggregated across exporter countries, while ENSO anomalies (a) are a global aggregate measure. The shaded bands around the solid lines represent 95% confidence interval bounds.



Methods

Banana price data. This study uses monthly series of the world price, UK wholesale price, and UK retail price for the banana market from 1998 to 2016. World banana prices (represented by the price of Ecuadorian bananas in New York) were sourced from the UN Food and Agriculture Organisation (FAO) (http://www.fao.org/economic/est/est-commodities/bananas/banana-prices/en/). UK wholesale prices give the price of bananas directly imported from the main suppliers to the UK and are available from UK's Department for Environment, Food and Rural Affairs (DEFRA) (https://www.gov.uk/government/statistical-data-sets/banana-prices). UK retail prices represent the average price of bananas per kg and are available from the UK's Office for National Statistics (ONS) (https://www.ons.gov.uk/economy/inflationandpriceindices/timeseries/czmv/mm23).

ENSO anomalies data. The El Nino Southern Oscillation (ENSO) index is one of the most popular metrics used to describe large scale fluctuations in weather patterns. The ENSO anomaly is derived from the deviation between the sea surface temperature in the central and eastern tropical Pacific Ocean. ENSO anomaly data was sourced from the National Oceanic and Atmospheric Administration (NOAA) (ENSO Index Dashboard: NOAA Physical Sciences Laboratory),

Producer/Exporter country temperature and precipitation anomaly data. Data on monthly temperature and precipitation from 1996 to 2016 for each country that exports bananas to the UK (i.e. Colombia, the Dominican Republic, Costa Rica, Ecuador, Belize, Cote d'Ivoire and Cameroon) were extracted from the CRU TS v.4.01 product (Harris et al. 2014; https://crudata.uea.ac.uk/cru/data/hrg/). Data extraction and an elevation-based correction of temperature specific to banana production areas were performed according to Varma and Bebber (2019). These data were used to calculate the month-wise average temperatures and precipitation for each month and for each exporting country. Observed deviations from the corresponding monthly averages represented country-specific monthly anomalies. The monthly temperature and precipitation anomalies were then separately aggregated across the exporting countries weighted by each country's share of the UK market to derive a single series for temperature and precipitation anomalies. Country-specific exports to the UK were sourced from the World Integrated Trade Solution database accessed from the World Bank. (World Integrated Trade Solution UN COMTRADE (WITS-UN COMTRADE) | Data Catalog (worldbank.org)). These weights were derived from the exports for each country relative to total exports for this group of countries, with the weights relating to 2011; the results are invariant to the year of weighting. Further analyses used the 1998 to 2016 subset of the processed climate data.

U.K. manufacturing input costs data. UK manufacturing input costs including fuel and raw materials (excluding wages and salaries of labour), controlled for other costs determining retail prices, and was sourced from the UK's Office for National Statistics (ONS; https://www.ons.gov.uk/economy/inflationandpriceindices/bulletins/producerpriceinflation/july2018)

Estimating price transmission: impulse response functions by local projection. To estimate the dynamic effects of shocks in world prices on UK wholesale prices, and shocks of UK wholesale prices on retail prices (reported in Figure 2), as well as shocks to the weather variables on the prices and the (retail–wholesale) price spread (reported in Figures 3), impulse response functions were calculated using the local projection technique pioneered by Jordà (2005, 2009). This involves estimating (or projecting), sequentially, a set of regressions comprising the information set available at time t, H periods into the future. Assuming that $y_t \equiv (y_{1t}, \ y_{2t,} \dots, y_{Kt})'$ and the information set contains p lags of y_t we have:

$$y_{t+h} = \alpha^s + B_1^h y_t + B_2^h y_{t-1} + \cdots B_p^h y_{t-p} + \mu_{t+h}, h = 1,2, \cdots, H \quad (1)$$

Here, the same set of lagged variables are used to predict the value of y_t $h = 1,2, \cdots, H$ periods ahead, meaning there are H separate models, each containing K equations (so the superscripts in equation (1) denote the horizon being considered rather than powers). Attention focuses on the $(K \times K)$ matrix of autoregressive coefficients B_1^h, $h = 1,2, \dots, H$. As is evident from equation (1), B_1^h, contain coefficients that measure the effect of changes in y_t on y_{t+h}, conditional on the information set available. As Jordà (2005) formally shows, this matrix contains coefficients that comprise the impulse response functions.

Direct estimation of these coefficients via equation (1) has several attractive properties, giving rise to the increasing popularity of local projection in the recent macro-econometrics literature (see, *inter alia*, Ronayne 2011; Brugnolini 2018). Most notably, the need to estimate and invert a Vector Autoregression (VAR) using the Wold decomposition in the usual two-step process is circumvented, since the coefficients of interest are estimated directly in equation (1). In cases where the VAR does not exist or offers a poor approximation to the data generating process, misspecification errors are compounded when obtaining the vector moving average (VMA) representation, giving rise to bias in the impulse response function as the horizon grows. Local projection is also simple to employ, since the impulse response for the j^{th} variable in y_t can be estimated by univariate regression of y_{jt+h} on lags of itself and other variables in the information set. A few other considerations are noteworthy. First, as Jordà (2005) shows, the regression errors μ_{t+h} from the projection in equation (1) are VMA of order h, implying that the use of a robust estimator of the variance covariance, such as the heteroscedasticity and autocorrelation consistent (HAC) estimator of Newey and West (1987) and Andrews (1991) is preferable to least squares. This practice is adopted here to calculate the confidence intervals displayed in the figures.

Second, as with all dynamic models, lag length selection is not an innocuous choice, although here too local projection tends to fair better in small samples than the alternative based on a VAR (see Brugnolini, 2018) owing to the direct estimation of an impulses response function. In the empirical analysis here, we select lag length based on AIC.

Effect of world price shocks on UK wholesale prices

The impulse response methods described above estimate the impact of world price shocks on UK wholesale prices, as given by:

$$p^{ws}_{t+h} = \alpha_h + \theta_h shock^{\wp}_t + \sum_{j=1}^{J} \beta_{j,h}\left(w_{t+1-j} - w_{t-j}\right) + u_{t+h}$$

where p^{ws}_{t+h} is the wholesale price at time t+h, and the $shock^{\wp}_t$ is the world price shock. The control variables w denotes the manufacturing costs in the U.K., and includes 6 lags (J=6). u_{t+h} is the prediction error term with $Var(u_{t+h}) = \sigma^2_{t+h}$. θ_h indicates the response of wholesale price to world price shocks at h-step ahead.

Impulse responses of retail prices to wholesale price shocks (Fig 2) is given by:

$$p^{rp}_{t+h} = \alpha_h + \vartheta_h shock^{ws}_t + \sum_{j=1}^{J} \beta_{j,h}\left(w_{t+1-j} - w_{t-j}\right) + \epsilon_{t+h}$$

where p^{rp}_{t+h} is the retail price at time *t+h*, and the $shock^{ws}_t$ is the wholesale price shock. The control variables w denotes the manufacturing costs in the U.K., and it include 6 lags (J=6). $\epsilon_{t+h}$is the prediction error term. ϑ_h indicates the response of wholesale price to world price shocks at h-step ahead.

Effect of anomalous weather shocks on the retail-wholesale price spread (Fig 3):

The impulse response methods are used to estimate the effect of anomalous weather shocks on the retail-wholesale price spread. Figure 3 relates to alternative features of the anomalous weather shocks as detailed below:

Impact of ENSO anomaly on wholesale-retail price spread:

$$p^{sp}_{t+h} = \alpha_{1,h} + \vartheta_{1,h} shock^{ENSO}_t + \sum_{j=1}^{J} \beta_{1,j,h}\left(w_{t+1-j} - w_{t-j}\right) + \sum_{j=1}^{J} \gamma_{1,j,h}\left(p^{\wp}_{t+1-j} - p^{\wp}_{t-j}\right) + \epsilon^1_{t+h}$$

Impact of temperature anomaly on wholesale-retail price spread:

$$p^{sp}_{t+h} = \alpha_{1,h} + \vartheta_{2,h} shock^{TEMP}_t + \sum_{j=1}^{J} \beta_{2,j,h}\left(w_{t+1-j} - w_{t-j}\right) + \sum_{j=1}^{J} \gamma_{2,j,h}\left(p^{\wp}_{t+1-j} - p^{\wp}_{t-j}\right) + \epsilon^2_{t+h}$$

Impact of precipitation anomaly of wholesale-retail price spread:

$$p_{t+h}^{sp} = \alpha_{2,h} + \vartheta_{3,h} shock_t \ + \sum_{j=1}^{J} \beta_{3,j,h}(w_{t+1-j} - w_{t-j}) + \sum_{j=1}^{J} \gamma_{3,j,h}(p_{t+1-j}^{\wp} - p_{t-j}^{\wp}) + \epsilon_{t+h}^{3}$$

where p_{t+h}^{sp} is the wholesale and retail price spread at time t+h. The $shock_t^{ENSO}$, $shock_t^{TEMP}$ and $shock_t$ represent the ENSO anomalies shocks, temperature anomalies shocks, and precipitation anomalies shocks, respectively. $\theta_{1,h}$, $\theta_{2,h}$ and $\theta_{3,h}$ indicate the response of price spreads to ENSO anomalies shocks, temperature anomalies shocks, and precipitation anomalies shocks at h-step ahead, respectively. w_t are other manufacturing input costs in the value chain that may also impact on the price spread. For our analyses, we imposed a shock representing one standard deviation change in the ENSO, temperature and precipitation anomalies, and the effect relates to the corresponding percentage change in the price spread following these shocks. $p_t^{\wp}$, are world banana prices that control for global shocks to the UK banana value chain.

Data availability

All data used are publicly available and open access. All banana data, climatic and topographic data sources are listed in the Methods.

References (Methods)

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Supplementary material

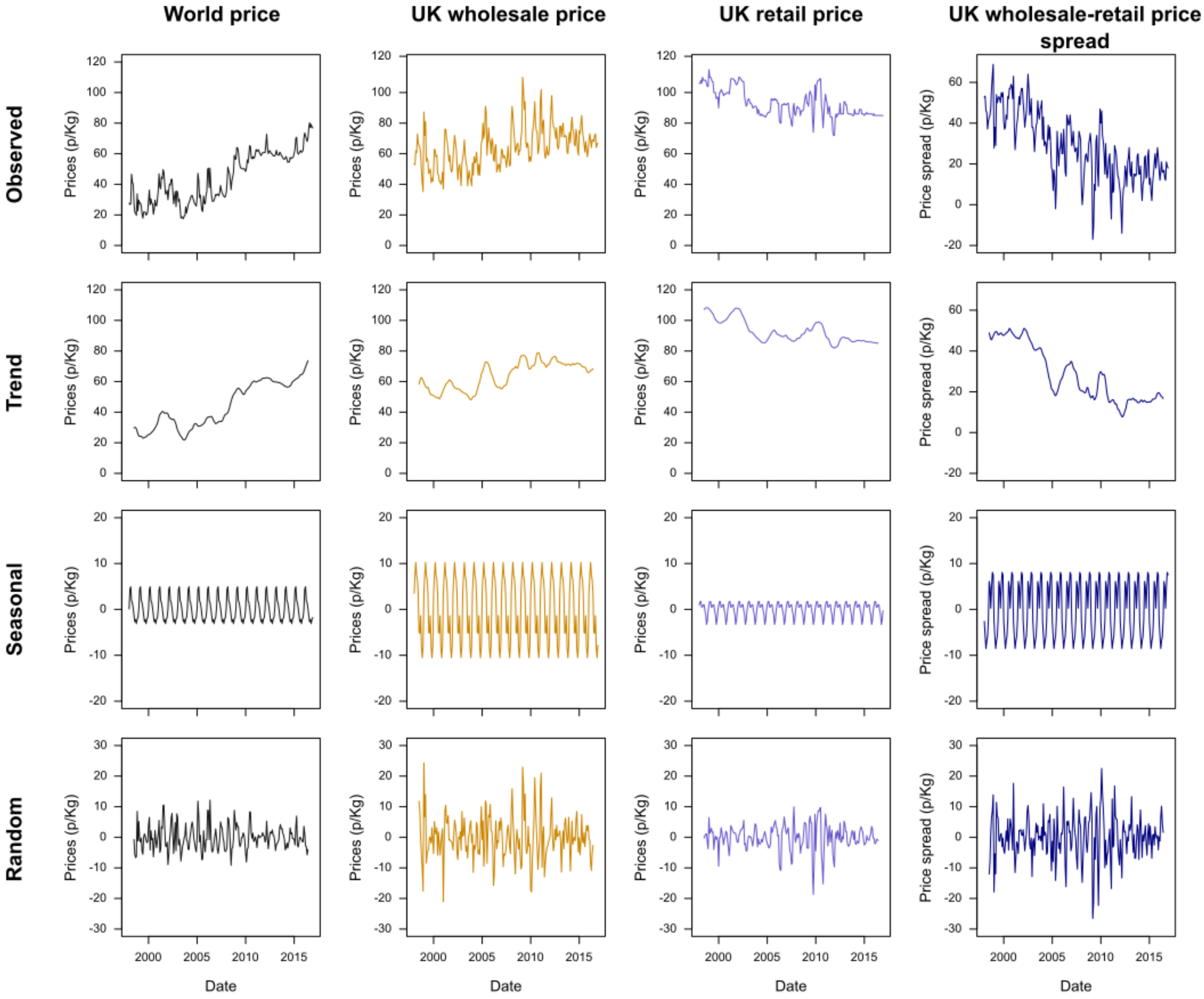

Figure S1 – time series deconstruction for banana world prices, UK wholesale prices, UK retail prices and UK wholesale-retail price spread. This deconstruction demonstrates that the UK wholesale-retail price spread data to be the most volatile of the four price series.

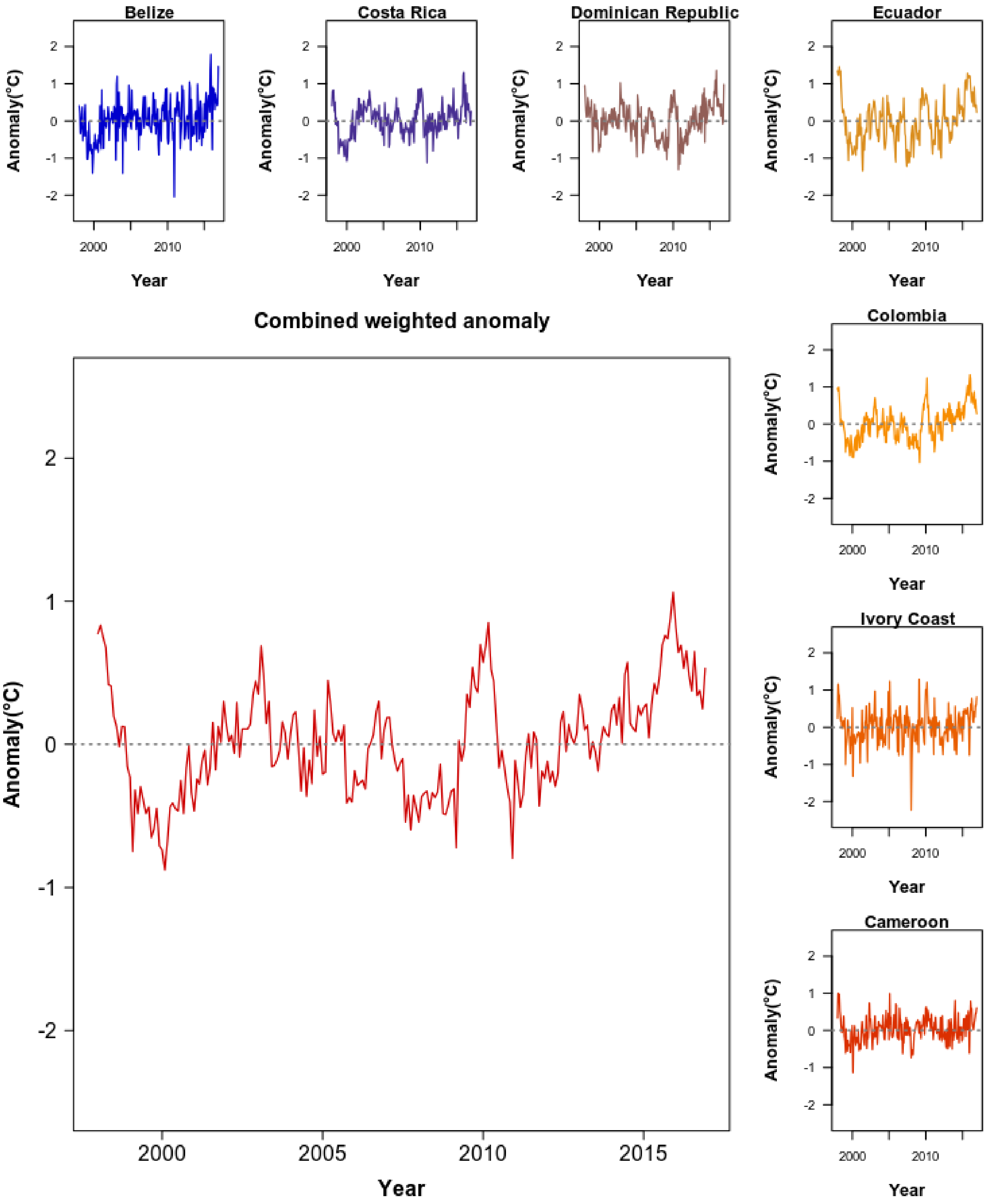

Figure S2 – Export country-specific temperature anomalies and combined export volume weighted temperature anomalies.

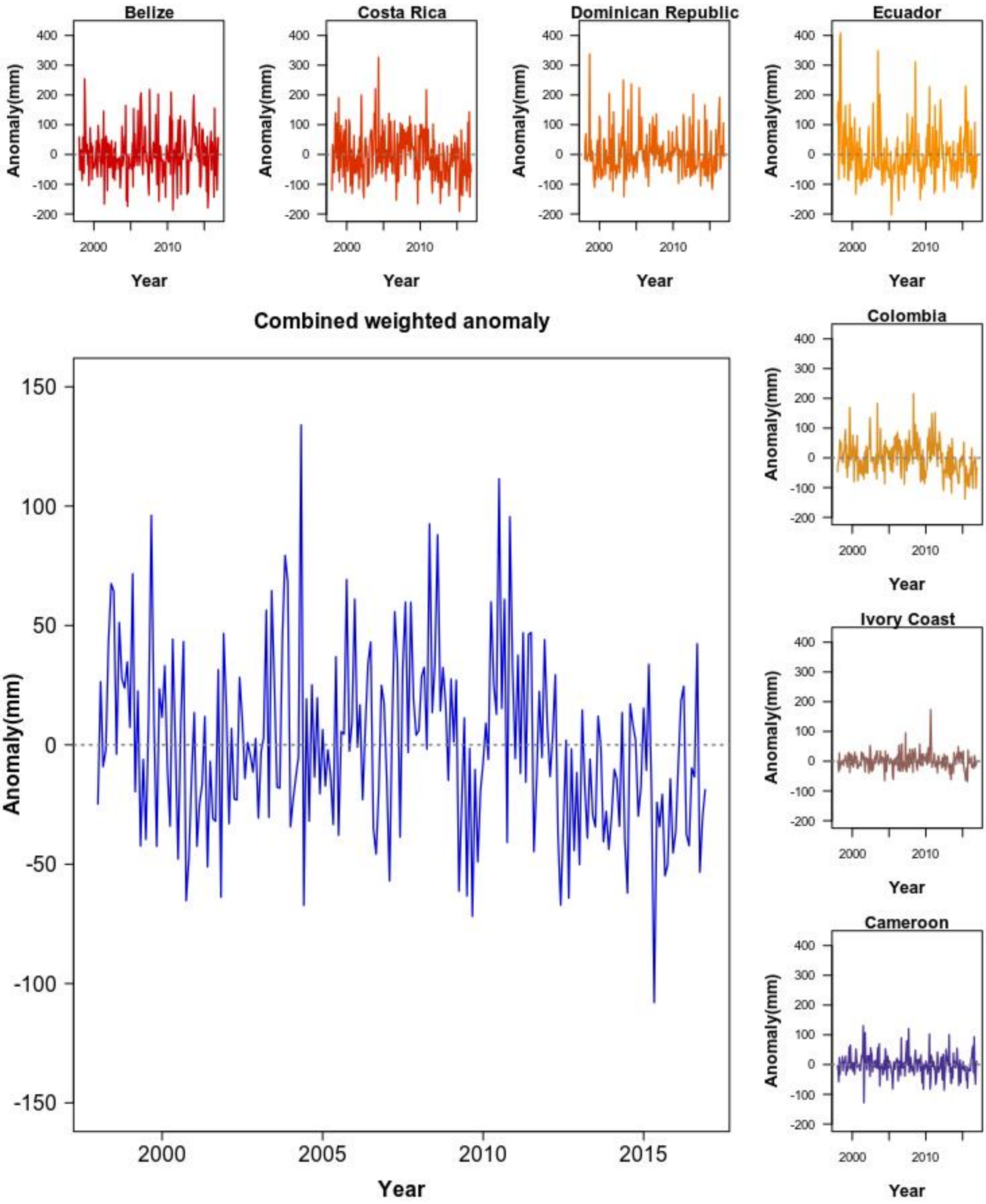

Figure S3 – Export country-specific precipitation anomalies and combined export volume weighted precipitation anomalies.

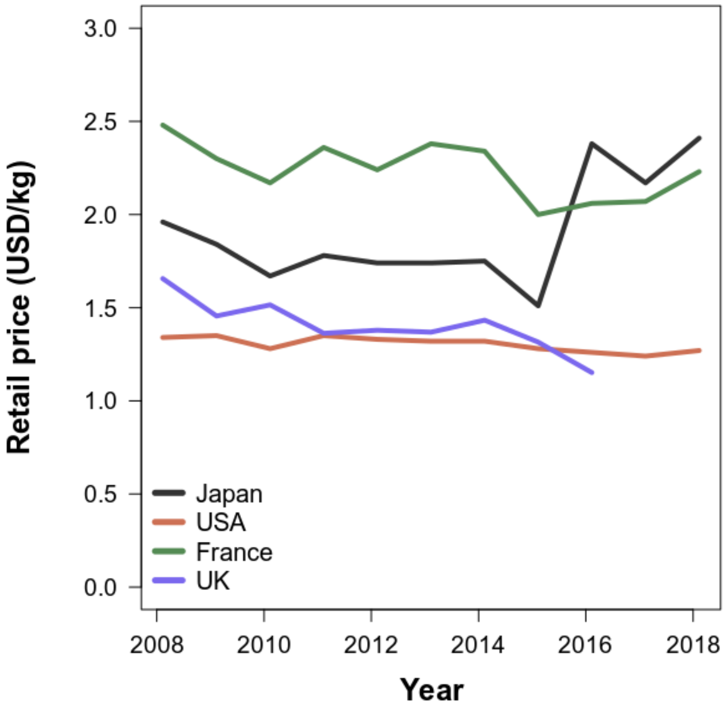

Figure S4 – Retail price data for major banana importing countries