

The Tall Tale of Heights

An Econometric History of 18th
Century British Living
Standards

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Part 1: Introduction and Review of the Literature

Every school child knows the Importance of the first Industrial Revolution. For all of previous recorded history the western world had toiled as a stable agricultural society. England rose up to become the first modern industrial society. We are led to believe that great inventions like the steam engine caused a massive movement from the farm to the factory. We are taught, quite paradoxically, about both the horrors of early factory conditions and the improvements to the quality of life. We mistakenly conclude that people of the past had worse living standards than we do today. The purpose of this paper is to examine the quality of life of the middle and lower classes in England during the beginnings of the first Industrial Revolution—during the 18th century.

The biggest problem that any economic historian faces is the lack of historical data. Per capita income is the gold standard in measuring a society's economic success. But is it always the best measurement? Sarah Horrell (1996) believes that household income is more suitable during the late 18th to mid-19th centuries. She compares household income to male income, and concludes that male income was more volatile during the British Industrial Revolution. Most statistical approximations of income-levels, like Horrell (1996), don't estimate any income-levels before the second half of the 18th century. Horrel (1996) calls the 18th century the rise of household income. During the first half of the 18th Century, peasants ate and produced all of their own food. And according to Komlos (1990), they had plenty of food. It was not until the second half of the 18th century that income-levels started to be estimated. Recent studies have been able to estimate working class income and cost of living, like Lindert (1986). But generally economic historians prefer nutrition levels to income levels before 1750 as a means of measuring economic prosperity.

This brings up an interesting question: How do you measure historic nutrition levels? Many economic historians are turning to estimations of average heights, based on military,

shipping and indentured servant records as a measure of living standards. Steckel (2004) even measured femur bones to get rough estimates of average heights for the past thousand years across various European peoples. Steckel (1995) theorized that height was influenced by: 1) diet, 2) disease, 3) work intensity, 4) maintenance and 5) genetics. Steckel (1995) and Komlos (1990) both claim that generally there is no racial height differences based on genetics, with the exception of the Far East. So the average adult height of a population reflects its health and living standards.

Steckel (1995) explained that the people grow primarily in two periods: early childhood and adolescence. He explains that growth in early childhood is usually twice as fast as growth in adolescence, but different nutritional levels have a far greater impact on growth during adolescence. Onis et al. (2001) examined the modern growth rate in adolescent boys in developing vs. developed countries. In Calcutta, a developing country, the maximum height velocity during adolescence occurs at the age of 13 years, while in most modern developed countries, height velocity maximum occurs around 14 years of age.

Komlos (Feb., 1993) and Floud et al. (1993) both examine the height measurements of Marine Society boys at ages 13 through 16 to determine the average heights of boys in Britain from 1730 to 1860. Although Komlos (Feb., 1993) and Floud et al. (1993) come to two different conclusions on the data based on the use of two different statistical techniques,¹ we can use their data to estimate the average maximum height velocity in 18th century Britain.

In addition, Komlos (1990) claims that the nutrition of a mother during pregnancy has a huge impact on the height of the child. Based on this assumption, he uses average adult heights

¹ Komlos (Feb., 1993) claims that generally average British boys heights degenerated, while Floud et al. (1993) claims that average boys heights had an upward trend. The Marine Society had basic height requirements. Komlos (Feb., 1993) claims that this made the average boy height proportional to the population, since the height requirements were adjusted over time. Floud et al. (1993) believes the heights should follow a normal curve distribution. He claims that minimum heights would only produce a cut in the normal distribution of the heights collected. He uses the heights to estimate the complete normal distributions.

to measure nutrition at birth. All these models suggest that nutrition effects future adult height primarily during pregnancy, early childhood and adolescence.

Before modern farming and food preservation techniques, food supply and nutrition were highly tied to the weather. Steckel (2004) explains that during the middle ages, average heights were about the same as they are today, yet during the 17th through 19th centuries, average heights were lower in Europe. This thus created a sort of U-Shape in average heights in the time-line. He identified possible causes as: 1) urbanization is bad for health, 2) the comeback of the bubonic plague at the end of the middle ages and 3) the changing climate. He concluded that the major cause for the change was the climate. The Little Ice Age (1550-1850) hurt food production and thus nutritional levels. Komlos (1990) theorized that favorable weather caused the break from Malthusian population limit and the industrial revolution. Before 1730, there was a given European population limit that population oscillated around. At the end of a peak of one of these cycles, favorable weather caused low food prices which caused a population boom. It wasn't until the later half of the 18th century that food prices were down, thus hurting nutrition. However, a significant population density created an earlier average marriage age continuing the already rapid population growth. Komlos (1990) suggests a model where both nutrition and population density influence population growth, while Steckel (1995) suggests a model where technology and weather influence average heights.

The literature so far tests limited models due to limited data. As far as I can tell, no one tests their theories against other theories. For instance, neither Steckel nor Komlos test whether weather or technology had more to do with worker's living standards during the 18th century. Economic Historians seem more concerned with reconstructing the height data and examining general trends. The purpose of this paper is to correct this oversight. This paper focuses on the 18th century to look at the critical turning point from the ancient to the modern age. I use this to

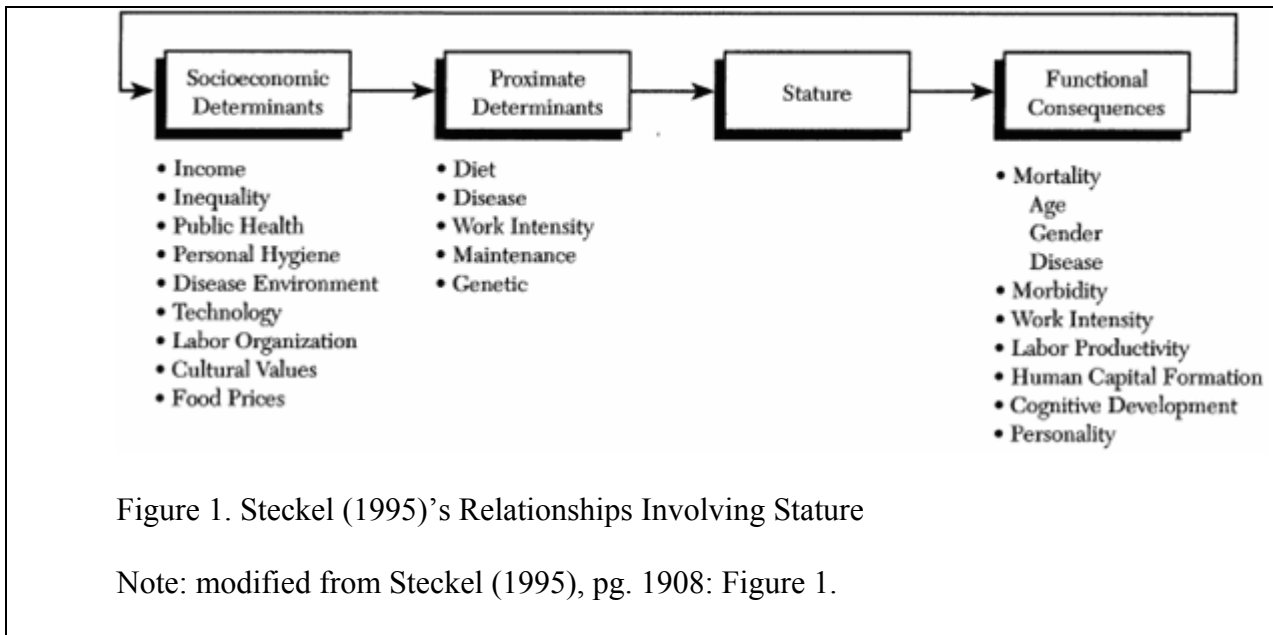
peak into the living conditions of the worker. I attempt to find the causality behind the workers changing living conditions. In addition I examine them by region and occupation.

Part 2: Economic Theory behind my Model

I have shown in my literature review that many economic historians use height as a measurement for diet. Steckel (1995) theorized that height (or stature) is influenced by the relationship indicated in Figure 1. Socioeconomic determinants, like income and prices, affect proximate determinants, like diet and disease. Proximate determinants in turn affect stature. Stature affects functional consequences, like productivity and personality, which affect the very socioeconomic factors that affected stature. For instance, lower wages would lead to a poorer diet. A poorer diet stunts your growth which would decrease your productivity. Lower productivity lowers your wages. So it's hard to say whether stature causes income or income causes stature. What we note is that stature and proximate determinants, like income, are related.

Reverse causality, however, is limited. Perhaps the stature of a parent affects a boy's socioeconomic factors more than his own. This would be especially true in the earlier years of childhood. I will explore this possibility further with my empirical model.

Notice that the most measurable traits are stature and the socioeconomic determinants. I use these traits to form the basis for my dependant and independent variables.



This model is useful for thinking in terms of the overall structure of the causes of stature, but the relations are too loosely constructed. For instance, income and technology don't affect genetics. Steckel (1995)'s model doesn't identify exactly what socioeconomic determinants affect which proximate determinants. In addition some factors of stature are exogenous such as temperature. Therefore Steckel (1995)'s model doesn't completely describe the causality in this model.

Komlos (1990) theorized that favorable weather caused the population boom of the 18th century. He used height data to show that most 18th Century great inventors were born in years of good nutrition. He indicated that higher temperatures led to a better diet. Based on this theory, I test the temperature during the farming season as an independent variable in my model. I show in appendix 1 that temperature during the month of June had the most significant effect on farming. Higher temperatures can yield better harvests or can spoil them. Since England is climatically a northern region, higher temperature will probably help harvests more than it will hurt them. To test for this diminishing effect, I test the quadratic of temperature in my model.

In addition, winter temperatures cause disease, because colder temperatures increase the reliance on clothing. In addition according to Fix (2007), the 18th Century saw a change from wool to cotton, which is much easier to clean (thus carrying less disease). In spite of this cleaning wasn't as regular as it is today, so we can assume that both fabrics carried some level of disease. A combination of both winter temperature and cotton fabrics would explain some of the causes of disease, but also the cost of fuel would need to be included in this analysis. If fuel prices were high, then the marginal costs of wearing more clothing would be lower; higher fuel costs will make me more willing to risk disease to stay warm.

Also changes in technology, sanitation, labor organization and cultural values are hard to measure. My model estimates them by using time (or year born) as a variable to catch these general trends. Although my dependant variable is adult heights of persons, analysis of the changes through time is needed. Many economic historians like Komlos (1990) and Steckel (1995) use average heights per year to create a time series analysis. If we have three persons heights for 1743 and one persons heights for 1747, then under this method, fitting the OLS estimates to all the three persons in 1743 is just as important as fitting it to the one person in 1747. To fix this statistical error, time series cannot be used. But changes do happen over time, so it is still needed to be fitted and analyzed in the model.

Furthermore, war can have huge socioeconomic effects on society. I add years of war as a dummy variable to my model to see if war acts more as a boost to industry or a burden of taxation during the 18th century relative to stature.

I take these changes and apply them to Figure 1 to create Figure 2 below.

The model in Figure 1 suggests the following econometric formula:

$$Stature = \beta_0 + \sum_{i=1}^{18} \beta_i X_i + u_{genetics} + u_{other}$$

X_1 = population growth

X_2 = winter temperature

$X_3 = (X_2)^2$

X_4 = cost of fuel

X_5 = cost of soap

X_6 = preference of cotton over wool

X_7 = land available

X_8 = amount of wheat consumed

X_9 = amount of other grains consumed

X_{10} = June temperature

$X_{11} = (X_9)^2$

X_{12} = wages with respect to cost of living

X_{13} = war index

X_{14} = war with France Index

X_{15} = wealth

X_{16} = cost of living

X_{17} = housing rents

X_{18} = time

Notice that this model is with respect to individual's stature, not relative to time. Instead we use time as an independent variable, X_{18} . This doesn't, however, suggest which costs, prices and temperatures during a person's lifetime to use. Obviously, the effects on stature are during years of high height velocity. Steckel (1995) indicated that height was determined in childhood and adolescence. Figure 3 shows an illustration of what a normal growth velocity is for a human.

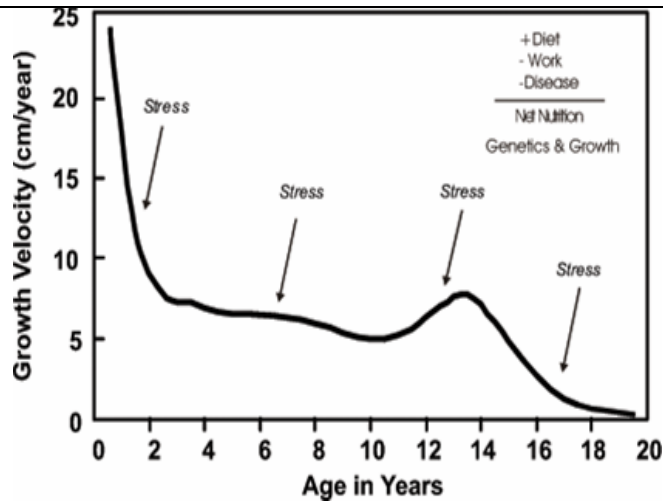


Figure 3: Illustration of Healthy Growth Velocity of a Human

Note: The stresses represent the following periods of growth from left to right: early childhood, late childhood, adolescence and late adolescence.

Source: Courtesy of Richard Steckel.

Note: Males generally experience their growth spurt in adolescence a little later than females so this is not entirely representative of our data.

Healthy males generally experience their growth spurt during adolescence a little later than indicated in the diagram. Instead of experiencing a growth spurt at age thirteen (the average for all humans), according to Onis et al. (2001), they experience their maximum adolescence height velocity when they are fourteen.

Adult male height can be determined by data from periods of the greatest potential growth velocity. Onis et al. (2001) shows that bad nutritional levels can make the average height velocity peak earlier during adolescence. Steckel (1995) explained that a period of “catch-up” growth can happen during years of plenty following a diminished growth period, so diminishing

determinants can cause the maximum height velocity to take place before or after the fourteenth year of age. Both possibilities, however, require bad determinants during the fourteenth year of age. Using the heights of the Marine Society of Boys, some of the average heights of boys in the late 18th century were estimated by Floud et al. (1993) and Komlos (Feb., 1993). Their estimates differed based on different statistical techniques, but both of their estimates indicate the greatest difference in height velocities were during a boy's fourteenth year of age. This is shown in Figure 4.

(a) Estimates based on Floud et al. (1993)

(b) Estimates based on Komlos (Feb., 1993)

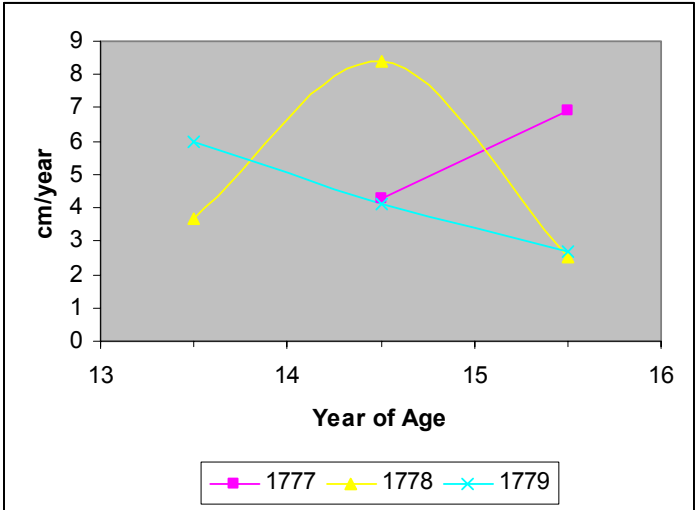
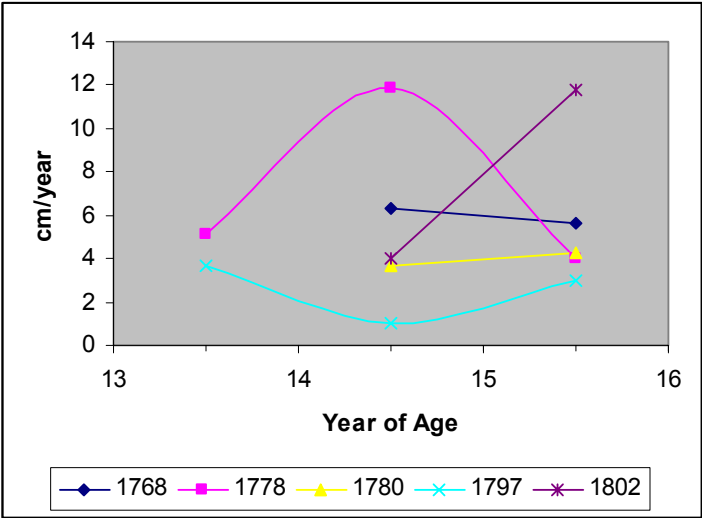


Figure 4: Estimates of height velocities in Britain during the late 18th century.

Figure 4 does not strongly indicate a period of catch-up growth after the age of 14 or an earlier peak in height velocity. This indicates that the peak in height velocity during adolescence can be before or after the age of fourteen based on diminished determinants. Therefore height velocity is crucially tied to the age of fourteen, even when the peak in height velocity is shifted. Thus it is most practical and appropriate to represent effects on adolescence growth during the fourteenth year of age.

Adolescence is not the only time when outside factors can greatly affect height. Komlos (1990) claims that nutrition during pregnancy has the biggest influence on an adults' height. Figure 3 indicates that early childhood growth can be likewise represented by age two; late childhood by age seven; and late adolescence and any "catch up" growth can be represented by age seventeen. Since these years are not local height velocity maximas, shifts in growth pattern during these years would have a diminished effect. In fact, according to Figure 3, age six would be just as good an estimate as age seven. Therefore I will test two models: one to test the effects of my determinants during pregnancy and during the fourteen year of age; and another to test the effects of my determinants during pregnancy, the second year of age, the seventh year of age, the fourteenth year of age and the seventeenth year of age. These models will look like:

Model 1:

$$Stature = \sum_{age=0,14} \left(\beta_0 + \sum_{i=1}^{18} \beta_i X_i \right) + u_{genetics} + u_{other}$$

Model 2:

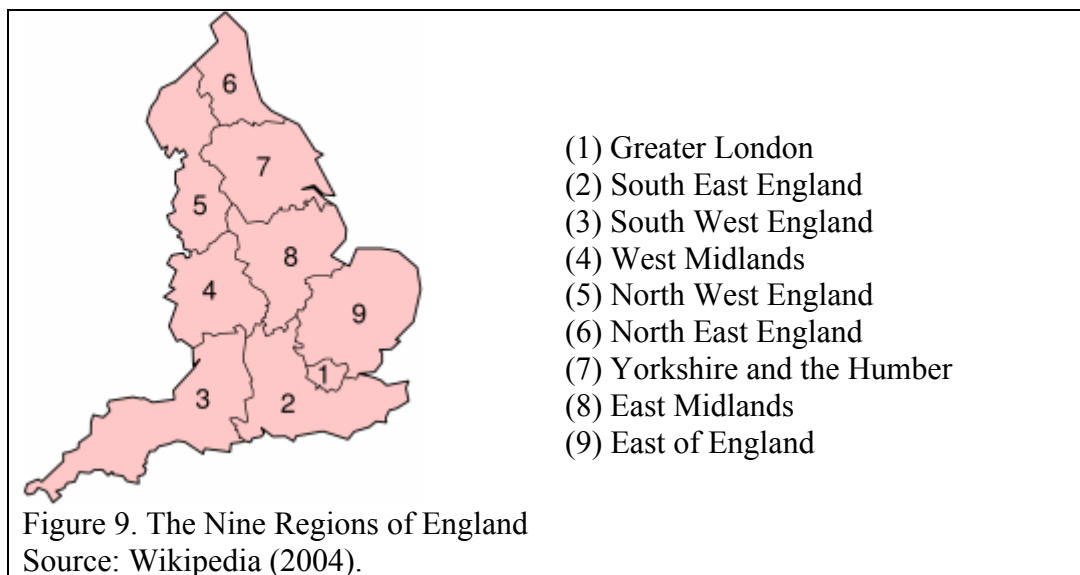
$$Stature = \sum_{age=0,2,7,14,17} \left(\beta_0 + \sum_{i=1}^{18} \beta_i X_i \right) + u_{genetics} + u_{other}$$

Therefore we should expect to find that the factors that determine diet are much more significant than the other factors. Most economic historians just use height to estimate nutrition, and my findings should to go along with their work. We should expect high correlations between many of my variables. For instance, the wage of a farmer is probably highly related to the amount of wheat produced. Diet, disease and work intensity influence each other. The correlation between some variables will make important variables seem less influential and important. Based on this assumption, I believe my coefficients on my model to be slightly biased toward zero, but of such a small scale that it has virtually no effect.

Part 3: A Description of the Data

For this paper I examined three different samples of heights: runaway apprentices, military deserters and runaway indentured servants. All three data samples were taken from advertisements in colonial newspapers in the United States by John Komlos in Komlos (2000) and Komlos (2001). There are 23 runaway apprentices, 258 military deserters and 1275 runaway indentured servants from England listed.² Since runaway indentured servants are the biggest data set their data becomes the data I test in my model.

Another advantage to using the runaway indentured servants' data is that Komlos (2001) recorded the home town off the newspaper advertisement. I split most of the runaway indentured servants (1245 of them) into coming from nine regions of England: (1) Greater London; (2) South East England; (3) South West England; (4) West Midlands; (5) North West England; (6) North East England; (7) Yorkshire and the Humber; (8) East Midlands; and (9) East of England. These regions are shown in Figure 5.



Some of the independent variables that I use in my model needed proxy variables. These are variables used to approximate other unknown variables. For instance, the temperature data

² I took out those individuals with missing data. This was most often age and/or birth place. Without this data, their statistics would mean nothing to my model.

only reflects mean high of months during the year. The real relation involves a continuous stream of weather for the selected time period. Since this would be impossible to measure and use in an econometric model, the mean high data is used to reflect actual temperatures used.

Also in many cases it is impossible to tell how much of a good is produced, the only data we have is imports and exports of that good. I use net imports to proximate what is happening in the market. The hazard of using this variable is that it is impossible to tell whether an increase in net imports is a result of increased demand or decreased supply. I assume that it is a result of increased demand, since it is widely accepted that the commercial and industrial revolution led to an increase in output. In addition, toward the end of the 18th century, in all cases imports far exceeded exports, indicating an increase of demand inside England.

Figure 6 reports my proxy variables.

Independent Variable	Proxy Variable	Reasoning
winter temperature*	The average of the mean high temperatures during the months December (of the previous year), January and February (of that year). Manley (1974)	These are the coldest months in the year. Therefore these months are more likely to cause winter diseases.
cost of fuel	Real price of coal (1770=1). Lindert-Levin (2002)	This seems to be the only fuel price available for that period. Although the increasing use of the steam engine would inflate the price toward the end of this period, the limited diffusion of the steam engine during the 18 th century would probably not bias it too much.
preference of cotton over wool	Opposite of Net wool imports over net cotton imports. Mitchell and Deane	Import data is the only data available on the consumption of cotton and wool. Prior to 1772, wool was imported in two different

		measures (great stones and bags). 1772 onward wool was measured in pounds. Therefore I use three different variables to measure the changing measurements and one dummy variable to measure years 1772 onward.
land available	Inverse of the estimate of the total population (times 10^7). Wrigley et. al (1997)	Assuming the amount of land in England is a constant, then the amount of land per persons would be inversely related to the total population.
Amount of wheat consumed	Net Imports in Wheat and Wheaten Flour (in thousands of quarts). Mitchell and Deane	Import data is the only data available on the consumption of wheat.
Amount of other grains consumed	Net Imports in Barley, Oats and Malt (average in thousands in quarters). Mitchell and Deane	Import data is the only data available on the consumption of wheat.
Figure 6. Descriptions of and Reasoning Behind Proxy Variables		

Some Independent Variables used in the model have been estimated. These models are explained in Figure 7.

Independent Variable	Construction
population growth	Compounded Annual Growth Rate Per 1000. Wrigley et. al (1997)
cost of soap	Real price of soap per 12 pound(1770=1). Lindert-Levin (2002)
June temperature	Mean high temperatures during the month June (of that year). Manley (1974)
wages with respect to the cost of living	The real wages of farmers, craftsman and laborers based on cost of living. Clark (2001)
war index*	Indicator Variable: 1 for when Britain was at war.
war with France Index*	Indicator Variable: 1 for when Britain was at war with France.
Wealth	Average of probate for given year. Lindert (2001)
time*	Use both Year of birth and Age as Variables

I also use several dummy or indicator variables to weed out the effect of events like war and region of birth. These variables are:

Dummy or Indicator Variable(s)	Reason
war index	War tends to change the structure of society. This is to test the effect of war on the populous.
war with France Index	France was closer than any other nation to England and War with France tended to get more competitive and spread to the colonies.
Birth Place Dummy Variables	To control for different environments in different areas of England. I take Greater London as my base for this model. ³
Act of Union 1707 and 1800	The British Empire changed its shape and shipping relations were changed. This could have a possible affect on (among other things) net imports.
1771 and onward	Wool imports were measured more accurately after 1771. I use wool in my model.

Figure 8: The Dummy (Indicator) Variables

In addition to this I interact the dummy variables place of birth with the variable year of birth to account for differing changes in living conditions across England. Different areas in England could very easily have changed at different paces during the 18th Century. A rural region could have stayed relatively the same while urban sectors quickly industrialize.

Some of my variables naturally lend themselves into the logarithmic formula. The wages variables, the price variables and the wealth (average probate) all yield themselves to a percentage interpretation. For instance, we would generally think of wages going up by a certain percent. Also height yields itself better to logarithmic form. Linearly an unborn child will grow relatively little during while inside its mothers whom compared with its percentage growth.

Your percentage growth during childhood has a clearer interpretation on adult height. It's hard

³ This means that when all the regional there is no dummy variable for the Greater London Region. All the other Regional dummy variables are with respect to Greater London.

to interpret the effect of a failure to grow three centimeters while the child is in the whom on future adult height. It's easier to think of a failure to grow five percent in the whom shrinking adult height by so many percent.

On the other hand, other variables shouldn't be logged are: temperature, time, net imports, preference to wool over cotton, land available, population growth and dummy (or indicators) variables. Variables like population growth and preference to wool over cotton are already percents or proportions, so it makes no sense to take percentages of those. Net Imports and temperature can be negative and zero, which makes logging impossible. It really doesn't make any sense in thinking about a percentage change in year. And dummy variables are only two numbers anyway so taking the log doesn't make much sense.

In order to detect the magnitude of the effect my significant variables have I took the Beta Coefficients of all my variables except my dummy variables.⁴ It is difficult to interpret the beta coefficients of the natural logarithm of my variables. A coefficient of one on the price of cotton would mean that an increase of one standard deviation of the percentage change in the price of cotton would increase height by one standard deviation percentage change. So in my empirical section, I report both the beta and the non-beta coefficients on all my independent variables. This way I get the best of both worlds.

Much of the estimates of my variables have holes of missing observations. The probate sample wasn't taken for every year. My population and growth rate statistic I used is for every five years. Much of this has to do with the fact that we don't have ideal data for the 18th century like we would for a modern economic model. There are many ways you can account for this missing data. I use the previous know data point as an estimate of a missing data.⁵ However, on

⁴ There are only two values in a dummy variable—one and zero. It doesn't make sense to think of its change in terms of standard deviations.

⁵ Except for the occasional case where I don't know the first data point of the variable. Then I use the first known data point.

importing and exporting data points, no data usually meant that there was virtually no shipping of that good. In this case I interpreted missing data as zero.

Most of my data is probably flawed. We don't know the actual population parameters. I used statistical estimates for pretty much all of my variables (with the possible acceptations of prices and temperature). There's no way I can control this measurement error. I used as accurate and reliable data that was available to try to minimize this as much as possible.

With the data available there is no way to account for genetics. This omitted variable has a huge effect on the explanatory power of my model. Genetics could account for different heights across different regions. Like Komlos (1990) and Seckel (1994), I assume that genetics is represented by the error term and is evened out across society. I assume that there is no average height difference in genetics across different areas of England.⁶

Part 4: Empirical Test

There were four models developed in Parts 2 and 3. These are to test whether or not some of the values should be logged or not; and whether and whether or not to use data from ages two, seven and seventeen. I tested all four of these models in the RESET Test for functional form and used a White Test to test for heteroskedasticity. The p-values for the White Test were so low, that I can conclude that there is no heteroskedasticity. The results of the RESET test for functional form are shown in the following table:

	At Birth and at Age 14	At Birth and at Ages 2, 7, 14 and 17
Logged Variables	0.2531	0.0927
Non-Logged Variables	0.4600	0.1018

Figure 9: RESET Prob > F

⁶ In addition changes in technology, sanitation, labor organization and cultural values are all omitted variables in my model. My model estimates them by using time (or year born) as a variable to catch these general trends. But the change from year to year was probably not constant. I don't see this biasing my variables in any significant way.

In the RESET test the higher p-value means a better functional form. Therefore I conclude that leaving all my models without logarithms is preferred.

The RESET test does not test which ages I should use in my model. So in the model that tests the data at birth and at ages 2, 7, 14 and 17, I test the probability that all the coefficients on the data for a particular age should be zero (an F-test). These results are in figure 10.

	At Birth and at Age 14	At Birth and at Ages 2, 7, 14 and 17
Birth	0.5264	0.8817
Two	-----	0.8932
Seven	-----	0.8738
Fourteen	0.2801	0.5992
Seventeen	-----	0.9480

Figure 10: Probability the coefficients on the data for a particular age should be zero

The lower p-values, the more significant the relation. When testing at Birth and at Ages 2, 7, 14 and 17, I find that the most significant age was fourteen. When testing the smaller model, I find that birth is the most significant. Based on this information I choose the model that only tests the data at birth and at age 14. This model is summarized in Figure 11.

Source	SS	df	MS	Number of obs = 1275
Model	119.895	66	1.81659	F(66, 1208) = 1.78
Residual	1230.65	1208	1.01875	Prob > F = 0.0002
Total	1350.55	1274	1.06008	R-squared = 0.0888
				Adj R-squared = 0.039
				Root MSE = 1.0093
				F-Statistic
				Sum of the Beta Coefficient
Variables:				
Region and Regional Interaction				0.0882
Year of Birth {P> t } = 0.562				---
Population Growth				0.0559
Real Coal Prices				0.9868
Real Soap Prices				0.536
Preference of Cotton over Wool				0.4073
Land available per Person				0.1086
Wheat Imported				0.7768

Other Grains Imported	0.4552	0.066354
Wealth (Average Probate)	0.1992	0.220491
Cost of Living	0.3826	1.793749
Housing Cost	0.3721	-2.574477
Effects on Proximate Determinates:		
Disease Influencing Variables	0.2577	-3.375866
Diet Influencing Variables	0.9303	-1.93865
Work Intensity Influencing Variables	0.7314	-1.133741
Maintenance Influencing Variables	0.7184	-1.532742
Temperature		
Winter Temperature	0.9731	-0.032157
Winter Temperature Squared	0.7059	0.153601
June Mean High Temperature	0.6709	-0.015899
June Mean High Temperature Squared	0.7181	-0.003754
Wages with Respect to Cost of Living		
Farmers Wages with Respect to Cost of Living	0.6989	-0.336602
Craftsman Wages with Respect to Cost of Living	0.2264	-0.581997
Craftsman Helper Wages with Respect to Cost of Living	0.3173	0.435233
	0.3105	-0.189838
Dummy Variables		
War	0.313	-9.639663
War against France	0.1729	0.386336
War against France	0.0886	-0.651952
Act of Union 1800	0.1286	-5.610557
Act of Union 1707	0.4893	-3.76349

Figure 11. My Model

This model has an R-squared of about 9%. This means that when even taking all these variables in the model only about 9% of height is explained. The rest are explained by variables left out of this model namely genetics. Persons' heights vary a lot in the modern world due to genetics. Plus we lost some explanatory power with the inaccuracies of using historical estimates. The important thing is that some of our height is determined by these variables. I expected a huge portion of the model to be determined by genetics. I expected error due to inaccurate information. The important thing is I assume that this causes my estimates to be unbiased. Therefore I expect and see no reason for omitted variable bias.

By examining the correlation, I found no perfect correlation between my variables. However, some of my variables were dropped due to perfect multicollinearity. This means that

the dropped variables are probably perfectly correlated with some combination of other variables. Since there is no real way to test for this, we can't improve the model. This is why I place much more emphasis on the significance of a group of variables than individual significance in my paper.

My F-Statistics show the significance of various groups of variables. The lower the F-statistic of a group of variables the stronger the probability that they are related to adult height. For instance, population growth has an F-statistic of 5.59%. This indicates a strong relationship between population growth and adult height. While the real prices of coal has an F-Statistic of 98.68%. This means that the price of coal didn't influence the adult heights.

The Sum of my Beta Coefficients demonstrates the severity of the most probable influence of a group of variables on adult heights. The farther away from zero, the bigger effect that variable has on adult height. For instance, the dummy variables had a sum of beta coefficients of about -9.64. This means that in my model, war had a strong effect on height.

It's important to note the difference between the F-statistic and the Beta coefficients. The F-statistic for the dummy variables was only 31.3%. This means that although the sum of beta coefficients indicates a strong possible relationship, there is a reasonable probability that there is no relationship. The 31.3% F-statistic indicates that we cannot really infer anything from the Beta coefficient.

Figure 12 shows the groups of Variables with significant F-statistics with the Sum of their Beta Coefficients.

<u>Variables:</u>	F-Statistic	Sum of the Beta Coefficient
Population Growth	0.0559	-0.257492
Region and Regional Interaction	0.0882	4.144361
War against France	0.0886	-0.651952
Land available per Person	0.1086	-1.168535
Act of Union 1800	0.1286	-5.610557
War	0.1729	0.386336
Wealth (Average Probate)	0.1992	0.220491
Farmers Wages with Respect to Cost of Living	0.2264	-0.581997
Disease Influencing Variables	0.2577	-3.375866

Figure 12. The Most Significant groups of Variables

These statistics indicates that region, the act of the union 1800 and farmers wages had the biggest affect on height. All three are significant. There “act of the union 1800” variable could have been significant due to other changes that happened in 1800, so all we can conclude is that maybe the changes in trade affected British people’s living standards. The significance of farmers’ wages indicates that good farmers’ wages hurt living standards. This means cheaper food was in general better for living standards. This indicates that most people, maybe even farmers, had to buy food on the market.

The huge effect of different regions on height in my model is in Figure 13 below.

	Coefficient	P-Value
(1) Greater London	Base Region	
(2) South East England	0.98824	0.001
(3) South West England	0.6115	0.01
(4) West Midlands	0.43539	0.025
(5) North West England	0.81593	0.006
(6) North East England	0.39776	0.454
(7) Yorkshire and the Humber	0.37818	0.105
(8) East Midlands	0.20107	0.62
(9) East of England	0.7545	0.051
Not Specified	0.31381	0.009

Figure 13. Coefficients and P-Values for Regional Variables

This indicates that Londoners were the shortest. It indicates that they had the worst living conditions in England. The coefficient on the dummy variable “South West England” indicates that we can statistically expect men in the South West England region to be 0.6115 standard deviations in height taller than men in than men in the Greater London region. Using the standard deviations, we can statistically expect the average man in born in the South West England region holding everything else constant to be 13.95754 inches taller than the average man born in the Greater London region. This is extreme value is probably a fault of the selectivity of becoming an Indenture Servant. The high P-Values on North East of England, East Midlands and East of England indicate that there is a good possibility that they shared the same average heights as Greater Londoners. This is where the beginnings of Industrialization took place so it supports the hypothesis that Industrialization hurt the living standards of the worker.

Conclusion

My test supports Komlos (1990)’s hypothesis that population and population growth fueled on the population boom of the 18th century. My test shows that urbanization hurt the living standards of workers during the Industrial Revolution. Although population was rapidly expanding, living standards were being brought down with the ever increasing population. People who lived in the more urbanized sectors of England had generally poorer living standards. The rapid movement from the fields to the factories made work cheaper, so Industrialists did not have to pay high wages. Although the initial population boom might have been a result of the weather, favorable weather did not have a significant effect on living standards.

War had a general positive effect on living standards of the lower classes, allowing them to advance. War against France, on the other hand, had a more negative influence on height.

This was probably because War against France generally spread to the colonies and would have hurt trade.

Also, in general, it supports Steckel (1995)'s thesis on the relationship between disease, diet, work intensity, maintenance and genetics and height. Surprisingly disease, and not diet, has the most significant effect on height. Meaning we cannot assume, like many economists, that height is purely based on our diets.

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Appendix 1: Why Use June Temperature

To be able to tell which month's temperature had the most significant effect on food, I ran a simple regression based of my proxy variable net imports in wheat (representing wheat consumed) on the mean high temperatures in England for all the months during my time period (1695 to 1806). The p-value on June temperature (0.134) was the most significant of all the temperatures. Therefore I use the mean high temperature for the month of June to test for the effect of temperature on crops.

In STATA:

```
reg wheat jantemp febtemp martemp aprtemp maytemp juntemp jultemp augtemp septemp
octtemp novtemp dectemp
```

Source	SS	df	MS	Number of obs = 112
Model	1.6E+07	12	1309057	F(12, 99) = 1.06
Residual	1.2E+08	99	1233582	Prob > F = 0.4009
Total	1.4E+08	111	1241742	R-squared = 0.114
				Adj R-squared = 0.0066
				Root MSE = 1110.7

wheat	Coef.	Std. Err.	t	P> t	[95% Confid. Interval]	
jantemp	-3.1518	53.7684	-0.06	0.953	-109.84	103.536
febtemp	-91.236	78.0756	-1.17	0.245	-246.15	63.6829
martemp	-91.523	88.5314	-1.03	0.304	-267.19	84.1421
aprtemp	129.031	89.7795	1.44	0.154	-49.111	307.173
maytemp	93.768	99.1862	0.95	0.347	-103.04	290.575
juntemp	-169.09	111.955	-1.51	0.134	-391.23	53.0521
jultemp	128.058	103.127	1.24	0.217	-76.569	332.685
augtemp	186.899	133.36	1.4	0.164	-77.716	451.515
septemp	-23.246	104.62	-0.22	0.825	-230.84	184.343
octtemp	35.7668	109.749	0.33	0.745	-182	253.533
novtemp	-41.31	50.7909	-0.81	0.418	-142.09	59.4703
dectemp	-93.389	75.2723	-1.24	0.218	-242.75	55.9672
_cons	-3181	2418.71	-1.32	0.191	-7980.2	1618.28