INSTITUTT FOR SAMFUNNSØKONOMI
DEPARTMENT OF ECONOMICS

SAM 2 2015
ISSN: 0804-6824
March 2015

Discussion paper

Weather shocks and English wheat yields, 1690-1871

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Abstract[1]

We estimate a time series model of weather shocks on English wheat yields for the early nineteenth century and use it to predict weather effects on yield levels from 1697 to 1871. This reveals that yields in the 1690s were depressed by unusually poor weather; and those in the late 1850s were inflated by unusually good weather. This has led researchers to overestimate the underlying growth of yields over the period by perhaps 50 per cent. Correcting for this effect would largely reconcile the conflicting primal and dual estimates of productivity growth over the period.

Keywords: weather, agriculture, productivity.

JEL Classification: N5, O3, Q1, Q2.

[1] This research was funded by the Economic and Social Research Council, the Fulbright Commission and Nuffield College, Oxford, under their Prize Research Fellowship programme. The paper was completed whilst I was a visitor at the Harvard economics department. I am grateful to James Foreman-Peck, Oliver Grant, Tim Leunig, Avner Offer, Joachim Voth and - especially - Lucy White for helpful comments. I would also like to thank seminar participants at Berkeley, British Columbia, Davis, Harvard, London School of Economics, McGill, Northern Universities' Conference in Economic History, Oxford and Stanford. Any remaining errors are entirely my own responsibility.

0. Introduction. In recent years a great deal of new data and analysis has been presented on output and productivity growth in England during the Industrial Revolution. In particular, there has been an increasing use of price data to estimate productivity growth using the dual method, in contrast to the more traditional use of quantity data to estimate productivity growth using the primal method.[2] One might hope and expect that the new light shed by this research would help to resolve old disagreements and create a new consensus about the nature and causes of English industrialization. But, in fact, the new evidence seems simply to be entrenching the opposing factions more deeply in their positions. This is particularly true in the arena of agriculture – the largest sector of the economy – where the price data employed by Clark in his dual estimates of productivity growth are hard to square with the quantity data employed by Allen, Crafts and Harley, and Overton in their primal estimates of productivity growth.[3] Another way of inferring labour productivity in agriculture, pioneered by Wrigley (1987), is to look at the share of the labour force in agriculture: in an economy with few imports, a smaller agricultural labour share implies higher labour productivity. Yet this indirect approach has proved equally controversial, with Broadberry *et al.* (2013) vigorously disputing the finding of Clark (2013) that there were little growth in labour productivity between mediaeval times and the mid-nineteenth century. Thus these recent contributions bring us no closer to resolving the debate.

Since there can be only one true historical value for productivity growth, it is evident that the estimates of at least one side must be inaccurate. The most likely cause of such inaccuracy is the nature of the underlying data. Inevitably, all the data that have been adduced can be criticized in general terms on the grounds of quantity, quality and/or representativeness. This paper has a more specific goal. It demonstrates and explains why one of the key data series for the primal estimates, that of wheat yields, is highly unrepresentative. The problem stems from the large and random impact of weather shocks on yields in the 1690s and late 1850s: yields were abnormally depressed in the 1690s and abnormally high in the late 1850s. The problem is sufficiently large that, if all crops were similarly affected, then correcting for this alone could potentially reconcile the primal and dual estimates of productivity growth in English agriculture.

[2] A very selective list would include Allen (1994); Antras and Voth (2003); Clark (2001); Crafts and Harley (1992).

[3] Allen (1994); Clark (2002); Crafts and Harley (1992); Overton (1996).

In section one we introduce a data source on wheat yields that has long been known to historians but which has not been used previously by quantitative economic historians – the annual yield estimates of the Liverpool corn merchants. We also introduce historical temperature and rainfall data for England. In section two we combine these data to estimate a time series model of weather shocks on English wheat yields. We then use the model to predict the annual effect of weather shocks on wheat yields over the period 1697 to 1871, demonstrating that the predicted annual shocks are consistent with qualitative evidence on the abundance of the harvest in each year. In section three we construct benchmark estimates of weather shocks and compare them to benchmark estimates of wheat yields. We show that the weather was unusually adverse in the 1690s and unusually benign in the late 1850s – likely leading to a 50 per cent overestimate of underlying yield growth, if we rely on the raw historical data. A rough calculation suggests that this is sufficient to explain most of the discrepancy between the primal and dual estimates of agricultural productivity growth. Section 5 concludes.

1. Time series data on English wheat yields and weather. The official annual estimates of average crop yields do not begin in England until 1883 – a rather surprising fact, since data on land use begin in 1866. Asking farmers to reveal their outputs – rather than their inputs – was initially thought to be too intrusive. Thus there is a dearth of systematic yield data between the decline of the monasteries (which bequeathed us excellent data) and the late nineteenth century. This has led researchers to fall back on alternative sources to try to estimate yields back from 1883 to the late seventeenth century. One approach has been to harness probate inventories (Overton, 1979, 1990; Allen 1988). Another approach has been to harness farm accounts (Turner, Becket and Afton, 2001). A significant problem with both of these data sources is that there are relatively few observations; this means that observations must be averaged over several years to get a statistically satisfactory estimate; and this means, in turn, that we do not have annual yield estimates. This effectively precludes the estimation of a model of weather shocks on wheat yields. We therefore turn to an alternative data source – that of the Liverpool corn merchants, as reported and discussed extensively by Healey and Jones (1962, 574-9).

The Liverpool corn merchants compiled annual yield estimates for the period 1815-59. They did this by sending out investigators in the run up to the harvest; each of them rode around a specified circuit and took samples of wheat growing in the fields. Their objective was to gain advance information about the abundance of the harvest in order to be able to price futures contracts in English wheat. They were therefore primarily interested in the extent to which the harvest was better or worse than usual in order to get some idea of the extent to which market prices would be higher or lower than usual. This motivation has important repercussions for the nature of the data. The Liverpool merchants' series has not been used widely by researchers because, as Healey and Jones note, it is 'liable to substantial positive bias'. This is partly due to the method that the merchants used to sample the grain, and partly due to their method of weighting the samples.

First, a sample was collected by taking a frame of one square yard and throwing it randomly into a field of wheat; the number of grains within the frame was then counted and the number of bushels per acre then estimated. Overall, this will induce a positive bias because plants in the middle of the field tend to have a higher average yield than those at the edge. Second, the yield of the sample square yard was then multiplied by 4840 to estimate the yield of an acre of land (1 acre=4840 square yards). But some of the land in each acre was actually given over to footpaths, headlands, hedges, et cetera, so the average yield of one acre of wheat land was less than 4840 times the yield of one square yard. To control for this 'footpath effect', the corn merchants suggested deflating the yield figures by 50/72 (0.694).

In fact, the mean wheat yield for the Liverpool series was 40 bushels, whereas a more plausible level for the national average yield for the period 1815-59 would be 25 bushels (Caird, 1852, 522). Fundamentally, the Liverpool merchants did not care whether their data accurately reflected the national average yield; they cared only that it accurately reflected the abundance of the harvest this year relative to other years. Our interest is very similar to that of the Liverpool merchants: we are not using their yield series to infer the national average yield, only to infer the response of yields to weather shocks. Of course, if the yields were overestimated more in good years than bad years then this would bias upwards our estimated coefficients. This is a distinct possibility owing to the way that the Liverpool merchants handled their sample. Suppose that the sown acreage is overestimated by two-fold (i.e. suppose that paths, hedges, et cetera actually comprise one half of an acre of wheat land).

Then not only will the average yield be overestimated by two-fold but so will the fluctuations. Therefore in this paper we have multiplied every observation by 0.625, thereby reducing the average from 40 to 25 bushels per acre but keeping the relative importance of the year-on-year fluctuations.[4]

Securing a wheat yield series is an essential first step in estimating the effect of annual weather shocks on yields. But we must complement these data with observations on weather. We are fortunate that the long and strong empiricist tradition in Britain generated a class of gentlemen who had interest, time, knowledge and means of recording temperature and rainfall. Many individual sources had to be combined to generate such a long time series and assembling these diverse data into a single series was evidently no easy task. We are therefore fortunate that meteorologists have already done it for us, with Manley (1974, 389-405) providing temperature data and Wales-Smith (1971, 345-62) providing rainfall data. Their data pertain to open country in central England, 100-200 feet above sea level. London was avoided because: it is not centrally located (i.e. it is too far east to be representative of the whole of England); its weather is idiosyncratic, owing to the effect of the Thames valley; and there would be urban weather effects that would increase over time. The series was specifically constructed to be as nationally representative of England as was feasible, given the historical records that have come down to us. The data are presented on a monthly basis – that is, monthly averages of the daily temperature maximum/minimum, monthly accumulated rainfall, and so on. This is a standard way of presenting weather information, even when more frequent data are available, since the daily data are typically rather volatile.

Let us now put these data to work in estimating a model of weather shocks on wheat yields.

Section 2. A time series model of weather shocks. For *c*. 1770, Brunt (2004) has estimated a cross-sectional model of English wheat yields that incorporates the effect of climatic variation across the country. We can think of climate as being the average outcome of year-specific weather shocks. Weather variables, such as rainfall, fluctuate from year to year in each place but their mean values nonetheless differ significantly from one place to another (i.e. different

[4] An alternative strategy would be to run the regression in natural logarithms, which would have a similar effect. We choose not to take that approach because we want to formulate a model that is as close as possible to the Brunt (2004) cross-sectional model in order to facilitate cross-checking of the results.

places have different climates). The important point for our analysis is that the annual fluctuation of weather variables in England is much greater than the cross-sectional variation. For example, in August the wettest place in England (Kendal in Cumbria) receives 3 times as much rainfall as the driest place (Hadleigh in Norfolk); but the wettest August on record (1878) received 330 times as much rainfall as the driest August (1730). This means that we cannot simply use a cross-sectional model to predict annual wheat yields because we would almost always be predicting a long way out of sample, which would cause substantial prediction errors. We therefore need to estimate a time series model that incorporates annual weather shocks.

Estimating a time series model of weather shocks and agricultural output is not simple, as evidence by the recent debate over US data between Deschênes and Greenstone (2007, 2012) and Fisher *et al.* (2012). A potential difficulty for us is that we do not have annual data on all the relevant inputs (fertilizer, crop rotation, labor, machinery, et cetera). In fact, this is not a serious problem. The annual fluctuations in wheat yields are overwhelmingly determined by the annual fluctuations in the weather. This is partly because crop yields are very sensitive to the impact of weather; but it is also because the year-on-year fluctuations of the weather are much greater than the year-on-year fluctuations of other inputs, such as technology or the capital stock. Hence we would expect any time series model of wheat yields to focus almost exclusively on weather variables; this is the approach taken by biologists (Chmielewski and Potts, 1995, 43-66; Nicholls, 1997, 484-5). We control for the possibility of a secular increases in capitalisation and technology by adding a time trend to our model.[5]

Another complication in estimating a time series model is that the date of the harvest changes from year to year. In his cross-sectional model, Brunt draws attention to the importance of weather in the last month before harvest (August) and the penultimate month (July). In our case, the last month will vary from year to year. The typical harvest date in England in the nineteenth century was the end of August, as revealed by contemporary sources such as Rothamsted (Lawes and Gilbert, 1864, 1884).[6] Thus August weather variables typically reflect the conditions faced by the wheat plants in the last month of their growth

[5] We first tested for a unit root in order to establish that a time trend was a reasonable functional form. The unit root was rejected at the 5 per cent level.

cycle. But if a harvest were two weeks late then most of its growth in the terminal month would actually occur in September rather than August; and if it were two weeks early then it would occur in July rather than August. Therefore if a harvest was two weeks later than average we substituted the September values of temperature and rainfall for the August values, and so on. In order to carry out this procedure we needed to estimate the date of the harvest. This is actually quite straightforward (Gooding and Davies, 1997). The maturity of a wheat crop is determined by the number of 'degree-days' that it accumulates through the growth cycle, where degree-days are defined as the maximum air temperature (in Celsius) occurring on each day (i.e. two calendar days with a maximum air temperature of 10 degrees Celsius constitute 20 degree-days). We calculated the calendar date of the thousandth degree-day after planting (assuming that planting occurred on the first day of October each year). If the thousandth degree-day was two weeks later (earlier) than the average for the whole period (1697-1871) then we assumed that the harvest was late (early).

Having prepared the data in this way, we estimated the model in table 1 below.

Table 1. A time series model of English wheat yields, 1815-1859 (bu/acre).

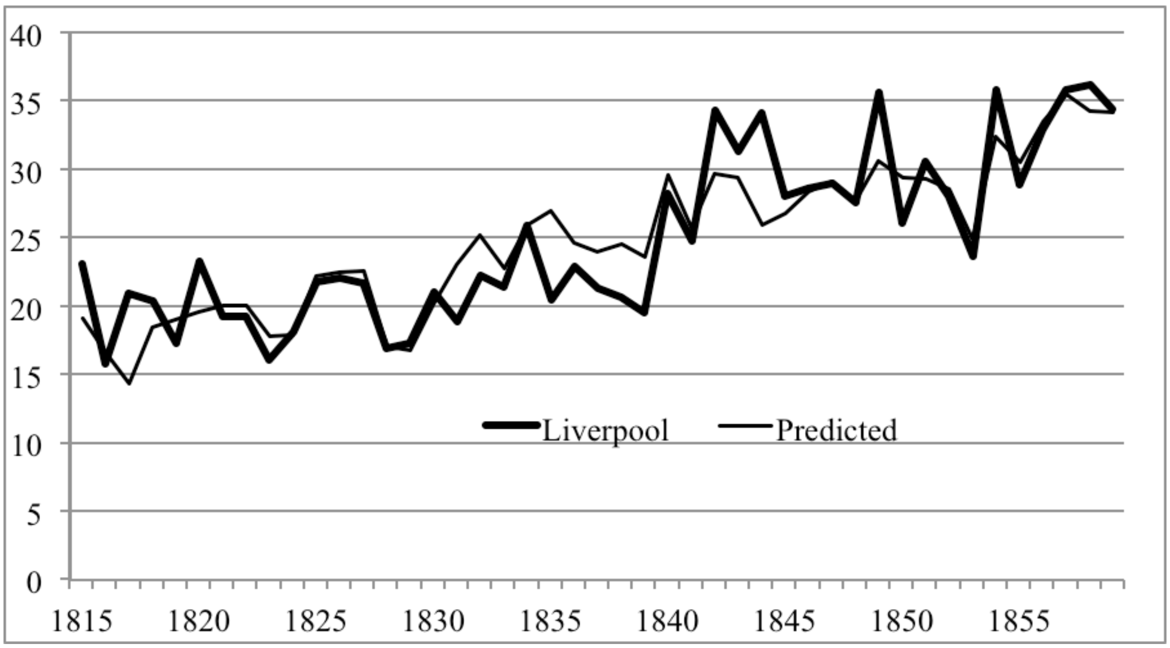
Variables Explaining **WHEAT YIELD**	Coefficient	t-statistic
July-August Rainfall	0.037	0.81
July-August Rainfall Squared	-2.917	-1.70
July-August Temperature Change (Cube Root)	0.835	1.95*
December-January Mean Temperature	21.560	1.77
December-March Rainfall	-0.021	-1.99*
Year	0.294	6.67**
R^2	**0.79**	
Adjusted R^2	**0.75**	
SE of the Equation	**3.03**	
F-statistic	**23.50**	
Durbin-Watson	**1.63**	
N	**45**	

Note: ** indicates statistical significance at the 1 per cent level; * indicates statistical significance at the 5 per cent level. The other variables are insignificant due to multicollinearity; we decided to retain them after an F-test showed that they had high explanatory power.

[6] Rothamsted is the world's oldest experimental farm, where thousands of experiments have been conducted since 1843. Rothamsted has been a pioneer in agronomy and related disciplines, such as genetics and statistics; it has exemplary recordkeeping, including of harvest dates back to 1844.

The weather variables retained in our time series model are essentially those that are significant in Brunt's cross-sectional model, and the estimated coefficients are similar (see the appendix for further analysis). The model gives a good fit of the data and seems to perform well throughout the period. This can be seen in figure 1 below, where we plot the annual yields predicted by the model against those registered by the Liverpool corn merchants.

Figure 1. Yields predicted by the model and recorded by the Liverpool merchants.

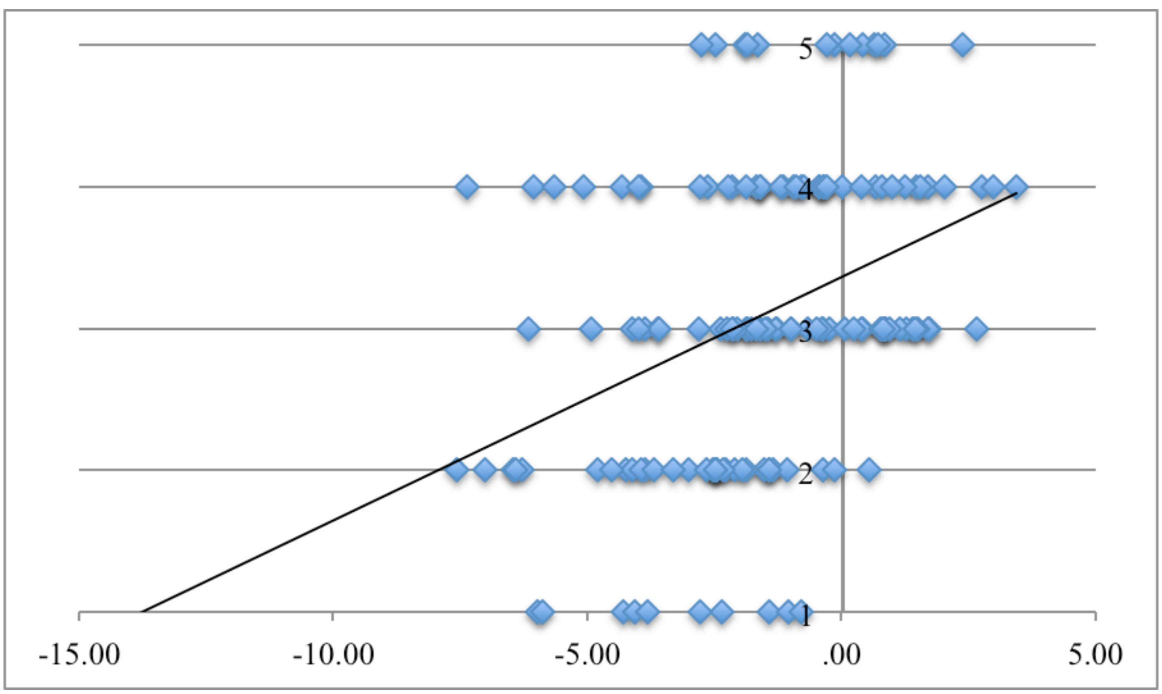


It is impossible to test our model directly against measured yield data because there are no such series available before the 1880s, even for a short period. However, we can verify our model against other sources. The time series model effectively breaks down the change in wheat yields into two components. First, there is an upward trend, determined by factors such as capital and technology, which we cannot model explicitly here owing to the lack of detailed data. Second, there is a substantial fluctuation around the trend caused by the annual fluctuations in the weather. Separating out these two effects allows us to test our model.

We use the weather coefficients estimated in the model to predict the effect of weather on the wheat yield in each year from 1697 to 1871. By ignoring the trend we are calculating the extent to which the wheat yield in any particular year was above or below 'normal'. Of course, a 'bad' year around 1870 could still have a higher yield than a 'good' year around

1700 because the level of yields was trending upwards. The series thus produced is comparable to the qualitative harvest assessments made by Jones (1964). On the basis of contemporary printed evidence and unpublished diaries, Jones assessed all the harvests between 1728 and 1911 and noted whether they were above or below average. We used his assessment to grade all the wheat harvests up to 1871 on a scale of 1 to 5. Average years were given a grade of 3; 'good' years earned a grade of 4; and 'very good' or 'bumper' years were graded 5; grade 2 years were 'bad'; and grade 1 years were 'very bad'. We correlated the annual estimates based on Jones' research with the new yield series generated by our model, finding that they are positively and significantly correlated (a correlation coefficient of 0.40 with a p-value of 0.014). This is in spite of the coarse nature of one of the data series (i.e. a simple scale of 1 to 5) and the fact that many of Jones' observations are of a rather local nature (after all, the fact that wheat yields were low in, say, Hampshire in a particular year does not necessarily imply that the national average was low). The two series are graphed in figure 2 below.[7]

Figure 2. Weather shocks to English wheat yields, 1728-1870 (bu/acre).



[7] The exceptionally large outlier predicted by the model in 1782 is probably due to inaccurate weather data

We have now estimated a time series wheat yield model for the period 1815-59. We showed that it is consistent with Brunt's cross-sectional findings for the late eighteenth century, and that it successfully predicts good and bad harvests in the period 1728 to 1871. In the next section we consider the implications for benchmark yield estimates.

3. Weather effects and benchmark yields. How plausible are the results of our weather exercise? And how can we verify them with reference to independent data? We noted above that there were no annual series of wheat yields against which we could test our model – hence we matched them instead against annual qualitative data. However, there are benchmark yield estimates available from a variety of sources. The available sources generally present survey data rather than census data, which is to say that they record yields in an average or typical year rather than any particular year. For example, there are probate inventories from the 1690s; government surveys from around 1800; Caird's survey of 1850; the Mark Lane Express of 1860; and farm accounts through the period. These sources are detailed in table 1.

In order to gauge the effects of weather shocks on these observed 'typical' yields, we constructed corresponding benchmark weather estimates based on the average effect over the preceding five years. That is, for the 1771 benchmark we took the average values of each of the variables (temperature, rainfall, et cetera) for the period 1767-71. Repeating this process for earlier and later benchmark years enables us to chart changes in the observed wheat yield resulting from weather shocks. In table 2 below we report the benchmark yield data and the contemporaneous effects of weather on wheat yields.

Table 2. Sources of the change in English wheat yields, 1701-1861 (bu/acre).

	1701	1771	1801	1816	1836	1851	1861
Weather effects	-1.14	-1.88	-2.77	-2.28	-0.71	-1.00	0.04
Measured yield	16.20	23.08	21.50	21.26	20.6	26.26	28.65
Liverpool corn merchants' yields				19.25	22.60	29.78	35.47

Sources: weather effects – author's calculations; measured yield – probate inventories (1690s) from Overton (1996, 77); British Government Crop Return (1801) from Turner (1982, 508-9); Board of Agriculture Surveys (*c*. 1816) and the Mark Lane Express (1861) from John (1986, 1048-50); Caird's survey (1851) from Caird (1852, 522); and farm accounts from Turner, Beckett and Afton (2001); Liverpool corn merchants' yields –

because the rainfall data are contaminated for that particular year; see Wales-Smith (1971, 360).

Healey and Jones (1962, 574-9). The Liverpool yields presented here is deflated, as described in the text. Note also that the Liverpool series begins only in 1815, so the 1816 figure is based on an average of only two years (rather than five); and the series ends in 1859, so the 1861 figure is based on an average from 1857-9 (rather than 1857-61); the correlation between the Liverpool series and the measured yields is 0.93.

One of the striking aspects of the yields reported in table 2 is that yields fell during the late eighteenth century. Indeed, this has led a number of commentators to doubt the accuracy of the 1771 estimates taken from Arthur Young (in particular, see Kerridge, 1968, 43-53, and Overton, 1996, 78, 129; but also see the more recent analyses of Allen and O'Grada, 1988, and Brunt, 2004). But the years leading up to 1801 were known to have had particularly poor harvests – in fact, this is exactly what prompted the government to attempt to collect yield data in 1801. Our model enables us to say something about the size of the negative weather effect: it reduced wheat yields by almost one bushel per acre, vis-à-vis 1771, which is two-thirds of the observed decline.

The probate inventories underlying the 1701 benchmark are drawn from throughout the 1690s, not just the last few years of the decade. But the available weather series start only in 1697, which is why our first benchmark is 1701. Thus it is not *prima facie* obvious that our weather model can tell us much about the low yields of the 1690s: after all, the absence of weather data before 1697 means that it is impossible to match precisely the weather model and the probate yield estimates, in terms of timing. But drawing such a downbeat conclusion underestimates the utility of the model because the model quantifies the *volatility* of weather shocks on wheat yields, as well as the average effect. We can use this insight as follows.

The weather in the 1690s is known to have been unusually poor (Overton, 1996, 77). But the weather effect for our 1701 benchmark is slightly less malign than the average for the whole period from 1697 to 1871 (only -1.14 bushels, rather than the average of -1.53). This is because the 1701 estimate is based on weather only from 1697 onwards. If the weather *before* 1697 were as bad as Overton suggests then this would drive down the expected wheat yield even further. But *how much* could the bad weather of the 1690s have plausibly driven down wheat yields? We can estimate this impact from our model. Suppose that the overall weather effect in the 1690s was one standard deviation (2.49 bushels) worse than average. Then the predicted weather effect benchmark – based on the model – would be -4.02 bushels (=-1.53-2.49). Improvements in the weather would then explain a third of the measured increase in yields up to 1771 (2.12/6.88 bushels). Of course, the weather effect of the 1690s could very plausibly have been more than one standard deviation below average, since around 17 per cent of the probability distribution lies below the one standard deviation limit. For example, if the weather of the 1690s lay two standard deviations (6.51 bushels) below average then the weather improvement up to 1771 would explain two thirds (4.63/6.88 bushels) of the overall improvement. These conjectures are sketched in table 3 below.

Table 3. Plausible weather effects on English wheat yields, 1690s-1861 (bu/acre).

	1690s	1771	1861
Measured yield	16.20	23.08	28.65
Measured yield increase since 1690s		6.88	12.45
Weather effects: a) if weather effect were one standard deviation < average or: b) if weather effect were two standard deviations < average	 -4.02 or -6.51	-1.88	0.04
Weather improvement compared to 1690s		2.24 or 4.63	4.06 or 6.55
The share of measured yield increase, since the 1690s, that is explicable by fortuitous improvements in the weather (%)		*32.56* *or* *67.30*	*32.61* *or* *52.61*

Sources: as in table 2 above.

Consider also the longer run changes. Table 3 above shows that the weather was notably less malign in the run-up to 1861, having an impact of 0.04 bushels compared to the average of -1.53 bushels for the whole period from 1697 to 1871. So now the improvement in the weather would generate an improvement of 4.06 or 6.55 bushels – compared to an overall increase of 12.45 bushels. Thus, again, the weather can explain one third to one half of the increase in wheat yields observed between the first benchmark and the last benchmark. This leads us to overestimate the increase in wheat output, due to human intervention, by up to 50 per cent. One of the most important results of our yield simulations is that variations in weather cause substantial fluctuations in the wheat yield even when averaged over periods as long as five or ten years. In consequence, benchmark output data can be very misleading and need to be treated with some caution.

Given that the magnitude of the annual fluctuations in wheat yields was ±40 per cent, our model probably gives a more accurate estimate of the 'typical' yield in any particular year than do the actual measured data. And here lies the kernel of an explanation for how to reconcile the greatly divergent primal and dual estimates of productivity growth for English agriculture. Allen (1994, 111) shows that the primal method tends to produce relatively high estimates of total factor productivity growth, such as 0.54 per cent per annum from the beginning of the eighteenth century to the mid-nineteenth century. But Clark (2002, table 2) shows that the dual method tends to produce much lower estimates, such as 0.25 per cent per annum for the same period. But the primal estimates are based on only half a dozen benchmark observations of output. This means that having one (unrepresentative) low yield observation in 1700 and one high (unrepresentative) yield observation in 1860 greatly skews upwards the estimated output and productivity growth. By contrast, the dual estimates are based on *annual* price observations weighted by a representative basket of quantities. In consequence, a few (unrepresentative) high price observations in 1700 and a few (unrepresentative) low price observations in 1860 do not greatly skew upwards the estimate of output and productivity growth. Correcting the observed yield data for the transient effect of weather – i.e. revising down the assumed yield growth by a half – would bring the primal estimates much closer to those of the dual. How much closer?

A complete reworking of the primal estimates of TFP growth is far beyond the scope of the present paper. However, a rough calculation suggests that revising downwards yield growth by 50 per cent would reduce estimated TFP growth from around 0.54 per cent per annum to 0.34 per cent per annum. Here we sketch the outline of the calculation, as reported in table 4 below. Suppose that the primal input index (I index) rose from 100 in the 1690s to 145 in 1861 (Allen, 1994, 110). This follows from an increase in land inputs of around 35 per cent over the period, labour inputs of around 15 per cent and capital of around 90 per cent. Suppose also that the output index (Q index) rose from 100 in the 1690s to 344 in 1861 (Allen, 1994, 110). Why? Land in production rose by around 35 per cent; fallow declined from perhaps one third of acreage to 5 per cent, thus increasing output by another 44 per cent; and yields rose by perhaps another 77 per cent (as reported in table 2 above). This pushes the output index up to 344 (=100*1.35*1.44*1.77). This gives an annual rate of growth of TFP of 0.54 per cent, the figure postulated by Allen.

Table 4. Possible effect of adjusting yields on primal TFP calculation, 1690s-1861.

	I index	Q index	Explanation for change in Q Index
1690s	100	100	1861 Q Index = 100*ΔAcreage*ΔShareAcreageSown*ΔYield
1861	145	345	= 100* 1.35 * 1.44 * 1.77
TFP	= 345/145 = 2.37		If TFP rises by a factor of 2.37, then annual ΔTFP = 0.54%
1690s	100	100	1861 Q Index = 100*ΔAcreage*ΔShareAcreageSown*ΔYield
1861	145	265	= 100* 1.35 * 1.44 * 1.36
TFP	= 265/145 = 1.83		If TFP rises by a factor of 1.83, then annual ΔTFP = 0.37%

Sources: author's calculations, as explained in the text.

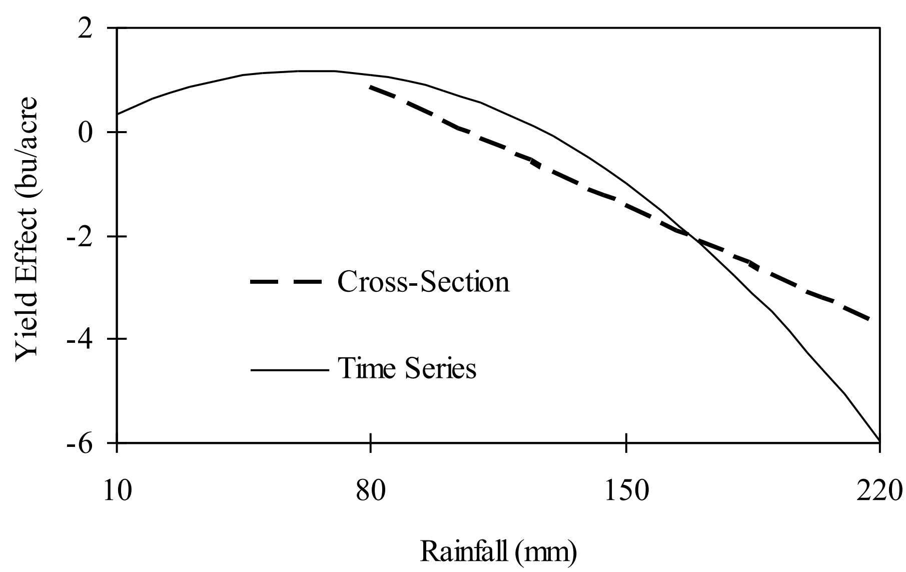
Now adjust the previous calculation so that yields rise by only half as much (i.e. suppose that the impact of weather had been no worse in the 1690s than it was around 1861, so the early yields were substantially higher). Now the 1861 output index rises to only 265 – as shown in the lower panel of table 4 above – and the implied rate of annual TFP growth falls to 0.37 per cent per annum. This moves us more than halfway from Allen's estimate of 0.54 per cent to Clark's estimate of 0.25 per cent. In fact, Clark's dual estimates are anyway rather low. Antràs and Voth (2003) use the dual to estimate TFP growth for the whole economy – not just agriculture – and are thus not directly comparable to the other figures here. However, their analysis can usefully inform our investigation. When Antràs and Voth run a sensitivity analysis for the whole economy (their table 5) they find that the Clark data on the returns to land – derived from the returns of the Charity Commissioners – give lower estimates of overall TFP growth than any other data series. Using these same Charity Commissioners data would obviously generate the same downward effect in Clark's (2002) analysis of agricultural TFP, which we have been examining here. Any upward revision to Clark's estimated TFP growth rate of 0.25 per cent per annum would put it indistinguishably close to the 0.37 per cent per annum that we sketched above.

5. Conclusions. Using a new time series wheat model, we have demonstrated that the weather was a crucial determinant of annual English wheat yields. Most importantly, simulations based on this model reveal that the weather likely dealt a joker to historical wheat yield data, depressing it abnormally in the 1690s and inflating it abnormally in the late 1850s. As a result, underlying wheat yield growth has been overestimated by perhaps 50 per cent, and agricultural total factor productivity growth by perhaps a third (using the primal method).

Correcting for these transient weather effects can help to reconcile the primal and dual measures of productivity growth; this is extremely desirable, since the dual estimates currently much lower than primal estimates for the eighteenth and early nineteenth centuries. Incorporating revised estimates of crop yields – based on changes in the underlying yields, rather than those impacted by weather – would bring the primal estimate almost indistinguishably close to that of the dual.

Appendix. It is instructive to compare time series and cross sectional models of wheat yields. The specifications differ slightly because weather variables take more extreme values over time than in cross-section. Thus a quadratic best describes the effect of July-August Rainfall in time series, whereas a linear relationship holds in cross-section. This is simply because all the cross-sectional observations lie above the turning point described by the time series data. Plotting the relationship estimated in this paper against Brunt (2004) gives figure A1 below. The two estimated curves are congruent when the data are measured over the same range.

Figure A1. The effect of rainfall on wheat yields: comparing time and space.



Notice that the cross-sectional curve is slightly flatter than the time series curve (i.e. yields are less responsive to rainfall in cross section). This is exactly what we would expect because the cross sectional estimates are based on 'normal' yields responding to 'normal' weather. So in the cross section the farmers can partly offset excessive local rainfall by adapting their farming practices, for example by choosing to cultivate wheat varieties that are more resilient to heavy local rainfall. By contrast, in the time series context the farmers plant their seed in October in expectation of an average amount of annual rainfall for their location; if rainfall is higher than usual then they are unable to respond by changing the variety of their seed, so the impact is more negative.

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