Information Rigidities in USDA forecasts

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Several previous studies find that revisions to USDA production and yield forecasts for major agricultural commodities are correlated, and conclude that they are biased away from what would be observed under rational expectations due to smoothing on the part of forecasters. Yet correlated revisions may also be explained by information rigidities that cause forecasts to be infrequently updated. We apply a recently-developed test to these USDA revisions for corn, soybeans, and wheat and—contrary to previous studies—find no significant evidence of smoothing in USDA forecasts. Rather, we show that information frictions are the more likely culprit, due to production and yield information that is either too costly to obtain or too noisy to make sense of in real time. Because our results offer robust evidence that consensus USDA production and yield forecasts are characterized by information rigidities rather than smoothing, their efficiency can be improved by investments, such as in better satellite or remote sensing technology, that make crop and production information less costly to obtain and/or more precise.

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Agricultural markets are characterized by volatile supply due to weather patterns, crop diseases, and pests, and therefore volatile prices. Given that regularity, to assist market participants the U.S. Department of Agriculture (USDA) has for decades provided the public with price, demand, and supply forecasts for major agricultural commodities over each marketing year. These reports play a key role in setting expectations and guiding private production, consumption, and inventory decisions along the supply chain. Markets react to their news. Isengildina-Massa et al. (2008) find that WASDE reports significantly impact corn and soybean futures markets. Adjemian (2012) demonstrates that futures prices rapidly incorporate government information following the publication of these reports. Irwin, Gerlow, and Liu (1994) and Isengildina-Massa et al. (2006) establish how market participants consider USDA forecasts as benchmarks while making supply chain decisions. Isengildina-Massa et al. (2021) show that USDA's January report clusters, which include final forecasts for several commodities' marketing year, have a significant impact on nearby futures prices. Further, Goyal and Adjemian (2021) show that unpublished USDA reports increase the cost of managing risk.

Yet several studies indicate that major USDA forecasts depart from rationality, a condition in which forecasters use all available information to form expectations. Nordhaus (1987) conceptualizes efficient forecasts as those whose (1) errors are independent of revisions, and (2) under which each revision is independent of all previous revisions. Because forecast errors can be written in terms of forecast revisions, conditions (1) and (2) imply each other. Related empirical work in the agricultural economics literature focuses on violations of condition (2), and concludes that the source of the problem is forecast "smoothing", the strategic avoidance by forecasters of large revisions perhaps to avoid sudden swings in commodity prices (given the sensitivity of the markets to USDA news). For example, Isengildina-Massa et al. conclude that corn and soybean production forecasts (2006) and yield forecasts (2013) are smoothed. Xiao et al. (2017) find that the USDA tends to underestimate ending stocks, and make inefficient projections that are consistent with smoothing. Isengildina-Massa et al. (2017) identify smoothing in wheat production forecasts (in addition to corn and soybeans), and show that market participants adjust for this inefficiency by not reacting to the predictable component of the market surprise and forecast revision.

These studies ignore the role of information rigidities, an alternative explanation for predictable forecast errors. Coibion and Gorodnichenko (2015) formalize the concept and use it to explain measured departures from full-information rational expectations (FIRE) present in fixed-event forecasts for macroeconomic time series. Under sticky information (Mankiw and Reis, 2002), agents update their information sets infrequently owing to the costs involved in data collection and the degree of information friction is the probability of not acquiring new information. In a world with noisy information (Woodford, 2001), although agents update their information sets frequently they do so via a signal extraction problem, and information rigidities occur because the fundamental process is only observed with noise. Coibion and Gorodnichenko (2015) show that both models (1) converge and (2) like smoothing, generate predictable forecast errors; however, these models produce a different association between forecast errors and forecast revisions than would be observed under smoothing. That is, information frictions permit departures from complete information while preserving the notion of rationality.

We use this approach to reassess USDA’s forecast revisions to its production and yield forecasts for corn, soybeans, and wheat from 1985 – 2018. Contrary to previous studies, we show that revisions to these series are consistent with models of information rigidity rather than smoothing, and estimate the degree of weight that rigidities lead USDA to place on previous information: on average, between 20% - 50% and between 5% - 45% in the case of production forecasts and yield forecasts, respectively, depending on the point in the forecasting cycle. Because they do not have access to full information, rigidities therefore cause USDA forecasters to underreact. We further show other competing explanations for predictable forecast errors do not apply. For example, forecast errors may be predictable if forecasters have an asymmetric loss function (Capistrán and Timmermann, 2009; Bora et al., 2020); yet asymmetric loss would generate a negative sign on contemporaneous forecast revisions and a positive sign on lagged revisions, opposite to what the data show. In addition, since USDA releases forecasts simultaneously, production forecasts are jointly determined with yield forecasts. Therefore, we consider a model in which the predictability of production forecast errors depends not only on production forecast revisions but also on yield forecast revisions. Our results show that adding the other variable’s forecast revisions does not offer any statistical improvements.

Beyond contributing to the literature as the first study to explore and demonstrate information rigidities in USDA forecasts, our findings imply different practical considerations for improving them. Although smoothing to production and yield forecasts could be addressed by simply making projections more flexible to incorporate new information—i.e., making forecasters act more rational—information rigidities imply that the new information itself is too costly or difficult to observe. Given our findings that USDA forecasts are consistent with rationality and information rigidity, USDA may be able to enhance its forecasts by improving its ability to observe new information about production or yields, perhaps by making investments in satellite or remote sensing technology that can offer more precise and up-to-date data.

Background

USDA is home to two of the 13 Federal Statistical System agencies: the Economic Research Service (ERS) and the National Agricultural Statistics Service (NASS) (Bora et al., 2020). NASS provides production forecasts for major domestic commodities like corn, soybeans, and wheat according to a set schedule around the production cycle (from August through November for corn and soybeans, and from May through August for wheat). NASS publishes an annual summary (usually released in January) including its final estimates for corn, soybeans; from 1985-1994, this summary also contained final estimates for wheat. From 1995 onward, USDA publishes final estimates for wheat in the September small grains annual summary report.

Production forecasts consist of two main components: expected yield per acre and harvested acreage (Schnepf, 2017). The agency conducts agricultural surveys of over 100,000 farmers across 10,000 area segments and 75,000 farms in the United States using a multiple-frame statistical methodology and reports the first projections for harvested acreage based on farmers' planting intentions (in March) and actual acreage decisions (in June) (USDA, 2012). NASS conducts two different yield surveys to inform its subsequent yield forecasts. A subsample of farmers participating in the June Agricultural Survey is selected to participate in monthly yield surveys. NASS also conducts direct field observations (objective yield surveys) in the primary producing states for these commodities. These surveys for winter wheat begin in April, and for other crops in July. Monthly visits are made to the selected fields to collect data. To determine net yield per acre, these surveys are adjusted for the estimated harvest loss. Each member of the NASS Agricultural statistics board reviews these surveys and brings their estimate to a collective review meeting, where they deliberate to form a consensus national yield forecast (Schnepf, 2017).

These production and yield projections are fed into the balance sheet forecasts USDA makes each month in the World Agricultural Supply and Demand Estimates (WASDE) report. WASDE balance sheets are themselves consensus forecasts generated by combining the NASS-derived production and yield data with insights from several other USDA agencies: the Foreign Agricultural Service, the Economic Research Service, the Farm Service Agency, and the Agricultural Marketing Service (Vogel and Bange, 1999; Goyal and Adjemian, 2021). Since the two reports are released concurrently, WASDE incorporates NASS production and yield forecasts in its estimates.

Data

Cornell University's library system maintains the monthly crop production. These reports provide projections on each forecast year's production, yield, and acreage (harvested acres). Like Isengildina-Massa et al., we extract crop production forecasts from NASS crop production reports (2006), and yield forecasts from WASDE reports (2013); between the 1985/86 and the 2018/19 marketing years USDA made 169 such forecasts of each kind for corn and soybeans, and 170 for wheat.[2] The January yield estimates are often revised in subsequent WASDE reports. However, Isengildina-Massa et al. (2013) note these revisions follow a long-time lag and are sporadic. In the models we estimate below, we also use CBOT closing futures prices for each commodity, and the nearby volatility index (VIX); we source these data from the Bloomberg platform. To form a continuous series of close-to-close changes in closing prices for each commodity, we rollover to the next deferred contract fifteen days prior to the contract expiration month.

For each commodity, we compute forecast errors as $x_{t+h} - F_t x_{t+h}$, where x_{t+h} is the log of final realization for the marketing year,[3] occurring at time $t+h$.[4] The time t consensus forecast for that value is represented by $F_t x_{t+h}$. Similarly, the forecast revision at time t is given by $F_t x_{t+h} - F_{t-1} x_{t+h}$.

Table 1 reports summary statistics for the USDA forecast errors of these elements for all three commodities. USDA's corn and soybean production and yield errors are highest in August and September; for wheat, yield forecast errors are largest in May and June, while production forecasts miss most in August. Average pooled projection errors are positive for corn, soybeans, and wheat yield, but slightly negative for wheat production, indicating the USDA's tendency to underestimate production and yield in most cases.

Likewise, table 2 displays summary statistics for USDA forecast revisions for each commodity. October production and yield estimates are largest for corn, whereas soybean production revisions are largest in November and the biggest yield revisions are shared by September and October. July

[2] Two missing report days occur over the period of observation: the October 2013 WASDE, which was simply curtailed, and the January 2019 WASDE, whose information was released the following month. For the latter, we use the information published in the February 2019 WASDE.
[3] Following Isengildina et al. (2006), we apply log transformations to account for increases in crop size over time.
[4] The quantity $t+h$ takes values from 1 to 5, corresponding to the monthly forecasts over USDA's forecast cycle for each commodity.

has the largest average forecast revisions for wheat production and yield. Pooled production and yield revisions are positive for all three commodities.

Are USDA Production and Yield Forecasts Smoothed?

Nordhaus (1987) defines forecasts as weakly efficient if their current information set consists of all past estimates, and forecast errors and revisions are independent of previous revisions. Therefore, USDA forecasts exhibit "weak-form" efficiency if:

$$E[x_{t+h} - F_t x_{t+h} | F_t x_{t+h} - F_{t-1} x_{t+h}, F_{t-1} x_{t+h} - F_{t-2} x_{t+h}, \ldots\ldots] = 0 \qquad (1)$$

$$E[F_t x_{t+h} - F_{t-1} x_{t+h} | F_{t-1} x_{t+h} - F_{t-2} x_{t+h}, \ldots\ldots] = 0 \qquad (2)$$

where, $x_{t+h} - F_t x_{t+h}$ is the forecast error at time *t*, and $F_t x_{t+h} - F_{t-1} x_{t+h}$ is the forecast revision at time *t*.

Forecast errors will be predictable if forecasters act strategically to minimize revisions, possibly to avoid short-run changes in forecasts and prevent sudden swings in market prices (Isengildina et al., 2017). Previous research studies (Isengildina-Massa et al., 2006, 2013, 2017) run the following base regression (or its modification where they include the sum of preceding months' forecast revisions, and the out-of-sample percent deviation as additional regressors) to test for smoothing:

$$F_t x_{t+h} - F_{t-1} x_{t+h} = \beta_0 + \beta_1 (F_{t-1} x_{t+h} - F_{t-2} x_{t+h}) + Error_t \qquad (3)$$

Clearly a statistically significant $\widehat{\beta_1}$ implies predictability of forecast revisions (and errors, given their fundamental relationship), which violates Nordhaus' definition of efficiency. However, it is not possible from equation (3) to determine the source of that predictability: whether due to strategic smoothing or information rigidities.

Information rigidities

Let $E_t x_{t+h}$ be the full-information rational expectation of x_{t+h} made at time *t*. Agents observe the full information set and use it to form these expectations, so any errors are random and unpredictable. In contrast, information friction models suggest that forecasters are rational, even though they don't have access to full information. This could be either because they are rationally inattentive (due to costs of acquiring information) or only view the process with noise; in either case, forecast errors are predictable. The full-information rational expectation error is given by $v_{t+h,t} = x_{t+h} - E_t x_{t+h}$. Following Ager et al. (2009), we define $v_{t+h,t}$ as:

$$v_{t+h,t} = \sum_{k=1}^{h} u_{t+k,t} \tag{4}$$

Where, $u_{t+k,t}$ is the shock occurring at time *t+k* and signals the arrival of new information in that period. Following Ager et al. (2009), we assume that $u_{t+k,t}$ is independently and identically distributed and follows a normal distribution, N(0, σ_u^2). The sum of all shocks occurring between *t+1* and *t+h* is given by $v_{t+h,t}$. Forecast errors in (4), $v_{t+h,t}$, are unpredictable. However, that is usually not the case with actual forecast errors ($F_t x_{t+h} - F_{t-1} x_{t+h}$), which tend to be predictable/correlated with one another (Vereda et al., 2021). Previous literature proposes two general theoretical models to explain predictable forecast errors: models of sticky and noisy information.

Sticky information models

When information is sticky, the fixed cost of obtaining it leads forecasters to update infrequently; they are rationally inattentive. Information rigidity in these models is defined as the probability of not acquiring new information in each period. Fully-updated information sets generate forecasts with unpredictable forecast errors. Following Mankiw and Reis (2002) and Coibion and

Gorodnichenko (2015), the time t forecast for x_{t+h} is given by a weighted average of past and current fully-updated forecasts as defined in equation (5).

$$F_t x_{t+h} = (1-\lambda)\sum_{i=0}^{\infty} \lambda^i E_{t-i}\, x_{t+h} \tag{5}$$

In this model, forecasters update their information set with probability $1-\lambda$. The probability of not acquiring new information (λ) can be interpreted as the degree of information rigidity. One can also interpret it as the probability of not forming FIRE forecasts in that period. Upon rearranging the terms in equation (5), Coibion and Gorodnichenko (2015) show that ex-post forecast errors and ex-ante mean forecast revisions have the following relationship:

$$x_{t+h} - F_t x_{t+h} = \frac{\lambda}{1-\lambda}\,(F_t x_{t+h} - F_{t-1} x_{t+h}) + v_{t+h,t} \tag{6}$$

When it is costless to acquire new information ($\lambda = 0$), there are no information frictions present, and the forecast errors are unpredictable using the information at time t or earlier. If frictions are present, then (6) reflects a slow and incomplete process of updating information from one period to the next. This anchors the department's forecast to the previous period's leading to a gradual adjustment of the USDA forecast and predictability of forecast errors. We can re-write (6) as:

$$x_{t+h} - F_t x_{t+h} = \beta(F_t x_{t+h} - F_{t-1} x_{t+h}) + v_{t+h,t} \tag{7}$$

where, $\beta = \frac{\lambda}{1-\lambda}$. Equation (7) is equivalent to the regression of forecast errors on forecast revisions.

In the online appendix, we also show that equation (7) is equivalent to:

$$F_t x_{t+h} - F_{t-1} x_{t+h} = \frac{\beta}{1+\beta} (F_{t-1} x_{t+h} - F_{t-2} x_{t+h}) + \frac{1}{1+\beta} (E_t x_{t+h} - E_{t-1} x_{t+h}) \quad (8)$$

Here, $(E_t x_{t+h} - E_{t-1} x_{t+h})$ is the FIRE forecast revision. We can re-write (8) as:

$$F_t x_{t+h} - F_{t-1} x_{t+h} = \lambda (F_{t-1} x_{t+h} - F_{t-2} x_{t+h}) + (1-\lambda)(E_t x_{t+h} - E_{t-1} x_{t+h}) \quad (9)$$

Equation (9) is equivalent to estimating a regression of forecast revisions on lagged forecast revisions. However, in this setup degrees of freedom are constrained since the first two observations for each marketing year are lost, with the first corresponding to the contemporaneous forecast revision, and the second observation associated with the lagged forecast revision. Equation (9) is equivalent to equation (3), used in the existing literature to detect smoothing (see, e.g., Isengildina-Massa et al., 2006, 2013, 2017). Here, comparing equations (3) and (9), we show that $\widehat{\beta_1} = \lambda$. Hence, $\widehat{\beta_1}$ can be interpreted as the probability of not acquiring new information, and hence tests for the presence of frictions, not smoothing, in forecasts.

In the background section, we note that USDA consensus production and yield forecasts are partially based on surveys of large numbers of producers, and are subject to the judgment of various analysts. These producers and analysts likely face a cost to update their information sets, leading to rational inattention on the part of survey participants and forecasters. Aggregation of these partially-updated forecasts leads to inefficiency in the consensus projection, resulting in predictability in forecast errors (Coibion and Gorodnichenko, 2015).

Noisy information models

Under this model, agents continuously update their information sets, and hence their forecasts, according to the following process:

$$E_t x_{t+h} = E_{t-1} x_{t+h} + v_{t+h,t} \quad (10)$$

Agents are trying to forecast x_{t+h}, whose value at time *t* is given by $E_t x_{t+h}$, but they do not directly observe $E_t x_{t+h}$. Instead, they observe noisy signals about the true state. Consider an agent *i* who observes the signal $Y^i_{t+h,t}$, given by equation (11):

$$Y^i_{t+h,t} = E_t x_{t+h} + \omega^i_{t+h,t} \tag{11}$$

where $\omega^i_{t+h,t}$ is "iid" normally distributed noise with mean 0 and variance σ^2_ω. Noise obstructs the direct observation of $E_t x_{t+h}$. To generate forecasts of $E_t x_{t+h}$, each agent solves a signal extraction problem. Specifically, they use (11) as a prediction equation and (10) as an update equation of the state-space Kalman filter to make predictions described by the following:[5]

$$F_t x_{t+h} = (1 - G) F_{t-1} x_{t+h} + G(E_t x_{t+h}) \tag{12}$$

where *G* is the Kalman gain and represents the weight placed on new information. We assume that $g^i_{t+h,t}$ (Kalman gain for individual *i* at time *t*) converges to *G*. If *G* = 1, we are back in the full-information rational expectations world with no noise. However, noisy signals due to information rigidities result in rejections of FIRE, causing predictability in forecast errors. In this model, (1-*G*) can be interpreted as the degree of information rigidity. Upon rearranging certain terms, Coibion and Gorodnichenko (2015) show that equation (12) is equivalent to:

$$x_{t+h} - F_t x_{t+h} = \frac{(1 - G)}{G} (F_t x_{t+h} - F_{t-1} x_{t+h}) + v_{t+h,t} \tag{13}$$

As Coibion and Gorodnichenko (2015) show, with $\beta = \frac{1-G}{G}$, equation (13) reduces to equation (7), so that both sticky-information models and noisy-information models establish a similar relationship between ex-post forecast errors and ex-ante forecast revisions. In the former case,

[5] The appendix includes a detailed derivation. Note that the proof has different Kalman filter equations compared to the derivation offered by Coibion and Gorodnichenko (2015), because those authors test across different horizons. Here, each marketing year has only one forecast horizon.

information rigidities represent the probability that forecasters do not use rational expectations based on complete information; in the latter, they represents the weight that agents place on past information. In the noisy-information framework, adjustment of beliefs takes place gradually. In the sticky-information setup, some agents do not update their information sets; those who do immediately achieve full-information rational expectations. In each, individual forecasters introduce rigidities in consensus forecasts.

<u>Forecast smoothing</u>

Forecasters who want to smooth, perhaps to prevent large swings in forecast revisions, face a dynamic optimization problem to minimize both forecast errors and revisions. Coibion and Gorodnichenko (2015) write it down as:

$$\min \sum_{j=0}^{h} \gamma^{j} E_t[\left(x_{t+h} - F_{t+j}x_{t+h}\right)^2 + \alpha\left(F_{t+j}x_{t+h} - F_{t+j-1}x_{t+h}\right)^2] \tag{14}$$

where, the actual realization is given by x_{t+h}, $F_{t+j}x_{t+h}$ is the forecast at time *t*+*j*, and $F_{t+j-1}x_{t+h}$ is the forecast in the previous period. Forecast error at time *t*+*j* is $\left(x_{t+h} - F_{t+j}x_{t+h}\right)$, and $F_{t+j}x_{t+h} - F_{t+j-1}x_{t+h}$ is the forecast revision in the same period. The relative weight a forecaster places on minimizing the revision is given by α, and γ is the discount factor. The authors show that equation (14) can be rearranged to produce:

$$\begin{aligned} x_{t+h} - F_t x_{t+h} & \\ &= -(1+\alpha\gamma)(F_t x_{t+h} - F_{t-1}x_{t+h}) + \alpha(F_{t-1}x_{t+h} - F_{t-2}x_{t+h}) \\ &+ Error_t \end{aligned} \tag{15}$$

According to (15), when related to the time *t* forecast error, the sign on contemporaneous forecast revision is negative, while the sign on the lagged revision is positive—a consequence of the intertemporal trade-off resulting from the costs associated with the adjustment to new information. For example, suppose the USDA decides to ignore today's production or yield information in order to smooth. In that case, tomorrow's expectation adjustment will have to be a lot stronger to keep up with the information trend (Beckmann and Reitz, 2020). Like Coibion and Gorodnichenko (2015), we estimate (15) for corn, soybeans, and wheat production and yield forecasts and report the results in Tables 3 and 4, respectively. Since the error in (15), $Error_t$, is correlated with the time *t* information set, an Ordinary Least Squares regression is inconsistent; like those authors we use instrumental variables (IV) methods to estimate the relationship between forecast errors and forecast revisions.

Specifically, we use the change in the natural log of the nearby futures closing price one day before the report release as an instrument for corn and soybeans production revisions and corn, soybeans, and wheat yield forecast revisions. Because this instrument is too weak for wheat production revisions, we use the change in natural log of the nearby volatility index (VIX) one day before the report release as an instrument for wheat production revisions.[6] Since the first-stage F-statistic is low in some cases (especially for wheat), we also report a standard weak instrument conditional likelihood (CL) ratio confidence interval: one that provides accurate inference under weak instruments (Moreira, 2003). Andrews et al. (2006) and Mikusheva (2010) show that the CL confidence interval has favorable power compared to other weak instrument confidence intervals such as the Anderson-Rubin test statistic (Anderson and Rubin, 1949).

Results

[6] We considered using a variety of instruments simultaneously (including the change in nearest-to-deliver log of the closing price, change in log VIX, change in log crude oil price, rainfall index, and global policy uncertainty index). But, doing so provided no significant increase in explanatory power. For simplicity, we used only one instrument for all IV regressions.

In table 3, we report the OLS and IV results for corn & soybeans production (pooled across September and October), and wheat (pooled across July and August). For IV regressions, table 3 also gives the CL confidence interval, for the endogenous time *t* revision. Opposite the prediction consistent with smoothing in equation (15), for all three commodities in table 3 the sign on the contemporaneous revision is positive (across different months and the pooled data). The sign on the lagged revision fluctuates across commodities, but lagged revisions in the table are never statistically significant—a similar finding to the results presented in Coibion and Gorodnichenko's (2015) own table 3. The first-stage F-statistic of 11.3 for pooled corn production indicates that the IV is sufficiently strong, and the 95% confidence interval [0.204, 1.837] does not contain negative values. We infer similar results for pooled soybeans production with the first-stage F-statistic of 12.07. For pooled wheat production, the first-stage F-statistic of 4.23 indicates that the instrument may be weak; moreover, the 95% CL confidence interval (robust to weak instruments) contains both negative and positive values. Taken together, contrary to previous studies we find no evidence of smoothing in production forecasts for corn and soybeans, but the results are indeterminate about the presence of smoothing in wheat production forecasts.

Table 4 reports the OLS and IV regression results for corn, soybeans, and wheat yield forecasts. IV regressions for the pooled corn yield forecast has a first-stage F-statistic of 20.2, and the coefficients are opposite to what equation (15) predicts in the case of smoothing. Our test of soybean yield forecasts offers the same perspective. For wheat, the first-stage F-statistic of 5.8 indicates that the instrument, nearby change in log futures closing prices, is weak. However, weak-instrument robust methods generate a 95% confidence interval for the contemporaneous revision that does not contain negative values.

Taken together, our results in tables 3 and 4 indicate that USDA production and yield forecasts for corn, soybeans, and wheat do not exhibit smoothing. This runs contrary to established findings in the literature (Isengildina-Massa et al., 2006, 2013, 2017; and Xiao et al., 2017). These findings necessitate further investigation as to whether these forecasts are inefficient or not. Next, we test for information rigidities in these projections. In an environment with zero rigidities, forecasters regularly update their information sets and place a 100% weight on new information. However, when rigidities are present forecasters place at least some weight on previous forecasts. Therefore, the value of information rigidity tells us either how frequently USDA updates its information set (in a costly-information world), or how much importance it gives to previous forecasts (in a noisy world). We do not distinguish between the applicability of either model.

Following Coibion and Gorodnichenko (2015), and Bordalo et al. (2020), we run the following regression:

$$x_{t+h} - F_t x_{t+h} = \beta_0 + \beta_1 (F_t x_{t+h} - F_{t-1} x_{t+h}) + v_{t+h,t} \tag{16}$$

According to the sticky and noisy information models (refer equations (7) and (13)), $\beta_1 > 0$ in equation (16) is consistent with the presence of information rigidities and departures from full-information rational expectations. Further, note that $\beta_1 > 0$ implies that the forecaster underreacts to their own information set, while $\beta_1 < 0$ confirms overreaction. Specifically, the sticky information model in equation (7) states that $\hat{\lambda} = \frac{\widehat{\beta_1}}{1+\widehat{\beta_1}}$, and the average duration between information updates is given by $\frac{1}{(1-\hat{\lambda})}$. On the other hand, the noisy information model in equation (13) states that $\hat{G} = \frac{1}{1+\widehat{\beta_1}}$. We use the Delta method to compute the standard errors for $\hat{\lambda}$, and $\hat{G}$, and then use the relations above to interpret the regression findings in the context of both models.

We report results for regression equation (3) in tables 5 and 6, for production and yield, respectively, and plot our implied rigidity coefficients in figures 1 and 2. Each table includes both OLS standard errors and the Newey-West (N-W) standard errors (Newey and West, 1987),[7] and also information rigidity parameters, $\hat{\lambda}$, and $\hat{G}$.[8]

Figure 1 documents visually how—in a costly information world— our results imply that, on average, USDA updates its information set within three months for corn and wheat, and two months for soybeans; note that over the forecasting cycle, the average duration between information updates declines for the three commodities. Alternatively, figure 2 shows graphically that—in a noisy information world—the implied weight USDA places on new information ranges between 60%-80% for corn, soybeans, and wheat; note that for all commodities USDA tends to place relatively more weight on new information it learns as the forecasting cycle progresses. Both figures demonstrate that as more precise information about the prospective harvest comes in, USDA forecasts display less indication of underlying informational rigidity.

Table 5 shows that for corn production, $\hat{\lambda}$ is statistically significant in regressions for every forecast revision, as well as the pooled revisions. For example, the October error-on-revision regression result of $\hat{\lambda}$ = 0.49 implies that USDA forecasters in aggregate update their information set about corn production every two months. Likewise, October's $\hat{G} = 0.51$ signifies in a noisy information world that while forming a corn production forecast USDA puts almost equal weight on the previous estimates and new information. Corn production's pooled $\hat{G} = 0.63$ (which is dragged up by November's $\hat{G} = 0.73$) implies that, at the mean, USDA on average places 63% more

[7] N-W standard errors assume heteroskedasticity and autocorrelation in the error structure, providing a more robust variance-covariance matrix estimate.
[8] For $\hat{\beta} \geq 0$, $\hat{\lambda} \in [0, 1]$, and $\hat{G} \in [0, 1]$.

importance on new information than previous forecasts and updates its corn information set every 1-2 months. At the beginning of the forecasting cycle, uncertainty is high, reflected in a higher value of $\hat{\lambda}$ for September and October regressions. However, as we move further along the cycle, either USDA updates its information relatively more quickly and gives more credence to newer information or observes more precise production signals.

Panel B of Table 5 reports statistically significant information rigidities in soybeans production for October, November, and Pooled regressions. The USDA updates its information set within two months ($\hat{\lambda}$ = 0.22) and places much higher weight on new information (77%, on average) compared to previous forecasts. Results for wheat are in panel C of Table 5. The maximum rigidity is observed in June (closer to the onset of the forecasting cycle) when the agency puts slightly lower weight on new information (48%). The Department updates its information set every two months and places more importance on new data for these balance sheet elements. Overall, our results for production forecasts show that, on average (average of $\hat{G}'s$ in column (4) of table 5), the USDA puts approximately 70% weight on new information and 30% on previous predictions.

Table 6 provides similar findings for corn, soybeans, and wheat yield forecasts. For pooled corn yield projections, USDA updates its information set within two months ($\hat{\lambda}$ = 0.33) and places 66% weight on new information compared to previous forecasts. For soybeans, USDA places much higher weight on new information sets for September, October, November, and Pooled data. Wheat's maximum rigidity is observed in June, and implies that USDA places only a 42% weight on new information. Like in the case of production, our pooled estimates imply that USDA updates its information about average yield forecasts about every two months, and forecasters put higher weight on new information than previous forecasts.

Our results for all three commodities confirm the presence of information rigidities in production and yield projections. Even though USDA conducts regular farmer surveys and yield measures to gather production and yield data, the cost or noise involved in updating individual (farmer or forecaster) information sets generates departures from the relationship between forecast errors and revisions that would obtain under fully efficient forecasts.

Alternate Explanations

Heterogeneous Loss Functions

Predictability in forecast errors could instead arise due to asymmetric loss functions, even with fully updated expectations, due to differential costs associated with overprediction and underprediction. Capistrán and Timmerman (2009) identify potential asymmetric loss-driven government forecasts. More recently, Bora et al. (2020) evaluate several USDA forecasts and find evidence of asymmetric loss. Coibion and Gorodnichenko (2015) use the "Linex" loss function proposed in Capistrán and Timmerman (2009) and show that under the asymmetric loss function, the correlation between forecast error and revision is negative.[9] This correlation is in the opposite direction to what we observe in tables 5 and 6, so we reject it as an explanation for predictable USDA production and yield forecast errors.

Generalized noisy-information models

As we note in the previous sections, the noisy-information model assumes that forecast errors depend only on forecast revisions of the variable under consideration. However, since production estimates are jointly determined with yield forecasts ($\mathrm{E[production]} = \mathrm{E[yield]} * \mathrm{E[harvested\ acreage]}$), the predictability of either set of forecast errors may depend on the predictability of the other. To test this, following Coibion and Gorodnichenko (2015), we specify

[9] For details, please refer to the online appendix of Coibion and Gorodnichenko (2015).

a two-variable vector autoregression (VAR) process with the specification given by equations (17) and (18):

$$x_{Prod,t+h} - F_t x_{Prod,t+h} = \beta_{11}(F_t x_{Prod,t+h} - F_{t-1} x_{Prod,t+h}) + \beta_{12}(F_t x_{Yield,t+h} - F_{t-1} x_{Yield,t+h}) + \gamma_{Prod,t} \tag{17}$$

$$x_{Yield,t+h} - F_t x_{Yield,t+h} = \theta_{11}(F_t x_{Yield,t+h} - F_{t-1} x_{Yield,t+h}) + \theta_{12}(F_t x_{Prod,t+h} - F_{t-1} x_{Prod,t+h}) + \epsilon_{Yield,t} \tag{18}$$

For such models, the state equation of the Kalman filter (Coibion and Gorodnichenko, 2015) is given by:

$$\begin{bmatrix} x_t^{(1)} \\ x_t^{(2)} \end{bmatrix} = z_t = \begin{bmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{bmatrix} z_{t-1} + u_t \tag{19}$$

where $x_t^{(i)}$ is the full-information rational expectation of variable $x^{(i)}$ at time *t*, and u_t is iid error distributed normally with mean 0 and variance Σ_u.

The measurement equation for the Kalman filter (Coibion and Gorodnichenko, 2015) is given by:

$$Y_{i,t} = z_t + \omega_{i,t},\ \omega_{\mathrm{i,t}} \sim \text{ iid N}(0, \Sigma_\omega) \tag{20}$$

Where $Y_{i,t}$ is the signal observed for variable z_t with noise $\omega_{i,t}$. Coibion and Gorodnichenko (2015) show that in such a setup, the Kalman gain G is given by $(M + I)^{-1}$. Where, M is an estimate from the following model: $z_t - z_{t|t} = M\left(z_{t|t} - z_{t|t-1}\right) + error_t$, an error-on-revision regression analogous to equation (3) in the univariate case. The diagonal elements of G represent the decrease in forecast error variance due to new information available at time *t*. For the univariate model, the forecast error of a variable depends only on that variable's revision. Following Coibion and Gorodnichenko (2015), we use these diagonal elements to compute the implied degree of information rigidity.

Table 7 and 8 reports the information rigidity measure (1- G) from the above model for production and yield forecasts, respectively. Following Coibion and Gorodnichenko (2015), we run 1000 simulations of the regression coefficients to generate robust estimates of implied information rigidity for both the univariate and the multivariate models. We also report the Bayesian Information Criterion (BIC) to compare the univariate and the multivariate model specifications.[10] We note that the univariate model has a lower BIC value for corn production and yield (except corn October yield), indicating it as the preferred model over the multivariate specification. Moreover, an F-test fails to reject the null hypothesis of equivalence between the information rigidities derived from the univariate and multivariate approaches. Panels B and C of table 7 show similar findings for soybeans and wheat production & yield forecasts. Even though the univariate specification for pooled wheat yield forecasts has a higher BIC value, we fail to reject the equivalence of the two specifications. Therefore, our results confirm that considering a multivariate setup does not alter our findings.

Conclusion

USDA's crop production and yield estimates are consensus forecasts generated by combining insights from farmer surveys, field observations, and a team of individual NASS forecaster perspectives. Several previous studies attribute correlated NASS forecast revisions to smoothing bias on the part of USDA, which—knowing that its reports contain market-moving information—

[10] BIC estimates the posterior probability of the estimated model being true; lower BIC values are preferred.

may wish to avoid causing price shocks. That sort of behavior would produce less-than-efficient forecasts; ignoring new information violates the rational-expectations assumption. We argue that correlated revisions can instead be generated when consensus forecasts like those produced by USDA are infrequently updated due to information frictions, such as when acquiring new information is very costly or when the information-gathering process is subject to noise. In both cases, when generating new projections forecasters place at least some weight on previous forecasts. In this setting, less-than-efficient forecasts can still be produced by forecasters who act rationally, but who do not have access to full information.

We use a test devised by Coibion and Gorodnichenko (2015) that is based on the relationship between ex-post forecast errors and ex-ante revisions to demonstrate that predictable USDA production and yield forecast errors are more consistent with information frictions rather than smoothing. We also rule out an alternative explanation that may generate predictable forecast errors, like asymmetric loss, and verify that a multivariate framework offers no statistical improvement on our univariate parameters. Our findings imply that, on average, these rigidities lead USDA to place substantial weight on the previous forecast: 20%-50% for production forecasts and 5%-45% for production and yield, respectively, across corn, soybeans, and wheat. Because our results offer robust evidence that consensus USDA production and yield forecasts are characterized by information rigidities rather than smoothing, their efficiency may be improved by investments, such as in better satellite or remote sensing technology, that make crop and production information less costly to obtain and/or more precise.

References:

Adjemian, M.K., 2012. “Quantifying the WASDE Announcement Effect.” *American Journal of Economics*. 94 (1): 238–56. Accessed at: https://www.jstor.org/stable/41331239

Ager, P., M. Kappler., and S. Osterloh, 2009. “The accuracy and efficiency of the Consensus Forecasts: A further application and extension of the pooled approach.” *International Journal of Forecasting.* 25(1): 167-181. Accessed at: https://doi.org/10.1016/j.ijforecast.2008.11.008

Anderson, T. W., and H. Rubin, 1949. “Estimation of the parameters of a single equation in a complete system of stochastic equations.” *The Annals of Mathematical Statistics*. 20(1): 46–63. Accessed at: https://www.jstor.org/stable/2236803

Andrews, D. W. K., M. J. Moreira, and J. H. Stock. 2006. “Optimal two-sided invariant similar tests for instrumental variables regression.” *Econometrica*. 74(3):715– 752. Accessed at: https://www.jstor.org/stable/4123100

Beckmann, J., and S. Reitz, 2020. "Information rigidities and exchange rate expectations." *Journal of International Money and Finance*. 105. Accessed at: https://doi.org/10.1016/j.jimonfin.2020.102136

Bora, S.S., A.L. Katchova, and T.H. Kuethe, 2020. “The Rationality of USDA Forecasts under Multivariate Asymmetric Loss.” *American Journal of Agricultural Economics*. 103(3): 1006-1033. Accessed at: https://doi.org/10.1111/ajae.12142

Bordalo, P., N. Gennaioli, Y. Ma, A. Shleifer, 2020. “Overreaction in Macroeconomic Expectations.” *American Economic Review*. 110(9): 2748-2782. Accessed at: https://www.aeaweb.org/articles?id=10.1257/aer.20181219

Capistrán, C., and A. Timmermann, 2009. “Forecast Combination With Entry and Exit of Experts.” *Journal of Business and Economic Statistics*. 27 (4): 428–440. Accessed at: https://doi.org/10.1198/jbes.2009.07211

Coibion, O., and Y. Gorodnichenko, 2015. “Information rigidity and the expectations formation process: a simple framework and new facts.” *American Economic Review*. 105(8): 2644–2678. Accessed at: https://www.aeaweb.org/articles?id=10.1257/aer.20110306

Goyal, R., and M.K. Adjemian, 2021. “The 2019 government shutdown increased uncertainty in major agricultural commodity markets.” *Food Policy*. 102. Accessed at: https://doi.org/10.1016/j.foodpol.2021.102064

Irwin, S.H., M.E. Gerlow, and T.R. Liu, 1994. "The Forecasting Performance of Livestock Futures Prices: A Comparison to USDA Expert Predictions." *Journal of Futures Markets.* 14: 861-875. Accessed at: https://doi.org/10.1002/fut.3990140707

Isengildina-Massa, O., S.H. Irwin, D.L. Good, 2006. "Are Revisions to USDA Crop Production Forecasts Smoothed?" *American Journal of Agricultural Economics*. 88(4): 1091-1104. Accessed at: https://www.jstor.org/stable/4123548

Isengildina-Massa, O., S.H. Irwin, D.L. Good, J.K. Gomez, 2008. "Impact of WASDE Reports on Implied Volatility in Corn and Soybean Markets." *Agribusiness*. 24(4): 473–490. *Agricultural* Accessed at: https://doi.org/10.1002/agr.20174

Isengildina-Massa, O., S.H. Irwin, D.L. Good, 2013. "Do Big Crops Get Bigger and Small Crops Get Smaller? Further Evidence on Smoothing in U.S. Department of Agriculture Forecasts." *Journal of Agricultural and Applied Economics*. 45(1):95-107. Accessed at: https://ageconsearch.umn.edu/record/143639?ln=en

Isengildina-Massa, B. Karali and S.H. Irwin, 2017. "Do Markets Correct for Smoothing in USDA Crop Production Forecasts? Evidence from Private Analysts and Futures Prices." *Applied Economic Perspectives and Policy.* 39(4): 559-583. Accessed at: https://doi.org/10.1093/aepp/ppx032

Isengildina-Massa, O., X. Cao, B. Karali, S.H. Irwin, M. Adjemian, R.C. Johansson, 2021. "When does USDA information have the most impact on crop and livestock markets?" *Journal of Commodity Markets.* 22. Accessed at: https://doi.org/10.1016/j.jcomm.2020.100137

Mankiw, N. G., and R. Reis, 2002. "Sticky Information versus Sticky Prices: A Proposal to Replace the New Keynesian Phillips Curve." Quarterly Journal of Economics, 117(4): 1295–1328. Accessed at: https://doi.org/10.1162/003355302320935034

Mikusheva, A., 2010. "Robust confidence sets in the presence of weak instruments." *Journal of Econometrics*. 157(2): 236–247. Accessed at: https://doi.org/10.1016/j.jeconom.2009.12.003

Moreira, M. J., 2003. "A conditional likelihood ratio test for structural models." *Econometrica*. 71(4):1027–1048. Accessed at: https://www.jstor.org/stable/1555489

Newey, W. K., and K. D. West, 1987. "A Simple, Positive Semi-Definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix." *Econometrica*. 55(3): 703-708. Accessed at: https://doi.org/10.2307/1913610

Nordhaus, W.D., 1987. "Forecasting Efficiency: Concepts and Applications." *Review of Economics and Statistics*. 69: 667– 74. Accessed at: https://doi.org/10.2307/1935962

Schnepf, R., 2017. "NASS and U.S. Crop Production Forecasts: Methods and Issues." *Congressional Research Service.* Accessed at: https://sgp.fas.org/crs/misc/R44814.pdf

United States Department of Agriculture, 2012. "The Yield Forecasting Program of NASS." *SMB Staff Report.* Accessed at: https://www.nass.usda.gov/Publications/Methodology_and_Data_Quality/Advanced_Topics/Yield%20Forecasting%20Program%20of%20NASS.pdf

Vereda, L., J. Savignon, and T. Gouveia da Silva, 2021. "A new method to assess the degree of information rigidity using fixed-event forecasts." *International Journal of Forecasting.* 37(4): 1576-1589. Accessed at: https://doi.org/10.1016/j.ijforecast.2021.03.001

Vogel F.A. and G.A. Bange, 1999. "Understanding USDA Crop Forecasts." Washington DC: U.S. Department of Agriculture, National Agricultural Statistics Service and Office of the Chief Economist, *World Agricultural Outlook Board.* Accessed at: https://www.nass.usda.gov/Education_and_Outreach/Understanding_Statistics/pub1554.pdf

Woodford, M., 2001. "Imperfect Common Knowledge and the Effects of Monetary Policy." NBER Working Paper 8673. *National Bureau of Economic Research, Inc.* Accessed at: https://ideas.repec.org/p/nbr/nberwo/8673.html

Xiao J., S.H. Lence and C.Hart, 2014. "USDA and Private Analysts Forecasts of Ending Stocks: How Good Are They?" Selected paper presented at 2014 AAEA Annual Meeting, Minneapolis, MN, July 2729, 2014.

Table 1: Average USDA Forecast Errors for Production and Yield (Log scale), 1985 - 2018

Mean Forecast Error	(1)	(2)	(3)	(4)	(5)
			Panel A: Corn		
	August	September	October	November	Pooled
Production	0.007	0.007	0.003	-0.0006	0.003
	(0.009)	(0.008)	(0.005)	(0.002)	(0.003)
Yield	0.009	0.009	0.002	-0.001	0.004
	(0.008)	(0.007)	(0.005)	(0.002)	(0.002)
			Panel B: Soybeans		
	August	September	October	November	Pooled
Production	0.014	0.013	0.005	-0.001	0.006
	(0.010)	(0.009)	(0.004)	(0.002)	(0.003)
Yield	0.017	0.016	0.007	0.00004	0.008
	(0.009)	(0.008)	(0.004)	(0.017)	(0.003)
			Panel C: Wheat		
	May	June	July	August	Pooled
Production	0.001	0.005	-0.004	-0.008	-0.001
	(0.011)	(0.009)	(0.003)	(0.002)	(0.003)
Yield	0.019	0.017	0.006	-0.0006	0.007
	(0.010)	(0.008)	(0.005)	(0.003)	(0.003)

Standard errors are reported in parentheses.
Source: Authors' calculations based on USDA data.

Table 2: Average USDA Forecast Revisions for Production and Yield (Log scale), 1985 -2018

Mean Forecast Revision	(1)	(2)	(3)	(4)	(5)
			Panel A: Corn		
	September	October	November	January	Pooled
Production	-0.0003	0.004	0.003	-0.0006	0.002
	(0.003)	(0.004)	(0.003)	(0.002)	(0.002)
Yield	0.0003	0.006	0.004	-0.001	0.002
	(0.003)	(0.004)	(0.004)	(0.002)	(0.001)
			Panel B: Soybeans		
	September	October	November	January	Pooled
Production	0.0009	0.007	0.008	-0.001	0.004
	(0.004)	(0.006)	(0.003)	(0.002)	(0.002)
Yield	0.008	0.008	0.001	0.00004	0.004
	(0.003)	(0.006)	(0.004)	(0.002)	(0.002)
			Panel C: Wheat		
	June	July	August	January/ September	Pooled
Production	-0.004	0.008	0.004	-0.008	0.0002
	(0.004)	(0.007)	(0.002)	(0.002)	(0.002)
Yield	0.002	0.014	0.005	-0.0006	0.005
	(0.003)	(0.006)	(0.003)	(0.003)	(0.002)

Standard errors are reported in parentheses.
Source: Authors' calculations based on USDA data.

Table 3: Test for Smoothing in Corn, Soybeans, and Wheat Production Forecasts

Forecast Error	(1)	(2)
Panel A: Corn		
	Pooled Revisions	
	OLS	IV
Revision (contemporaneous)	0.592***	0.860**
	(0.101)	(0.329)
Revision (lagged)	-0.091	-0.208
	(0.096)	(0.181)
1st stage F-statistic	-	11.26***
Weak-Instrument Interval	-	(0.204, 1.837)
Panel B: Soybeans		
	Pooled Revisions	
	OLS	IV
Revision (contemporaneous)	0.345***	0.633***
	(0.061)	(0.205)
Revision (lagged)	0.012	-0.044
	(0.053)	(0.002)
1st stage F-statistic	-	12.07***
Weak-Instrument Interval	-	(0.271, 1.309)
Panel C: Wheat		
	Pooled Revisions	
	OLS	IV
Revision (contemporaneous)	0.175***	0.038**
	(0.054)	(0.874)
Revision (lagged)	0.013	0.043
	(0.049)	(0.098)
1st stage F-statistic	-	4.23**
Weak-Instrument Interval	-	(-4.617, 0.939)

*** p<0.01, ** p<0.05, * p<0.1
Source: Authors' Calculations based on USDA data.

Table 4: Test for Smoothing in Corn, Soybeans, and Wheat Yield Forecasts

Forecast Error	(1)	(2)
Panel A: Corn		
	Pooled Revisions	
	OLS	IV
Revision (contemporaneous)	0.514***	0.702***
	(0.09)	(0.192)
Revision (lagged)	-0.068	-0.139
	(0.082)	(0.118)
1st stage F-statistic	-	20.18***
Weak-Instrument Interval	-	(0.261, 1.252)
Panel B: Soybeans		
	Pooled Revisions	
	OLS	IV
Revision (contemporaneous)	0.351***	0.688***
	(0.058)	(0.228)
Revision (lagged)	-0.009	-0.079
	(0.051)	(0.071)
1st stage F-statistic	-	9.77***
Weak-Instrument Interval	-	(0.300, 1.576)
Panel C: Wheat		
	Pooled Revisions	
	OLS	IV
Revision (contemporaneous)	0.059	0.588
	(0.071)	(0.354)
Revision (lagged)	0.000073	-0.141
	(0.069)	(0.129)
1st stage F-statistic	-	5.74**
Weak-Instrument Interval	-	(0.065, 3.648)

*** p<0.01, ** p<0.05, * p<0.1

Source: Authors’ Calculations based on USDA data.

Table 5: Regression Results and Information Rigidities for Corn, Soybeans, and Wheat Production

Forecast Error	(1)	(2)	(3)	(4)
		Panel A: Corn		
	September	**October**	**November**	**Pooled**
$\hat{\beta}$	0.764**	0.969***	0.362***	0.581***
OLS S.E.	0.458	0.191	0.105	0.126
N-W. S.E.	0.298	0.209	0.047	0.093
$\hat{\lambda}$	0.433***	0.492***	0.266***	0.367***
$\hat{G}$	0.567***	0.508***	0.734***	0.633***
S.E.	0.029	0.054	0.026	0.037
		Panel B: Soybeans		
	September	**October**	**November**	**Pooled**
$\hat{\beta}$	0.189	0.393***	0.381***	0.286***
OLS S.E.	0.349	0.108	0.105	0.104
N-W. S.E.	0.211	0.036	0.048	0.051
$\hat{\lambda}$	0.159	0.282***	0.276***	0.222***
$\hat{G}$	0.841***	0.718***	0.724***	0.773***
S.E.	0.149	0.019	0.025	0.031
		Panel C: Wheat		
	June	**July**	**August**	**Pooled**
$\hat{\beta}$	0.917***	0.224***	0.408***	0.339***
OLS S.E.	0.329	0.079	0.168	0.092
N-W. S.E.	0.15	0.059	0.079	0.045
$\hat{\lambda}$	0.478***	0.183***	0.289***	0.253***
$\hat{G}$	0.522***	0.817***	0.711***	0.747***
S.E.	0.041	0.039	0.039	0.025

*** p<0.01, ** p<0.05, * p<0.1
significance stars are based on N-W standard errors.
Source: Authors' Calculations based on USDA data.

Table 6: Regression Results and Information Rigidities for Corn, Soybeans, and Wheat Yield

Forecast Error	(1)	(2)	(3)	(4)
		Panel A: Corn		
	September	**October**	**November**	**Pooled**
$\hat{\beta}$	0.673**	0.845***	0.262***	0.509***
OLS S.E.	0.428	0.188	0.069	0.119
N-W. S.E.	0.281	0.196	0.034	0.105
$\hat{\lambda}$	0.402***	0.458***	0.208***	0.337***
$\hat{G}$	0.598***	0.542***	0.792***	0.663***
S.E.	0.1	0.057	0.021	0.046
		Panel B: Soybeans		
	September	**October**	**November**	**Pooled**
$\hat{\beta}$	0.194	0.391***	0.308***	0.276***
OLS S.E.	0.329	0.108	0.086	0.103
N-W. S.E.	0.189	0.037	0.054	0.049
$\hat{\lambda}$	0.163	0.281***	0.236***	0.216***
$\hat{G}$	0.837***	0.718***	0.764***	0.784***
S.E.	0.133	0.019	0.031	0.03
		Panel C: Wheat		
	June	**July**	**August**	**Pooled**
$\hat{\beta}$	1.413***	0.062	0.257*	0.245***
OLS S.E.	0.389	0.141	0.163	0.099
N-W. S.E.	0.181	0.081	0.158	0.052
$\hat{\lambda}$	0.585***	0.059	0.205**	0.197***
$\hat{G}$	0.414***	0.941***	0.795***	0.803***
S.E.	0.031	0.071	0.1	0.034

*** p<0.01, ** p<0.05, * p<0.1
significance stars are based on N-W standard errors.
Source: Authors' Calculations based on USDA data.

Table 7: Implied Information Rigidities for Corn, Soybeans, and Wheat Production

Model	Measure	September	October	November	Pooled
Panel A: Corn					
Univariate	Information Rigidity	0.40 (0.17)	0.48 (0.07)	0.26 (0.05)	0.36 (0.06)
	BIC	-107	-149	-197	-590
Multivariate	Information Rigidity	0.71 (0.6)	0.85 (0.41)	0.54 (1.47)	0.14 (0.33)
	BIC	-103	-147	-194	-586
p-value for test of model equivalence		0.61	0.30	0.85	0.51
Panel B: Soybeans					
Univariate	Information Rigidity	0.10 (0.32)	0.28 (0.05)	0.26 (0.04)	0.21 (0.07)
	BIC	-96	-152	-207	-561
Multivariate	Information Rigidity	0.61 (0.74)	0.26 (0.26)	0.31 (0.56)	0.25 (0.19)
	BIC	-92	-149	-203	-556
p-value for test of model equivalence		0.51	0.97	0.95	0.84
Panel C: Wheat					
Univariate	Information Rigidity	0.53 (0.09)	0.18 (0.08)	0.23 (0.1)	0.27 (0.07)
	BIC	-102	-167	-199	-577
Multivariate	Information Rigidity	0.83 (1.09)	0.29 (0.09)	0.22 (0.17)	0.28 (0.07)
	BIC	-73	-122	-172	-482
p-value for test of model equivalence		0.78	0.38	0.96	0.88

Source: Authors' Calculations based on USDA data.

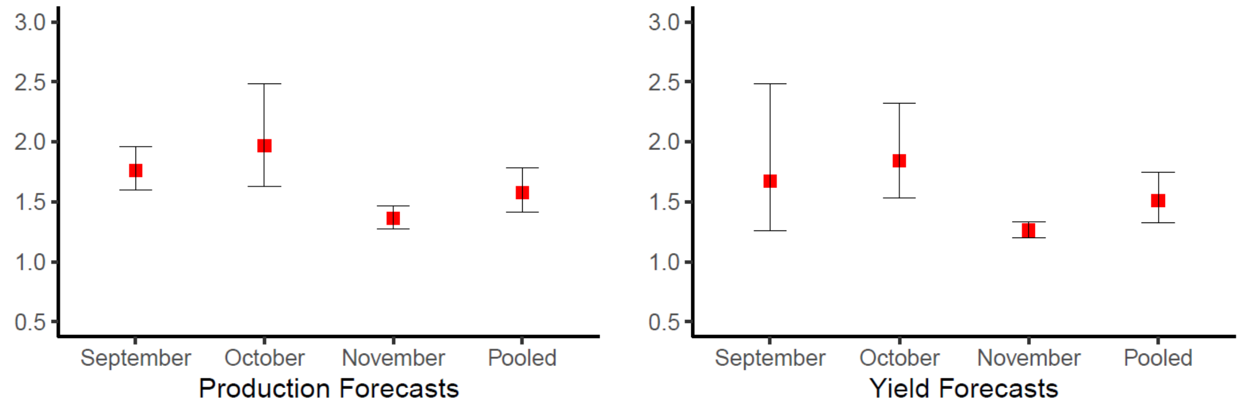
Table 8: Implied Information Rigidities for Corn, Soybeans, and Wheat Yield

Model	Measure	September	October	November	Pooled
Panel A: Corn					
Univariate	Information Rigidity	0.37 (0.17)	0.44 (0.07)	0.21 (0.04)	0.33 (0.06)
	BIC	-112	-151	-223	-610
Multivariate	Information Rigidity	0.68 (0.53)	-0.04 (1.18)	0.17 (0.89)	0.00 (0.37)
	BIC	-108	-157	-221	-606
p-value for test of model equivalence		0.56	0.69	0.96	0.38
Panel B: Soybeans					
Univariate	Information Rigidity	0.11 (0.29)	0.28 (0.05)	0.25 (0.04)	0.21 (0.07)
	BIC	-99	-156	-218	-574
Multivariate	Information Rigidity	0.49 (0.79)	0.20 (0.28)	-0.32 (0.79)	0.04 (0.25)
	BIC	-96	-153	-216	-570
p-value for test of model equivalence		0.63	0.79	0.45	0.50
Panel C: Wheat					
Univariate	Information Rigidity	0.58 (0.06)	0.10 (0.1)	0.22 (0.15)	0.21 (0.07)
	BIC	-95	-115	-152	-524
Multivariate	Information Rigidity	0.80 (0.55)	-0.05 (0.16)	0.14 (0.24)	0.06 (0.09)
	BIC	-92	-115	-149	-527
p-value for test of model equivalence		0.68	0.42	0.77	0.22

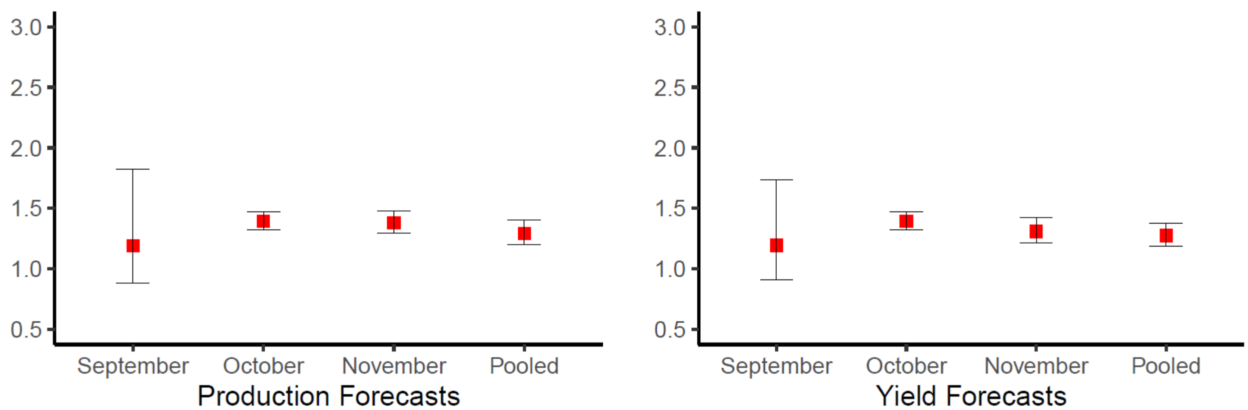
Source: Authors' Calculations based on USDA data.

Figure 1. Average Duration between Information Updates, 1985-2018

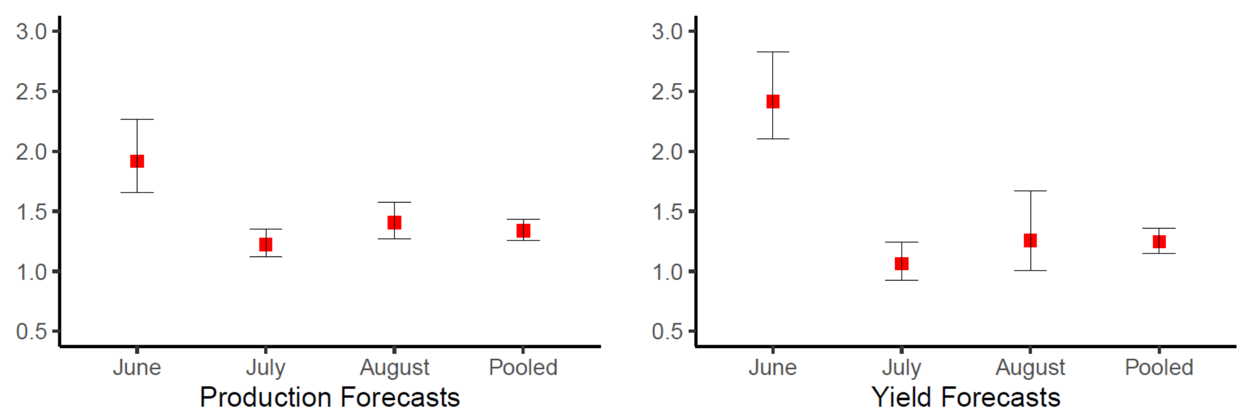
Panel 1.a: Corn



Panel 1.b: Soybeans



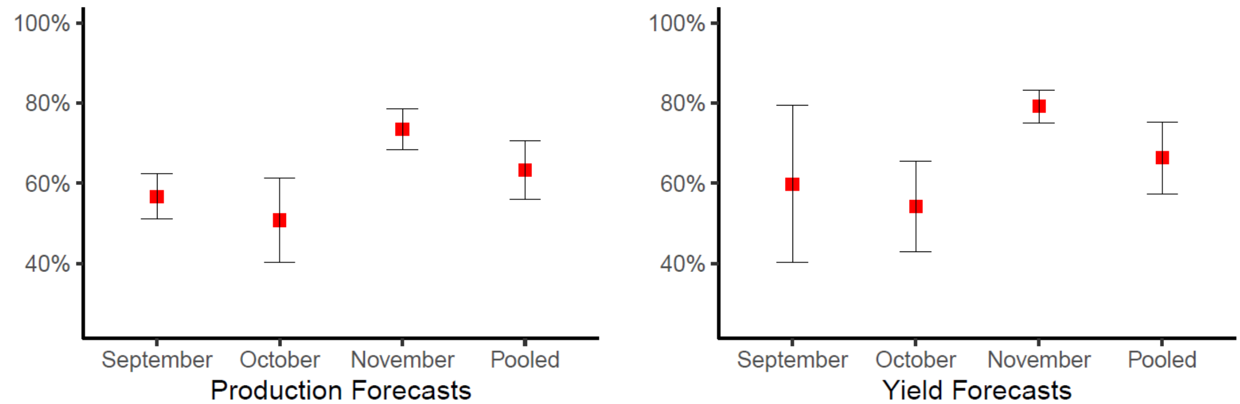
Panel 1.c: Wheat



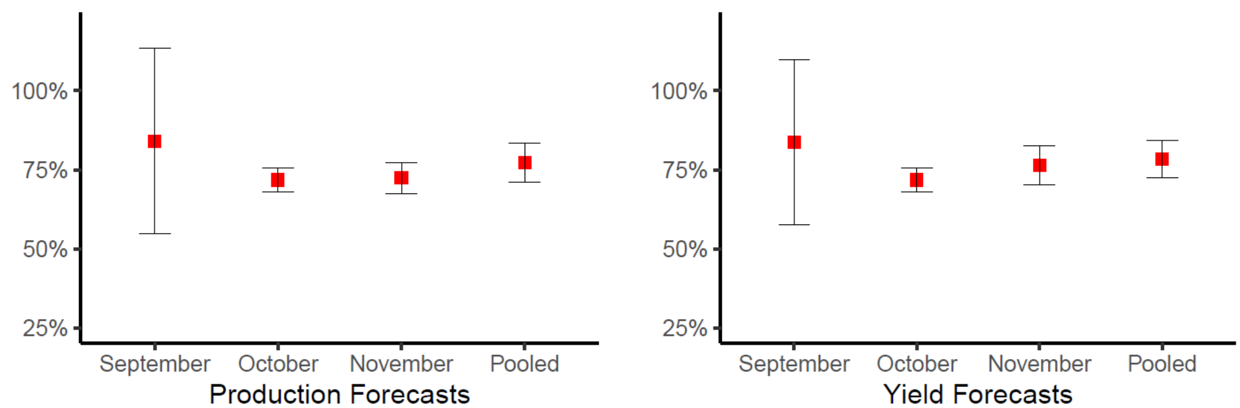
Source: Authors' Calculations based on USDA data.

Figure 2. Implied Weight USDA Places on New Information, 1985-2018

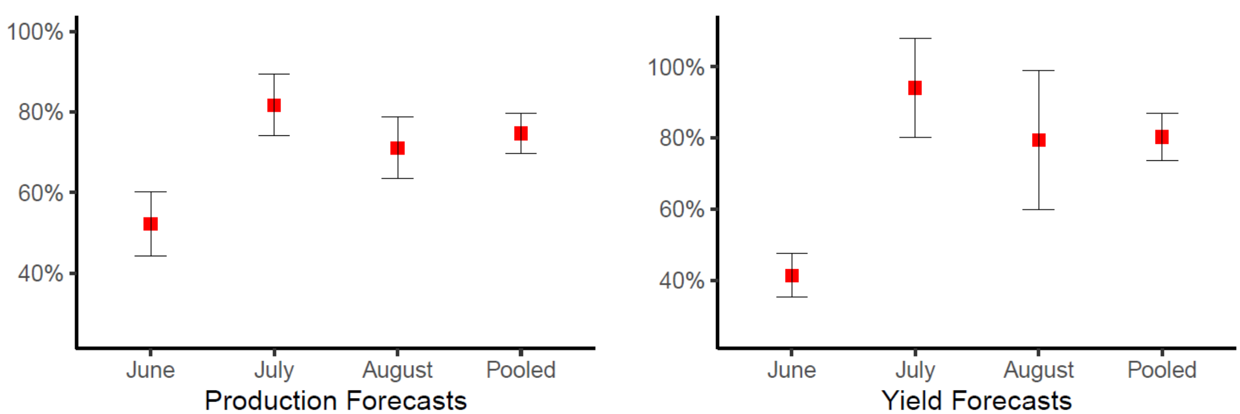
Panel 2.a: Corn



Panel 2.b: Soybeans



Panel 2.c: Wheat



Source: Authors' Calculations based on USDA data.

Appendix

Sticky information model

Coibion and Gorodnichenko (2015) show that the time t forecast for x_{t+h} is given by a weighted average of past and current fully-updated forecasts as defined in equation (A.1).

$$F_t x_{t+h} = (1-\lambda)\sum_{i=0}^{\infty} \lambda^i E_{t-i}\, x_{t+h} \tag{A.1}$$

$$F_t x_{t+h} = (1-\lambda)E_t x_{t+h} + (1-\lambda)\lambda E_{t-1} x_{t+h} + (1-\lambda)\lambda^2\, E_{t-2} x_{t+h} + \cdots \tag{A.2}$$

$$F_t x_{t+h} = (1-\lambda)E_t x_{t+h} + \lambda F_{t-1} x_{t+h} \tag{A.3}$$

Using $v_{t+h,t} = x_{t+h} - E_t x_{t+h}$ (refer to equation (4) in the main text), we get:

$$F_t x_{t+h} = (1-\lambda)(x_{t+h} - v_{t+h}) + \lambda F_{t-1} x_{t+h} \tag{A.4}$$

Adding and subtracting $\lambda F_t x_{t+h}$ on the R.H.S. of equation (A.4), and rearranging the terms gives us the following:

$$(1-\lambda)(F_t x_{t+h} - x_{t+h}) = -\lambda(F_t x_{t+h} - F_{t-1} x_{t+h}) - (1-\lambda) v_{t+h,t} \tag{A.5}$$

$$x_{t+h} - F_t x_{t+h} = \frac{\lambda}{1-\lambda}\,(F_t x_{t+h} - F_{t-1} x_{t+h}) + v_{t+h,t} \tag{A.6}$$

We can rewrite (A.6) as:

$$x_{t+h} - F_t x_{t+h} = \beta(F_t x_{t+h} - F_{t-1} x_{t+h}) + v_{t+h,t} \tag{A.7}$$

where, $\beta = \frac{\lambda}{1-\lambda}$. Equation (A.7) is equivalent to running the regression of forecast errors on forecast revisions. We use this equation to test for the presence of information rigidities in the production and yield forecasts. We can re-write equation (A.7) as:

$$x_{t+h} - F_{t-1}x_{t+h} = \beta\,(F_{t-1}x_{t+h} - F_{t-2}x_{t+h}) + v_{t+h,t-1} \qquad \text{(A.8)}$$

Subtracting (A.8) from (A.7), we get:

$$(1+\beta)(F_t x_{t+h} - F_{t-1}x_{t+h}) = \beta\,(F_{t-1}x_{t+h} - F_{t-2}x_{t+h}) + v_{t+h,t-1} - v_{t+h,t}$$

Solving this further:

$$(1+\beta)(F_t x_{t+h} - F_{t-1}x_{t+h}) = \beta\,(F_{t-1}x_{t+h} - F_{t-2}x_{t+h}) + E_t x_{t+h} - E_{t-1}x_{t+h}$$

$$F_t x_{t+h} - F_{t-1}x_{t+h} = \frac{\beta}{1+\beta}\,(F_{t-1}x_{t+h} - F_{t-2}x_{t+h}) + \frac{1}{1+\beta}(E_t x_{t+h} - E_{t-1}x_{t+h}) \qquad \text{(A.9)}$$

Here, $(E_t x_{t+h} - E_{t-1}x_{t+h})$ is the new information available at time *t*.

Equation (A.9) is equivalent to equation (3) in the main text. We show that equations (A.7) and (A.9) are equivalent. Note that equation (A.9) is used in the existing literature to detect smoothing (see, e.g., Isengildina-Massa et al., 2006, 2013, 2017). Here, we show that this equation tests for the presence of frictions, not smoothing, in forecasts.

Noisy information model

Under this model, Coibion and Gorodnichenko (2015) show that agents continuously update their information sets, and hence their forecasts, according to the following process.

$$E_t x_{t+h} = E_{t-1} x_{t+h} + v_{t+h,t-1} \tag{A.10}$$

Agents do not directly observe $E_t x_{t+h}$. Instead, they observe noisy signals about the true state. Consider an agent *i* who observes the signal $Y^i_{t+h,t}$, given by equation (A.11):

$$Y^i_{t+h,t} = E_t x_{t+h} + \omega^i_{t+h,t} \tag{A.11}$$

The best estimator of $E_t x_{t+h,t}$ based on the information set available to individual *i* at time *t-1* is given by:

$$\left(\widehat{E_t x_{t+h}}^{\,i}\right)^- = E^i_{t-1}(E_t x_{t+h}) = E^i_{t-1}(E_{t-1} x_{t+h} + v_{t+h,t-1}) \tag{A.12}$$

$$\left(\widehat{E_t x_{t+h}}^{\,i}\right)^- = E^i_{t-1}(E_t x_{t+h}) = E^i_{t-1}(E_{t-1} x_{t+h}) + E^i_{t-1}(v_{t+h,t-1}) \tag{A.13}$$

Since $E^i_{t-1}\left(v_{t+h,t}\right) = 0$, we get:

$$\left(\widehat{E_t x_{t+h}}^{\,i}\right)^- = E^i_{t-1}(E_t x_{t+h}) = E^i_{t-1}(E_{t-1} x_{t+h}) \tag{A.14}$$

Based on the concept of Kalman Filters, we know that the best estimator for $E_t x_{t+h}$can be obtained by:

$$\left(\widehat{E_t x_{t+h}}^{\,i}\right)^+ = \left(\widehat{E_t x_{t+h}}^{\,i}\right)^- + g^i_{t+h,t}\left(\widehat{\omega_{t+h,t}}^{\,i}\right)^- \tag{A.15}$$

where, $\left(\widehat{\omega_{t+h,t}}^{\,i}\right)^-$is the measurement residual given by: $\left(\widehat{\omega_{t+h,t}}^{\,i}\right)^- = Y^i_{t+h,t} - \left(\widehat{E_t x_{t+h}}^{\,i}\right)^-$.

Therefore, we can re-write equation (A.15) as:

$$\left(\widehat{E_t x_{t+h}}^{\,i}\right)^{+} = \left(\widehat{E_t x_{t+h}}^{\,i}\right)^{-} + g^{i}_{t+h,t}\left[Y^{i}_{t+h,t} - \left(\widehat{E_t x_{t+h}}^{\,i}\right)^{-}\right] \tag{A.16}$$

$$\left(\widehat{E_t x_{t+h}}^{\,i}\right)^{+} = g^{i}_{t+h,t}(Y^{i}_{t+h,t}) + (1 - g^{i}_{t+h,t})\left(\widehat{E_t x_{t+h}}^{\,i}\right)^{-} \tag{A.17}$$

From (A.10), we get:

$$\left(\widehat{E_t x_{t+h}}^{\,i}\right)^{+} = g^{i}_{t+h,t}(E_t x_{t+h} + \omega^{i}_{t+h,t}) + (1 - g^{i}_{t+h,t})\left(\widehat{E_t x_{t+h}}^{\,i}\right)^{-} \tag{A.18}$$

Now, we assume that the Kalman gain, $g^{i}_{t+h,t}$, converges to G. And, averaging it across all individuals to get consensus forecasts:

$$\frac{1}{I}\sum_{i=1}^{I}\left(\widehat{E_t x_{t+h}}^{\,i}\right)^{+} = \frac{G}{I}\sum_{i=1}^{I}(E_t x_{t+h} + \omega^{i}_{t+h,t}) + \frac{1-G}{I}\sum_{i=1}^{I}\left(\widehat{E_t x_{t+h}}^{\,i}\right)^{-} \tag{A.19}$$

$$\Rightarrow \frac{1}{I}\sum_{i=1}^{I}\left(\widehat{E_t x_{t+h}}^{\,i}\right)^{+} = \frac{G}{I}\sum_{i=1}^{I}(\omega^{i}_{t+h,t}) + G(E_t x_{t+h}) + \frac{1-G}{I}\sum_{i=1}^{I}\left(\widehat{E_t x_{t+h}}^{\,i}\right)^{-}$$

We can reasonably assume that $\frac{1}{I}\sum_{i=1}^{I}(\omega^{i}_{t+h,t}) = 0$, and $\frac{1}{I}\sum_{i=1}^{I}\left(\widehat{E_t x_{t+h}}^{\,i}\right)^{+} = F_t x_{t+h}$, and from equation (A.14), we know:

$$\frac{1}{I}\sum_{i=1}^{I}\left(\widehat{E_t x_{t+h}}^{\,i}\right)^{-} = \frac{1}{I}\sum_{i=1}^{I}E^{i}_{t-1}(E_{t-1}x_{t+h}) = \frac{1}{I}\sum_{i=1}^{I}E^{i}_{t-1}(E_{t-1}x_{t+h}) = \frac{1}{I}\sum_{i=1}^{I}E^{i}_{t-1}(x_{t+h})$$
$$= F_{t-1}x_{t+h}$$

Therefore, we can rewrite equation (A.19) as:

$$F_t x_{t+h} = (1-G)F_{t-1}x_{t+h} + G(E_t x_{t+h}) \tag{A.20}$$

Equation (A.20) is equivalent to Coibion and Gorodnichenko's (2015) own equation (8). Using equation (A.10), we can re-write (A.20) as:

$$F_t x_{t+h} = (1-G)F_{t-1}x_{t+h} + G(x_{t+h} - v_{t+h,t})$$

Adding and subtracting x_{t+h}, we get:

$$\Longrightarrow F_t x_{t+h} = (1-G)F_{t-1}x_{t+h} + G\left(x_{t+h} - v_{t+h,t}\right) + x_{t+h} - x_{t+h}$$

Re-arranging certain terms:

$$\Longrightarrow F_t x_{t+h} - x_{t+h} = (1-G)(F_{t-1}x_{t+h} - x_{t+h}) - G\left(v_{t+h,t}\right) + (1-G)(F_t x_{t+h}) - (1-G)(F_t x_{t+h})$$

$$\Longrightarrow F_t x_{t+h} - x_{t+h} = (1-G)(F_{t-1}x_{t+h} - F_t x_{t+h}) - G\left(v_{t+h,t}\right) + (1-G)(F_t x_{t+h} - x_{t+h})$$

$$\Longrightarrow \qquad x_{t+h} - F_t x_{t+h} = \frac{(1-G)}{G}(F_t x_{t+h} - F_{t-1}x_{t+h}) + v_{t+h,t} \qquad \text{(A.21)}$$

with $\beta = \frac{1-G}{G}$, equation (A.21) reduces to equation (A.8). Therefore, both sticky-information models and noisy-information models establish a similar relationship between ex-post forecast errors and ex-ante forecast revisions.