Malthusian Dynamics in a Diverging Europe: Northern Italy 1650-1881

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Abstract

Recent empirical research has questioned the validity of using Malthusian theory in pre-industrial England. Using real wage and vital rate data for the years 1650-1881, I provide empirical estimates for a different region – Northern Italy. The empirical methodology is theoretically underpinned by a simple Malthusian model, in which population, real wages and vital rates are determined endogenously. My findings strongly support the existence of a ‘Malthusian’ economy where population growth depressed living standards, which in turn influenced vital rates. In addition, I find no evidence of Boserupian effects as increases in population failed to spur sustained technological growth.

JEL Classifications: N33, J13
Keywords: Economic History, Demographic Economics

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1 Introduction

Pre-industrial economic stagnation is typically explained through the use of a Malthusian-style model, in which living standards are trapped by a self-equilibrating system of population and vital rates. However, recent empirical assessments have questioned model’s validity in pre-industrial England. The negative relationship between living standards and death rates, the positive check, may have vanished before the industrial revolution. Meanwhile, the positive correlation between the birth rates and living standards, the preventive check, persisted for longer, although it too disappeared before the industrial revolution. Variations in living standards ceased to be a matter of life and death in England before the transition to modern economic growth.

This paper is motivated by the need to explore the validity of a Malthusian-style model beyond the confines of the much-studied case of England. Considering data constraints, the focus of previous research on England is understandable. However, reliable annual demographic and economic statistics have also been computed for pre-industrial (1650-1881) Northern Italy. These data highlight some substantial differences between the two regions. Between 1650 and 1881 the English economy, and consequently English living standards, rose dramatically. This was not the case in Northern Italy, or indeed most of Europe, where economic conditions stagnated. England, and to a lesser extent the Netherlands, were exceptions in pre-modern Europe. Thus, I argue that my empirical estimates for Northern Italy provide a more accurate representation of the Malthusian relationship in early modern Europe. Additionally, the population of Northern Italy grew rapidly, while subsistence crises and epidemic disease caused vital rates to fluctuate wildly.

The above description strongly suggests a role for Malthusian theory in describing pre-industrial Northern Italy. To investigate this relationship formally, I use a methodological approach which fits both the theory and the data. Firstly, I estimate a textbook vector autoregression (VAR) model in differences on to test for the presence of the equilibrating mechanisms, or checks. I find that a real wage rise causes the death rates to fall and birth rates to rise. Additionally, I find that the impact occurred within two years, suggesting that living standards were very much at a subsistence level. To understand how these relationships changed over time, I divide the time-series into three sub-periods. By re-applying the VAR methodology, I find that the magnitude of both relations was relatively stable across time. There does not appear to be any indication that Northern Italy was leaving the Malthusian world by the turn of the 19th century.

\[^1\text{See Nicolini (2007), Møller & Sharp (2008), Crafts & Mills (2009) and Kelly & Ó Gráda (2010).}\]
The VAR methodology does not empirically test the relationship between population and living standards. To examine this, I specify a structural model which can be estimated in State Space. The structural model results are consistent with the VAR estimates and also yield additional information such as the speed at which the model converges towards equilibrium and the movement of unobservable elements. Firstly, I find slow convergence, which indicates the system is best characterized as that of one in weak homeostasis. This result suggests that while the main elements of the Malthusian model were indeed present, this model was working somewhat lightly in the background of the Northern Italian demographic regime. Furthermore, I confirm the presence of diminishing returns, as population growth had a negative causal impact on real wages. Theory defines technological growth as real wage growth after population is held constant. Using this definition I find that no evidence of sustained technological growth during this period. Diminishing returns in the face of population growth suggest the absence of Boserupian feedback effects. Necessity was not the mother of invention in early modern Northern Italy.

This article is motivated by recent developments in the theory of very long-run growth. The emergence of unified growth theory presents us with a blueprint explaining how the western world transformed from centuries of economic stagnation to modern economic growth via the so-called European fertility transition. The Galor & Weil (2000) model occurs in three phases. The first phase assumes the existence of a Malthusian steady state equilibrium. This article tests whether this assumption holds in early modern Italy. These results hold contemporary relevance. Understanding how the transition between economic stagnation and modern growth occurred is relevant to policy makers concerned about the developing world. If demographic change is a cause of economic growth, policies which encourage demographic adjustment could be powerful tools in the long-run development of less developed countries.

The rest of the paper is structured as follows. The following sections present a simple Malthusian model and a review of the relevant literature. Section Four provides a discussion of the available data sources and their historical context. The specification and results from a differenced vector autoregression is shown in Section Five, while I estimate a structural model which permits unobserved time-varying influences to enter the model in Section Six. The empirical results from both models are remarkably consistent and strongly suggest that the population and economic dynamics in Northern Italy are captured by the Malthusian model described in Section Two.

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2 A Simple Malthusian Model

The following equations demonstrate a simple model which captures the main elements of Malthusian theory. Consider a one sector, one period, non-overlapping generations model where one homogeneous good is produced using two factors of production, land and labor. Production is captured by the following Cobb-Douglas function with constant returns to scale:

\[ Y_t = A_t X_t^\alpha N_t^{1-\alpha}, \quad \alpha \in (0,1) \] (1)

where \( Y_t, N_t \) and \( X_t \) denote levels of output, population (labor) and land while \( A_t \) measures productivity – all at time \( t \). Diminishing returns are exhibited as the elasticity of output with respect to population (labor) is less than zero. The real wage is equivalent to per capita output and and can be expressed:

\[ W_t = \frac{Y_t}{N_t} = A_t N_t^{-\alpha} \] (2)

where \( W_t \) is the real wage and land is assumed as a normalized constant factor of production. Taking logs produces the following wage equation:

\[ \ln w_t = a_t + \beta \ln p_t + s_t \] (3)

where \( w_t, a_t \) and \( p_t \) are the natural logarithms of real wages, the level of productivity and population, \( \beta(= -\alpha) \) measures the elasticity of real wages with respect to population, and \( s_t \) is introduced as a white noise error term to capture unsystematic shocks. The negative relationship between population and living standards is implied by \( \beta < 0 \). The level productivity or technology, \( a_t \), evolves according to the value of two variables, the lagged stock of technology and this period’s growth rate:

\[ a_t = g_t + a_{t-1} \] (4)

where \( g_t \) measures technological growth, and thus \( \dot{a} = g \). The rate of technological progress is modeled as a random walk since this unit root process captures the transition from Malthusian stagnation, where \( g_t \) has no trend, to modern economic growth, where \( g_t \) trends upwards. Therefore, the rate of technological growth is:

\[ g_t = g_{t-1} + \nu_t \] (5)

where \( \nu_t \) is an IID error term.

The Malthusian checks provide the population correction mechanisms and can be modeled like linear demand and supply functions:

\[ b_t = n_0 + \mu w_t + r_t \] (6)

\[^3\text{I abstract from including marriages here, see Møller & Sharp (2008) for a theoretical treatment.}\]
\[ d_t = m_0 + \delta w_t + u_t \]  

where \( b_t \) and \( d_t \) measure the birth and death rates over time.\(^4\) Both \( r_t \) and \( u_t \) represent unsystematic shocks like war and climactic variation. Additionally, equations (4) and (5) also provide an algebraic form of the positive (\( \delta < 0 \)) and preventive (\( \mu > 0 \)) checks.

Steady state solutions exist when there are no unsystematic shocks (\( s_t = r_t = u_t = \nu_t = 0 \)). Consequently, technological growth collapses to a constant value (\( a_t = \bar{a} \)). Performing the rudimentary algebraic manipulations produces the following:

\[ w^* = \frac{m_0 - n_0}{\mu - \delta} \]  

(8)

\[ b^* = d^* = \frac{-n_0\delta + m_0\mu}{\mu - \delta} \]  

(9)

\[ p^* = \frac{1}{\beta}(\bar{a} - w^*) \]  

(10)

where \( p^*, b^* \) and \( d^* \) denote the steady state values. The results of the following comparative statics: \( \frac{\partial w^*}{\partial \bar{a}} = 0 \) and \( \frac{\partial p^*}{\partial \bar{a}} = \frac{1}{\beta} > 0 \) demonstrate how technological progress affects the level of population but not the level of subsistence, in the long run.

Figure 1 is a schematic illustration of the system. The left hand graph shows the equilibrating relationship between the natural logarithm real wage (\( w^* \)) and both crude birth and crude death vital rates (\( V^* \)). At point A the birth and death rates are equal and there is no population growth. The right hand side demonstrates the real wage-population relationship. The downward sloping \( LD_0 \) schedule is the labor demand curve. Point B illustrates the level of population or labor demand, \( p_0 \) corresponding to the equilibrium

\(^4\)These rates are calculated as number of births or deaths divided by the population unless stated otherwise.
real wage, $w^*$, given a fixed level of technology, $\bar{a}$. Imagine a technological shock which causes an exogenous outward labor demand shift ($LD_0$ shifts to $LD_1$). Initially, the population level (labor supply) is fixed at $p_0$ and demand shift results in the real wage rising from $w^*$ to $w_1$, such that point C is reached. The effect of this shock on vital rates is displayed on the left hand side. At a real wage of $w_1$ the vital rates will be out of equilibrium as the extra resources lead to lower rates of mortality and higher fertility – the Malthusian checks. The excess of births over deaths, the gap between points D and E, results in population growth. However, these rates cannot remain out of equilibrium in the long run, because the resulting increases in population induces a movement along the $LD_1$ curve, until point F, the new equilibrium, is reached. Hence, technological shocks only improve economic welfare in the short run. An inelastic labor supply always responds to technological innovations, such that the long-run real wage is constant. This is the equilibrating mechanism or Malthusian trap.

3 Demography and the History of Economic Development

The empirical literature examining Malthusian regimes has continued to grow for three primary reasons. Firstly, the expansion of demographic and real wage data has led to a continuous improvement in the accuracy, coverage and overall quality. Secondly, the advancement of more sophisticated econometric techniques has stimulated new methodological strategies which gave new perspectives on an outstanding research question. Finally, and most importantly, the persistence of research on this topic is demand driven. Understanding the dynamics of economic growth and what caused the transition from stagnation to modern economic growth is quite arguably the most important research topic facing the economic history discipline.

Population grows (assuming no migration) according to the identity:

$$p_t = p_{t-1} + b_{t-1} + d_{t-1}$$  \hspace{1cm} (11)

which alongside the system of equations presented in (3) to (7) highlights the two primary difficulties which challenge empirical estimates of Malthusian demography: simultaneous equation bias and non-stationarity. Real wages affect birth and death rates which in turn determine population and population (labor supply) is a function of the real wage. The circularity of this argument illustrates how any attempt to correctly identify the system is non-trivial. For example, an ordinary least squares estimate of equation of equation (6) will potentially overestimate $\mu$ since $\text{Cov}(w_t, r_t) > 0$. Furthermore, since technological...
progress, $a_t$, is a random walk with drift it is probable that the demographic and real-wage series evolve as unit root processes. This problem is exacerbated when we allow for the possibility of time-varying intercepts in the check equations.\footnote{For example, the death rate equation intercept may vary according to public health innovations and birth rates as the costs (including opportunity costs) of rearing children rises.} If these series contain unit roots the standard statistical tools are likely to become redundant as the estimated parameters could have non-degenerate limiting distributions.

Much of the work appraising Malthusian population dynamics has been concerned with overcoming the various issues discussed above. Earlier work by Lee (1981) argued that deviations in wheat prices from a moving average could be seen as short-run exogenous shock on living standards. The effect of this exogenous shock was estimated using autoregressive distributed lag regressions and the magnitude of the check relations was measured using cumulative elasticities in mortality, fertility and nuptiality. Lee’s results suggest that the positive check was eradicated in England before the industrial revolution, while the preventive checks continued to prevail. Galloway (1988) employed a similar methodology in his comprehensive pan-European study. The results of which showed that the preventive check dominated in most regions while the scale of the positive check was negatively correlated with economic growth.

The results of contemporary estimates of Malthusian model in England have been ambiguous. Nicolini (2007) argued that the English demographic (excluding marriages) and real wage series are stationary and concluded a textbook VAR analysis appropriate. The results suggested that the endogenous adjustment of population to real wage fluctuations ceased to exist after 1740, with the positive check eradicated long before the industrial revolution. These results are echoed by Crafts & Mills (2009), who in addition to VAR also provide structural model estimates of the Malthusian system in state space. This technique found weak homeostasis (the system adjusts very slowly to equilibrium) in state space which operated almost solely through the preventive check on fertility. Møller & Sharp (2008) included marriages and argued that the system exhibits persistence (contains a unit root) and can be modeled as a system of cointegrated equations. The results were broadly in line with Nicolini and Crafts & Mills – the preventive check prevails, operating through marriages.

That early-modern England ceased to be a positive check society has been challenged by the even more recent work of Kelly & Ó Gráda (2010) and Rathke & Sarferaz (2010). Using a multi-level empirical model, Kelly & Ó Gráda show that the strength of the positive check varied considerably over time, but was still eminent in 18th century. The time-dependent parameter instability of the positive check is also addressed by Rathke & Sarferaz, who use a time-varying VAR to demonstrate how the positive check
actually increased in strength during the industrial revolution up until the mid-19th century.

4 The Data and Context

The demographic series used in this article is directly taken from Galloway’s 1994 reconstruction of the Northern Italian population. As with all historical time-series, the need to assess its accuracy is paramount. The area chosen by Galloway (1994), and henceforth referred to Northern Italy, consists of the five provinces shown in figure 2: Piedmont, Lombardy, Emilia, Veneto and Tuscany. The northern regions of Liguria and Trento were excluded from the analysis due to their lack of historical data. All five regions selected contain a rich amount of published sources detailing parish registers of burials (deaths), baptisms (births) and marriages. In total, these data include 11 city parishes and 222 rural parishes. The annual population series is inferred from the population growth rate – the birth rate minus the death rate – as the population total from the 1881 census was interpolated backwards, a method known as inverse projection.

Figure 2: Northern Italian regions

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These demographic data are reliant on several assumptions and caveats, which in turn need to be considered. Previous demographic reconstructions, such as in France and Spain, have been undermined by registration issues, typically involving infant and child mortality. However, this problem appears to have been much less severe, if not entirely absent, in the Northern Italy data. After the Council of Trent (1563), parish registration of all vital rates was compulsory and came under the strict control of the Catholic Church, the *Rituale Romanum* (Del Panta & Rettaroli, 1994). The absence of under-registration issues has been highlighted in previous research articles, such as Del Panta & Livi-Bacci (1980, p.103).

Another crucial assumption of the inverse population method concerns migration. Migration flows exist for the 1861-1881 period, and the data have been adjusted to account for this. Zero net migration is assumed in for all pre-1861 data. Reviewing the requisite literature does not invalidate this assumption. Given language and cultural barriers, migration within Europe was likely to have been small. Migration to the new world was similarly insignificant before the age of mass migration at the end of the 19th century. Indeed, the United States Census Bureau (1975, p.106) recorded only 13,793 emigrants from all of Italy in the period 1820-1860, a total which amounted to approximately 0.1% of the 1861 Northern Italian population. The data on economic conditions do not support the thesis of substantial inward migration.

Living conditions in preindustrial urban Europe were notoriously bad, and urban centers in Northern Italy were no exception. Over-crowding, poor sanitation and the absence of adequate public health provisions distorted demographic statistics. The difference between urban and rural demography was striking. Galloway (1994) found that life expectancy in the cities was only 26 years, in comparison to the rural figure of 36. Meanwhile, urban infant mortality was some forty percent higher than rural. The heterogeneity which characterizes the urban and rural demographic regimes is evident. These differences would be problematic for my analysis if there was any substantial change in the relative urban-rural population proportions. However, the available urbanization statistics do not lend support to this objection. Defining urbanization as the proportion of individuals living in a city with a population greater than 5,000, Malanima (2003) found that this figure was static, growing only by only one percentage point, from 15.2% to 16.2%, for the large majority of the period in question (1650-1861).

Figure 3 presents the relevant demographic series. It is worth examining how well these figures correspond to the existing evidence on Northern Italian demography. To understand the trends in Figure 3, it is necessary to go back further than 1650. In 1629/30 plague swept across Northern Italy. While this was the last occurrence in the region, the death toll was massive. Estimates suggest that 27% of the region’s population perished.
in the epidemic (Cipolla, 1997, p.318). The rapid population growth from 1650 to 1730 is relatively unsurprising. Following Malthusian logic, the plague of 1629-30, spread by French and Spanish troops fighting in the War of the Mantuan Succession (1628-31), can be seen as an independent, or exogenous, shift in the labor demand schedule which caused population to fall below its long-run steady state level. The first portion of the series can be classified as a recovery phase, where excess births over deaths spurred population growth.

![Figure 3: Demographic Series](image)

The population trajectory in figure 3 illustrates two other periods of population growth, firstly, a slow-down in the 1730s, followed by a rapid acceleration in the 1820s. However, to interpret how these demographic series evolved it is necessary to introduce the other key component of Malthusian theory: living standards. Various sources contain both quantitative and qualitative accounts of pre-industrial living standards in both Europe and Northern Italy. Overall the picture is quite unambiguous – between 1650 and 1881 the standard of living for the average Northern Italian failed to improve. Figure 4 displays cross-country comparisons, taken from Malanima (2009, p.289), of per capita GDP in pre-20th century Europe. It is clear that England and the Netherlands were the exceptions in terms of economic growth. The series for Italy support the notion that
Italian economic conditions were more comparable to those in other European regions.\(^7\) In 1600 Italian GDP is marginally higher than in England. In 1700 the ratio of English to Italian GDP falls to 0.76, and by 1870 it had diminished to 0.43.

\begin{figure}[h]
\centering
\includegraphics[width=\textwidth]{gdp_per_capita.png}
\caption{GDP per Capita Comparisons (PPP 1990 International Dollars).}
\end{figure}

Population density figures provide a rough estimate of available resources. In a purely neo-classical world, increases in population density will cause greater strain on resources, once all other factors are held constant. However, it is certainly arguable that a higher population density is more representative higher productivity such as the improvement of agricultural techniques. Untangling the causality between population and living standards is dealt with elsewhere in this paper. Nevertheless, a comparison of population densities across Europe, taken from Malanima (2009, p.16), and the cross-country GDP per capita figures can reveal a lot about the productive capacities of economies. These figures are displayed in figure 5. Northern Italy had both a high population density and level of national income in 1500. This finding indicates that by the end of the Renaissance Northern Italy had some form of productivity advantage compared to most other regions excluding the Netherlands. However, the courses of population density and per capita GDP throughout this period suggest that by 1800 this productivity advantage had been

\(^7\)The growth trajectory for the Northern Italy is the same.
wiped out – as GDP per capita declined in the face of a rising population density. By contrast, England and the Netherlands both saw a simultaneous explosion in population density and national income. An observation which strongly suggests high productivity growth. Patterns in the other regions, France, Spain and Germany, show a closer resemblance to Northern Italy than England.

![Figure 5: Population Density Comparisons (Inhabitants per sq. km).](http://www.paolomalanima.it/)

Other measures of living standards exist alongside the aforementioned GDP data. Nearly all the previous empirical research has used real wages and accordingly I turn to the various real wage sources. These series either contain information rural or urban workers. The difference between urban and rural environments in pre-industrial Italy has been noted above, and hence it is worth considering a series which acknowledges the difference between the two. Federico & Malanima (2004) cautioned against the use of urban wages as unrepresentative, and provided an alternative real wage index which combines both urban and rural wage data, but adjusting for the relative population proportions.⁸ To understand the trends in the available series, I equate the urban, rural and compromise series to 100 in 1650 and study their trajectories over the sample period. This information is displayed in Figure 6. All series are strongly correlated, although the

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⁸Available at [http://www.paolomalanima.it/](http://www.paolomalanima.it/)
trends of urban and rural real wages also differ strongly, as urban wages fell dramatically. The index wage is closely related to the agricultural wage – reflecting the relative shares of population.

Figure 6: Northern Italian Wage Series

Malanima’s indexed series presents the most accurate measure of living standards in the region. Other sources of economic welfare are consistent with this. By the 17th century the collapse of the Mediterranean region as a maritime commercial center caused a substantial decrease in urban economic output. Cipolla (1956) provided a vivid account of how the ‘industrial structure had almost collapsed’ in the 17th century. The decline of the Florentine woolen cloth industry provides a useful illustration. Between the end of the 16th century and first quarter of the 17th the number of firms and output nearly halved.9 Nevertheless, the deterioration of urban industry and its effect on living standards was not matched in the more populous rural regions, where a certain degree of innovation and technological progress could be found. The emergence of mulberry tree cultivation in the 18th century spawned a network of industrial activity in silk production outside of urban areas. Furthermore, the diffusion of maize as a staple crop in the 17th century

9Other examples, such as Como, Genoa, Monza and Pavia, abound.
doubled calorie yields per acre and its adoption also improved soil fertility.\footnote{However, the impact of this diffusion on living standards is somewhat ambiguously defined since maize prices were only half those of wheat and its adoption also resulted in well-known nutritional defects (Livi-Bacci, 1986).}

The indexed series is also consistent with the GDP series displayed in figure 4. A comparison of real wages in Italy and England in 1700, as in Malanima (2009, p.272), reveals only a minor difference between the two regions. Using the urban series overstates the economic decline during the period. The decline in Malanima’s compromise series is less severe, and is consistent with the alternative evidence sources. I proceed on the basis that the compromised annual indexed real wage series is the most accurate measure of economic welfare. The anthropometric evidence tallies well with the measures of economic development discussed above. A’Hearn (2003) found a sizable decrease in the heights of Lombard army recruits for the period 1730 to 1860. It is noteworthy that the urban-rural divide is once again evident as, on average, urban recruits were smaller.

I now proceed to analyze if these data are correlated as suggested by theory. A levels scatter-plot of population and real-wage, in natural logarithms, is shown in figure 7. The relationship implied by this corresponds well with theory as the slope of the line measures of labor’s output elasticity, or $\beta$, is negative. An elasticity of -0.44 is well-below one, thus fitting the constant returns to scale assumption and also suggesting that a 1% increase in population reduces the real wage by 0.44%. Figure 8 shows the correlations between wages and vital rates. I difference the data to remove trends since all variables are flows. These graphics are as theory suggests – a higher real wage is associated with higher birth and lower death rates. However, these correlations are only suggestive, and may be the result of a number of potential biases. Accordingly, I now turn to empirical models which are robust to these biases.
\[ w_t = 11.73 - 0.44p_t \]

Figure 7: Population Wage Scatterplot

\[ \Delta w_t = -0.002 - 0.23\Delta d_t \]

\[ \Delta d_t = 0.0004 + 0.13\Delta w_t \]

Figure 8: Population Wage Scatterplot
To look at how real wages influenced vital rates I estimate a VAR model. A similar strategy was pursued by Nicolini (2007). However, the augmented Dickey-Fuller unit root tests displayed in table 1 caution against the use of a VAR in levels. Birth and marriage \((m_t)\) rates are clearly non-stationary, death rates are stationary and real wages appear to be trend stationary. Differing degrees of integration also invalidate the cointegration approach pursued by Moller & Sharp (2008). However, it should be noted that birth rates and marriage rates are cointegrated and therefore a portion of the preventive check can be attributed to the delay, or postponement, of marital unions. Since these data are not compatible with either the levels VAR or cointegrated VAR approach, I posit that a VAR in differences is the most appropriate methodology to proceed with.

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Table 1: Augmented Dickey-Fuller Tests

The model is defined as:

\[
\Delta X_t = \sum_{i=1}^{k} \phi_i \Delta X_{t-i} + \Phi D_t + \varepsilon_t
\]  

where \(X_t = [\Delta b_t, \Delta d_t, \Delta w_t]^\top\) is a vector of birth rates, death rates and real wages, \(D_t\) contains year dummy vectors and \(\varepsilon_t\) are the white noise error terms – all at time \(t\). Table
Table 2: VAR Model Coefficients

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<td>-1.1826**</td>
<td>0.0473</td>
</tr>
<tr>
<td></td>
<td>(0.0358)</td>
<td>(0.0823)</td>
<td>(0.0684)</td>
</tr>
<tr>
<td>$\Delta b_{t-2}$</td>
<td>-0.2525***</td>
<td>-0.2111</td>
<td>-0.2593*</td>
</tr>
<tr>
<td></td>
<td>(0.0752)</td>
<td>(0.1733)</td>
<td>(0.144)</td>
</tr>
<tr>
<td>$\Delta d_{t-2}$</td>
<td>0.0287</td>
<td>-0.4227***</td>
<td>-0.0338</td>
</tr>
<tr>
<td></td>
<td>(0.0289)</td>
<td>(0.0665)</td>
<td>(0.0553)</td>
</tr>
<tr>
<td>$\Delta w_{t-2}$</td>
<td>0.1055***</td>
<td>-0.0306</td>
<td>-0.2025***</td>
</tr>
<tr>
<td></td>
<td>(0.0361)</td>
<td>(0.0831)</td>
<td>(0.0691)</td>
</tr>
<tr>
<td>$\Delta b_{t-3}$</td>
<td>-0.0167</td>
<td>0.0914</td>
<td>-0.3778***</td>
</tr>
<tr>
<td></td>
<td>(0.0676)</td>
<td>(0.1557)</td>
<td>(0.1294)</td>
</tr>
<tr>
<td>$\Delta d_{t-3}$</td>
<td>-0.0442</td>
<td>-0.257***</td>
<td>0.0672</td>
</tr>
<tr>
<td></td>
<td>(0.0273)</td>
<td>(0.0628)</td>
<td>(0.0522)</td>
</tr>
<tr>
<td>$\Delta w_{t-3}$</td>
<td>0.0231</td>
<td>-0.0732</td>
<td>-0.1428**</td>
</tr>
<tr>
<td></td>
<td>(0.0368)</td>
<td>(0.0848)</td>
<td>(0.0705)</td>
</tr>
<tr>
<td>$D_{1693}$</td>
<td>0.062</td>
<td>0.4007***</td>
<td>-0.0941</td>
</tr>
<tr>
<td></td>
<td>(0.0484)</td>
<td>(0.1116)</td>
<td>(0.0927)</td>
</tr>
<tr>
<td>$D_{1855}$</td>
<td>0.0956*</td>
<td>0.4044***</td>
<td>0.0313</td>
</tr>
<tr>
<td></td>
<td>(0.0495)</td>
<td>(0.1139)</td>
<td>(0.0947)</td>
</tr>
</tbody>
</table>

Standard errors in parentheses.
* denotes significance at 10 per cent, ** at 5 and *** at 1 percent.

Table 2 reports the results from the VAR model with year dummies for 1693 and 1855 and a lag-length of three. All rates are first differences of logs and can be read as elasticities. Initially, I estimated the VAR model without year dummies. However, the post-estimation residual diagnostic tests reject normality. An inspection of the residuals revealed two outliers in the mortality series, 1693 and 1855. The unusually high mortality recorded in both years was the result of infectious disease outbreaks. Arguably, these years can be seen as exogenous shocks in the system. I included dummies to control for these ‘shocks’, however their inclusion does not have substantial impact on the results. The inclusion of these dummies improves the post-estimation diagnostics considerably, as shown in table 3.

It can be seen that real wage variation strongly influences vital rates. The positive check elasticity is -0.18 in the following year and effectively zero thereafter. The preventive check elasticity is stronger and also more dispersed over time, 0.2 and 0.11 in the following years.
VAR without dummies | VAR with dummies
--- | ---
Test Stat | Test Stat | DoF | DoF | P-Value | P-Value
Portmanteau Test (asymptotic) | 126.45 | 117 | 0.26 | 131.45 | 117 | 0.17
ARCH (multivariate) | 210.12 | 180 | 0.06 | 206.30 | 180 | 0.09
JB-Test (multivariate) | 32.70 | 6 | 0.00 | 11.61 | 6 | 0.07
Skewness only (multivariate) | 13.23 | 3 | 0.00 | 4.49 | 3 | 0.21
Kurtosis only (multivariate) | 19.47 | 3 | 0.00 | 7.12 | 3 | 0.07

Table 3: Residual Diagnostics

two years. However, these results may be biased due simultaneity. To correct for this potential bias and I perform an analysis of the orthogonalized impulse response functions. Identification requires restrictions such that the variables to follow a causal chain. Biology dictates that birth rates be the first variable because fertility will not (or is very highly unlikely to) respond to either a ‘shock’ in the level of subsistence or death rate in, the same calendar year. The next step is to establish the correct order between death rates and real wages. I argue that death rates do not respond in the same calendar year to real wage innovations because the effects of reduced living standards affect mortality with a lag. Hence, the order of variables in the VAR runs from the crude birth rate to the crude death rate to the real wage rate.\textsuperscript{13}

\textsuperscript{13}It should be noted that the results shown here change little when either the order between death rates and real wages is changed or when the order invariant generalized impulse responses are used.

Figure 9: The Checks

18
Figure 9 plots the cumulative impulse responses of the both the birth and death equations to a one standard deviation innovation in the wage error term, alongside 95% bootstrapped confidence intervals. To capture both the immediate and long-run impact of a real wage innovation these cumulative responses are traced over ten periods. We can see that real wages affect both vital rates as previously argued. The short-run impact is immediate, and severe, for both vital rates. After which both responses fall to their respective long-run levels. The long-run elasticities are similar. The preventive check is 0.13 and the positive check is -0.1, indicating that a 10% increase in the real wage causes a 1.3% rise in births and a 1% fall in the death rate. This positive check elasticity is stronger than the figures reported for early modern England by Kelly and Ó Gráda (2010).

The Preventive Check

<table>
<thead>
<tr>
<th>Period</th>
<th>Preventive Check</th>
</tr>
</thead>
<tbody>
<tr>
<td>1651-1729</td>
<td>-0.01</td>
</tr>
<tr>
<td>1730-1819</td>
<td>0.00</td>
</tr>
<tr>
<td>1820-1881</td>
<td>0.01</td>
</tr>
</tbody>
</table>

The Positive Check

<table>
<thead>
<tr>
<th>Period</th>
<th>Positive Check</th>
</tr>
</thead>
<tbody>
<tr>
<td>1651-1729</td>
<td>-0.04</td>
</tr>
<tr>
<td>1730-1819</td>
<td>-0.03</td>
</tr>
<tr>
<td>1820-1881</td>
<td>-0.02</td>
</tr>
</tbody>
</table>

Figure 10: The Checks Evolution

Differing population growth trends in the population series shown in figure 3, suggest that there may have been structural changes in Northern Italian demographic regime during the 1650-1881 period. A visual inspection the population series suggests two breaks, occurring roughly around 1730 and 1820. These breaks also appear to be present in the wage series. The results of a simple Chow test run separately on the two series fails to reject the hypothesis of no structural breaks. To further investigate the existence of these changes, and their affect on the check mechanisms I estimate the VAR model of equation (12) separately for the three periods. Figure 10 shows the long-run effects, derived from the impulse response functions, of real wage innovations in these three periods.

---

14All with p-values less than 0.001.
overlapping periods. That the checks magnitude is uniform across time is apparent, as I find that Malthusian population control mechanisms were remarkably stable across the three sub-periods.

The VAR methodology in this section finds clear evidence supporting the presence of both positive and preventive checks in early modern Northern Italy. However, I have thus far ignored any attempt to examine the impact of population on real wages, or diminishing returns – an issue which I turn to in the next section.

6 Structural Model

We have seen that real wage variation caused vital rate movements in the manner predicted by my simple Malthusian style model. However, this analysis imposed a number of restrictions which I now seek to rectify. In this section I present a state space model which links real wages, fertility and mortality via population in the manner originally proposed by Lee & Anderson (2002). This methodology includes the wage and check equations equations (3), (6) and (7). Each equation contains a time-varying intercept and therefore the model parameters refer to the variables in levels. The presence of unit roots is captured by the evolution of the time-varying intercepts, the states, which can be used as a proxy for secular change such as technological progress. Thus, the check intercepts evolve according to the following random walks: \( m_t = m_{t-1} + \zeta_t \) and \( n_t = n_{t-1} + \vartheta_t \).

The variables which capture unsystematic shocks \( (s_t, r_t \text{ and } u_t) \) like climactic variation and disease prevalence tend to be correlated from year to year. To account for this I amend equations (3), (6) and (7) so that the errors are the following stationary second order autoregressive processes:

\[
\begin{align*}
  s_t &= \gamma_1 s_{t-1} + \gamma_2 s_{t-2} + \omega_t \quad (13) \\
  r_t &= \kappa_1 r_{t-1} + \kappa_2 r_{t-2} + \varsigma_t \quad (14) \\
  u_t &= \lambda_1 u_{t-1} + \lambda_2 u_{t-2} + \varphi_t \quad (15)
\end{align*}
\]

where \( \omega_t, \varsigma_t \text{ and } \varphi_t \) are all assumed to be white noise.

The full matrix form of the state space system is included as an appendix. Once the state space form is specified estimation is performed via the Kalman filter within a maximum likelihood algorithm. To ease convergence I specify an initial state vector and

\(^{15}\)Where the mortality intercept, \( m_t \), is distinct from the marriage rate in table 1.
variance-covariance matrix and provide initial parameter values, which are estimated using MA models with independent variables. The maximum likelihood estimates together with their standard errors is displayed in table 4.

### The Wage Equation

<table>
<thead>
<tr>
<th>$\beta$</th>
<th>$\gamma_1$</th>
<th>$\gamma_2$</th>
<th>var(exp($\nu_t$))</th>
<th>var(exp($\omega_t$))</th>
</tr>
</thead>
<tbody>
<tr>
<td>-0.40756***</td>
<td>0.879468***</td>
<td>-0.29582***</td>
<td>-4.94594***</td>
<td>-12.7117***</td>
</tr>
<tr>
<td>(0.143985)</td>
<td>(0.073694)</td>
<td>(0.065084)</td>
<td>(0.080512)</td>
<td>(0.550781)</td>
</tr>
</tbody>
</table>

### The Preventive Check

<table>
<thead>
<tr>
<th>$\mu_1$</th>
<th>$\mu_2$</th>
<th>$\kappa_1$</th>
<th>$\kappa_2$</th>
<th>var(exp($\delta_t$))</th>
<th>var(exp($\varsigma_t$))</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.003311***</td>
<td>0.004818***</td>
<td>-0.00222</td>
<td>-0.0011</td>
<td>-14.4517***</td>
<td>-13.5822***</td>
</tr>
<tr>
<td>(0.001127)</td>
<td>(0.001082)</td>
<td>(0.008379)</td>
<td>(0.003338)</td>
<td>(0.261531)</td>
<td>(0.145618)</td>
</tr>
</tbody>
</table>

### The Positive Check

<table>
<thead>
<tr>
<th>$\delta_1$</th>
<th>$\lambda_1$</th>
<th>$\lambda_2$</th>
<th>var(exp($\varphi_t$))</th>
</tr>
</thead>
<tbody>
<tr>
<td>-0.00703***</td>
<td>0.349117***</td>
<td>0.016911</td>
<td>-11.3058***</td>
</tr>
<tr>
<td>(0.00207)</td>
<td>(0.060638)</td>
<td>(0.074789)</td>
<td>(0.068165)</td>
</tr>
</tbody>
</table>

Standard errors in parentheses.

* denotes significance at 10 per cent, ** at 5 and *** at 1.

Table 4: State Space Estimates

The estimated wage-population elasticity is -0.41. I find that population growth depressed living standards, as the presence of diminishing returns is confirmed. This result tallies well with the constant returns to scale assumption ($\beta < 1$). The roots of autoregressive error term coefficients, $\lambda_1$ and $\lambda_2$, lie outside the unit disc ($1.47 \pm 1.09i$), and demonstrate how the estimated wage equation is a stationary process after specifying the intercept term to be a random walk with drift. The direction and magnitude of both positive and preventive checks is consistent with the evidence provided in the VAR analysis. However, the state space model accommodates the contemporary correlation between real wages and vital rates, and consequently the short-run elasticities are slightly larger. Dividing by means yields the relevant elasticities. A positive check of -0.24 and a preventive check of 0.24 (over two years) clearly demonstrate the constraints which living standards placed on vital rates.

These short-run elasticities are much larger than those found in Lee & Anderson (2002) for England, a finding which is congruent with evidence of comparative living standards in the two regions at the time, as illustrated by figure 4. The greater sensitivity
of vital rates to real wage variation is unsurprising given the observed divergence in living standards across the two regions. Quite simply, the lower purchasing power of the Northern Italian population put a greater proportion of their population at the edge of biological survival. The relative importance of lagged real wages in England in comparison to Northern Italy also warrants closer inspection. Recent research by Kelly & Ó Gráda (2010) demonstrated the existence of a number of additional safeguards that served to protect the poorest in English society, in particular introduction of state funded poor relief or Poor Law. Additionally, a substantial wage premium existed for those who wished to move from rural to urban centers in early-modern England.\footnote{Most likely as compensation for the increased chance of morbidity.} The relative importance of lagged real wages in England is likely to stem from combination of these observations. In effect, the Poor Law had the ability to sustain those on the biological edge of survival, while the urban wage premium created incentives for the poorest to migrate into England’s burgeoning urban areas thus spreading infectious diseases. The absence of these factors in Northern Italy offers a plausible explanation for why the effect of real wages on vital rates was both instantaneous and severe.

Figure 11: Wage Equation States

Figure 11 shows the evolution of the two wage equation states, the natural log of labor demand $a_t$ and the rate at which labor demand increases, or technological progress, $g_t$. The failure of either series to show any sustained increase agrees with all other evidence of economic stagnation in Northern Italy during this period. Effectively, these series tell us that the population growth which occurred during this period entailed a
heavy cost. Real wages were forced down, through diminishing returns, as the Northern Italian economy failed to absorb a rising population. There is no evidence to suggest that population growth causes technological progress in the manner proposed by scholars such as Boserup (1965) and Kremer (1993). The trajectory of the birth rate intercept, $n_t$, is almost identical to that of the underlying series and indicates that real wages played a relatively little part in the evolution of this vital rate. The death rate intercept collapsed to a constant, as expected.

Lee & Anderson propose a simple methodology to examine the strength of homeostasis in the system. The product of the lag sum of fertility minus mortality (0.015159) and the (negative) population elasticity (0.041) determines the rate of convergence towards equilibrium in this system. Here it is at an exponential rate of 0.0062 per year. The half-life of a shock can be found by solving: $0.5 = \exp(-0.0062)$, for $T$. Here, I find that the half-life of a shock is 112 years. This figure is quite high, indicating that this system is best characterized as one of weak homeostasis or slow convergence. This finding demonstrates that while all the features of a Malthusian system were present, this regime was one in which could move away from the equilibrium of figure 1 for sustained periods of time.

7 Conclusion

Whether or not a stylized Malthusian model captures the relationship between living standards and population in pre-industrial England is debatable. The estimates I provide here are less ambiguous and strongly suggest a role for Malthusian theory in preindustrial Northern Italy. My findings have relevance to the current research agenda on the empirical validity of unified growth theory. The results of this exercise roughly concur with the theory. Between 1650 and 1881, economic growth in the region stalled. However, this was not at a Malthusian steady state. I find slow convergence and therefore exogenous forces could move the economy away from any so-called steady state for prolonged periods. Nevertheless, the presence of the population control mechanisms, or checks, is apparent over the entire 1650-1881 series. Additionally, diminishing returns meant that any technological improvement was eroded by population growth as Northern Italy appeared to be Malthusian both before and after the life of Malthus.

Unified growth theory stresses the role of fertility transitions as a key causal factor in the departure from Malthusian stagnation to modern economic growth. Again the results of this paper are consistent with both this idea and previous literature on Italian demographic and economic history. For example, Livi Bacci (1967) found that there was
no fertility transition before the last decade of the 19th century in Italy. The period 1650-1881 appeared to be punctuated by high marital fertility rates, low investment in children and consequently poorer outcomes. The Italian transition to a modern growth regime developed in unison with major changes in the demographic landscape and only after the age of mass migration provided a new mechanism by which population pressure could be corrected.
A State Space System

This appendix provides a quick overview of the state space system used in this paper. A state space system is composed of the following two equations,

the transition equation:

\[ \theta_t = G\theta_{t-1} + w_t \]  

(16)

and

the measurement equation:

\[ y_t = F\theta_t + v_t \]  

(17)

where \( y_t \) is the output vector and \( \theta_t \) is the state vector which contains the values of both the observed and unobserved variables. The matrices \( G \) and \( H \) contain both the constrained and unconstrained coefficients matrices. The \( w_t \) and \( v_t \) are vectors of noise terms and zeros.

Real wages, death rates and birth rates have the following representation in state space:

\[ y_t = \begin{bmatrix} w_t & d_t & b_t \end{bmatrix}^\top \]  

(18)

where \( y_t \) is the 3×1 output vector and

\[ \theta_t = \begin{bmatrix} a_t & p_t & s_t & s_{t-1} & c_t & m_t & (\Delta w_t + w_{t-1}) & w_{t-1} & u_t & u_{t-1} & n_t & r_t & r_{t-1} \end{bmatrix}^\top \]  

(19)

is the 13×1 state vector. Consequently the coefficient matrices are:

\[ F = \begin{bmatrix} 1 & \beta & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & \mu_1 & \mu_2 & 0 & 0 & 1 & 1 & 0 \end{bmatrix} \]  

(20)

and

\[ G = \begin{bmatrix} 0 & 0 & 0 & 0 & 1 & \delta_1 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & \mu_1 & \mu_2 & 0 & 0 & 1 & 1 & 0 \end{bmatrix} \]

\[ H = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix} \]

\[ v_t = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix} \]

\[ w_t = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix} \]

\[ u_t = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix} \]

\[ n_t = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix} \]

\[ r_t = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix} \]

\[ \Delta w_t = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix} \]

\[ w_{t-1} = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix} \]

\[ u_{t-1} = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix} \]

\[ n_{t-1} = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix} \]

\[ r_{t-1} = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix} \]

\[ \delta_1 = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix} \]

\[ \mu_1 = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix} \]

\[ \mu_2 = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix} \]

\[ \beta = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix} \]

\[ \Delta \] represents the change in the variable.

See Harvey (1989) for a complete overview of state space models in economics.
\[
G = 
\begin{bmatrix}
1 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & \gamma_1 & \gamma_2 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & \lambda_1 & \lambda_2 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \kappa_1 & \kappa_2 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0
\end{bmatrix}
\tag{21}
\]
References


