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Innovation and Productivity Advances in British Agriculture: 1620–1850

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Theory, historiography, and empirical evidence suggest that agriculture is the key to economic development. This article examines the extent to which productivity advances in British agriculture during the period 1620–1850 were driven by technological progress. Measuring technology by patents and new book titles on agricultural methods, the results are consistent with endogenous growth theory, indicating that technological progress has played a significant role in agricultural productivity advances.

JEL Classification: O30, O40

1. Introduction

Theory, historiography, and empirical evidence suggest that agriculture is the key to economic development. Theoretically, Gollin, Parente, and Rogerson (2002) show that industrialization can be substantially delayed by low agricultural productivity. Once agriculture switches from traditional to modern technology labor is released to the industrial sector and the economy grows at higher rates. Based on their analysis, Gollin, Parente, and Rogerson (2002, p. 164) conclude that "the key message that emerges from our analysis is that a greater understanding of the determinants of agricultural productivity will enhance our understanding of the development process for those nations that are currently poor." The development literature also argues that agricultural productivity is central to development (see, e.g., Timmer 1988).

Historiography supports the proposition of Gollin, Parente, and Rogerson (2002). In explaining the different stages of economic development, Rostow (1959) claims that one of the essential conditions for the successful take-off of the British economy was the technological revolution in agriculture. He argues that while Britain experienced a rise in total population at the onset of industrial progress, there was a disproportionate increase in the number of urban dwellers. Technological progress in the agricultural sector had prevented the debacle of

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modernization through supporting this larger pool of population in the economy. Similarly, Deane (1969) argues that in England the British Agricultural Revolution was closely associated with the Industrial Revolution, given that development in the agricultural sector increased purchasing power for industrial products and that agriculture provided substantial amounts of the financial capital required for industrialization. Overton (1996a, b), Allen (2005, 2008), and Brunt (2003, 2004) analyze productivity advances during the British Agricultural Revolution and conclude that technological improvements played a significant role for agricultural productivity gains.

Empirical evidence supports the conjecture that productivity advances within agriculture are strongly related to economic development. Caselli (2005) finds that most of the cross-country productivity variation in the world today is due to productivity differences in agriculture. His counterfactual simulations show that if agricultural productivity throughout the world was equal to that in the United States then cross-country inequality would virtually disappear. This analysis is supported by van Zanden (1991), who finds that agricultural productivity among the European countries in 1870 was strongly and positively correlated with the share of employment in nonagricultural industries and per capita income.

Despite the importance of agriculture for industrial revolutions, economic development, and take-off, very little work, if any, has been undertaken to explain agricultural productivity advances based on innovative activity in an explicit regression framework. This article examines the role of innovations in explaining the productivity advances in British agriculture over the period from 1620 to 1850. More specifically, it examines how innovative activity has contributed to productivity advances where innovative activity is measured by patent counts and the number of titles of first published technical farming books.

Explaining agricultural growth in terms of research effort, however, requires a functional relationship between growth and research and development (R&D) to be established. In other words, it has to be decided which growth theory describes the mapping between research effort, knowledge stock, and technological progress. It is not sufficient to regress labor productivity growth on technology indicators because different endogenous growth theories yield different predictions about the functional relationship between growth and innovative activity. The first-generation models of Romer (1990) and Aghion and Howitt (1992) predict a positive relationship between the levels of research effort and productivity growth. However, it is now acknowledged that there is no consistent positive relationship between the number of research workers and productivity growth rates on an economy-wide scale: while the number of R&D workers in OECD countries has increased substantially over the past century, their growth rates have not changed much (Jones 1995; Ha and Howitt 2007).

To overcome this deficiency the two second-generation endogenous growth theories, namely, the semiendogenous and Schumpeterian, have taken over as the dominant endogenous growth models. Semiendogenous growth models suggest that it is the relative change and not the level of research effort that influences growth, while Schumpeterian growth models assume that growth is proportional to research intensity, measured as research effort divided by product variety. These models assume that a larger population increases the number of people who can enter an industry with a new product, results in more horizontal innovations, and dilutes R&D expenditure over a larger number of separate projects (Peretto 1998; Peretto and Smulders 2002; Zachariadis 2003; Ha and Howitt 2007; Madsen 2008). The analysis in this article embodies the predictions of the first-generation as well as the second-generation growth models.

An important issue addressed in this article is the extent to which the modern endogenous growth framework can be applied to the British Industrial Revolution and, particularly, the British Agricultural Revolution. The analysis of Madsen, Ang, and Banerjee (2010) show that the Schumpeterian growth framework is suitable in explaining the British Industrial Revolution; however, this does not mean that the same framework is useful in explaining the British Agricultural Revolution because it is not clear whether R&D expenditures are diluted over a larger number of separate projects in agriculture—an issue we will discuss in the next section. Thus, although the predictions of the first-generation growth models have been ruled out as useful in explaining the growth regimes in industrialized countries, the same cannot be said for using this framework in explaining agricultural modernization.

The primary objectives of this article are to examine the role played by innovative activity during the British Agricultural Revolution and to test whether any innovation-based growth models can adequately explain British agricultural growth during the period 1620–1850. In order to fulfill these objectives, an innovation-based growth model for the agricultural sector is presented in the next section. Data and some graphical analysis are presented in section 3. Empirical estimation is conducted in sections 4 and 5, and the last section concludes.

2. R&D-Based Growth Models with Land as a Fixed Factor of Production

This section outlines the basic framework that is used to explain agricultural labor productivity growth. The model integrates the predictions of endogenous growth models and Malthusian models in which population growth is a drag on labor productivity growth for an agrarian economy. First, consider the following homogenous Cobb-Douglas production function with labor and land as factors of production:

$$Y = A\overline{N}^{\alpha}L^{1-\alpha}, \tag{1}$$

where Y is real output in the agricultural sector, A is total factor productivity in the agricultural sector, $\overline{N}$ measures the size of land under cultivation, which is assumed to be fixed, L is agricultural labor, α is the share of income going to land, and (1–α) is the share of income going to labor. The production function exhibits constant returns to scale in $\overline{N}$ and L, but increasing returns to scale in A, $\overline{N}$, and L together.

Equation 1 can be expressed in per labor terms as follows:

$$\frac{Y}{L} = A\left(\frac{\overline{N}}{L}\right)^{\alpha}. \tag{2}$$

Taking logs and differentiating yields labor productivity growth:

$$g_y = g_A - \alpha g_L, \tag{3}$$

where g_y is labor productivity growth, g_A is the growth in total factor productivity, and g_L is the growth in the labor force. Here growth in the labor force reduces labor productivity growth due to diminishing returns introduced by land as a fixed factor of production.

While population affects labor productivity growth directly, knowledge production influences labor productivity indirectly through technological progress. The following general ideas about production function can be used to map the relationship between the knowledge stock, research effort, and ideas production and to discriminate between different endogenous growth models (Ha and Howitt 2007; Madsen 2008; Ang and Madsen 2011):

$$g_A = \frac{\dot{A}}{A} = \lambda \left(\frac{X}{Q} \right)^{\sigma} A^{\phi - 1}, \quad 0 < \sigma < 1, \phi \leq 1, \tag{4}$$

$Q \propto L^{\kappa}$ in steady state, where σ is the duplication parameter (zero if all innovations are duplications and one if there are no duplicating innovations), ϕ is the returns to scale in knowledge, κ is the coefficient of product proliferation, λ is the research productivity parameter, Q is a measure of product variety, L is employment or population, and X is R&D inputs. The first-generation endogenous growth theory of Romer (1990) and Aghion and Howitt (1992) assumes that $\phi = 1$, $\sigma > 0$, and $\kappa = 0$. Semiendogenous growth theory assumes that $\phi < 1$, $\sigma > 0$, and $\kappa = 0$ (see, e.g., Jones 1995), whereas the Schumpeterian models of Aghion and Howitt (1998), Dinopoulos and Thompson (1998), Peretto (1998), Howitt (1999), and Peretto and Smulders (2002) assume that $\phi = 1$ and $\sigma > 0$.

The mapping between the labor force and product variety in Schumpeterian models follows the relationship $Q = \psi L^{\kappa}$, where ψ is a constant and κ is a parameter that, in most circumstances, is constant and equal to one (see for theoretical and empirical justifications Peretto 1998 and Laincz and Peretto 2006). When profits per firm are inversely related to the number of firms and the cost of variety creation is constant, the number of firms is proportional to the population in the steady state. Note that the relationship between Q and L need not be a power function if markups are endogenously determined by the number of firms (see Peretto 1999). Assuming constant markups, Cobb-Douglas technology, and zero returns to variety in production, the mapping between the labor force and product variety simplifies to $Q = \psi L$, which is the functional form between the two variables assumed in this article.

Imposing the restrictions predicted by various growth theories on the ideas production function yields

$$\frac{\dot{A}}{A} = \lambda X^{\sigma}, \qquad \text{first-generation} \tag{4a}$$

$$\frac{\dot{A}}{A} = \lambda X^{\sigma} A^{\phi - 1}, \qquad \text{semiendogenous} \tag{4b}$$

$$\frac{\dot{A}}{A} = \lambda \left(\frac{X}{Q} \right)^{\sigma}. \qquad \text{Schumpeterian.} \tag{4c}$$

From Equations 4*a*–4*c* the growth effects from research effort for different models can be seen. The first-generation models predict that productivity growth is proportional to research effort. Thus, if the fraction of the labor force that is innovating is constant, an increase in world population will increase the productivity growth rate to a permanently higher level. Semiendogenous growth models propose that changes in research efforts have only temporary growth effects because there is no scale effect in ideas production. If the allocation of time spent on research is constant for each worker, these models predict that the productivity growth rate will converge toward the population growth rate along the balanced growth path. More formally, in steady state, Equation 4*b* can be written as $\sigma \ln X = (1-\phi)\ln A$ or $\dot{A}/A = [\sigma/(1-\phi)]\dot{X}/X$, suggesting that A is growing only if X is growing in steady state. This can occur only if the population growth rate is positive in steady state. Finally, Schumpeterian growth models predict that growth is driven by improved product quality and that productivity growth can be maintained at a constant positive rate provided that R&D per worker remains constant. In other words, R&D has to increase over time to counteract the increasing range of products that lowers the productivity effects of R&D activity in order to ensure sustained productivity growth.

Combining Equation 3 and the predictions of the second-generation endogenous growth models yields the following stochastic model for growth in agricultural labor productivity (see, for derivation, Madsen 2008):

$$\Delta \ln\left(\frac{Y}{L}\right)_t = \beta_0 + \beta_1 \ln(X)_t + \beta_2 \ln(Q)_t + \beta_3 \Delta \ln X_t + \beta_4 \Delta \ln POP_t + \varepsilon_t, \tag{5}$$

where Y is agricultural output, L is male employment in the agricultural sector, X is an indicator of innovative activity in the agricultural sector, Q is a measure of product variety, Δ is a 5- or 20-year difference operator, POP is the total British population, and ε is a stochastic error term. Here the first-generation growth theory predicts that $\beta_1 > 0$ and $\beta_2 = \beta_3 = 0$, semiendogenous growth models predict that $\beta_3 > 0$ and $\beta_1 = \beta_2 = 0$, and Schumpeterian growth theory predicts $\beta_1 > 0$, $\beta_1 = -\beta_2$, and $\beta_3 = 0$. Product variety is measured by the male agricultural labor force, following from the steady-state result that the number of product lines is proportional to the size of the labor force (see, for example, Ha and Howitt 2007).

Now, given that endogenous growth theory is adapted to apply to the modern economy, the question is whether it can be used to explain the British Agricultural Revolution. This is potentially the case, given that the productivity advances in British agriculture were driven by innovations such as the use of better technologies and methods, as discussed in depth in section 3. Some of the new inventions may have been luck; however, the great majority were the outcomes of informal but systematic efforts to develop new and better technology (Mokyr 2005). In that sense the modern endogenous growth framework could potentially be useful in explaining the progress in British agriculture.

However, the functional relationship between productivity growth and X and Q is likely to have been quite different for British agriculture during its agricultural revolution vis-à-vis the modern industrialized economy in which agriculture plays only a minor role in overall economic activity. The prediction of Schumpeterian growth theory that product proliferation counteracts R&D has been developed within the industrial organizational framework and is supposed to work for the modern company. Furthermore, in their model of factor elimination, Peretto and Seater (2008) show that nonreproducible factors of production are gradually eliminated through spending on R&D. Reducing the importance of land in the production function through R&D outlays counterbalances the drag that land has on the marginal productivities of the reproducible factors of production.

While strong empirical support for the Schumpeterian hypothesis has been found for modern industrial economies including the Asian miracle economies (e.g., Madsen 2008; Madsen, Ang, and Banerjee 2010; Madsen, Saxena, and Ang 2010; Ang and Madsen 2011;

Banerjee 2012) the circumstances are quite different for an agrarian economy. A large fraction of R&D by Sony, Philips, Braun, Panasonic, and Bang & Olufsen is used to create product varieties that will not enhance growth because it results only in the creation of product varieties. However, the improvements of the plough and the introduction of high-yield crops during the British Agricultural Revolution may not have been subject to proliferation effects. Although competing types of plough were introduced during the British Agricultural Revolution, as discussed in Overton (1996a) and Brunt (2007), this variety does not measure up against the product variety within agricultural machinery that we experience today. Thus, while product dilution may apply across the whole economy Schumpeterian theory does not necessarily apply to all macro sectors of the economy. As the economy transits from agriculture to manufacturing, the Schumpeterian mechanism takes over.

Extending Equation 5 to allow for control variables, the following growth model is regressed to examine the importance of innovative activity during the British Agricultural Revolution:

$$\begin{aligned}\Delta \ln (Y/L)_t = {} & \beta_0 + \beta_1 \ln X_{t-1} + \beta_2 \ln Q_{t-1} + \beta_3 \Delta \ln X_{t-1} + \beta_4 \Delta \ln POP_{t-1} \\ & + \beta_5 \ln X^{na}_{t-1} + \beta_6 \Delta \ln (M/Y^n)_t + \beta_7 \Delta \ln TO_t + \beta_8 \ln UNC_t \\ & + \beta_9 \Delta \ln LE_t + \beta_{10} \Delta \ln HK_t + u_t\end{aligned} \tag{6}$$

where X^{na} is nonagricultural patents, M is monetary stock, Y^n is nominal income, TO is trade openness, UNC is macroeconomic uncertainty, LE is life expectancy at birth, HK is human capital measured by literacy, and u is the stochastic error term. Growth in innovative activity and population are lagged one period in the model to allow for the slow adjustment of productivity to innovations and to ensure that there are no feedback effects from labor productivity to innovative activity and population growth rates. Contemporaneous values of X and Q are allowed for in the section on robustness checks.

Product variety is measured by male employment in the agricultural sector, following the condition that the number of product varieties is equal to the labor force in steady state. However, as discussed above, the number of product varieties is unlikely to have been increasing along with the labor force employed in agriculture over the considered period. Practically, the number of varieties of machines and implements used in agricultural production was probably very limited back then. Intermediate product varieties are essentially the number of crop varieties, different types of ploughs and seed drills, different livestock breeds, and various agricultural drain systems. Interestingly, the number of intermediate product varieties may even have shrunk during the British Agricultural Revolution. Before the more advanced ploughs were introduced during the Agricultural Revolution ploughs were produced by local blacksmiths (Overton 1996a). Thus, development was more toward standardization rather than variety as the revolution evolved. In the absence of better measures of product variety the labor force is used as the measure of product variety in the regressions, following the convention in the empirical literature. Alternative measures of product variety are used in the robustness checks.

The choice of control variables is dictated by their importance in economic growth theory and, particularly, by data availability. The number of non-agricultural patents (X^{na}) is included in the regressions to allow for the effects of knowledge spillovers from the nonagricultural sector to agricultural productivity. The variable M/Y is a proxy for financial deepening. Financial deepening is potentially growth enhancing because it improves investment diversification opportunities and facilitates more efficient use of resources (see, e.g., Zilibotti

1994; Acemoglu and Zilibotti 1997; Gancia and Zilibotti 2005). Openness to international trade is included in the regression because it is often considered as being important for growth for various reasons (see Vamvakidis 2002; Lucas 2007; Madsen 2009). While trade openness is not an ideal proxy for openness, better data on openness, such as tariffs and nontariff trade barriers, are not available for the past four centuries. Inflation variability, as a proxy for macroeconomic uncertainty, is a drag on the economy because it is often associated with fiscal mismanagement, wars, and crop failures.

Moreover, productivity growth is often assumed to be a positive function of life expectancy because the incentives to invest in the future are positively correlated with the number of years in which an individual is expected to be productive (Cervellati and Sunde 2005). The longer an individual is expected to live the larger are the expected returns to schooling. Furthermore, since a long life often goes hand-in-hand with a healthy life, individuals that live longer are likely to be more productive during their adult years. Human capital is an essential variable in endogenous growth models as it increases the capacity to produce new and higher volumes of quality products, as emphasized in the models of Lucas (1988), Mankiw, Romer, and Weil (1992), and Vandenbussche, Aghion, and Meghir (2006).

3. Data, Graphical Analysis, and Sources of Productivity Advances

Data

Labor productivity is measured as real agricultural output divided by males working in agriculture using the data provided by Clark (2002). Financial deepening is measured as the sum of notes in circulation and deposits in commercial and savings banks divided by economy-wide nominal GDP (see, e.g., Ang and McKibbin 2007). The sum of imports and exports divided by nominal GDP captures trade openness. Macroeconomic uncertainty is measured as the five-year standard deviation of consumer price inflation. Details on data sources and data construction are provided in the Appendix.

The number of agricultural patent applications (P_t) and the number of titles of first published technical farming books (F_t) are used as measures of innovative activity. The number of patent applications by domestic residents, as opposed to patents granted to residents, is used as the measure of innovative activity, since the length of the processing period varies substantially over time (Griliches 1990). The main criticisms of patents as a measure of innovative activity are that the quality of patents varies over time, not all innovations are patented, the propensity to patent may change over time, and the high costs of patenting give inventors strong incentives to keep their inventions secret (Boehm and Silberston 1967). While the law of large numbers tends to render the average quality of patents relatively constant in recent years (Griliches 1990), this is unlikely to hold true in the early part of the sample period when the number of patents was quite modest.

While the number of patents is a direct measure of innovative activity, the number of published technical farming books measures the discovery and the dissemination of new and existing knowledge of agricultural methods and, as such, captures innovative activity. The advantage of technical books over patents in measuring the role of technological progress is that it is difficult to acquire monopoly profits from new farming techniques in the agricultural sector.

Ideas were, to a large extent, nonexclusive in the agricultural sector because new techniques would eventually become common knowledge to all farmers through technical books and meetings. Once a farmer has learned a new technique, it is hard to prevent other farmers or the same farmer from using the same technology. Therefore, agricultural technical books and manuals spread farming ideas or knowledge and facilitate the transmission of technical know-how among farmers, irrespective of patents. This reasoning provides a good basis for the use of the number of technical book titles on farming published as a complement to agricultural patent counts for measuring technological progress in the sector. Furthermore, Baten and van Zanden (2008) suggest that book production measures the degree of literacy and human capital among the population.

With regard to the issue of the constancy of the propensity to patent, Sullivan (1989) does not find any evidence of shifts in the propensity to patent in individual sectors of the economy or changes in the industrial distribution of patents. Considering the expense of patents, their high costs of acquisition should at least, in principle, have led to patents of high quality and with high commercial promise and, as such, weeded out low-quality ones that are unimportant for growth. Thus, the high cost of patents is highly likely to improve their average quality as a measure of innovative activity and, as such, count in favor of patents as measures of innovative activity. Furthermore, Khan and Sokoloff (2007) find that 87% of the great inventors in Britain over the period from 1750 to 1930 were patentees, indicating that most of the important innovations are captured by patent counts.

Griliches (1990, p. 1702) concludes that "in spite of all the difficulties, patent statistics remain a unique resource for the analysis of the process of technical change." Although patent data are widely used in the literature (see, e.g., Oxley and Greasley 1998; Greasley and Oxley 2007; Madsen 2008; Madsen, Ang, and Banerjee 2010; Banerjee 2012) going as far back as four centuries, one cannot deny that there are flaws in patents as indicators of innovative activity. What this essentially means is that the number of patents is potentially a noisy indicator in large parts of the estimation period and, as such, may bias the parameter estimates of X toward zero. Thus, our estimates are likely to understate the importance of innovative activity for growth in the agricultural sector during the sample period.

Sullivan (1984) suggests that the number of titles of farming technical books published is an appropriate measure of agricultural innovation. It was widely observed that new crops that could not be patented at that time were promoted mainly through agricultural books. Books were effective ways of diffusing technology and new methods since famers were fairly well educated, at least in 1770 (Brunt 2003). Since about 50% of the population was literate between 1700 and 1800, increasing to 60% thereafter (Schofield 1973), it is likely that a large fraction of farmers was able to follow the new trends in methods and technology through book reading. Furthermore, Sullivan (1984) argues that farming books are at least as good as patents as indicators of advancement in agrarian technology because they contain a lot more innovative ideas compared to patents, which merely describe the implementation and mechanical devices of technologies. For example, a new plowing technique may be patented, but its implementation is not explained by that patent. This can only be found in a farming technical book.

Quality of the Data

Analyzing an economy in the sixteenth or seventeenth century is not an easy task for researchers because of the difficulties associated with the collection of data and of ensuring that the data quality is maintained. The *agricultural output* and *agricultural labor* series of Clark (2002) is chosen as opposed to any other historical sources for two main reasons. First, most of the previous studies in the literature either have constructed the agricultural output data on a noncontinuous basis and at long intervals, such as the output data at 50-year intervals in Allen (2000), or have not provided any data before 1700. For example, the first data point for agricultural output in Lindert and Williamson (1982) is for the year 1688, followed by 1759, 1801, and then on a decennial basis from 1801 onward. Similarly, the agricultural output data of Deane and Cole (1962) are available only from 1700 onward. Thus, to our knowledge, the best data source for agricultural output and agricultural labor, which is continuous, covering the entire sample period 1620–1850 and available on short intervals (10-year intervals), is Clark (2002).

Second, Clark (2002) constructs the output data using input cost data in contrast to estimating output by calculating total crop yields. The main limitation of the crop-yield method is the lack of knowledge of how much of the potential agricultural land was under crop production and consequently how much was devoted to each type of crop. Furthermore, this approach generally looks only at the arable sector, which was only half of the total agricultural output in England during the sixteenth and seventeenth centuries. The input cost measure avoids these limitations. Although the method is limited to calculations of the quantity of input, Clark (2002) has ensured that the data quality is maintained and developed methods to construct continuous decennial data series between 1550 and 1912 based upon the earlier available data of Lindert and Williamson (1982) and Allen (2000).

Data on *agricultural patents* and the number of *agricultural book titles* are collected from Sullivan (1984). This is a unique database for measuring technological progress in the history of English agriculture in the sixteenth and seventeenth centuries. Sullivan (1984) compiles the agricultural patent series from a subject index of patents issued in Britain provided by Woodcroft (1857). The number of agricultural patents issued is recorded in English history from 1611 onward. All patents specified in Woodcroft (1857) under the heading "Agriculture" are included in Sullivan's series and the data have been checked so that each patent is counted only once. Specifically, the following patents were included under agriculture: Cutting Vegetable Substances, Grinding, Cutting, Crushing Corn and other grain, Manure, Farm and Dairy Process Apparatus, Farriery, and Medical treatment of Animals. Patents under "Water and other Fluids – Draining land and Mines" were also included except where the patent referred to an activity other than draining land (e.g., draining mines).

Sullivan (1984) obtains the number of *agricultural book titles* from Perkin's (1932) bibliography. The document records the number of printed agricultural book manuals from 1521 onward, and it is worth noting that the data go even further back than the first recorded date of agricultural patents issued. Subjects that were considered as technical farming books include agricultural chemistry, botany, grasses and weeds, drainage, improvements, weights and measures, entomology, and biography. Those excluded are manuscripts, books on foreign and colonial agriculture, translations, serials, journals, catalogs, books on general chemistry and botany, forestry and timber, gardening and horticulture, surveying and land management, farriery and veterinary, law, cider, orchards, poultry, bees, goats, farm architecture, and agricultural politics and economics (see Sullivan 1984, p. 282).

As mentioned above, the following control variables are used in the empirical estimates: *human capital*, *financial deepening*, *trade openness*, *nonagricultural patents, life expectancy,* and *macroeconomic uncertainty*. The control variables that cover a shorter timespan than 1620–1850 are interpolated. *Human capital* (literacy) is first available from 1750 from the record of marriages registered in England, where the couples were able to sign at the time of their marriage (see Schofield 1973). The money stock, which is used as a proxy for *financial deepening*, is measured by the sum of notes in circulation and deposits in commercial and savings banks (Mitchell 1988) and is available only from the year 1750. Although the Bank of England was established in the year 1694, there is no proper record of monetary circulation of coins and deposits on a continuous basis before 1750. To ensure that the sample size is not compromised by the unavailability of these data before 1750, missing data for the period 1620–1749 are generated by backward extrapolation using the geometric growth rate over the period 1750–1850.

Annual import and export data, which are used for the construction of the trade openness measure, are available only from 1697 onward. The trade openness series is kept constant and equal to the 1697 figure, for the period 1620–1697. Note that the results are similar if backward extrapolation is used (results are not shown). To ensure that our results are not driven by the way the above missing data are dealt with, the estimations are also carried out without control variables and by restricting the sample period to 1720–1850. In both cases, the key findings in this article remain intact, suggesting that our results are not affected by the unavailability of some data in the early years.

Finally, data on *nonagricultural patents*, *life expectancy* at birth, and the consumer price index (CPI), which is used to measure *macroeconomic uncertainty*, are available for the entire sample period. In particular, life expectancy at birth for England can be dated back to the year 1363 (Wrigley et al. 1997) and are available on a decennial basis after 1625. Allen (2001) provides the annual CPI and wages data for London and Oxford from as early as 1264. The literature considers this as one of the best available sources of price data (for example, see Federico and Malanima 2004; Clark 2005; Broadberry and Gupta 2006; Temin 2006).

Graphical Analysis

Figures 1a and 1b display the time-series plots of agricultural production and agricultural labor input. Figure 1a shows that agricultural output grew briskly between 1620 and 1750 largely because of yield increases induced by the spread of nitrogen-fixing crops that could be used to feed livestock and improvements in the quality of grassland that improved animal nutrition (Overton 1996a). Production declined over the period from 1750 to 1810, which, to a large extent, was consistent with the fact that Britain experienced successions of poor harvests between 1760 and 1816 (Mokyr and Voth 2006). Agricultural production expanded by no less than 50% over the period 1810 to 1850, or equivalently, an annual geometric growth rate of 1%, highlighting a very strong gain in production; however, labor productivity increased at much slower rates because of an almost proportional increase in agricultural employment (Figure 1b). Figure 1c displays the growth rates in labor productivity over the period from 1620 to 1850. The data are annualized growth rates in five-year intervals. The largest growth rates are experienced over the periods 1645–1740 and 1815–1850.

Figures 2a to 2c show the time series plots of the level and growth in innovative activity and research intensity. Book production fluctuates around a relatively constant upward trend during the whole period while patenting fluctuates around a constant mean up to 1765 and increases thereafter (Figure 2a). The level of innovative activity was at least twice as high at the end of the entire period compared to the years before 1700 and is, therefore, potentially important for explaining the productivity advances during the Agricultural Revolution. The growth rates in innovative activity do not, however, show any trend but are pretty steady during the whole period and, as such, are not consistent with the profile in productivity

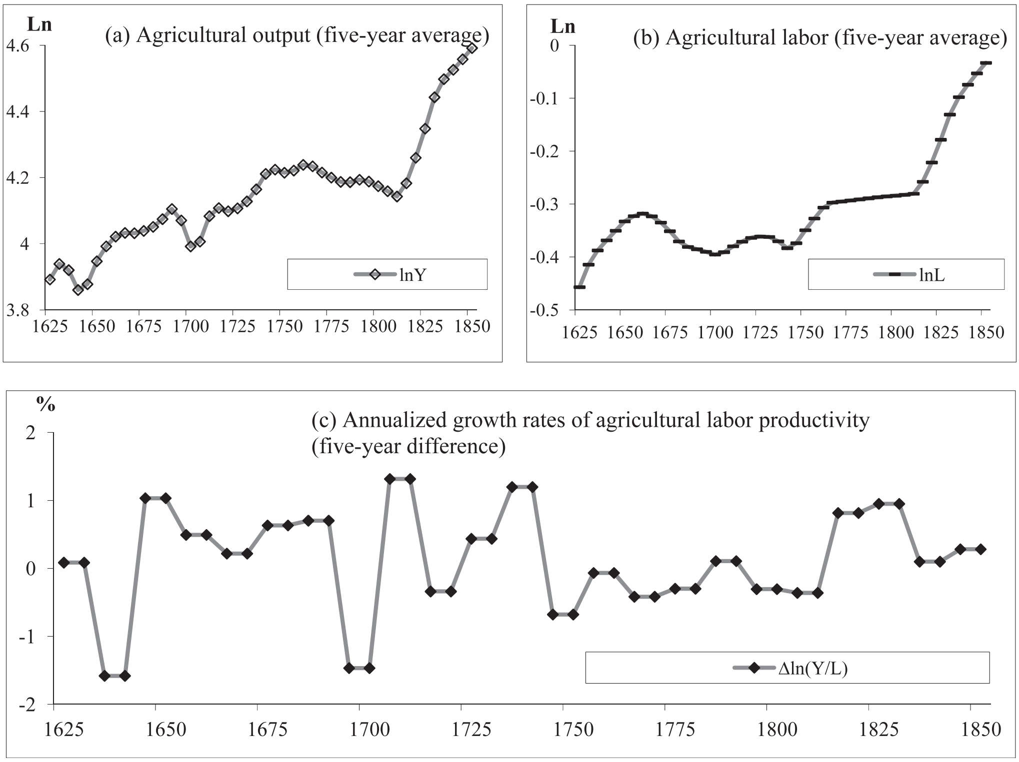

Figure 1. Time series plots for agricultural output, labor, and productivity (1620–1850). Data for labor productivity are annualized growth rates in five-year differences, whereas those of agricultural output and agricultural labor are in five-year averages.
Note: Data for labor are annualized growth rates in five-year differences whereas those of agricultural output and agricultural labor are in five-year averages.

growth. Finally, Figure 2c displays the time series path of research intensity, ln(X/Q). Its time profile is almost the same as that of the level of innovative activity except that ln(X) increased faster than ln(X/Q) after 1760, a widening gap that is difficult to identify visually.

Figure 3 displays the relationships between innovations and productivity growth. Figures 3a and 3d show a positive relationship between productivity growth and the number of patents as well as the number of books. This positive relationship suggests that there are potential scale effects in ideas production in the sense that innovative activity has permanent growth effects. Thus, the economy will continue to grow as long as new patents or books are produced. Figures 3b and 3e show that there is no clear relationship between growth in labor productivity and growth rates in innovative activity, as predicted by semiendogenous growth theory. Finally, Figures 3c and 3d depict a positive relationship between productivity growth and research intensity, again pointing toward scale effects in ideas production. Overall, from the figures it is not clear whether it is the level of innovations or research intensity that is driving productivity growth; only regression analysis can give insights into that.

The Historiography of Productivity Advances

Since the figures above indicate that innovations played a potentially important role in the productivity advances during the British Agricultural Revolution it is of interest to consider the

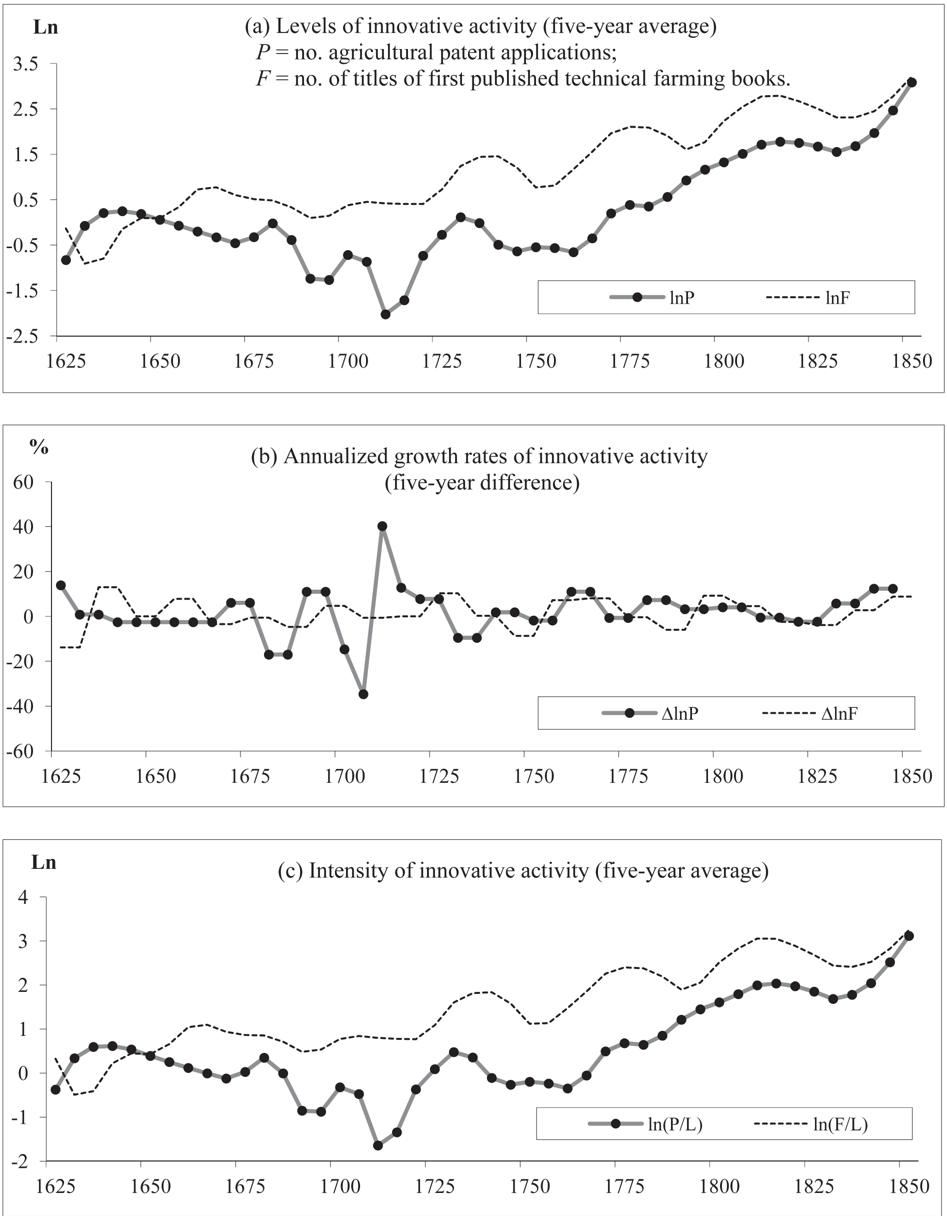

Figure 2. Time series plots for productivity growth and indicators of innovative activity. P = the number of agricultural patent applications, and F = the number of titles of first published technical farming books. Data in panel (b) reflect annualized growth rates in five-year differences, whereas those in panels (a) and (c) are in five-year averages. Note: P = the number of agricultural patent applications and F = the number of titles of first published technical farming books. Data in panel (b) reflect annualized growth rates in five-year differences whereas those in panels (a) and (c) are in five-year averages.

historiography of particular innovations, institutional changes, and the introduction of new methods that may have been important for the modernization of British agriculture. The key factors and events that are often highlighted in the literature as being vital for the British Agricultural Revolution are the enclosure movement, mechanization, crop rotation, selective breeding, and the increasing

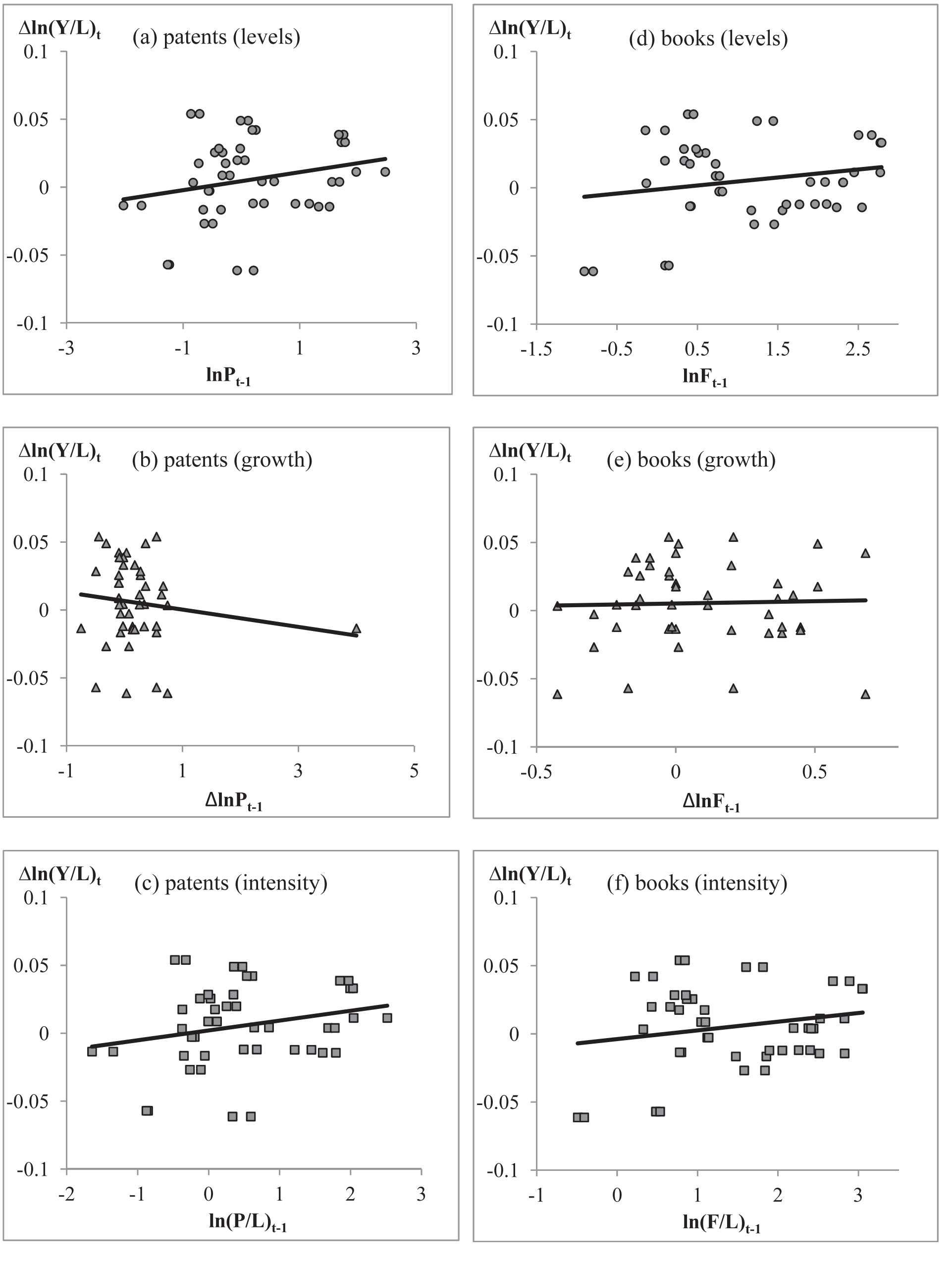

Figure 3. The Relationships of Agricultural Productivity Growth and Innovative Activity

dissemination of knowledge and new methods that were rendered possible by technological progress within book production (Overton 1996a).

Enclosures potentially increased productivity as mechanization during the eighteenth century required large, enclosed fields to be workable and gave famers larger incentives to improve the productivity of soil through land sharing, crop rotation, plowing, and addition of fertilizer. Some of the common fields in England tilled under the traditional open field system were gradually enclosed into individually owned fields, a process that accelerated in the fifteenth and sixteenth centuries and was largely completed by the end of the eighteenth century (Chambers and Mingay 1966; Overton 1996a, ch. 4). Advances in selective breeding (mating two animals with desirable characteristics) and inbreeding were also improving productivities (Overton 1996a, p. 114). The selective breeding by Robert Bakewell commencing in the 1740s was a particularly important impetus for livestock productivity. Improvements in animal nutrition also contributed to livestock productivity (Overton 1996a, p. 114).

The largest improvements in technology over the period considered in this article were the improvements of the plough, especially the substitution of iron for wood. The most significant breakthrough was the introduction of the Rotherham plough, which was patented in 1730 (Overton 1996a, p. 122). It was easy and cheap to produce and yet very efficient and required fewer horses to pull. Brunt (2003) finds that advances in plough technology enhanced productivity substantially. Furthermore, the introduction of the seed drill in 1731 by Jethro Tull was a further enhancement in agricultural technology. The mechanical seeder distributed seeds efficiently across the land and enabled more efficient weeding (Overton 1996a, p. 122; Brunt 2003). Its introduction reduced the normal seed requirement by 30% (Overton, 1996a, p. 122). The launch of a bagging hook and then a scythe were also important labor-saving devices. Until the mid-eighteenth century the crop was harvested with a sickle, where its use subsequently reduced to 20% in the mid-nineteenth century (Overton 1996a, p. 123). Finally, the introduction of the threshing machine in 1786 further improved productivity (Overton 1996a, p. 125).

Advancements in crop rotations are also considered important for the productivity advances during the British Agricultural Revolution. Four-field rotation was introduced in Great Britain in the early eighteenth century and is considered the cornerstone of the British Agricultural Revolution (Overton 1996a, p. 2 and ch. 3), predominantly because land no longer had to lay fallow after two or three crop rotations and because the fertility of the soil increased through fertilizer supplements when clover and turnips were added into the crop-rotation schedule. Clover, which was often grown after two or three rotations, has the property of fixing atmospheric nitrogen in the soil—a characteristic that is not possessed by cereal crops. Turnips added humus to the soil, helped to suppress weeds, and recycled nitrogen in a more efficient manner than the traditional break crops (Brunt 2003). Furthermore, the growth of turnips and clover introduced a fodder crop and a grazing crop, thus allowing livestock to be bred year round. Additionally, the resulting manure could be used for fertilizer. Clover and turnips were introduced into British agriculture in the late seventeenth century, and by 1710 about 50% of farms grew these crops (Overton 1996a, p. 100).

Brunt (2004) investigates wheat yields across England, as a function of environmental and technological factors around 1770 using cross-sectional data analysis. He finds that the turnip, as a part of the three or four crop rotation, marling, and seed drilling, were the most important factors for wheat yield. The diffusion of seed drilling was an important factor behind the productivity advancement because it reduced the cost of weeding substantially. Brunt (2004) argues that turnips, drilling, and marling were probably the primary causes of increasing wheat yields between 1700 and 1850 and, therefore, important contributors to the productivity advances in British agriculture during the same period. Finally, using a biological model of nitrogen, Allen (2008) finds that increasing growth of nitrogen-fixing plants and better cultivation, seed, and drainage were the most important factors behind the increasing crop yield in the United Kingdom in the period 1300 to 1800.

Table 1. Five-Year Estimates of Agricultural Labor Productivity Growth (X = Patents; Q = Agricultural Labor)

Dep. Var. = $\Delta \ln(Y/L)_t$	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\ln X_{t-1}$	0.019**	0.023**	0.019**	0.018**	0.021**	0.020**	0.018**	0.025**
	(0.025)	(0.009)	(0.026)	(0.032)	(0.014)	(0.019)	(0.034)	(0.011)
$\ln Q_{t-1}$	−0.045	0.032	−0.048	−0.036	−0.080	−0.040	−0.043	−0.022
	(0.593)	(0.739)	(0.576)	(0.667)	(0.362)	(0.640)	(0.614)	(0.828)
$\Delta \ln X_{t-1}$	−0.004	−0.002	−0.004	−0.004	−0.005	−0.004	−0.004	−0.003
	(0.550)	(0.773)	(0.558)	(0.536)	(0.483)	(0.583)	(0.534)	(0.615)
$\Delta \ln POP_{t-1}$	−0.645**	−0.423	−0.653**	−0.628**	−0.688**	−0.700**	−0.644**	−0.565*
	(0.017)	(0.152)	(0.018)	(0.021)	(0.012)	(0.013)	(0.018)	(0.078)
$\ln X^{na}_{t-1}$		−0.009						−0.007
		(0.112)						(0.263)
$\Delta \ln(M/Y)_t$			−0.011					−0.007
			(0.769)					(0.865)
$\Delta \ln TO_t$				−0.026				−0.023
				(0.350)				(0.485)
$\ln UNC_t$					−0.013			−0.019*
					(0.196)			(0.071)
$\Delta \ln LE_t$						−0.180		−0.156
						(0.415)		(0.491)
$\Delta \ln HK_t$							0.172	0.231
							(0.441)	(0.352)
Intercept	0.003	0.050	0.002	0.007	−0.043	0.006	0.003	−0.020
	(0.924)	(0.219)	(0.934)	(0.816)	(0.341)	(0.842)	(0.929)	(0.708)
R^2	0.195	0.246	0.196	0.213	0.229	0.208	0.207	0.332

The estimation covers the period 1620–1850 and includes 46 observations. p-values are reported in the brackets, where *, **, and *** denote significance levels at 10%, 5%, and 1%, respectively.

4. Estimation Results

Core Results

Equation 6 is regressed in five-year nonoverlapping first differences using data over the period 1620–1850. Table 1 shows the estimation results for the restricted and unrestricted versions of Equation 6 in five-year differences, and innovative activity is measured by patents. The estimated coefficients of the logs of patents (X_{t-1}) are consistently significant. The coefficients of male agricultural labor are all insignificant, suggesting either that there was no product proliferation in the agricultural sector during that period and/or that agricultural labor is a bad proxy for product variety.

The coefficients of growth in innovative activity are insignificant and carry the wrong sign, which are inconsistent with the predictions of semiendogenous growth models. The main implication of these findings is that research effort has permanent growth effects following the spirit of the first-generation endogenous growth models. Labor productivity will continue to grow as long as the number of patents is increasing.

The coefficients of book titles, as a measure of innovative activity, are significant in all the regressions in Table 2. The coefficients of the change in innovative activity and the agricultural labor force remain insignificant, but there is still significant evidence of the existence of a

Table 2. Five-Year Estimates of Agricultural Labor Productivity Growth (X = First Books Printed; Q = Agricultural Labor)

Dep. Var. = $\Delta\ln(Y/L)_t$	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\ln X_{t-1}$	0.014*	0.022**	0.014*	0.014*	0.013*	0.015*	0.015*	0.022**
	(0.079)	(0.010)	(0.083)	(0.066)	(0.096)	(0.064)	(0.057)	(0.015)
$\ln Q_{t-1}$	0.005	0.095	0.004	0.004	0.001	0.012	−0.010	0.047
	(0.955)	(0.284)	(0.964)	(0.960)	(0.988)	(0.880)	(0.898)	(0.618)
$\Delta\ln X_{t-1}$	−0.004	0.003	−0.004	−0.004	−0.002	−0.006	−0.003	0.010
	(0.793)	(0.844)	(0.807)	(0.802)	(0.898)	(0.736)	(0.834)	(0.586)
$\Delta\ln POP_{t-1}$	−0.555**	−0.242	−0.557**	−0.557**	−0.545*	−0.607**	−0.588**	−0.323
	(0.044)	(0.414)	(0.046)	(0.042)	(0.053)	(0.035)	(0.033)	(0.326)
$\ln(X^{na})_{t-1}$		−0.014**						−0.011
		(0.035)						(0.124)
$\Delta\ln(M/Y)_t$			−0.004					0.006
			(0.914)					(0.884)
$\Delta\ln TO_t$				−0.035				−0.035
				(0.216)				(0.281)
$\ln UNC_t$					−0.003			−0.012
					(0.793)			(0.315)
$\Delta\ln LE_t$						−0.165		−0.058
						(0.473)		(0.799)
$\Delta\ln HK_t$							0.286	0.392
							(0.216)	(0.121)
Intercept	0.003	0.058	0.003	0.004	−0.006	0.006	−0.004	0.005
	(0.921)	(0.154)	(0.924)	(0.892)	(0.904)	(0.859)	(0.904)	(0.935)
R^2	0.135	0.229	0.135	0.168	0.136	0.146	0.168	0.301

The estimation covers the period 1620–1850 and includes 46 observations. p-values are reported in the brackets, where *, **, and *** denote significance levels at 10%, 5%, and 1%, respectively.

population growth drag. These results reinforce those obtained in Table 1 and suggest that technological progress, driven by innovations and the use of new methods, has been the driving force behind productivity advances in agriculture during the British Agricultural Revolution. Moreover, it is important to note that the coefficients of the constant terms are insignificant in all the regressions, suggesting that the productivity advances have been explained well by innovative activity.

The coefficients of population growth are negative and significant in almost all regressions in Tables 1 and 2. The average coefficient is about −0.6, which is close to land's income share (Clark 2002). Hence, the positive productivity effects of technological progress were negated by the growth in the population—particularly after the Napoleonic Wars (1799–1815). Overall, these results give support to the hypothesis that population growth is a drag on the economy due to diminishing returns introduced by land as a fixed factor of production.

The number of patents in the nonagricultural sector is included as an additional regressor in the second column in Tables 1 and 2. Its coefficient is found to be either insignificant (Table 1) or significant but negative (Table 2). These results imply that the agricultural productivity advances were not driven by the Industrial Revolution but rather by innovations that are specific to the agricultural sector. More surprisingly, there were no knowledge spillovers from the nonagricultural sector to agricultural productivity. The estimated

Table 3. Alternative Measures of Product Variety (Five-Year Estimates)

Dep. Var. = $\Delta\ln(Y/L)_t$	(1) Q_t = *Agr labor* × *human capital*	(2) Q_t = *Agr labor* × *Agr TFP*	(3) Q_t = *Agr labor* × *human capital* × *Agr TFP*	(4) Q_t = *Agr real output*	(5) Q_t = *Agr labor & squared Agr labor*
$\ln X_{t-1}$	0.024***	0.024***	0.024***	0.023**	0.024**
	(0.007)	(0.009)	(0.007)	(0.016)	(0.018)
$\ln Q_{t-1}$	0.065	−0.020	0.004	−0.025	−0.123
	(0.237)	(0.691)	(0.959)	(0.656)	(0.608)
$\ln Q^2_{t-1}$					−0.217
					(0.641)
$\Delta\ln X_{t-1}$	−0.003	−0.004	−0.003	−0.004	−0.003
	(0.698)	(0.584)	(0.623)	(0.570)	(0.660)
$\Delta\ln POP_{t-1}$	−0.535*	−0.567*	−0.545*	−0.561*	−0.574*
	(0.077)	(0.070)	(0.080)	(0.071)	(0.078)
Intercept	0.090	−0.023	−0.010	0.080	−0.028
	(0.312)	(0.591)	(0.715)	(0.696)	(0.628)
R^2	0.358	0.334	0.331	0.335	0.336

X_t is measured by the number of agricultural patents. The estimation covers the period 1620–1850 and includes 46 observations. *p*-values are reported in the brackets, where *, **, and *** denote significance levels at 10%, 5%, and 1%, respectively. All control variables are included in the estimations but are not reported here for brevity.

coefficients of all other control variables are mostly statistically insignificant, which may be an outcome of measurement errors or reflecting that they were not that important for the agricultural productivity growth.

Robustness Checks

Alternative Measures of Product Variety

Different proxies for product variety are used in this section to investigate whether the insignificance of the log of agricultural labor in the regressions above reflect measurement problems. The following variables are used as alternative proxies for product variety in the regressions in Table 3: agricultural labor multiplied by human capital (literacy), agricultural labor multiplied by agricultural TFP, agricultural labor multiplied by human capital and TFP, and agricultural real output as well as agricultural labor and its squared term.

Agricultural labor is multiplied by agricultural TFP following Ha and Howitt (2007) who adjust labor for TFP given that innovation may become more complex as technology deepens. Agricultural GDP is used as a measure of product variety following Krugman (1989) in the context of international trade. However, one needs to be cautious when interpreting output as a measure of product variety since income is the numerator of the dependent variable and only one lag of income separates the two variables. Finally, squared agricultural labor, in addition to agricultural labor, is included as a proxy for product variety following the model of Peretto (2008) in which the relationship between product varieties and employment becomes nonlinear when land is introduced as a fixed factor of production. Peretto (2008) derives the following relationship between labor and product variety: $Q = \theta \cdot L \cdot y(N/L)$, where θ is a constant and y is per capita expenditure. From this relationship product varieties depend on per capita expenditure, which in turn depends on the land-labor ratio.

Table 4. Other Robustness Checks

Dep. Var. = $\Delta\ln(Y/L)_t$	(1) $\Delta\ln(Y/POP)_t$ as dep. var. (5-year estimates)	(2) 20-year estimates	(3) 20-year estimates	(4) 20-year estimates (lagged X, Q, and POP)	(5) 20-year estimates (lagged X, Q, and POP)	(6) Period: 1720–1850 (5-year estimates)	(7) Period: 1620–1720 (5-year estimates)
$\ln X_{t-1}$ or	0.019*	0.030**	0.058***	0.023*	0.054***	0.067***	0.006
$\ln X_t$	(0.086)	(0.029)	(0.000)	(0.075)	(0.000)	(0.001)	(0.771)
$\ln Q_{t-1}$ or	0.160	0.507***		0.556***		0.063	−0.169
$\ln Q_t$	(0.185)	(0.003)		(0.001)		(0.601)	(0.663)
$\Delta\ln X_{t-1}$ or	−0.003	−0.003*	−0.004***	−0.003*	−0.004***	0.021	−0.009
$\Delta\ln X_t$	(0.719)	(0.058)	(0.009)	(0.058)	(0.007)	(0.294)	(0.419)
$\Delta\ln POP_{t-1}$ or	−0.526	−0.065	−0.202**	−0.075	−0.220**	−0.221	−1.380
$\Delta\ln POP_t$	(0.163)	(0.522)	(0.029)	(0.437)	(0.013)	(0.546)	(0.113)
Intercept	0.089	0.117	−0.134***	0.138	−0.134***	0.129	−0.216
	(0.170)	(0.201)	(0.001)	(0.125)	(0.001)	(0.183)	(0.305)
R^2	0.403	0.512	0.489	0.511	0.482	0.634	0.652
N	45	207	207	207	207	26	19

X_t is measured by the number of agricultural patents and Q is measured by male agricultural labor. The estimation covers the period 1620–1850. p-values are reported in the brackets, where *, **, and *** denote significance levels at 10%, 5%, and 1%, respectively. All control variables are included in the estimations but are not reported here for brevity.

The results, using the different measures of product variety, are presented in Table 3. Importantly, coefficients of the number of agricultural patents remain consistently positive and significant and the coefficients of product variety are consistently insignificant, suggesting that product dilution effects may not have been an important driving mechanism during the British Agricultural Revolution. However, as discussed above, it should be noted that we are in fact seeking to measure product variety in terms of the number of crop varieties, different types of ploughs and seed drills, different livestock breeds, and various agricultural drain systems—factors that are incredibly difficult to measure.

Other Robustness Checks

The dependent variable is measured as agricultural GDP per capita in the regression in the first column of Table 4 to investigate whether the productivity advances were predominantly driven by increasing demand for labor in the nonagricultural sectors. Furthermore, total population is likely to be more precisely measured than the agricultural labor force. The coefficient of patents remains significant while the coefficient of population growth is rendered insignificant. The significance of patent applications in this regression indicates that the productivity advances in the British agricultural sector have not so much been driven by increasing demand for labor in the urban sector but rather by progress within the agricultural sector—an issue that we will look into more in section 5.

The regressions in columns 2 to 5 in Table 4 are based on 20-year overlapping differences. Long differences have the benefit of capturing the slow movements in labor productivity and productivity growth and, as such, are not influenced as much by erratic productivity fluctuations as are the five-year difference estimates. X and Q are lagged one period (20 years) in the regressions in columns 2 and 3 but are unlagged in the regressions in columns 4 and 5 under the assumption that innovations may influence productivity within the first 20 years of the time at which the patent applications are filed. Patent applications are significant in all four cases and are particularly more significant when product variety is excluded from the regressions. The product variety indicator (Q_t or Q_{t-1}) is omitted from the regressions in columns 3 and 5 because they are positive and significant in the regressions in columns 2 and 4. That the coefficients of product variety are positive and significant highlights further that proliferation effects were not prevalent in the agricultural sector during the British Agricultural Revolution.

Finally, the estimation period is split up in the period after and before 1720 to investigate structural stability of the estimates. The coefficient of innovative activity is highly significant in the post-1720 regression, while it is insignificant in the pre-1720 regression. The results are unaltered if all control variables are excluded. The insignificance of patent applications before 1720 may reflect the fact that the sample is very small and that the quality of the data is declining as we go back in time. Furthermore, the patents may not have been as good an indicator of innovative activity before 1720 as after that year it could well have taken many years for innovators to have knowledge of and understand the patent system after its introduction.

5. Output Regressions

Although labor productivity is probably the most used metric of productivity advances, it is also of interest to investigate the forces that have shaped output during the British Agricultural Revolution. There are several benefits of using output, as opposed to labor productivity, as the dependent variable. First, generally speaking, land productivity, proxied by output, is determined by factors that enhance crop yield and livestock productivity such as draining methods, soil improvements, and breeding methods, while labor productivity is influenced more by mechanization and other labor-saving technological progress. Thus, output regressions will capture other aspects of innovations than will labor productivity regressions.

Second, since part of the agricultural labor force is underutilized due to hidden unemployment within agriculture, labor productivity advances may be, partly or entirely, driven by demand for labor in other sectors of the economy due to industrialization. Third, male agricultural labor input is measured with some errors, particularly because there are no data on hours worked during the year and because female and child labor is not accounted for. Of course, classical econometrics does not consider measurement errors of the dependent variable as a problem since it leads to unbiased parameter estimates; however, as soon as the measurement errors between the dependent and independent variables become correlated, the point estimates become biased. Ideally we would have preferred to use land productivity instead of output as the dependent variable. However, since estimates of land under cultivation are only available in 50-year intervals (Allen 2000) and do not change much over time, we can consider agricultural output as an approximation of land productivity.

The coefficients of patent applications are consistently significant in the output regression in Table 5, suggesting that the innovations were key factors in the advances in output and, approximately, in land productivity. The significance of this result is not only that the innovations were important for agricultural output but also that the productivity advances in agriculture were not driven by increasing demand for labor in the urban sector. Note that the population growth is no longer significant; however, it should be positive, and not negative. This can be seen from rewriting Equation 3 as follows:

Table 5. Five-Year Annual Estimates of Agricultural Output Growth (X = Patents)

Dep. Var. = $\Delta\ln(Y)_t$	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\ln X_{t-1}$	0.020**	0.024**	0.020**	0.019**	0.022**	0.022**	0.019**	0.029***
	(0.036)	(0.013)	(0.035)	(0.045)	(0.022)	(0.023)	(0.049)	(0.009)
$\ln Q_{t-1}$	−0.055	0.037	−0.063	−0.049	−0.092	−0.047	−0.052	−0.024
	(0.566)	(0.731)	(0.518)	(0.617)	(0.362)	(0.624)	(0.589)	(0.834)
$\Delta\ln X_{t-1}$	−0.003	−0.001	−0.003	−0.003	−0.004	−0.003	−0.003	−0.002
	(0.689)	(0.941)	(0.698)	(0.680)	(0.622)	(0.733)	(0.666)	(0.828)
$\Delta\ln POP_{t-1}$	−0.300	−0.032	−0.321	−0.287	−0.344	−0.384	−0.298	−0.217
	(0.320)	(0.924)	(0.293)	(0.345)	(0.255)	(0.217)	(0.324)	(0.543)
$\ln(X^{na})_{t-1}$		−0.011*						−0.010
		(0.093)						(0.179)
$\Delta\ln(M/Y)_t$			−0.030					−0.032
			(0.503)					(0.486)
$\Delta lnTO_t$				−0.019				−0.007
				(0.534)				(0.841)
$\ln UNC_t$					−0.014			−0.021*
					(0.241)			(0.080)
$\Delta\ln LE_t$						−0.275		−0.248
						(0.273)		(0.338)
$\Delta\ln HK_t$							0.231	0.234
							(0.366)	(0.405)
Intercept	−0.001	0.057	−0.001	0.002	−0.048	0.004	−0.001	−0.018
	(0.986)	(0.222)	(0.965)	(0.940)	(0.353)	(0.901)	(0.980)	(0.771)
R^2	0.172	0.230	0.181	0.180	0.201	0.197	0.189	0.324

X_t is measured by the number of agricultural patents and Q is measured by male agricultural labor. The estimation covers the period 1620–1850 and includes 46 observations. p-values are reported in the brackets, where *, **, and *** denote significance levels at 10%, 5%, and 1%, respectively.

$$g_Y = g_A + (1-\alpha)g_L, \tag{7}$$

which shows that the growth in output, g_Y, is positively related to the labor force because the positive output effects of additional labor more than counter the population growth drag. Thus, we would expect the coefficient of labor growth to be positive and not negative, although statistically insignificant, in the regressions in Table 5. This result is likely to reflect hidden labor, in other words, that agriculture at times underutilized labor.

6. Concluding Remarks

While the importance of innovative activity during the British Agricultural Revolution has been widely recognized in the literature, so far there has been no empirical study that formally tests the roles of innovative activity, the population growth drag, and human capital in agricultural growth and development. The lack of empirical analysis may reflect the fact that the endogenous growth models, which are capable of explaining growth, have only recently been developed and that long data have only recently become available. Using long historical data over the period 1620–1850, this article examined the importance of human capital, and, particularly, innovative activity in boosting agricultural productivity while allowing for the population growth drag in the estimation. As a by-product of the analysis, the article also tested the ability of endogenous growth models in explaining the British Agricultural Revolution and, therefore, examined whether the modern endogenous growth framework is useful in explaining growth during the Malthusian and the post-Malthusian epochs.

The results show that innovative activity was the prime mover of productivity growth during the British Agricultural Revolution. The estimates show that growth is driven by the levels of research activity measured by patents and new book titles. The increasing research activity after the Napoleonic Wars contributed significantly to productivity advances in agriculture. However, the technological progress did not materialize into strong labor productivity advances as the increasing population posed a significant drag on labor productivity growth rates and, consequently, prevented a strong take-off in the agricultural sector.

An intriguing aspect of the results is that the first-generation endogenous growth theory is capable of explaining agricultural productivity growth that dates back four centuries, despite the fact that endogenous growth models are mainly designed to explain the modern growth regime for the aggregate economies in the OECD since the post–World War II period. The main implication of this finding is that the nature of technological progress and growth was the same several centuries ago as it is today. The finding in favor of the first-generation growth theory stands in contrast with the economy-wide estimates of Ha and Howitt (2007), Madsen (2008), Madsen, Ang, and Banerjee (2010), Madsen, Saxena, and Ang (2010), Ang and Madsen (2011), and Banerjee (2012), who find evidence in favor of Schumpeterian growth theories. However the very distinct difference between this article and the others is that we have focused only on agriculture and not the whole economy.

The results provide insights into the productivity advancements in agriculture that rendered the British Industrial Revolution possible. The upward shifts in the proportion of resources allocated to research effort and in the dissemination of information on agricultural methods and techniques contributed to an upward shift in agricultural productivity. The scale effects in the ideas production function ensured that the number of new patents and new book titles had permanent growth effects. However, the increasing population growth rate during the British Industrial and Agricultural Revolutions was a large drag on labor productivity advances and prevented a speedy take-off in the British economy.

Appendix: Data Sources and Measurement Issues

Agricultural Patents

The data on the number of agricultural patents issued over the period 1620–1850 are taken from Sullivan (1984, table 1, p. 274). The data points are available for every decade starting from 1611 through to 1850, where each data point represents the total agricultural patents issued in that decade. Each figure in the series is first divided by 10 to achieve the yearly average, and then all the benchmark years (10-year data) are geometrically interpolated to obtain a complete series on an annual basis for the period 1620–1850.

Nonagricultural Patents

The data on nonagricultural patents are calculated by subtracting the number of "agricultural patents issued" from the number of "total patents issued" for all sectors on an annual basis. Data on "total patents issued" are collected for the period 1620–1660 from Mitchell (1988, p. 438) and for the period 1661–1850 from Sullivan (1989, table A1, p. 448). The latter series is spliced with the former to get a complete series on an annual basis.

Technical Books on English Farming

The data are taken from Sullivan (1984, table 1, p. 274). They are available for the period 1521–1913 but only on a decennial basis. The benchmark years (10-year data) are geometrically interpolated to derive an annual series for the sample period 1620–1850. In the original article by Sullivan (1984), the titles of technical agricultural manuals published are divided into first printed and total printed numbers, where the latter shows the reprinted but updated versions of the earlier books. To avoid the issue of double counting, only the number of first printed technical books is used in this analysis.

Agricultural TFP

Data on agricultural total factor productivity (TFP) is taken from Clark (2002, table 5, p. 16). The data are available from 1550–1912 on a decennial basis. Missing data between the benchmark years over the period 1620–1850 are geometrically interpolated to derive a complete series on an annual basis.

Agricultural Output

Real agricultural output is taken from Clark (2002, table 5, p. 16). The data are available from 1550–1912 on a decennial basis. Benchmark years between 1620 and 1850 are geometrically interpolated to derive complete series on an annual basis. Real agricultural output is measured as nominal GDP in the agricultural sector deflated by an agricultural price index. Data for nominal agricultural GDP are collected from Clark (2002, table 4, p. 14). The agricultural price index is provided in Clark (2004).

Agricultural Labor

Data on the agricultural labor force (number of males) for the period 1620–1850 are taken from Clark's (2002, table 3, p. 12) preferred estimate. The data are available from 1521 to 1913 on a decennial basis. Missing data are interpolated to obtain an annual series.

Population

For the period 1801–1850, the population includes England, Wales, Scotland, and Ireland. This population series is spliced with the population of England only for the period 1620–1801 due to unavailability of data for Wales, Scotland, and Northern Ireland during that period. The sources are Mitchell (1988, pp. 7–14) for the period 1620–1829, which are compiled from Wrigley and Schofield (1981), and the online database of Maddison (available at http://www.ggdc.net/maddison/) for the period 1830–1850.

Human Capital

The series is calculated on the basis of literacy rates, which are defined as the percentages of population who are able to sign at marriage. The data for the period 1750–1840 are obtained from Schofield (1973) and for the period 1840–1850 from Flora (1983). Missing data in the period 1620–1749 are extrapolated backwards using the geometric growth rate over the period 1750–1850.

Trade Openness

The series is measured as the sum of total exports and imports over aggregate nominal GDP. The trade data for Britain start from 1697. Trade openness is kept constant in the years 1620–1697 under the assumption that British trade captured a constant share of GDP in the years before 1697. Trade data are available for the years 1697–1771 for England and Wales, 1772–1795 for Great Britain, and 1796–1944 for the United Kingdom. The latter is spliced upwards to obtain a complete series from 1697–1850. The source is from Mitchell (1988, pp. 448–54). The nominal aggregate GDP data for Britain are obtained from Clark (2001, table 3, pp. 19–20), which are available on a decennial basis from 1259/60 to 1869/70. Missing data are interpolated to derive an annual series over the period 1620–1830. For the period 1830–1850, Maddison's data are used (available online at: http://www.ggdc.net/maddison/).

Financial Deepening

Financial deepening is measured as the sum of notes in circulation and deposits in commercial and savings banks divided by economy-wide nominal GDP. Monetary aggregate data are available from 1750 onward in Mitchell (1988), which are measured by the sum of notes in circulation and deposits in commercial and savings banks. Data for the period 1620–1749 are extrapolated backwards using the geometric growth rate over the period 1750–1850. The source for nominal output is as aforementioned (see trade openness).

Life Expectancy

Data on life expectancy at birth are compiled from Wrigley et al. (1997) for the period 1620–1837. The data points are available for every decade starting from 1625. The benchmark years have been interpolated in between and extrapolated backwards for the period 1620–1625 using the geometric growth rate over the period 1625–1630 to obtain a complete series on an annual basis for the period 1620–1837. For the period 1838–1850, the data are collected on an annual basis from the Human Mortality database (available at http://www.mortality.org/) and then spliced with the former series.

Macroeconomic Uncertainty

Uncertainty is measured as the five-year standard deviation of inflation. The rate of inflation is constructed as the annual growth rate of the consumer price index (CPI). CPI data for the period 1620–1850 are collected on an annual basis from London Wages, Prices & Living Standards: The World Historical Perspective (average of London and Oxford) compiled by Robert Allen. To express the local weights and measures in the same units and the currencies in the same standard, Allen converted the weights and measures into metric equivalents and the currencies into grams of silver, which was the leading medium of exchange at that time. The data can be obtained online at http://www.economics.ox.ac.uk/Members/robert.allen/WagesPrices.htm.

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