Appendix

Appendix Table of Contents

A Theory Appendix

This section presents the details of the theory that embeds the emergence of a group of professional inventors into a model of endogenous growth. The model builds on elements from Romer (1990), Unified Growth Theory (Galor & Weil, 2000; Galor, 2011) and uses some of the structure of Acemoglu (2002). The goal is to show how the arrival of a group of professional inventors, engineers, can act as a mechanism through which the economy transitions from a slow "pre-modern" growth into more rapid "modern" economic growth regime, as well as to connect my analysis to existing work on the factors that contributed to the onset of the Industrial Revolution.

A.0.1 Demand

The model is written in continuous-time and, for simplicity, time subscripts are suppressed when possible. The population of the economy is fixed at 1. There is a homogeneous final good with a price normalized to P=1. The model admits an infinitely lived representative consumer with CRRA preferences over consumption of the final good:

$$\int_0^\infty \frac{C^{1-\sigma}-1}{1-\sigma} e^{-\rho t} dt \,, \tag{1}$$

where σ is the coefficient of relative risk aversion and ρ is the time preference parameter. The budget constraint is given by, $C + I + F \leq Y$ where Y is total output of final goods, I is the amount of final goods used in the production of machinery, and F is a fixed cost associated with undertaking research.

A.0.2 Production of final goods

Final goods are produced using skilled labor H, unskilled labor L, and machines, in a perfectly competitive market with a constant returns to scale technology. The aggregate production function is,

$$Y = \frac{1}{1-\beta}\left(\int_0^N x(j)^{1-\beta} dj\right)\left[(\iota H)^\alpha + L^\alpha\right]^{\frac{\beta}{\alpha}} \tag{2}$$

where N is the level of technology (number of machine designs available), $x(j)$ is the quantity of machine type j used in production, $\alpha \in (-\infty, 1)$ and $\beta \in (0, 1)$ are production function parameters, and $\iota \in (0, 1)$ is the fraction of high-skilled workers' time left over for productive activities after they undertake the education necessary to become skilled (so $1 - \iota$ reflects the cost, in terms of time, of acquiring skill). Final goods producers solve a standard optimization problem taking as given the wage for low-skilled workers (w_L), wages for high-skilled workers (w_H), and a price $\chi(j)$ for machines of type j. The first order conditions are,

$$w_L = \frac{\beta}{1-\beta} \left(\int_0^N x(j)^{1-\beta} dj \right) [(\iota H)^\alpha + L^\alpha]^{\frac{\beta-\alpha}{\alpha}} L^{\alpha-1} \tag{3}$$

$$w_H = \frac{\beta}{1-\beta} \left(\int_0^N x(j)^{1-\beta} dj \right) [(\iota H)^\alpha + L^\alpha]^{\frac{\beta-\alpha}{\alpha}} \iota^{\alpha-1} H^{\alpha-1} \tag{4}$$

$$x(j) = \chi(j)^{\frac{-1}{\beta}} [(\iota H)^\alpha + L^\alpha]^{\frac{1}{\alpha}} \tag{5}$$

A.0.3 Machine producers

Machine producers hold a perpetual monopoly over their machine design, which they produce using final goods. Machines depreciate fully after use. Setting aside for now the cost of obtaining a machine design, the profits of machine makers are given by $\pi(j) = (\chi(j) - \phi)x(j)$ where ϕ reflects the cost of producing a new machine in terms of output used. Using the first order conditions from the final goods producers' problem together with the first order condition for the machine makers' optimization problem gives $\chi(j) = \frac{\phi}{1-\beta}$. Thus, the machine price is just a constant mark-up over the marginal cost. Using this, we can rewrite the machine makers' profits as,

$$\pi(j) = \beta \left(\frac{1-\beta}{\phi} \right)^{\frac{1-\beta}{\beta}} [(\iota H)^\alpha + L^\alpha]^{\frac{1}{\alpha}} \tag{6}$$

It is useful to note here that profits are independent of the technology level. However, profit does depend on the number of high and low-skilled workers active in producing final goods.

A.0.4 Occupation choice and technology development

Individuals are endowed with one unit of time and must choose discretely to either become a low-skilled worker or to invest in skills and then become either a high-skilled worker or a professional researcher. Skills depreciate completely each period. Let E denote the quantity of professional researchers (engineers), so $L + H + E = 1$. Low skilled workers earn w_L while high-skilled workers earn ιw_H (since they have to devote a fraction $1-\iota$ of their time to becoming skilled). Professional researchers, which also must spend a fraction $1-\iota$ of their time to become skilled, allocate the remainder of their time to producing new inventions.

New technologies arise from two sources. First, new technologies may be developed by professional researchers (engineers). Since these researchers must have skills, the total time available for research is ιE. In addition, they must pay some fixed cost f to undertake research. Each professional researcher then produces a new machine design with a probability ηN. This productivity scales with N, a standard feature of endogenous growth models following Romer (1990). This reflects the idea that professional researchers are more likely to generate a new technology if they have more existing ideas and tools to work with. As (Romer, 1990) explains, "The engineer working today is more productive because he or she can take advantage of all the additional knowledge accumulated as design problems were solved..." The overall number of new technologies generated by the professional research sector within a period is then $\eta N \iota E$.

In addition, new technologies may be developed by high-skilled workers as a serendipitous byproduct of production.[46] This occurs for each high-skilled worker with probability γN. It is useful to note that making the probability of a serendipitous discovery increasing in N is not a vital assumption for the model, but it is useful for helping the model match the patterns observed in the data.[47] Given this

[46] The assumption that only high-skilled workers and not low-skilled workers generate new inventions as a byproduct of production is not critical for the main results of the theory, but it seems more reasonable to confine the development of new technologies to only those with skills.

[47] Specifically, if instead the rate of serendipitous discoveries occurred at rate γ rather than γN, then the growth rate of technologies generated through this channel is declining over time. That does not match the patterns in the patent data, which show that innovations by non-engineers grew at a constant (but low) rate during my study period.

formulation, the number of new technologies generated through this channel is $\gamma N\iota H$.

Motivated by the results presented in my empirical analysis, I make the following key assumption:

Assumption: $\eta > \gamma$, so professional researchers are more productive at generating new technologies than high-skilled workers engaged mainly in goods production.

Technological change in the economy is $\dot{N} = \gamma N\iota H + \eta N\iota E$ and the rate of change is,

$$\frac{\dot{N}}{N} = \gamma\iota H + \eta\iota E \tag{7}$$

The discounted present value of a new machine design depends on the profits of machine makers according to $V = (\pi + \dot{V})/r$, where r is the interest rate and $\dot{V}$ accounts for changes in future profits.[48]

When a professional researcher develops a new technology, their ability to capture the rents from their design depends on the strength of intellectual property protection. The strength of IP protection is represented by the parameter $\lambda \in (0, 1)$ which reflects the probability that an inventor retains ownership over a design. If they retain ownership, then they sell of the design to one out of a large group of potential machine making firms, thus capturing the full discounted present value of the invention. If they do not, I assume that the design is appropriated by the government which sells the design for the full value and then distributes the proceeds to all individuals in the economy through equal lump-sum payments. For simplicity, I assume that when high-skilled workers generate serendipitous inventions they are not able to monetize the value. Instead, the invention is appropriated by the government, auctioned off to a machine firm, and the value is returned to individuals through lump-sum transfers. This is not a critical assumption. It is made only because it simplifies the exposition

[48]It is worth noting that $\dot{V} \leq 0$ in this model. To see this, note that profits depend only on the amount of skilled and unskilled workers employed in final goods production. As shown below, for low levels of N all workers will be used in final goods production, and this amount will fall if at some point some workers begin choosing to become researchers. Thus, profits can only fall over time in the model.

of the model and helps emphasize the fact that growth during the pre-modern period is not dependent on the availability of intellectual property protection.

The expected return to low-skilled workers, high-skilled workers, and researchers, respectively, is,

$$ER_L = w_L = \beta(1-\beta)^{\frac{1-2\beta}{\beta}}\phi^{\frac{\beta-1}{\beta}}\left[(\iota H)^{\alpha}+L^{\alpha}\right]^{\frac{1-\alpha}{\alpha}}L^{\alpha-1}N \tag{8}$$

$$ER_H = \iota w_H = \beta(1-\beta)^{\frac{1-2\beta}{\beta}}\phi^{\frac{\beta-1}{\beta}}\left[(\iota H)^{\alpha}+L^{\alpha}\right]^{\frac{1-\alpha}{\alpha}}\iota^{\alpha}H^{\alpha-1}N \tag{9}$$

$$ER_E = \iota\lambda\eta VN - f = \frac{\iota\lambda\eta\beta}{r}\left(\frac{1-\beta}{\phi}\right)^{\frac{1-\beta}{\beta}}\left[(\iota H)^{\alpha}+L^{\alpha}\right]^{\frac{1}{\alpha}}N + \frac{\iota\lambda\eta\dot{V}}{r}N - f \tag{10}$$

I assume that professional researchers are able to insure each other against the risk of not producing an invention in any particular period, so that in choosing an occupation they care only about the expected returns.

In equilibrium, individuals will choose between being a low-skilled worker, a high-skilled worker, or a researcher, to maximize their expected return. Since both high and low-skilled workers are vital to the production of final goods (since $\alpha < 1$), we know that there will be positive quantities of both of these types of workers. This implies that in equilibrium $ER_H = ER_L$. Using this and Eqs. 8 and 9 we can solve for the equilibrium relationship between L and H. This is $H/L = \iota^{\frac{\alpha}{1-\alpha}}$. This equation tells us that when high and low-skilled workers are substitutes ($\alpha > 0$) the share of high-skilled workers in the economy will increase when the costs of becoming skilled falls (higher ι). Otherwise, if $\alpha < 0$, the share of high-skilled workers will fall as the cost of obtaining skill falls. The relevant case for our setting is likely to be $\alpha > 0$, so that locations where it is easier to acquire skills also have more skilled workers.

One feature in Eq. 10 that is worth noting is that the ι parameter increases the returns to being a professional researcher in two ways. First, there is a direct effect on engineers through easier access to skills. Second, easier access to skills raises the return to being a researcher by increasing the number of skilled workers in the economy able to work with the new technologies that professional researchers discover. This channel, represented by the ιH term, reflects another connection between the theory and the empirical setting, where historical evidence suggests that the availability of skilled craftsman in England who could construct new machines played an important role in incentivizing the development of those technologies.[49]

A.0.5 Development path and key results

Consider the development path of the economy starting from a very low initial technology level. The first useful prediction of the theory is that the professional research sector will be inoperative when the technology level is sufficiently low.

Prop. 1: There exists some $\underline{\mathrm{N}}$ such that for all $N < \underline{\mathrm{N}}$, $ER_E < ER_H = ER_L$ when $E = 0$ and therefore no individuals choose to become professional researchers.

Proof of Prop. 1: This follows directly from the fact that ER_E, ER_H and ER_L are continuous functions of N and that $\lim_{N\to 0} ER_E < 0$ while $\lim_{N\to 0} ER_H = 0$.

The intuition here is simple. Since the productivity of researchers scales with N, at low levels of N they are unproductive, and so it does not pay to become a professional researcher given the fixed costs involved.

Starting from an initially low level of N, Proposition 1 tells us that the economy will initially be one in which there are no professional researchers. This initial "premodern" period is characterized by relatively slow growth, which may be very slow if γ is low, and no professional research sector. This pre-modern period may potentially last for a very long time; under certain conditions the economy may be stuck in premodern growth forever, as explained shortly. In periods characterized by pre-modern growth (where $E = 0$) we have the following equilibrium allocations of high and low skilled workers,

$$\tilde{H} = \frac{1}{1 + \iota^{\frac{-\alpha}{1-\alpha}}} \qquad \tilde{L} = \frac{\iota^{\frac{-\alpha}{1-\alpha}}}{1 + \iota^{\frac{-\alpha}{1-\alpha}}}$$

derived by using the conditions $ER_L = ER_H$ and $H + L = 1$.

[49] See Mokyr (2009), Chapter 6.

It is important to note during pre-modern growth, technological progress is not dependent on the availability of intellectual property protection, so the model can capture historical periods in which new technologies were developed even though inventors received little or no monetary reward from their discoveries.

Next, I show that when the professional research sector is operating, the growth rate increases.

Prop. 2: When $\eta > \gamma$, the growth rate is increasing in E.

> **Proof of Prop. 2:** The growth rate $g = \dot{N}/N = (\gamma\iota H + \eta\iota E)$. Using $H + L + E = 1$ and substituting in $L = H\iota^{\frac{-\alpha}{1-\alpha}}$, we have $H = (1-E)/(1+\iota^{\frac{-\alpha}{1-\alpha}})$. Thus,
>
> $$\frac{\dot{N}}{N} = \frac{\gamma\iota}{1+\iota^{\frac{-\alpha}{1-\alpha}}} + E\left(\eta\iota - \frac{\gamma\iota}{1+\iota^{\frac{-\alpha}{1-\alpha}}}\right)$$
>
> which is increasing in E when $\eta > \gamma$.

The growth rate in the proof above has an intuitive structure. The first term is the rate of growth in the pre-modern period while the second term is the product of the share of researchers in the economy and the difference between the rate that they produce inventions ($\eta\iota$) and the rate of serendipitous discovery by high-skilled workers ($\gamma\iota$) and accounting for the fact that only a fraction of non-researchers end up becoming skilled (reflected in the $1 + \iota^{\frac{-\alpha}{1-\alpha}}$ term).

The next proposition describes the conditions under which the economy will eventually transition into modern growth. It is useful to begin by defining the following key condition:

Condition 1: $(1-\beta)\lambda\eta\iota - (\gamma\iota\sigma)/(1+\iota^{\frac{-\alpha}{1-\alpha}}) > \rho$

Prop. 3: If Condition 1 holds, there exists some $\bar{N}$ such that for any $N > \bar{N}$, $ER_E > ER_H = ER_L$ when $E = 0$ and therefor at least some individuals choose to become researchers. If Condition 1 fails, then there is no N such that $ER_E > ER_H = ER_L$ when $E = 0$ and the professional research sector never emerges.

Proof of Proposition 3: To prove the first statement, by contradiction, suppose that $(1-\beta)\lambda\eta\iota - (\gamma\iota\sigma)/(1+\iota^{\frac{-\alpha}{1-\alpha}}) > \rho$ but that $ER_L > ER_E$ for all N. This implies that $\lim_{N\to+\infty} ER_L - ER_E \ge 0$. Since there is no professional research sector, the economy will be in a balanced growth path characterized by $E = 0$, $H = \frac{1}{1+\iota^{\frac{-\alpha}{1-\alpha}}}$, $L = \frac{\iota^{\frac{-\alpha}{1-\alpha}}}{1+\iota^{\frac{-\alpha}{1-\alpha}}}$, and $\dot{V} = 0$.
Thus,

$$\lim_{N\to+\infty} N\left[\beta(1-\beta)^{\frac{1-2\beta}{\beta}}\phi^{\frac{\beta-1}{\beta}}\left[(\iota H)^{\alpha}+L^{\alpha}\right]^{\frac{1-\alpha}{\alpha}}L^{\alpha-1} - \frac{\iota\lambda\eta\beta}{r}\left(\frac{1-\beta}{\phi}\right)^{\frac{1-\beta}{\beta}}\left[(\iota H)^{\alpha}+L^{\alpha}\right]^{\frac{1}{\alpha}} + \frac{f}{N}\right] \ge 0$$

This is true only if,

$$\beta(1-\beta)^{\frac{1-2\beta}{\beta}}\phi^{\frac{\beta-1}{\beta}}\left[(\iota H)^{\alpha}+L^{\alpha}\right]^{\frac{1-\alpha}{\alpha}}L^{\alpha-1} \ge \frac{\iota\lambda\eta\beta}{r}\left(\frac{1-\beta}{\phi}\right)^{\frac{1-\beta}{\beta}}\left[(\iota H)^{\alpha}+L^{\alpha}\right]^{\frac{1}{\alpha}}$$

Substituting in for L and H and solving gives, $r \ge (1-\beta)\lambda\eta\iota$.
We now need to substitute in for r using the intertemporal optimization condition. Since the professional research sector does not operate in this scenario, the stead state growth rate is is $\dot{N}/N = \gamma\iota H = \gamma\iota/(1+\iota^{\frac{-\alpha}{1-\alpha}})$. The intertemporal optimization condition implies that $(r-\rho)/\sigma = \gamma\iota/(1+\iota^{\frac{-\alpha}{1-\alpha}})$. Solving for r and substituting in we have,

$$\rho \ge (1-\beta)\lambda\eta\iota - \frac{\gamma\iota\sigma}{(1+\iota^{\frac{-\alpha}{1-\alpha}})}$$

But this contradicts the initial assumption.
To prove the second statement, given Proposition 1, it is sufficient to show that $(1-\beta)\lambda\eta\iota - (\gamma\iota\sigma)/(1+\iota^{\frac{-\alpha}{1-\alpha}}) < \rho$ implies $d(ER_E - ER_L)/dN < 0$ for any N.

$$\frac{d(ER_E-ER_L)}{dN} = \frac{\iota\lambda\eta\beta}{r}\left(\frac{1-\beta}{\phi}\right)^{\frac{1-\beta}{\beta}}\left[(\iota H)^{\alpha}+L^{\alpha}\right]^{\frac{1}{\alpha}} + \frac{\iota\lambda\eta\dot{V}}{r} - \beta(1-\beta)^{\frac{1-2\beta}{\beta}}\phi^{\frac{\beta-1}{\beta}}\left[(\iota H)^{\alpha}+L^{\alpha}\right]^{\frac{1-\alpha}{\alpha}}L^{\alpha-1}$$

Since $\dot{V} \le 0$, for $d(ER_E - ER_L)/dN < 0$ it is sufficient that,

$$\frac{\iota\lambda\eta\beta}{r}\left(\frac{1-\beta}{\phi}\right)^{\frac{1-\beta}{\beta}}\left[(\iota H)^{\alpha}+L^{\alpha}\right]^{\frac{1}{\alpha}} - \beta(1-\beta)^{\frac{1-2\beta}{\beta}}\phi^{\frac{\beta-1}{\beta}}\left[(\iota H)^{\alpha}+L^{\alpha}\right]^{\frac{1-\alpha}{\alpha}}L^{\alpha-1} < 0$$

Reorganizing and substituting in for L and H, we have,

$$(1-\beta)\iota\lambda\eta < r$$

Thus, whenever this condition holds, $d(ER_E - ER_L)/dN < 0$. It remains to show that this must hold under the initial assumption of $(1-\beta)\lambda\eta\iota-(\gamma\iota\sigma)/(1+\iota^{\frac{-\alpha}{1-\alpha}}) < \rho$. This can be reorganized to obtain $(1-\beta)\lambda\eta\iota < \rho + (\gamma\iota\sigma)/(1+\iota^{\frac{-\alpha}{1-\alpha}})$. Thus, a sufficient condition for $(1-\beta)\iota\lambda\eta < r$ is $\rho + (\gamma\iota\sigma)/(1+\iota^{\frac{-\alpha}{1-\alpha}}) \leq r$. This can be reorganized to,

$$\frac{\gamma\iota}{(1+\iota^{\frac{-\alpha}{1-\alpha}})} \leq \frac{r-\rho}{\sigma}$$

To see that this must be true note that the intertemporal optimization condition requires that $(r-\rho)/\sigma = g$ where g is the growth rate of the economy, and that $g \geq \gamma\iota/(1+\iota^{\frac{-\alpha}{1-\alpha}})$ (see Proposition 3). Thus, if $(1-\beta)\lambda\eta\iota - (\gamma\iota\sigma)/(1+\iota^{\frac{-\alpha}{1-\alpha}}) < \rho$ it can never be the case that $ER_E > ER_L$ with $E = 0$ and so the professional research sector can never begin operating.

The intuition here is that, under Condition 1, the return to professional researchers increases more rapidly with N than returns in the production sector (when $E = 0$). As a result, eventually the return to becoming a researcher exceeds the wage of production workers and some individuals have an incentive to become professional researchers.[50]

Proposition 2 is a central result of the theory. It tells us that the professional research sector emerges only under certain conditions. In particular, the emergence of the professional research sector depends crucially on the availability of institutions that allow inventors to monetize their inventions, reflected in the λ parameter.

[50]This begs the question of why the return to the research sector does not continue to rise faster than wages in the production sector after the research sector begins to operate. The reason that this does not happen is that as fewer individuals choose to become workers, the profits of the machine making firms fall (see Eq. 6) pulling down the value of new inventions and thus the returns to becoming a professional researcher.

Whether a professional research sector emerges also depends on the ease with individuals can acquire skills, reflected in the ι parameter (note that the left-hand side of Condition 1 is increasing in ι). Only when these conditions are satisfied will a professional research sector eventually emerge, allowing growth to accelerate. Thus, Proposition 2 connects the model to the features of the historical setting, specifically the availability of useful knowledge, a culture of learning, access to training in craft skills (such as through apprenticeships), and institutions that allowed inventors to monetize inventions.

Once modern economic growth begins, the economy approaches a new long-run balanced growth path. On the equilibrium balanced growth path, $ER_L = ER_H = ER_E$, $\dot{V} = 0$, and as $N \to +\infty$ the economy approaches fixed shares of researchers, skilled, and unskilled workers (described in Appendix A.0.6).[51] The long-run ratio of researchers to production workers in the economy is,

$$\theta = \frac{E}{H+L} = (1-\beta)\lambda\eta\iota - \frac{\gamma\sigma\iota^{\frac{1}{1-\alpha}}}{1+\iota^{\frac{\alpha}{1-\alpha}}} - \rho \tag{11}$$

This share is increasing in the productivity of researchers η, as we would expect, as well as the importance of machines in the production function $(1-\beta)$ and the strength of IP protection represented by λ. The share is decreasing in the rate at which high-skilled manufacturing workers generate new technologies (γ), decreasing in the time discount factor ρ, and decreasing in the coefficient of relative risk aversion σ. This is intuitive given that the value of research is mainly realized in the future.

As indicated by Prop. 2, the long-run growth rate in the modern economy with an active professional research sector is faster than the rate experienced in the pre-modern period. Thus, the emergence of professional researchers has pushed the economy onto a more rapid growth path. How much growth increases depends on the difference between η and γ.

Finally, it is useful to show that the model provides additional predictions that are consistent with the historical record:

Prop. 4: When Condition 1 holds, the economy converges to a long-run balanced

[51] Note that the no-Ponzi game condition requires that $(1-\sigma)g < \rho$, which restricts the admissible set of parameter values.

growth path in which the share of skilled workers in the economy is higher than the share during the pre-modern growth period.

Proof of Proposition 4: To prove this proposition it is sufficient to show that, under Condition 1, $\tilde{L} > L*$, where $\tilde{L} = 1/(1 + \iota^{\frac{\alpha}{1-\alpha}}$ is the amount of low-skilled workers in the pre-modern period and L^* is given by Eq. 12. It will be the case that $\tilde{L} > L*$ when,

$$\frac{1}{1 + \iota^{\frac{\alpha}{1-\alpha}}} > \frac{\eta\sigma\iota + \rho}{(1-\beta)\lambda\eta\iota(1 + \iota^{\frac{\alpha}{1-\alpha}}) - \gamma\sigma\iota^{\frac{1}{1-\alpha}} + \eta\sigma\iota(1 + \iota^{\frac{\alpha}{1-\alpha}})}$$

$$(1-\beta)\lambda\eta\iota(1+\iota^{\frac{\alpha}{1-\alpha}}) - \gamma\sigma\iota^{\frac{1}{1-\alpha}} + \eta\sigma\iota(1+\iota^{\frac{\alpha}{1-\alpha}}) > \eta\sigma\iota(1+\iota^{\frac{\alpha}{1-\alpha}}) + \rho(1+\iota^{\frac{\alpha}{1-\alpha}})$$

$$(1-\beta)\lambda\eta\iota(1 + \iota^{\frac{\alpha}{1-\alpha}}) - \gamma\sigma\iota^{\frac{1}{1-\alpha}} > \rho(1 + \iota^{\frac{\alpha}{1-\alpha}})$$

$$(1-\beta)\lambda\eta\iota - \frac{\gamma\sigma\iota^{\frac{1}{1-\alpha}}}{(1 + \iota^{\frac{\alpha}{1-\alpha}})} > \rho$$

$$(1-\beta)\lambda\eta\iota - \frac{\gamma\sigma\iota}{(1 + \iota^{\frac{-\alpha}{1-\alpha}})} > \rho$$

This is exactly Condition 1.

Thus, the onset of modern economic growth is characterized not just by an accelerated rate of technological progress but also by an increase in the share of skilled individuals in the economy.[52]

A.0.6 Long-run balanced growth path

Once modern economic growth begins (if it does), the economy begins to approach a new long-run stead state characterized a fixed proportion of high-skilled workers,

[52]It is worth noting that this increase is driven by the demand for skilled workers in the professional research sector. The ratio of skilled to unskilled production workers is unchanged.

low-skilled workers, and professional researchers. In equilibrium, $ER_L = ER_E$, so,

$$\beta(1-\beta)^{\frac{1-2\beta}{\beta}}\phi^{\frac{\beta-1}{\beta}}\left[(\iota H)^{\alpha}+L^{\alpha}\right]^{\frac{1-\alpha}{\alpha}}L^{\alpha-1}N=\frac{\iota\lambda\eta\beta}{r}\left(\frac{1-\beta}{\phi}\right)^{\frac{1-\beta}{\beta}}\left[(\iota H)^{\alpha}+L^{\alpha}\right]^{\frac{1}{\alpha}}N+\frac{\iota\lambda\eta\dot{V}}{r}N-f$$

On the balanced growth path, $\dot{V}=0$ and so as $N\to+\infty$ the economy approaches,

$$\beta(1-\beta)^{\frac{1-2\beta}{\beta}}\phi^{\frac{\beta-1}{\beta}}\left[(\iota H)^{\alpha}+L^{\alpha}\right]^{\frac{1-\alpha}{\alpha}}L^{\alpha-1}=\frac{\iota\lambda\eta\beta}{r}\left(\frac{1-\beta}{\phi}\right)^{\frac{1-\beta}{\beta}}\left[(\iota H)^{\alpha}+L^{\alpha}\right]^{\frac{1}{\alpha}}$$

This together with $H=\iota^{\frac{\alpha}{1-\alpha}}L$ can be used to show,

$$L=\frac{r\iota^{-1}}{(1-\beta)\lambda\eta(1+\iota^{\frac{\alpha}{1-\alpha}})}$$

$$H=\frac{r\iota^{\frac{\alpha}{1-\alpha}-1}}{(1-\beta)\lambda\eta(1+\iota^{\frac{\alpha}{1-\alpha}})}$$

$$E=1-\frac{r\iota^{-1}}{(1-\beta)\lambda\eta}$$

The standard intertemporal optimization condition implies that $(r-\rho)/\sigma=g=\gamma\iota H+\eta\iota E$. Substituting for H and E and solving for r, we have,

$$r=\frac{(1-\beta)\lambda\eta(1+\iota^{\frac{\alpha}{1-\alpha}})(\eta\iota\sigma+\rho)}{(1-\beta)\lambda\eta(1+\iota^{\frac{\alpha}{1-\alpha}})-\gamma\iota^{\frac{\alpha}{1-\alpha}}\sigma+\eta\sigma(1+\iota^{\frac{\alpha}{1-\alpha}})}$$

Substituting this back in, we have,

$$L^{*}=\frac{\eta\iota\sigma+\rho}{(1-\beta)\lambda\eta\iota(1-\iota^{\frac{\alpha}{1-\alpha}})-\gamma\sigma\iota^{\frac{1}{1-\alpha}}+\eta\sigma\iota(1+\iota^{\frac{\alpha}{1-\alpha}})}\tag{12}$$

$$H^{*}=\frac{\iota^{\frac{\alpha}{1-\alpha}}(\eta\iota\sigma+\rho)}{(1-\beta)\lambda\eta\iota(1-\iota^{\frac{\alpha}{1-\alpha}})-\gamma\sigma\iota^{\frac{1}{1-\alpha}}+\eta\sigma\iota(1+\iota^{\frac{\alpha}{1-\alpha}})}\tag{13}$$

$$E^* = \frac{(1-\beta)\lambda\eta\iota(1+\iota^{\frac{\alpha}{1-\alpha}}) - \gamma\sigma\iota^{\frac{1}{1-\alpha}} - \rho(1+\iota^{\frac{\alpha}{1-\alpha}})}{(1-\beta)\lambda\eta\iota(1+\iota^{\frac{\alpha}{1-\alpha}}) - \gamma\sigma\iota^{\frac{1}{1-\alpha}} + \eta\sigma\iota(1+\iota^{\frac{\alpha}{1-\alpha}})} \tag{14}$$

The growth rate is,

$$g = \frac{\gamma\iota}{1+\iota^{\frac{-\alpha}{1-\alpha}}} + E\left(\eta\iota - \frac{\gamma\iota}{1+\iota^{\frac{-\alpha}{1-\alpha}}}\right)$$

Here, the first term is the growth rate of the economy when there are no professional researchers, and the second term is the share of professional researchers in the economy multiplied by the difference between the rate at which professional researchers produce innovations and the rate at which high-skilled workers produce innovations, scaled by $1+\iota^{\frac{-\alpha}{1-\alpha}}$ to reflect the fact that if the share of professional researchers falls there is a less-then-proportional increase in the share of high-skilled workers in the economy.

B Evidence from Google Ngrams

Figure 4 describes the usage of the term "engineer" in books contained in the Google Books repository, as reported by Google Ngrams (`https://books.google.com/ngrams`), from 1700-1850.

Figure 4: Google Ngram for "engineer"

Data from Google Ngrams, June 18, 2020.

C Verb stem analysis appendix

This appendix describes in more detail a text analysis exercise that aims to identify the functional activities that characterized the early engineering profession. The starting point for this analysis is biographical data from the ODNB, a rich data source that has been used in numerous previous studies.[53] These biographies cover only a select sample of the most successful or notable individuals, so an analysis of this data will not be representative of all engineers. However, it will reflect the activities of upper-tail engineers, the group most likely to invent valuable new technologies and therefore the primary interest in this paper.

I begin by collecting the text of the biographies of all those classified by the ODNB as engineers born before 1850 (439 in total), as well as two natural comparison groups: manufacturers (349 biographies) and those non-engineers classified as involved in science or technology (1547 biographies).[54] Using natural language processing methods, I parse the biographies and identify all verb stems. These verb stems reflect the types of activities that individuals undertook during their lifetime. This procedure identifies 924 verb stems. I focus on the 338 verbs that appear in at least 100 out of the 2335 biographies used in the analysis. To provide a point of comparison, I identify a set of 'neutral' verbs (e.g., is, do, died, sat, etc.) that are unlikely to reflect activities associated with a particular occupation. I then run the following regression specification:

$$VERB_{vi} = \sum_{v \in \tilde{V}} (\gamma_v \, ENG_i \, \theta_v) + \phi_i + \eta_v + \epsilon_{vi}$$

where $VERB_{vi}$ is an indicator for whether verb stem v shows up the biography of individual i, ϕ_i is a set of individual biography fixed effects, which accounts for

[53] Previous studies using these data include Allen (2009a), Meisenzahl & Mokyr (2012), Nuvolari & Tartari (2011), and Khan (2018).

[54] Within the ODNB, these are the two natural comparison groups. Most engineers were classified as part of those involved in science and technology, so it is natural to compare to that group. Manufacturers were the other major group of inventors during the study period, as the patent data will show. I exclude military engineers from the engineers group. I also include iron masters as manufacturers. Of those individuals classified as working in science or technology, I do not include manufacturers, artists/engravers, alchemists, or fossil collectors.

variation in the length of individual biographies, and η_v is a set of verb fixed effects, to account for variation in the baseline frequency with which each verb is used. The explanatory variables of interest in this regression are constructed by interacting an indicator for whether an individual is an engineer (ENG_i), with θ_v, an indicator variable for each verb in the set of verbs $\tilde{V}$ that excludes neutral verbs. The estimated coefficient for each verb in this set, γ_v, reflects the extent to which that verb is particularly common in engineer biographies. Since I am looking at many outcomes, I adjust for multiple hypothesis testing by calculating sharpened p-values, following Benjamini *et al.* (2006) and Anderson (2008).

Table 10 presents the full listing of verbs strongly associated with engineers (sharpened p-values below 0.05), when comparing to both manufacturers and non-engineers involved in science and technology. The presence of verbs such as "design", "invent" and "patent" indicate the important role of inventive activities to the engineering profession. Out of all the verbs, the one most closely associated with engineers is "design". There are also terms indicating the role that engineers played in implementing their new designs and inventions, words such as "build," "erect," "employ," "lay," and "supervise." Other important roles played by engineers are indicated by the presence of "consult," "report," and "survey." These terms give us a sense of the types of activities that set engineers apart from others.

The words least associated with engineers can also be informative. When compared to manufacturers, the five verbs most associated with that group, relative to engineers, are "sell," "expand," "produce," "manufacture," and "buy." For non-engineers involved in science and technology, the verbs most associated with that group, relative to engineers, are "publish," "graduate," "write," "study," and "collect." The contrast between these terms and the words in Table 1 highlights the defining differences, in terms of activities, between these various groups.

Table 11 presents the top-20 verbs related to engineers from four alternative estimation approaches. The results in the first two columns correspond to my preferred approach. That approach uses an indicator for whether a verb appears in a biography as the outcome variable and compares to biographies from both manufacturers and non-engineers involved in science and technology. The next two columns compare only to manufacturers, followed by two columns comparing only to those involved

Table 10: Verb stems associated with engineers with sharpened p-values below 0.05

Verb stem	**T-stat**	**Sharpened p-value**	**Verb stem**	**T-stat**	**Sharpened p-value**
design	14.61	0.001	install	3.91	0.001
build	11.53	0.001	replace	3.88	0.001
construct	9.58	0.001	advocate	3.60	0.002
consult	8.16	0.001	operate	3.42	0.003
patent	6.74	0.001	engage	3.37	0.003
employ	6.23	0.001	apprentice	3.36	0.003
report	6.10	0.001	knight	3.28	0.003
erect	5.59	0.001	develop	3.11	0.005
survey	5.27	0.001	act	3.07	0.006
drive	5.15	0.001	train	3.01	0.006
complete	5.10	0.001	manufacture	2.98	0.007
open	5.01	0.001	assist	2.90	0.008
supervise	4.87	0.001	adopt	2.85	0.009
improve	4.83	0.001	join	2.75	0.011
lay	4.56	0.001	devise	2.74	0.012
advise	4.40	0.001	commission	2.72	0.012
supply	4.36	0.001	run	2.69	0.013
connect	4.24	0.001	test	2.66	0.014
propose	4.11	0.001	promote	2.48	0.02
invent	4.01	0.001	introduce	2.26	0.032

Estimated coefficients and t-statistics based on robust standard errors. Sharpened p-values are calculated using the approach from Anderson (2008). Regressions include verb and individual fixed effects. N=789,230 (2335 biographies x 338 verbs).

in science and technology. While these two sets of results are similar, we can see some interesting contrasts. For example, relative to manufacturers, engineers were more likely to be engaged in activities such as publishing and writing. This is not true when comparing engineers to non-engineers involved in science and technology. Similarly, engineers were more likely to be involved in activities such as manufacturing or supervising when compared to non-engineers involved in science or technology, but not when compared to engineers. However, when comparing to either group we consistently see that engineers are closely associated with activities such as designing, consulting, constructing, and surveying ("invent" and "patent' also have p-values below 0.05 when compared to either group, though they fall outside of the top 20 terms in some cases). The last two columns present results where the count of verbs in a biography is used in place of an indicator for whether a verb appears. This alternative approach also delivers very similar results.

Table 11: Verb stem results using alternative comparison groups or outcome variables

Baseline		Compare to manufacturers only		Compare to sci/tech only		Using verb counts as outcome	
Verb stem	**Sharpened p-value**	**Verb stem**	**Sharpened p-value**	**Verb stem**	**Sharpened p-value**	**Verb stem**	**Sharpened p-value**
design	0.001	design	0.001	design	0.001	design	0.001
build	0.001	construct	0.001	build	0.001	build	0.001
construct	0.001	consult	0.001	construct	0.001	construct	0.001
consult	0.001	complete	0.001	employ	0.001	consult	0.001
patent	0.001	publish	0.001	consult	0.001	employ	0.001
employ	0.001	survey	0.001	patent	0.001	patent	0.001
report	0.001	report	0.001	open	0.001	report	0.001
erect	0.001	propose	0.001	erect	0.001	erect	0.001
survey	0.001	award	0.001	manufacture	0.001	improve	0.001
drive	0.001	advise	0.001	report	0.001	complete	0.001
complete	0.001	assist	0.001	supply	0.001	drive	0.001
open	0.001	connect	0.001	drive	0.001	supervise	0.001
supervise	0.001	test	0.001	improve	0.001	open	0.001
improve	0.001	consider	0.001	supervise	0.001	lay	0.001
lay	0.001	engage	0.001	survey	0.001	propose	0.001
advise	0.001	undertake	0.001	install	0.001	survey	0.001
supply	0.001	act	0.001	lay	0.001	connect	0.001
connect	0.001	prepare	0.001	operate	0.001	supply	0.001
propose	0.001	supervise	0.001	replace	0.001	advise	0.001
invent	0.001	lay	0.001	complete	0.001	act	0.001

Estimated coefficients and t-statistics based on robust standard errors. Sharpened p-values are calculated using the approach from Anderson (2008). Regressions include verb and individual fixed effects. In the first and last set of results, N=789,230. When comparing only to manufacturers, N=266,344. When comparing only to non-engineers working in science or technology, N=671,268.

Table 12 presents the top ten verbs associated with engineers based on the matched patent-ODNB data set. In these results, engineers are identified using the occupations reported in the patent data (based one each inventor's modal occupation) and the comparison group is made up of those individuals in the matched data set with a unique modal occupation other than engineering. Note that this data set includes a much smaller set of biographies, so the results are not as strong as those shown above.

Despite that, a number of the terms shown in Table 12, most notably "design," are also found in the tables above.

Table 12: Verb stems associated with engineers based on matched patent-ODNB data

Verb stem	**p-value**	**Sharpened p-value**	**Verb stem**	**p-value**	**Sharpened p-value**
design	0.0001	0.014	cast	0.0065	0.242
erect	0.0003	0.025	develop	0.0083	0.242
drive	0.0004	0.025	manufacture	0.0083	0.242
construct	0.0043	0.242	install	0.0136	0.315
achieve	0.0057	0.242	apprentice	0.0139	0.315

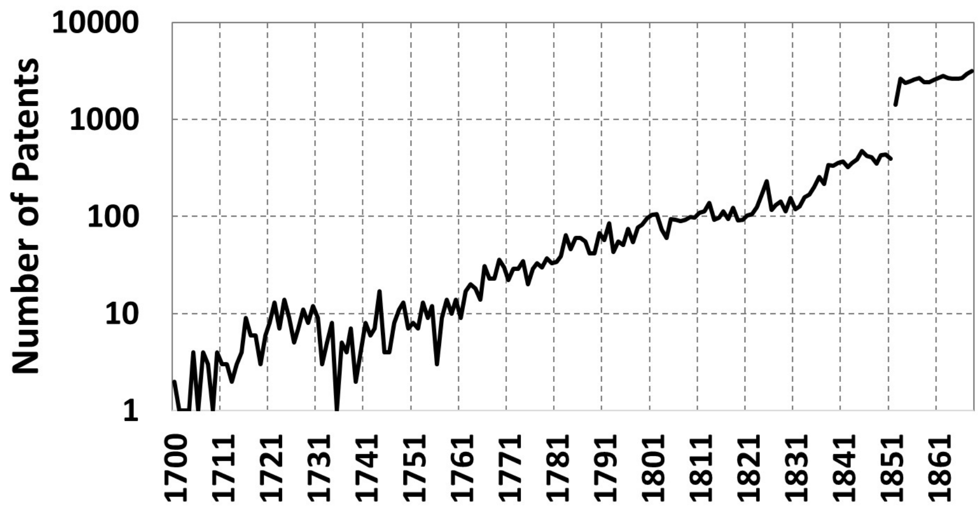
Estimated coefficients and t-statistics based on robust standard errors. Sharpened p-values are calculated using the approach from Anderson (2008). Regressions include verb and individual fixed effects. N=41,940 (180 biographies with unique modal occupations x 233 verbs).

D British patent data appendix

D.1 Number of patents over time

Figure 5 describes how the number of patents increased across the study period. The graph uses a log scale and excludes patents received as a communication from a person abroad.

Figure 5: Number of patents by year, 1700-1849 (log scale)



D.2 Patent linking appendix

This section discusses the procedures used to link up patent entries associated with the same unique inventor. At the outset it is important to recognize that this linking problem is different in a number of important ways than the more well-known problem of linking individuals across various censuses (see Abramitzky *et al.* (Forthcoming) and Bailey *et al.* (Forthcoming) for discussions of census linking). The most important differences are:

1. Unlike standard census to census linking, the linking undertaken in this paper aims to match up all patents associated with a single individual. This means that rather than searching for unique one-to-one matches, some patents may correctly link to numerous other patents, while many others may correctly not link to any others. One consequence of this is that standard statistics such as link rate are less meaningful in my context.

2. A second important difference relative to the standard census matching problem is that, because patenting is a rare activity typically undertaken by a relatively elite group, I am working with a much smaller universe of observations that need to be linked. Working with a much smaller sample makes linking easier, since it means that it is much less likely that an observation for one individual will have observations for multiple other individuals that are plausible matches. Working with a small universe (not sample) of observations also means that a manual linking approach, similar to the one pioneered by Ferrie (1996), can be used.

3. A third important difference has to do with the quality of the underlying data in my sample. Unlike an historical census, which is collected by thousands of enumerators talking with individuals who themselves may not be literate, and may not even speak the same language well, the patent data that I study was provided and collected by a relatively elite group of individuals. Literacy was almost certainly universal within this group. Moreover, patent filers had strong incentives to ensure that their information was registered correctly, since incorrect filings could potentially raise subsequent legal issues. These differences

mean that the underlying data is likely to have substantially fewer errors than raw census microdata. As one indicator of this, I do not find any nicknames, such as "Bill" or "Bob", in the data. This does not eliminate all name errors, since there are transcription errors, but it means that one important source of error in standard census linking is unlikely to be substantial in my setting.

4. A fourth difference relative to standard linking problems is that I am working with a different, and in many ways richer, set of information to link on. The examples provided below illustrate the type of data that goes into my links. One implication of this rich set of linking data is that we can typically have a high level of confidence in individual links. A second consequences is that implementing automated linking methods in this setting is likely to be more challenging, another reason to prefer a manual linking procedure.

Given these features, I have chosen to use a manual linking procedure. This procedure involves the following steps:

1. First, I manually reviewed the names and cleaned up obvious transcription errors.

2. Next, I use automated methods to parse names into separate first name and surname fields. This is relatively straightforward except that it requires the removal of suffixes such as "Jr." or "the younger".

3. Next, in an Excel file, I sort the data based on (i) first name and (ii) surname and then work down the list of patents to identify potential matches. In the majority of cases, similar names will be located near one another, unless there has been a transcription error in one of the first few letters of the first name. For each potential match, I review available information including the full name, occupation, location, patent description, and co-inventors (see examples below) in order to identify matches.

4. After fully working through the data once, I then re-sort the data based on (i) surname and then (ii) first name and repeat the procedure. Under this sorting approach, entries for the same individual should be very close to one another

unless there has been a serious transcription error in the first few letters of the surname or in the procedure use to parse out surnames.

The best way to get a sense of the information that goes into forming a match is to review some examples. A somewhat arbitrary place to start is to look at the first few entries in the dataset when sorting by first name. These are presented in Table 13. One thing that can be seen in this table is that, because the universe of entries is small, there are quite a few obviously unique names. There are also a number of obvious potential matches, such as those associated with Abraham Buzaglo and Abraham Henry Chambers. One transcription error can be seen in the data, in the last line, but when sorting by either fist name or surname that entry will still end up near the other patents by the same individual. It is not hard to imagine working down this list and identifying likely matches. Or course, there are other names that are much more common, so it is not always this easy.

Before coming to some more challenging examples, it is useful to get a sense of the information that goes into making a match. Table 14 presents the first few sets of matched patents in the data (sorting by first names) where I have filled in the inventor's location and the patent description from the original sources. We can see that quite a lot of information is available to make matches. Often, one type of information, such as occupation or location, may vary across entries. We can see this in the case of Abraham Buzaglo, though it is worth noting that an experienced reviewer may note that St. Mary-le-Strand and Strand are essentially equivalent and that both are in close proximity to the City of London. The information on type of invention can be quite useful. Even though the first two entries differ in the listed occupation and location, a comparison of the inventions would strongly suggest a match, even if the name wasn't as unique as Abraham Buzaglo. The last two entries, where one had a transcription error in the name, illustrate that exact name matches are not required to identify a link. These entries also highlight how useful coauthor information can be in confirming a link, though even without that, the almost identical patent descriptions would be enough to identify a link.

The entries in Table 14 are representative of the vast majority of matches, which are straightforward. However, it is also useful to consider some more challenging

Table 13: First 25 entries in the patent data when sorting by first name

Patent No.	Pat. Year	Name (as originally entered)	Occupation
7292	1837	Aaron Fearn	Dyer
2166	1797	Aaron Garlick	Manufacturer
393	1713	Aaron Hill	Esquire
5137	1825	Aaron Jennens	Manufacturer and japanners
4558	1821	Aaron Manby	Iron master
9141	1841	Aaron Ryles	Agent
7923	1839	Abel Morrall	
10553	1845	Abel Siccama	Bachelor of arts
2569	1802	Abner Cowell Lea	Manufacturer
6196	1831	Abraham Adolf Moser	Engineer
8744	1840	Abraham Alexander Lindo	Gentleman
2242	1798	Abraham Bosquet	Esquire
7843	1838	Abraham Bury	Esquire
826	1765	Abraham Buzaglo	Gentleman
928	1769	Abraham Buzaglo	Warming machine maker
1211	1779	Abraham Buzaglo	Warming machine maker
7882	1838	Abraham Collen	Esquire
380	1707	Abraham Darby	Smith
5369	1826	Abraham Dixon	Manufacturer
845	1766	Abraham Foster	Peruke maker
5962	1830	Abraham Garnett	Esq.
4441	1820	Abraham Henry Chambers	Esquire
4527	1821	Abraham Henry Chambers	Esquire
4906	1824	Abraham Henry Chambers	Esquire
5114	1825	Abraliam Henry Chambers	Esquire

examples, which highlight the advantages of a manual linking procedure. The first example is for patentees named Henry Smith, a fairly common name. The first two columns include the patent number and patent title for each patent with an inventor with this name. The third column presents the unique individual ID generated by my name matching process. The first two Henry Smiths (nos. 3804 and 3805) are unique. The third Henry Smith (no. 3806) is matched to three different patents. For this inventor, the match between patents 9291 and 10808 is fairly straightforward, but the match to patent 12266 is more difficult. In that case, the inventor has moved to a different town and the entry is missing an occupation. However, the very specific nature of the invention, railway wheels, makes it extremely unlikely that these are

Table 14: First few matches in the data when sorting by first name

Pat. No.	Pat. Year	Name (pre-cleaning)	Occupation	Location	Invention	Coinventors
826	1765	Abraham Buzaglo	Gentleman	City of London	Machine for warming rooms of all sizes with a coal fire	
928	1769	Abraham Buzaglo	Warming machine maker	Catherine St., St. Mary-le-Strand	New invented warming machine	
1211	1779	Abraham Buzaglo	Warming machine maker	Strand, Westminster, Middlesex	New invented muscular strength and health restoring exercise	
4441	1820	Abraham Henry Chambers	Esquire	Bond St., Middlesex	Improvement in the preparing or manufacturing of substances for the formation of highways and other roads	
4527	1821	Abraham Henry Chambers	Esquire	Bond St., Middlesex	Improvements in the manufacture of building cement, composition, stucco...	
4906	1824	Abraham Henry Chambers	Esquire	New Bond St., Middlesex	Improvements in preparing and paving horse carriage ways	
5114	1825	Abraliam Henry Chambers	Esquire	Stratford Pl., St. Mary-le-Bone	New filtering apparatus	Ennis Chambers, Charles Jearrard
1843	1791	Abraham Hill	Saw maker	Whiteley Wood, Sheffield	New method of making scythes with steel blades	
1972	1793	Abraham Hill	Saw maker	Whitley Wood, Sheffield	New invented method of making with iron backs steel knives for cutting hay and straw	
11737	1847	Abraham Solomons	Merchant	City of London	Certain improvements in the manufacture of charcoal and other fuel	Bondy Azulay
12165	1848	Abraham Solomons	Merchant	City of London	Improvements in the manufacture of gas, tar, charcoal and certain acids	Bondy Azulay
10547	1845	Adam Og Den	Gentleman	Hey Chapel, Ashton-under-Lyne	Certain improvements in machinery for preparing and cleaning wool, cotton and similar fibrous substances	John Sykes
11798	1847	Adam Ogden	Wool cleaner and machine maker	Huddersfield, York	Improvements in machinery for cleaning wool, cotton, and similar fibrous substances	John Sykes

coming from a different inventor. Thus, patent no. 12266 is matched to the Henry Smith with individual ID 3806. The fourth entry, individual ID 3807, could potentially be a match for the patent with individual ID 3805 because the name and location are the same and the timing is proximate. However, Birmingham is a large city and there is no similarity in the subject matter of the invention. Therefore, these two entries are not matched. Finally, the Henry Smith with individual ID 3808 is matched to two patents. Both are straightforward given the occupation and location. These are more representative of the types of matches that are common in the database.

Table 15: Names matching for "Henry Smith"

Pat No.	Pat year	Indiv. ID	Name	Occupation	Address	Patent title
2658	1802	3804	Henry Smith	Lieutenant, H.M. Navy		New improved vessel or barrel for the more safe and expeditious carriage and conveyance of gunpowder
8446	1840	3805	Henry Smith	Lamp manufacturer	Birmingham	Improvements in gas burners and in lamps
9291	1842	3806	Henry Smith	Engineer	Liverpool	Improvements in the construction of wheels and breaks for carriages
9838	1843	3807	Henry Smith		Birmingham	Improvements in apparatus for fastening doors and in apparatus for giving action to alarms
10241	1844	3808	Henry Smith	Agricultural implement maker	Stamford, Lincolnshire	Certain improvements in the construction and arrangement of hand rakes and horse rakes, and in machinery for cutting vegitable substances
10808	1845	3806	Henry Smith	Engineer	Liverpool	Improvements in the manufacture of wheels for railways, and in springs for railway and other carriages, and in axle guards for railway carriages
11638	1847	3808	Henry Smith	Agricultural implement maker	Stamford, Lincolnshire	Certain improvements in machinery for cutting and separating vegetable substances
12266	1848	3806	Henry Smith		Vulcan Works, West Bromwich	Improvements in the manufacture of railway wheels

The second example is for a subset of individuals named John Browne. Here, the first two entries are an obvious match. The next two individuals are also a clear match given the address and occupation. The fifth John Browne, from Brighton, also appears to be unique. The remaining five patents are all matched to one individual, no. 5485. There is some question about whether these should be matched given that there is an address change and there does not appear to be a commonality in the subject matter of the inventions. However, patent 12452 makes it clear that the patent listing an address on New Bond Street belong to the same individual who later lived on Great Portland St. The difficult patent is then 12326, which has a different address but the same occupation as patent no. 12452. However, it is clear that the individual moved during this period and a search of Google maps reveals that Osnaburgh St. is in very close proximity to both New Bond St. and Great Portland St. in London. Together, this information is enough to conclude that all five patents likely came from the same individual.

Table 16: Names matching for "John Browne"

Pat No.	Pat year	Indiv. ID	Name	Occupation	Address	Patent title
5496	1827	5480	John Browne	Merchant and copartner	Bridgewater, Somerset	A certain composition or substance which may be manufactured or moulded either into bricks or into blocks of any form...
6742	1834	5480	John Browne	Merchant	Bridgewater, Somerset	An improved instrument or apparatus for ascertaining levels
7863	1838	5482	John Browne	Esquire	Castle St., Middlesex	Improvements in paving roads and streets
8050	1839	5482	John Browne	Esquire	Castle St., Middlesex	Improvements in saddles and stirrups for horses and other animals
9349	1842	5484	John Browne	Gentleman	Brighton	Improvements in the manufacture of mud boots and overalls
10104	1844	5485	John Browne	Esquire	New Bond St., Middlesex	Improvements in urinary utensils
10180	1844	5485	John Browne	Esquire	New Bond St., Middlesex	Improvements in apparatus for protecting the human face, or part of the human face, from the inclemency of the weather
12326	1848	5485	John Browne	Gentleman	Osnaburgh St., Middlesex	Improvements in fire escapes, and in apparatus to facilitate persons employed in cleaning windows
12452	1849	5485	John Browne	Gentleman	Formerly of Bond St., now of Great Portland St.	Improvements in constructing and rigging vessels, and improvements in atmospheric and other railways
12686	1849	5485	John Browne	Esquire	Great Portland St., Middlesex	Improvements in apparatus to assist combustion in stoves or grates

To summarize, it is hoped that these examples provide a useful illustration of the linking procedure used in this paper. It should be clear that the combination of a relatively small universe of observations, together with a rich set of data to match on, lend themselves to a manual matching procedure, and that such a procedure can generate matches where, in the substantial majority of cases, there is little doubt about the accuracy of the resulting link.

D.3 List of top patent holders

Table 17 lists those patent holders with 10 or more patents during the 1700-1849 period, excluding communicated patents. This list includes a number of famous engineers. Many of the names on this list appear in the ODNB (indicated in italics).

Table 17: Top patent filers during the 1700-1849 period

Inventor	**Pats.**	**Inventor**	**Pats.**
William Church	18	*Robert William Sievier*	11
Samuel Hall	17	William Chapman	11
Joseph Bramah	16	Christopher Nickels	11
Marc Isambard Brunel	15	*David Napier*	11
Joseph Clisild Daniell	15	Augustus Applegarth	11
William Palmer	14	*Thomas Hancock*	11
Robert Dickinson	14	John George Bodmer	11
Elijah Galloway	13	Joseph Manton	10
Edward Massey	13	Thomas Robinson Williams	10
John Heathcoat	13	*William Hale*	10
John Dickinson	13	*Joseph Maudslay*	10
William Congreve	13	Richard Witty	10
William Crofts	12	*Samuel Brown*	10
Lemuel Wellman Wright	12	*Edmund Cartwright*	10
Andrew Smith	12	William Losh	10
Benjamin Cook	12	Anthony George Eckhardt	10

Top patent filers from 1700-1849, excluding communicated patents. Names in italics have been matched to the ODNB.

D.4 Details on occupation groups in the patent data

Table 18 presents the most common occupations within each of the broad occupation groupings used in my analysis. We can see that some groups, such as engineers, esquires, merchants and gentlemen, have a few very common occupations. Others, particularly those in manufacturing, often have a much larger number of unique occupations, each with fewer patents.

Table 18: Major occupations within each broad grouping

Agric/Food/Drinks		**Machinery & Tools**		**Gentleman**	
Farmer	71	Machinist	159	Gentleman	2037
Brewer	44	Machine maker	151	Baronet	21
Miller	30	Mechanic	128	Knight	17
Sugar refiner	21	Watch maker	112		
Distiller	19	Gun maker	66	**Other**	
		Mathmatical inst. maker	44	Artist	65
Chemical		Engine maker	29	Printer	56
Chemist	232	Smith	22	Manager	30
Manufacturing chemist	88	Cutler	20	Stationer	30
Apothecary	18			Hatter	23
Practical chemist	12	**Merchant**		Agent	21
Soap boiler	12	Merchant	679	Master mariner	21
		Wine merchant	17		
Construction		Timber merchant	11	**Prof. services**	
Millwright	59	Grocer	10	Surgeon	114
Builder	49			Clerk	75
Carpenter	38	**Metal & Mining**		Doctor of medicine	49
Plumber	35	Ironmonger	106	Architect	48
Potter	23	Iron master	100	Patent agent	44
		Brass founder	96	Optician	36
Engineering		Iron founder	90	Mechanical draughts	36
Engineer	1250	Whitesmith	27	Surveyor	33
Civil engineer	540	Iron manufacturer	23		
Gas engineer	13			**Textiles**	
Millwright & engineer	9	**Misc. Manufacturing**		Cotton spinner	113
		Manufacturer	328	Lace manufacturer	98
Esquire		Coachmaker	64	Clothier	68
Esquire	840	Musical instrument maker	62	Dyer	64
		Cabinet maker	44	Calico printer	53
		Paper maker	36	Weaver	43
		Tanner	33		
		Hat manufacturer	27		

Counts are based on data from 1700-1849.

D.5 List of top patenting engineers by decade

Table 19 lists the top 5 individuals filing patents with an engineering occupation (in the patent data) in each decade up to the 1840s (counting only patents where they list their occupation as engineer). This provides a rough guide to prominent engineers, though note that engineers may fail to make the list simply because their patents were spread across different decades, and some of these individuals may have filed additional patents in a decade under a different occupation which would not be included here.

Table 19: Top engineer inventors by decade

Decade	**Name**	**Pats.**	**Decade**	**Name**	**Pats.**
1720s	Thomas Benson	1	1800s	Joseph Bramah	6
	Isaac De La Chaumette	1		Archibald Thompson	4
				Samuel Miller	4
1730s	John Kay	1		William Chapman	4
	Thomas Benson	1		Richard Trevithick	4
1740s	Moses Hadley	1	1810s	Samuel John Pauly	5
	John Wise	1		William Davis	5
				Marc Isambard Brunel	4
1750s	George John	1		Bryan Donkin	3
				Joseph Bramah	3
1760s	Robert Mackell	1			
	William Blakey	1	1820s	Lemuel Wellman Wright	9
	Jonathan Greenall	1		Jacob Perkins	7
	Thomas Perrins	1		James Fraser	6
	Charles Nicholas Michel Babu	1		John Hague	6
				James Neville	5
1770s	John Budge	1			
	John Rastrick*	1	1830s	John Ericsson	11
	Christopher Chrisel	1		Joseph Gibbs	10
	Matthew Wasbrough	1		Andrew Smith	9
				John George Bodmer	7
1780s	James Watt	5		Joseph Whitworth	7
	Robert Cameron	4			
	William Playfair	3	1840s	Henry Bessemer	13
	John Besant	1		Joseph Maudslay	8
	Joseph Hateley	1		John George Bodmer	8
				Elijah Galloway	8
1790s	James Rumsey	3		John Coope Haddan	7
	Joseph Bramah	3			
	Joseph Hateley	2			
	Thomas Mead	2			
	William Whitmore	2			

Patents indicate the number of patents that the inventor produced in a decade where there occupation was listed as an engineer. Inventors in italics appear in the ODNB. *John Rastrick is not included in the ODNB, but his son of the same name was included for his work as an engineer and inventor.

D.6 Additional details on the BPO technology category data

Table 20 describes the number of patents and share patents in top technology categories by period. Before 1750, the largest category of inventions was "Water and Fluids", which includes pumps, water-wheels, etc. Weaving and Spinning were important in the early period and grew even more important over time. Three other technologies associated with the Industrial Revolution, such as steam engines, metal, and railways, also become much more important over time while technologies such as Musical instruments and Coaches a road conveyances declines.

Table 20: Top ten technology categories by period

	1700-1749		
1700-1749	**Technology category**	**Patents**	**Share**
1	Water and Fluids	94	0.051
2	Navigation I: Ship-Building, Rigging, and Working	79	0.043
3	Weaving and Preparing for Weaving	71	0.038
4	Spinning and Preparing for Spinning	68	0.037
5	Weapons of Defence, Ammunition	68	0.037
6	Coaches and Other Road Conveyances	64	0.035
7	Motive-Power and Propulsion	57	0.031
8	Musical Instruments	46	0.025
9	Medical and Surgical Treatments	46	0.025
10	Steam-Engines and Boilers	45	0.024
	1750-1799		
	Technology category	**Patents**	**Share**
1	Water and Fluids	132	0.050
2	Weaving and Preparing for Weaving	119	0.045
3	Spinning and Preparing for Spinning	110	0.042
4	Metals and Metallic Substances	106	0.040
5	Medical and Surgical Treatments	99	0.038
6	Coaches and Other Road Conveyances	91	0.035
7	Navigation I: Ship-Building, Rigging, and Working	84	0.032
8	Fireplaces, Stoves, Furnaces, Ovens, and Kilns	67	0.025
9	Motive-Power and Propulsion	64	0.024
10	Steam-Engines and Boilers	62	0.024
	1800-1849		
	Technology category	**Patents**	**Share**
1	Steam-Engines and Boilers	751	0.054
2	Motive-Power and Propulsion	722	0.052
3	Spinning and Preparing for Spinning	711	0.051
4	Weaving and Preparing for Weaving	694	0.050
5	Railways and Railway Rolling-Stock	492	0.035
6	Metals and Metallic Substances	472	0.034
7	Navigation I: Ship-Building, Rigging, And Working	402	0.029
8	Smoke Prevention: Consumption of Fuel	354	0.025
9	Coaches and Other Road Conveyances	353	0.025
10	Printing	305	0.022

Excludes communicated patents.

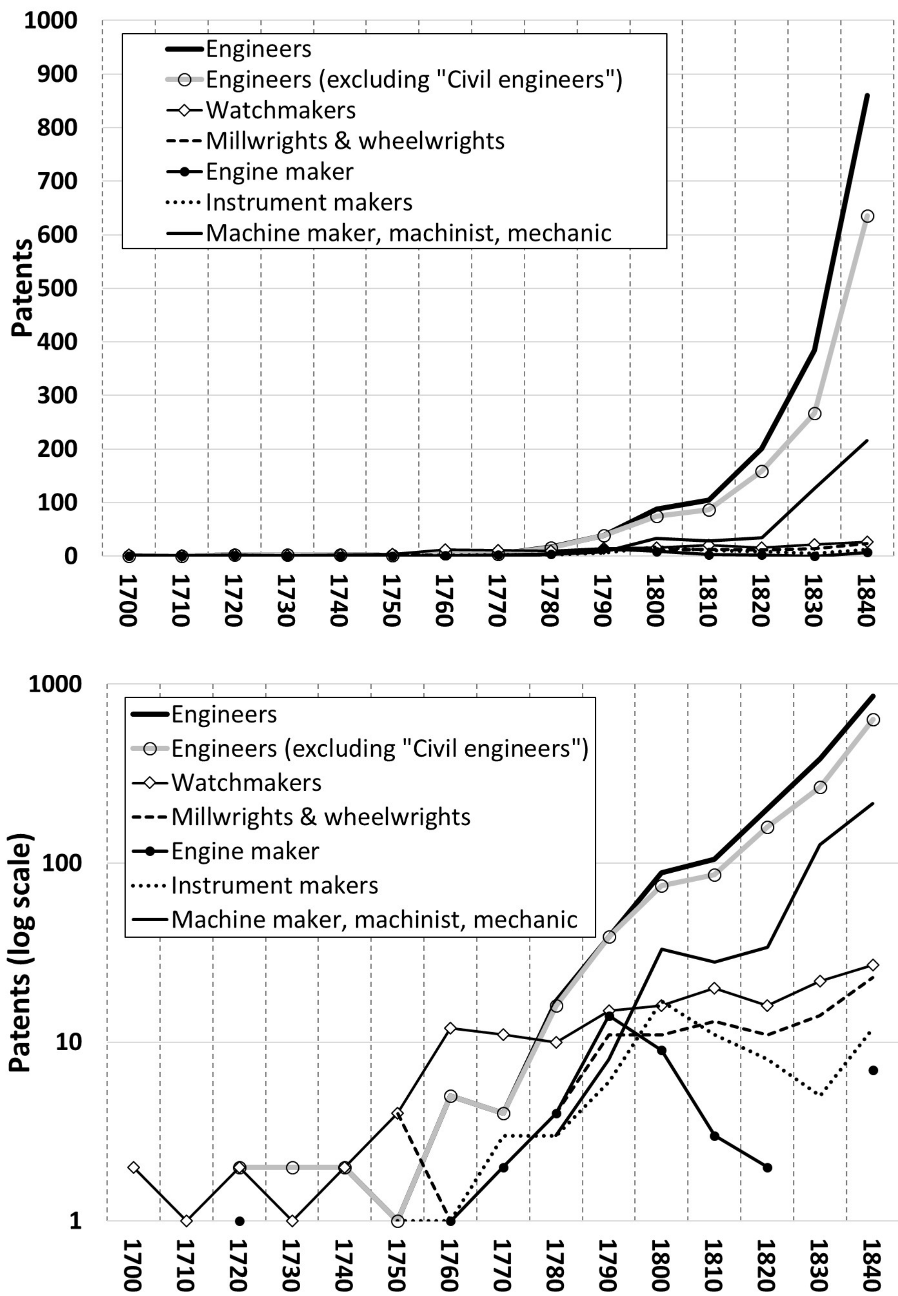
E British patent analysis appendix

E.1 Additional comparisons to specific occupation groups

This appendix provides additional comparisons between engineers and a selection of more detailed occupation groups that have been highlighted as making an important contribution to innovation during the Industrial Revolution. In particular, I compare engineers to watchmakers (including clockmakers), millwrights and wheelwrights, engine makers, instrument makers, and a general category encompassing those described as machine makers, machinists or mechanics. I also considered comparing to coal viewers/mining engineers, but there too few patents by inventors listing those occupations to allow any useful comparison.

The top panel of Figure 6 describes patents by each of these groups across the study period. Note that, as in the main analysis, the engineers category includes civil engineers. If an individual lists occupation as spanning both engineering and another one of these groups, such as "Engineer and millwright", I count the patent in both groups to allow a fair comparison. It is clear from the top panel of this figure that only among engineers to we see a take-off in patenting in the decades just after the onset of the Industrial Revolution. In fact, the difference is so extreme that, when graphed in levels, it is hard to see much action among the other occupation groups, with the exception of the broader "Machine maker, machinist and mechanic" category, which shows some increase after 1820. To deal with this, the bottom panel provides the same figure but using a log scale on the y-axis. There we can see some more interesting patterns. Patents by watchmakers, for example, increased substantially between 1730 and 1760, before leveling off. This suggest that watchmakers were making an important contribution to innovation in the middle of the eighteenth century, a pattern that is in line with other evidence on the importance of watchmakers at this time (Kelly & Ó Gráda, 2016).

Figure 6: Comparing engineers to a selection of detailed occupations



Excludes communicated patents.

E.2 Patents per inventor using alternative ways of identifying engineers

In the main analysis I identify engineers as those where engineering is the modal occupation among the occupations listed in each inventor's patents and those without a unique modal occupation are excluded from the analysis. In Table 21, I look at results for the number of patents per inventor when using other alternative definitions of engineer. To ease comparison, Column 1 presents results following the approach used in the main text. Note that this differs from the estimates shown in Table 4 only because I am not estimating a separate coefficient for manufacturers. In Column 2, I present results where I still identify engineers based on having engineering as a unique modal occupation, but instead of dropping those without a unique modal occupation I include them as non-engineers. In Column 3, I count as engineers anyone with at least one patent listing engineering as their occupation. In Column 4, engineers are those with at least one-third of their patents listing engineering as their occupation. In Column 5, engineers are those with two-thirds of their patents listing engineering as their occupation. This is a fairly restrictive definition which excludes a number of people who clearly should be counted as engineers, including William Chapman (inventor of the railroad bogie), William Symington (builder of the first practical steamboat), and William Playfair.

All of these alternative results provide strong evidence that engineers were more productive than other types of inventors. It is interesting to note that the size of the coefficient on engineers actually increases as I apply less restrictive criteria for identifying engineers. This signals that in identifying engineers, type one errors (failing to correctly identify engineers) are probably dominating type two errors (incorrectly identifying those who are not engineers as engineers), so that when more restrictive criteria are used, more productive individuals, who look like they should be classified as engineers, are instead being grouped in the non-engineer category. In any case, Column 1 shows that the use of modal industry while excluding those inventors without a unique modal industry, as is done in the main text, represents a reasonable middle-ground approach.

Table 21: Patents per inventor using alternative definitions of engineer

	DV: Number of patents per inventor				
	(1)	(2)	(3)	(4)	(5)
	Approach from main text	Including those without unique modal occupations	Engineer is anyone with a patent listing engineering	Engineers have $\geq$ one-third patents listing engineering	Engineers have $\geq$ two-thirds patents listing engineering
Engineer	0.606***	0.546***	0.884***	0.722***	0.488***
	(0.0906)	(0.0901)	(0.0938)	(0.0867)	(0.0888)
Tech. cat. FEs	Yes	Yes	Yes	Yes	Yes
Observations	7,966	8,327	8,327	8,327	8,327
R-squared	0.044	0.041	0.060	0.050	0.039

*** p<0.01, ** p<0.05, * p<0.1. OLS regressions with robust standard errors in parenthesis. The unit of observation is an inventor. The outcome variable is the number of patents per inventor across all years. The explanatory variable is an indicator for whether the inventor's modal occupation is engineer. All columns include controls for the modal technology category for each inventor within each period. In all of these, if there is a tie for the modal category then one is selected randomly.

E.3 Results including other groups as engineers

In the results presented in the main text, the engineers category excludes those described as engine builders as well as mining engineers (also called coal viewers).[55] One may worry that this is too restrictive a definition for engineers. In Table 22, I present results generated following the procedure used in the main text, but including these groups as engineers rather than in the machinery manufacturers or mining category.[56] These results are effectively identical to those presented in the main text, which tells us that the decision of whether or not to include engine builders and mining engineers in the engineering category has no impact on my results. This should not be surprising given that both of these groups are small relative to the large number of inventors who identify as engineers.

[55] Engine builders also includes those described as, for example, engine makers or engine manufacturers.

[56] Note that this changes the sample size slightly because it means that some inventors that previously did not have a modal occupation, and were therefore not included in the analysis, now have a modal occupation.

Table 22: Patents per inventor including engine makers and mining engineers

	DV: Number of patents per inventor					
	All years	All years	1770-1789	1790-1809	1810-1829	1830-1849
	(1)	(2)	(3)	(4)	(5)	(6)
Engineer	0.677***	0.629***	0.805**	0.740***	0.315**	0.474***
	(0.0844)	(0.0876)	(0.380)	(0.220)	(0.125)	(0.0911)
Manufacturer	0.0596*	0.0113	-0.0720	-0.0184	-0.0470	0.00514
	(0.0326)	(0.0372)	(0.0627)	(0.0602)	(0.0590)	(0.0535)
Tech. cat. FEs		Yes	Yes	Yes	Yes	Yes
Observations	7,965	7,965	652	1,209	1,803	4,215
R-squared	0.018	0.047	0.183	0.124	0.064	0.055

*** p<0.01, ** p<0.05, * p<0.1. OLS regressions with robust standard errors in parenthesis. The unit of observation is an inventor. The outcome variable is the number of patents per inventor across all years (Column 1-2) or with 20-year periods (Columns 3-6). The explanatory variable is an indicator for whether the inventor's modal occupation is engineer. Inventors without a unique modal occupation are not included. The regression in Column 2 controls for the modal technology category for each inventor looking across all of that inventor's patents by including a full set of technology category fixed effects. In Columns 3-6, I control for the modal technology category for each inventor within each period. In all of these, if there is a tie for the modal category then one is selected randomly.

E.4 Additional results using patent renewal data

Table 23 present a more complete set of regression results using patent renewal data. The results in Panel A are based on OLS regressions, while Panel B presents corresponding results from Probit regressions. All of these results indicate that patents by engineers were more likely to be renewed at both three and seven years, and the results are both large in magnitude and strongly statistically significant. The magnitude of the results generated using OLS and Probit regressions are very similar. Manufacturer-inventors were also more likely to renew their patents, but much less likely than engineers.

Table 23: Additional results using patent renewal data

Dep. var:	**Patent renewed at three years**			**Patent renewed at seven years**		
A. OLS regressions						
	(1)	(2)	(3)	(4)	(5)	(6)
Engineer	0.0555***	0.0557***	0.0462***	0.0244***	0.0244***	0.0200***
	(0.00619)	(0.00619)	(0.00899)	(0.00429)	(0.00429)	(0.00637)
Manufacturer	0.0222***	0.0221***	0.0140*	0.0124***	0.0121***	0.00870*
	(0.00515)	(0.00517)	(0.00772)	(0.00342)	(0.00342)	(0.00520)
Year FEs		Yes	Yes		Yes	Yes
Tech. cat. FEs			Yes			Yes
Observations	30,579	30,579	54,736	27,436	27,436	41,214
R-squared	0.003	0.003	0.020	0.001	0.002	0.015
B. Probit regressions (marginal effects)						
	(7)	(8)	(9)	(10)	(11)	(12)
Engineer	0.057***	0.057***	0.047***	0.025***	0.025***	0.019***
	(0.0064)	(0.0064)	(0.009)	(0.0046)	(0.0046)	(0.0062)
Manufacturer	0.023***	0.023***	0.015*	0.013***	0.013***	0.009*
	(0.0054)	(0.0054)	(0.0080)	(0.0036)	(0.0036)	(0.0053)
Year FEs		Yes	Yes		Yes	Yes
Tech. cat. FEs			Yes			Yes
Observations	30,579	30,579	54,736	27,436	27,436	41,214

*** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in Columns 1-2, 4-5, 7-8 and 10-11. In Columns 3, 6, 9 and 12, standard errors are clustered by patent number to deal with the fact that patents may appear multiple times if they are classified into multiple technology categories. The analysis in Column 1-3 and 7-9 cover patents originally filed from 1856-1869. The analysis in Columns 4-6 and 10-12 cover patents originally filed from 1853-1866.

E.5 Additional patent quality index results

Tables 24-25 present additional results using the patent quality indices. Table 24 presents more complete results using the same approach taken in the main text. In that approach, engineer and manufacturer patents are identified based on the occupations listed in the entry for each patent. Table 25 presents results from an alternative approach in which engineer and manufacturer patents are identified based on the modal industry of each inventor.

Table 24: Additional results using patent quality indices

Dep. var:	WRI Index			BCI index		
	(1)	(2)	(3)	(4)	(5)	(6)
Engineer	0.0825***	0.0689***	0.0389	0.250***	0.251***	0.230***
	(0.0270)	(0.0258)	(0.0306)	(0.0359)	(0.0381)	(0.0435)
Manufacturer	-0.0596***	-0.0653***	-0.0510**	-0.0598***	-0.0676***	-0.105***
	(0.0192)	(0.0187)	(0.0252)	(0.0171)	(0.0181)	(0.0306)
Year FEs		Yes	Yes		Yes	Yes
Tech. cat. FEs			Yes			Yes
Observations	12,622	12,616	18,473	12,622	12,616	18,473
R-squared	0.002	0.105	0.134	0.010	0.036	0.058

*** p<0.01, ** p<0.05, * p<0.1. OLS regressions. Columns 1-2 and 4-5 present robust standard errors. In Columns 3 and 6, standard errors are clustered by patent number to deal with the fact that patents may appear multiple times if they are classified into multiple technology categories. The analysis in Column 1-3 covers patents originally filed from 1856-1869. The analysis in Columns 4-6 covers patents originally filed from 1853-1866.

Table 25: Patent quality index results using inventors' modal industry

Dep. var:	WRI Index			BCI index		
	(1)	(2)	(3)	(4)	(5)	(6)
Engineer	0.127***	0.110***	0.0822**	0.273***	0.273***	0.278***
	(0.0300)	(0.0297)	(0.0335)	(0.0386)	(0.0409)	(0.0475)
Manufacturer	-0.0488***	-0.0606***	-0.0470*	-0.0860***	-0.0941***	-0.130***
	(0.0189)	(0.0184)	(0.0242)	(0.0161)	(0.0170)	(0.0278)
Year FEs		Yes	Yes		Yes	Yes
Tech. cat. FEs			Yes			Yes
Observations	12,622	12,616	18,473	12,622	12,616	18,473
R-squared	0.003	0.106	0.135	0.013	0.039	0.062

*** p<0.01, ** p<0.05, * p<0.1. OLS regressions. Columns 1-2 and 4-5 present robust standard errors. In Columns 3 and 6, standard errors are clustered by patent number to deal with the fact that patents may appear multiple times if they are classified into multiple technology categories. The analysis in Column 1-3 covers patents originally filed from 1856-1869. The analysis in Columns 4-6 covers patents originally filed from 1853-1866.

E.6 Additional results and discussion using the Great Exhibition data

The Great Exhibition of 1851 was the first major "World's Fair." As discussed in Moser (2005) and Moser (2012), inclusion in the Great Exhibition can be used as an indicator of the quality of an invention, since only the best inventions were chosen by expert juries. The full listing of exhibits in the Great Exhibition of 1851 were digitized by Moser, who generously shared them with me. Moser digitized data includes an indicator for whether an exhibit was patented, based on information from the description of each invention.

For each patented invention in Moser's database, I attempt to match the exhibitor (or in some cases a different inventor, if one is named in the exhibit description) to those patent holders in my database from 1830-1849. This match was done manually using the surname and first initial of each inventor, their address, as well as details on the nature of the invention. In total, out of the 683 patented inventions with inventors listing an address in England or Wales in Moser's data, I am able to match 351 to individuals in my patent data, or just over 50%. There are a number of reasons why I may fail to find match. For example, some exhibits were done by companies rather than individuals, which makes it impossible to match to an individual inventor. Also, for those with common names it is often impossible to make a match given that only first initials are provided in the exhibition data, and in some cases (e.g. "Jones and Sons") even first initials are not available. In total, 14.4% of the inventors that patented from 1830-1849 were engineers, but they make up 21% of those who matched to exhibits.

Table 26 presents some additional results using the Great Exhibition data. The first two columns present OLS regressions while the second two columns show marginal effects from Probit regressions. In Columns 1 and 3, the sample includes all inventors who filed a patent from 1830-1849 and the outcome variable is whether they match to an exhibition. We can see that both the OLS and Probit results tell a similar story. Engineers were more likely to match to patented exhibits in the Great Exhibition than other types of inventors and, while manufacturer-inventors were also more likely to exhibit, they were less likely to do so than engineers (the difference between the engineer and manufacturer coefficients is statistically significant at the 95% confidence level in both specifications).

The results in Column 2 and 4 look at whether, conditional on exhibiting, an inventor was more likely to win an award. These results indicate that, conditional on being an exhibitor, both engineers and manufacturer-inventors were more likely to with awards than other types of inventors, but the two groups are statistically

Table 26: Additional results using Great Exhibition data

	OLS regressions		**Probit marginal effects**	
	Exhibited	Awarded	Exhibited	Awarded
	(1)	(2)	(3)	(4)
Engineer	0.0441***	0.138*	0.0468***	0.137*
	(0.0131)	(0.0742)	(0.0144)	(0.0723)
Manufacturer	0.0159*	0.157**	0.017*	0.0157***
	(0.00835)	(0.0614)	(0.0090)	(0.0609)
Observations	4,469	329	4,469	329
R-squared	0.003	0.022		

*** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in parenthesis. In the "Exhibited" columns, the sample is the set of all inventors who patented from 1830-1849 and the outcome variable is an indicator for whether an inventor matches to a patented exhibit. In the "Awarded" column, the sample is the set of patent holders who match to a patented exhibit in the exhibition database and the outcome variable is an indicator for whether the exhibit received an award. In both types of regressions, the explanatory variables are based on the modal occupation of each inventor. Inventors without unique modal occupations are not included in the analysis.

indistinguishable from each other in their likelihood of winning an award.

E.7 Additional results measuring patent quality using the ODNB

This section provides some additional discussion of results using appearance in the ODNB to assess patent quality (Table 5 Column 6). Note first that this analysis is not based on the main ODNB dataset, which identifies engineers based on the occupations listed in the ODNB. Instead, this analysis is based on a dataset constructed by (i) starting with all patent holders who filed two or more patents, (ii) searching and manually matching these patent holders to the ODNB database, and (iii) looking at how the probability that individuals in the patent data were found in the ODNB data varies based on their occupation classification, where the occupation classifications come from the patent data. Constructing the dataset in this way allows a fair comparison between the occupations appearing in the patent data.

There are roughly two thousand individuals with two or more patents in the 1700-1849 period. Given the effort involved in manually matching each name to the ODNB, it is necessary to limit to this set of more productive inventors, rather than searching for every individual that filed a patent. I manually search for each of these individuals in the ODNB, verifying a match by comparing information in the ODNB to the details such as patent number, subject, and year, inventor address and occupation, and co-inventors in the patent data. In many cases the ODNB lists the actual patent number of patents filed by famous inventors. This procedure yields 245 matches, a match rate of 11.9% (this rate rises to 18.7% for inventors with three or more patents and 23.8% for those with four or more). Given that this is a careful manual match relying on multiple sources of information for verification, it is unlikely that there are many false matches in the matched set. It is possible that some matches are missing due to, for example, misspellings and other sources of name variation, but these are unlikely to by systematic across different occupation groups.

Of the patent holders matched to the ODNB data, the three most common broad occupation groups (based on occupations in the patent data) are engineers, manufacturers, and gentleman/esquires. Table 27 describes the number of inventors in each of these three main groups with two or more patents (first column) which were searched for in the ODNB database, the number actually found in the ODNB databases (second column), and a breakdown of those found in the ODNB database that were born up to 1780 (third column) or after 1780 (fourth column).[57] The most important pattern to note here is that engineers made up 15.5% of the inventors searched for in the ODNB database but 26.9% of those found in ODNB, and 34.2% of those born after 1780. This suggests that, even conditional on having produced at least two patents, engineers were more likely to have become noteworthy individuals than other types of patentees. Since inventors were likely to become noteworthy through the success of their inventions, this indicates that engineers were more likely to produce noteworthy inventions than other types of inventors.

A notable feature of the data in Table 27 is that engineers made up over one third of those inventors with at least two patents born after 1780 that achieved a substantial level of prominence in their lives, a greater share than any other group, even when all manufacturing inventors are grouped together. This provides another indication of the substantial contribution made by engineer inventors to technological progress.

In fact, these figures likely understate the relative success of engineers, since other types of inventors were more likely to find their way into the ODNB for reasons other than the success of their inventions; the gentry category, for example, includes several Earls, who were naturally more likely to be included in ODNB, while manufacturers could make it in for building up large and successful firms. We can see this reflected in the data. I have also digitized the text of the matched ODNB biographies and undertaken a text analysis. This shows that "patent" appears in 81 percent of the matched biographies for engineers but only 68 percent of matched biographies for non-engineers. Similarly, "invent" appears in 70 percent of the biographies for engineers but only 53 percent for non-engineers.

Table 28 presents regression results where the data set are those inventors with 2+ patents who were searched for in the ODNB and the outcome variable is an indicator for whether the inventor was found in ODNB. Since this outcome is an indicator variable, I run both OLS and Probit regressions. As explanatory variables, I focus on whether the modal occupation associated with each name was engineering. In Columns 2, 4, and 6 I control for the actual number of patents associated with each

[57] In a small number of cases the year of baptism is used in place of the year of birth because the year of birth is not reported in the ODNB.

Table 27: Appearances in the ODNB data by broad occupation group

	Inventors with ≥2 patents	Inventors in ODNB database	Inventors in ODNB born by 1780	Inventors in ODNB born after 1780
Engineers	220	56	17	39
	15.5%	26.9%	18.1%	34.2%
Manufacturers	584	54	20	34
	41.1%	26.0%	21.3%	29.8%
Gentlemen & Esquires	300	46	26	20
	21.1%	22.1%	27.7%	17.5%

Includes only inventors with a unique modal occupation. The percentages in the first column reflect each occupation group's share of total inventors searched for in the ODNB (those with $\geq$ 2 patents). The percentages in the second column are the shares of inventors from each occupation group found in the ODNB relative to all inventors found in the ODNB. The shares in the last two columns are the shares of inventors from each occupation group found in the ODNB born before or after 1780, relative to all inventors found in the ODNB born before or after 1780.

name.

The results in Table 28 indicate that engineers were more likely to end up in the ODNB and this is true even conditional on the number of patents filed. In terms of magnitudes, focusing on the results from the linear probability models in Columns 1-2 we can see that the chances an individual is in the ODNB increases by just over 6 percentage points if they are an engineer, or over 9 percentage points if I do not control for the number of patents that they produced. These are large differences relative to the sample mean of 12.8%.[58] This much greater probability suggests that the technologies that engineers were producing were more impactful than those produced by other types of inventors, even after controlling for the fact that they were, on average, producing more inventions than other types of patentees. As expected, filing more patents is also strongly associated with the chances that an individual ends up in the ODNB. Inventors with manufacturing occupations, in contrast, were less likely on average to end up in the ODNB (gentlemen, esquires, and other types of inventors fell in between).

I have also digitized the text of the ODNB biographies for all of those inventors

[58]This sample mean differs from the 11.9% of inventors with 2+ patents found in the ODNB because it includes only inventors with a unique modal occupation.

Table 28: Regression results using ODNB data

	DV: Indicator for being in the ODNB					
	OLS regressions				Probit (marginal effect)	
	(1)	(2)	(3)	(4)	(5)	(6)
Engineers	0.0948***	0.0575**	0.0808***	0.0393	0.075***	0.0351
	(0.0254)	(0.0244)	(0.0262)	(0.0253)	(0.0252)	(0.0226)
Manufact.			-0.0374**	-0.0472***	-0.0397**	-0.0457***
			(0.0149)	(0.0146)	(0.0155)	(0.0149)
No. of patents		0.0325***		0.0330***		0.0215***
		(0.00467)		(0.00470)		(0.0029)
Observations	1,987	1,987	1,987	1,987	1,987	1,987
R-squared	0.010	0.069	0.013	0.073		

*** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in parentheses. Engineers and manufacturers are identified based on unique modal occupation. Inventors without a unique modal occupation are not included.

in the matched patent-ODNB data. One thing that we can look at in the ODNB biographies is the length allocated to each inventor. This provides an additional way to quantify the prominence of the various inventors, since more important individuals are granted more extensive biographies. The length of the ODNB biographies in my matched data set range from 188 words (Joseph Clinton Robertson) to 9,968 (James Watt), with a mean length of 1,208 words. There is a clear correlation with the importance of each inventor. The top five engineers, by word count, are Watt, George Stephenson (4,897), Richard Trevithick (3,126), Charles William Siemens (2,934), and Henry Bessemer (2,924).[59] While one could naturally argue about whether any particular inventor receives the space (and appreciation) that they deserve, in broad strokes this statistic seems informative.

Table 29 presents the average word count per inventor by occupation group. We can see that engineers typically have longer articles than others, with the exception of Gentlemen and Esquires. This suggests that, even conditional on being included in the ODNB, engineers may have been more successful than other types of inventors.

[59] After Watt, the next longest articles are on Thomas Cochrane, Earl of Dundonald, the Naval hero, followed by Henry Seymour Conway, a cousin of Waldpole who rose to be Commander in Chief and played an important role in the American Revolution.

Table 29: Words per article by inventor type

Occupation	Avg. words	Occupation	Avg. words
Agric., food/drink makers	699	Manufacturing	954
Construction/millwrights	992	Merchant	1,162
Engineering	**1,323**	Other occ.	752
Esquire	1,112	Prof. services	997
Gentry	1,378	Unknown	1,563

E.8 Analyzing the make-up of coinventor teams

In this appendix I examine the composition of teams of coinventors and how these differ for inventors within broad occupation groups. These patterns can be viewed in Table 30, where I separate engineers, those with manufacturing occupations, gentlemen and esquires, and all others. The way to read this table is as follows. Each cell reflects the share of multi-inventor patents including one or more inventors from the row occupation and the column occupation, divided by the total number of multi-inventor patents filed by inventors in the row occupation. Thus, the values sum to (close to) one looking across the row, with the discrepancy due to the fact that some multi-inventor patents have more than two inventors.

Looking across the top row, the first cell reflects the share of multi-inventor patents by engineers that include one or more other engineers as coinventors. The second cell of the first row reflects the share of multi-inventor patents by engineers that include one or more manufacturers as coinventors, relative to the total number of multi-inventor patents by engineers, and so on.

There are a couple of intriguing patterns to notice in this table. First, those with manufacturing occupations were much more likely to coauthor with other manufacturers than engineers were to coauthor with other engineers. In part, this may reflect that there were, overall, more other manufacturers to coauthor with, but it also hints at the possibility that because manufacturers were more focused on technologies related to their specific industries, they were more likely to coauthor with others working in that industry. In contrast, looking across the top row shows that engineers are often found to be working with inventors from other groups. This may reflect, for example, partnerships between inventors and manufacturers or with gentlemen who could contribute financing or political connections to a project. This pattern is even more pronounced for Gentlemen and Esquires, a group that regularly patents with every other group.

Table 30: Make-up of coinventor teams by inventor type

		Coauthoring with:			
		Engineers	Manufact.	Gentl/Esq.	Others
Patents by:	Engineer	0.419	0.215	0.215	0.234
	Manufacturer	0.081	0.596	0.137	0.247
	Gentry/Esq.	0.196	0.330	0.265	0.271
	Other	0.133	0.372	0.170	0.546

See text for details of the construction of these figures.

E.9 Additional within-inventor regression results

Table 31 presents some additional within-inventor regression results. Specifically, these regressions include quadratic controls on time since first patent. In all cases, the estimated effect of becoming an engineer is even stronger than that reported in the main text.

Table 31: Within-inventor regressions robustness

	DV: Share of patents with multiple inventors			**DV: Patents per year**		
	(1)	(2)	(3)	(4)	(5)	(6)
Engineer	0.0585**	0.0581**	0.0896***	0.278***	0.294***	0.0919**
	(0.0237)	(0.0236)	(0.0305)	(0.0339)	(0.0380)	(0.0373)
Years since first patent	0.000639	0.00116	0.00109	-0.00847***	-0.0304***	-0.0302***
	(0.00128)	(0.00170)	(0.00170)	(0.00196)	(0.00339)	(0.00351)
Years since first, squared	-5.30e-05	-8.62e-05	-7.87e-05	0.000194***	0.00136***	0.00139***
	(4.24e-05)	(9.15e-05)	(9.08e-05)	(7.14e-05)	(0.000202)	(0.000211)
Years since first, cubed		3.98e-07	4.03e-07		-1.26e-05***	-1.29e-05***
		(1.21e-06)	(1.17e-06)		(2.31e-06)	(2.41e-06)
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Dropping first year as Eng.			Yes			Yes
Observations	5,333	5,333	5,152	18,787	18,787	18,641
R-squared	0.548	0.548	0.552	0.238	0.248	0.247

*** $p<0.01$, ** $p<0.05$, * $p<0.1$. Standard errors are clustered by individual. The Engineer variable is an indicator for each individual that takes a value of one starting from the first year in which an individual listed their occupation as engineer in a patent, and zero otherwise.

E.10 Distribution of engineer patents across tech. categories

Table 32 lists the technology categories where engineers made up the larges fraction of patentees. Table 33 lists the technology categories that accounted for at least 2% of all patents by engineers in the 1700-1849 period. Both of these show that engineers played an important role in key Industrial Revolution technologies, including machine tools, steam engines, railroads, etc. However, we can also see that engineers were fairly diverse in the types of technologies in which they patented. Clearly, they were not a group that was working in just one or a small number of technology types.

Table 32: Technology categories with a high share of patents from Engineers

Technology category	**Share by Engineers**
Boring, Drilling, Punching	0.622
Steam; Steam-Engines and Boilers.	0.517
Boilers and Pans	0.484
Railways and Railway Rolling-Stock	0.419
Gas Manufacture and Consumption	0.400
Bridges, Arches, Viaducts, Aqueducts	0.356
Air and Wind: Air and Gas Engines and Windmills	0.351
Turning	0.333
Tunnels, Excavations, And Embankments	0.286
Smoke Prevention. -Consumption Of Fuel	0.284
Measuring And Numbering	0.283
Motive Power and Propulsion	0.282
Casks And Barrels	0.280

This table lists the share of patents within a technology category with "engineer" listed as the occupation, excluding communicated patents. Data cover 1700-1849.

Table 33: Top technology categories for patents by Engineers

Technology category	**Patents**	**Share of engineer patents**
Steam-Engines And Boilers	444	0.148
Motive-Power And Propulsion	238	0.080
Railways And Railway Rolling-Stock	207	0.069
Smoke Prevention -Consumption Of Fuel	125	0.042
Water And Fluids	112	0.037
Boilers And Pans	93	0.031
Metals And Metallic Substances	90	0.030
Gas Manufacture And Consumption	86	0.029
Spinning And Preparing For Spinning	86	0.029
Fireplaces, Stoves, Furnaces, Ovens, And Kilns	85	0.028
Heat, Heating, Evaporating, And Concentrating	73	0.024
Coaches And Other Road Conveyances	66	0.022
Ship-Building, Rigging, And Working	65	0.022
All others	1221	0.408

This table lists the share of patents with "engineer" listed as the occupation represented by each technology category, for those categories that accounted for at least 2% of patents by engineers, excluding communicated patents. Data cover 1700-1849.

E.11 Number of technology categories per inventor regressions

Table 34 presents regression results looking at the how the number of technology categories patented in varies with inventor type. The results in the first column, which use data from the full sample period, show that engineer inventors patent in more technology categories than other types of inventors, while manufacturer-inventors patent in fewer categories. These results are not driven by the fact that engineers are concentrated toward the latter part of the sample. Columns 2-5 show that similar patterns are also observed in every two-decade sub-period from 1770-1849.

Table 34: Number of technology categories per inventor regressions

	DV: Number of technology categories per inventor				
	All years	1770-1789	1790-1809	1810-1829	1830-1849
	(1)	(2)	(3)	(4)	(5)
Engineer	0.824***	2.437***	0.855***	0.534***	0.705***
	(0.0916)	(0.904)	(0.302)	(0.153)	(0.109)
Manufacturer	-0.125***	-0.0302	-0.100	-0.165***	-0.130**
	(0.0322)	(0.0805)	(0.0658)	(0.0614)	(0.0518)
Observations	7,917	648	1,204	1,789	4,195
R-squared	0.031	0.089	0.030	0.022	0.025

*** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in parenthesis. The unit of observation is an inventor. The outcome variable is the number of different technology categories that the inventor patented in across all years (Column 1) or within 20-year periods (Columns 2-5). The explanatory variable is an indicator for whether the inventor's modal occupation is engineer. Inventors without a unique modal occupation are not included. Data cover 1700-1849.

E.12 Alternative Billington-Hanna technology category data

This section looks at whether the results using the technology category data are robust to using an alternative set of technology categorizations. As an alternative to the BPO categorizations, I use a machine-learning based classification generated by Billington & Hanna (2018) using the text of patent titles to allocate patents into 20 categories. In the analysis below, I use their "TopicOne" categorization, though similar results are also obtained from their "TopicTwo" categorization.

Table 35 presents a breakdown showing the average number of Billington-Hanna technology categories that individual inventors in each occupation group patented in. We can see from this table that in general inventors were substantially less likely to be active in multiple Billington-Hanna technology categories, a natural consequence of the fact that there are far fewer categories than in the British Patent Office classification. However, we also see that engineers are, on average, active in more technology categories than any other group. The regression results in Table 36 confirm that this difference is statistically significant across the full sample period as well as every twenty-year sub-period from 1770.

Table 35: Average Billington-Hanna technology categories per inventor, by occupation type

Occupation group	Avg. number of tech. categories per inventor	Occupation group	Avg. number of tech. categories per inventor
Agric., food/drink makers	1.144	Merchant	1.153
Chemical manuf.	1.288	Metals and mining	1.228
Construction	1.127	Misc. manuf.	1.183
Engineering	**1.570**	Other occ.	1.144
Esquire	1.376	Prof. services	1.196
Gentry	1.304	Textiles	1.134
Machinery and tool manuf.	1.207	Unknown	1.079

Based on the modal occupation group of each inventor. Inventors without a unique modal occupation group are not included. Excludes patents that are communications.

Table 36: Number of Billington-Hanna technology categories per inventor regressions

	DV: Number of technology categories per inventor				
	All years	1770-1789	1790-1809	1810-1829	1830-1849
	(1)	(2)	(3)	(4)	(5)
Engineer	0.363***	0.559*	0.470***	0.236***	0.334***
	(0.0447)	(0.317)	(0.144)	(0.0864)	(0.0547)
Manuf.	-0.0121	-0.00736	-0.00685	-0.0499	0.0104
	(0.0152)	(0.0346)	(0.0347)	(0.0380)	(0.0236)
Observations	7,964	652	1,210	1,803	4,213
R-squared	0.023	0.028	0.030	0.010	0.020

*** $p<0.01$, ** $p<0.05$, * $p<0.1$. Robust standard errors in parenthesis. The unit of observation is an inventor. The outcome variable is the number of different technology categories that the inventor patented in across all years (Column 1) or within 20-year periods (Columns 2-5). The explanatory variable is an indicator for whether the inventor's modal occupation is engineer. Inventors without a unique modal occupation are not included.

E.13 Analyzing inventors' background

In this appendix, I consider the background of patent holders that can be matched to the ODNB. To construct this data set, I began with all individuals responsible for at least two patents in my main study period (1700-1849) and attempted to manually match each to the ODNB. Out of the 2,052 inventors with two or more patents searched for, I find 245 matches, a match rate of 11.9%. This approach allows a fair comparison between the backgrounds of inventors in different occupations groups, where occupation is identified based on the patent data definition.

I focus on the type of education each inventor had based on a manual review of the biographical information in the ODNB. This can shed light on the extent to which engineers differed from other types of inventors in terms of their educational background, though of course it is important to remember that this is a selected sample of only the most successful inventors.

Table 37 describes the share of inventors in the matched ODNB data with each type of educational background broken down by occupational group (based on the modal occupation listed for each inventor). The categories I focus on are university education, apprenticeship, a purely working background (beyond basic primary schooling), private pupillage, learning through working in a family business, and whether the individual attended a grammar or boarding school (as opposed to a village or smaller private school). Note that these shares do not need to add up to one since for some the background is unknown and for others they may have taken advantage of more than one option (e.g., an apprenticeship and then university).

As a starting point, it is notable that the overall patterns shown in Table 37 bear a great deal of similarity to patterns reported in previous studies based on biographical sources. For example, Meisenzahl & Mokyr (2012) find a university attendance rate of 15%, while Howes (2017) finds a rate of 18%. The top row of Table 37 shows that the rate among my matched patent-ODNB data is 17.3%. For apprenticeships, Meisenzahl & Mokyr (2012) report a rate of 40% while 31% of the inventors in the expanded databases used by Howes (2017) were apprenticed. The rate in my data is very similar to Howes', at 27%. Howes (2017) also finds that 8% of his inventors were private pupils, which is similar to the 9.6% in my data. These similarities provide an indicator that the overall patterns identified in the set of patentees I focus on are similar to those found among the prominent inventor samples used in previous studies.

In the first column of Table 37, we see that engineers were, if anything, less likely to have attended university than other types of inventors except manufacturers. Gentlemen and the "other" category (which included a number of doctors) were more likely to have attended university. However, for those engineers that did spend time at university, it was almost always at a Scottish university, particularly Edinburgh, whereas most of the university attendees in other groups attended Oxford or Cambridge.

The most common educational background for engineers was an apprenticeship. In this they were similar to inventors who listed a manufacturing occupation. Engineers were also substantially more likely to have a purely working background, which almost always meant that they were mainly self-taught in their spare time. The remaining columns show that engineers were just slightly more likely to have been a private pupil, and they were much less likely to have learned through working in a family business than manufacturers. Finally, engineers were less likely to have attended a grammar, boarding, or higher-end private school than other types of inventors, though their rate was similar to manufacturers. This is perhaps not surprising given that these schools often favored teaching Latin and Greek over more practical mechanical skills.

Table 37: Educational background of different types of inventors from ODNB data

	University	Apprenticed	Working	Private pupillage	Family business	Grammar/ boarding sch.
All	0.173	0.274	0.096	0.096	0.183	0.212
Engineers	0.107	0.375	0.143	0.125	0.179	0.125
Gentl/Esq.	0.196	0.196	0.065	0.109	0.109	0.326
Manufact.	0.111	0.333	0.074	0.056	0.315	0.111
Others	0.288	0.173	0.096	0.096	0.115	0.308

Inventors are classified based on their modal occupation. Inventors without a unique modal occupation are not included.

A natural question about the patterns shown in Table 37 is whether the differences across occupations are due to differences in the period in which most of the inventors in a particular group were born. To examine this, Table 38 breaks down the education results based on the date of birth of each individual (which is reported in the ODNB for almost all of the matched inventors). Perhaps surprisingly, this reveals that the overall share of inventors coming from each type of background was fairly stable over time. However, among engineers, we see a much high share of inventors with a working background among those born before 1750, while the importance of apprenticeships rises over time from 25% for those born before 1750 to 48% for those born after 1800.

In contrast, among manufacturers, the share apprenticed was declining over time, replaced mainly by a rising share trained in within the family business or as private pupils. University education rose among engineers, from zero before 1750 to 19% for those born after 1800, and a similar increase is observed among manufacturers.

Table 38: Educational background of different types of inventors from ODNB data

	No inventors	Univ.	Appr.	Working	Private pupillage	Family business	Grammar/ boarding sch.
Born before 1750							
All	34	0.235	0.235	0.147	0.059	0.206	0.265
Engineers	4	0.000	0.250	0.500	0.000	0.250	0.250
Gentl/Esq.	8	0.250	0.125	0.250	0.125	0.125	0.375
Manufact.	6	0.000	0.667	0.000	0.000	0.333	0.333
Others	16	0.375	0.125	0.063	0.063	0.188	0.188
Born from 1750-1800							
	No inventors	Univ.	Appr.	Working	Private pupillage	Family business	Grammar/ boarding sch.
All	117	0.128	0.282	0.085	0.085	0.171	0.214
Engineers	31	0.065	0.323	0.129	0.065	0.194	0.097
Gentl/Esq.	24	0.167	0.208	0.000	0.167	0.125	0.375
Manufact.	32	0.094	0.344	0.094	0.031	0.250	0.094
Others	30	0.200	0.233	0.100	0.100	0.100	0.333
Born 1800 or later							
	No inventors	Univ.	Appr.	Working	Private pupillage	Family business	Grammar/ boarding sch.
All	57	0.228	0.281	0.088	0.140	0.193	0.175
Engineers	21	0.190	0.476	0.095	0.238	0.143	0.143
Gentl/Esq.	14	0.214	0.214	0.071	0.000	0.071	0.214
Manufact.	16	0.188	0.188	0.063	0.125	0.438	0.063
Others	6	0.500	0.000	0.167	0.167	0.000	0.500

Inventors are classified based on their modal occupation. Inventors without a unique modal occupation are not included.

F French patent analysis appendix

This section presents some additional descriptive statistics and results obtained from the French patent data. As a starting point, Figure 7 plots the number of patents in France across the study period, 1791-1843. We can see that relatively few patents were filed from the initiation of the system until the end of the Napoleonic Wars. After 1820, the number of patents per year increased substantially.

Figure 7: Patents in France during the study period

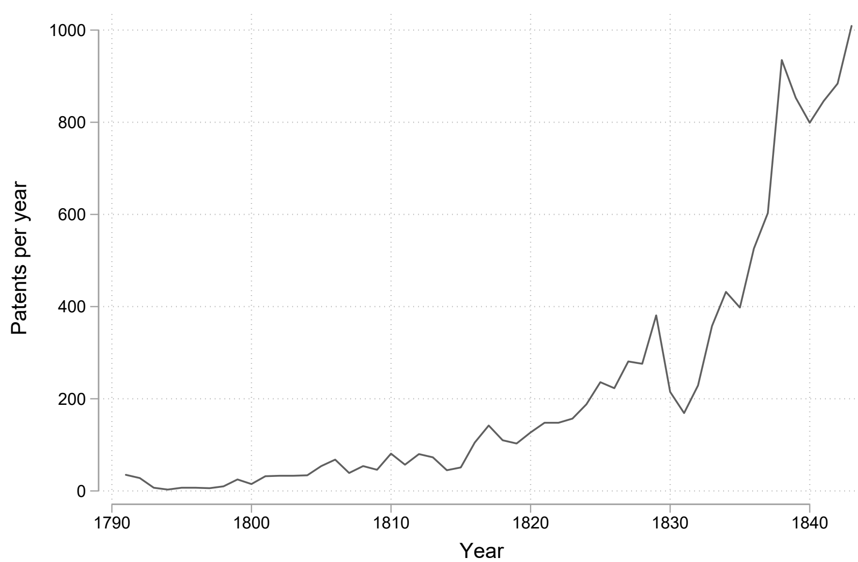


Figure 8 plots the share of French patents by different occupation groups. Two patterns are notable here. First, the overall distribution of patents changes very little across the study period, with the exception of a mild decline in patents by “other” occupations, those that are essentially unclassifiable. We see no evidence of the rise of engineering as an important part of the innovation system, nor do any other occupation groups show substantial increases. Second, main group of inventors by far across the period are manufacturer-inventors, particularly those in the miscellaneous manufacturing category, which includes a diverse set of manufacturer-inventors: glass makers, makers of shoes and hats, etc.

Figure 8: Share of French patents by occupation groups

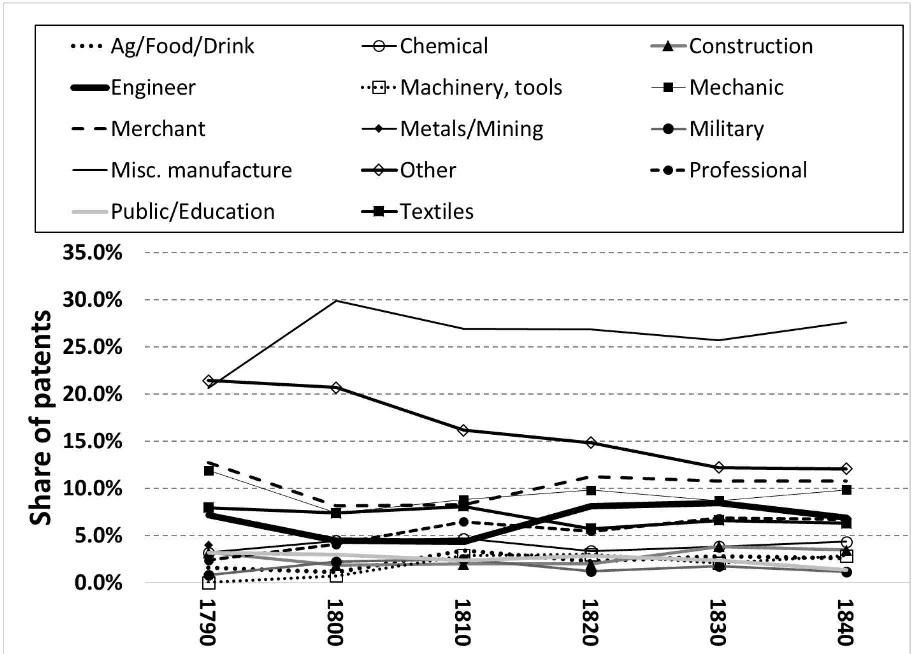


Table 39 presents averages of patents per inventor, the length of patent term per inventor, and the number of technology categories per inventor, for different occupation groups. These results reveal that engineers filed more patents than any other occupation group, they filed patents with longer terms on average than any other occupation group, and they patented in more technology categories than any other occupation group.

Table 39: Average characteristics by occupation group in France

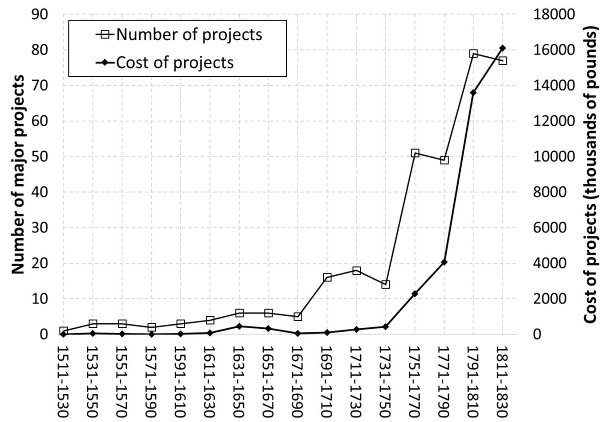
Occupation group	Avg. patents per person	Avg. length of patent term (years)	Avg. numer of tech. categories
Ag/Food/Drink	1.17	7.65	1.10
Chemical	1.33	8.52	1.23
Construction	1.15	7.27	1.10
Engineer	**2.29**	**9.72**	**1.91**
Machinery, tools	1.31	6.85	1.11
Mechanic	1.42	7.66	1.27
Merchant	1.18	8.57	1.11
Metals/Mining	1.21	8.05	1.13
Military	1.32	8.72	1.18
Misc. manufacture	1.26	7.14	1.12
Other	1.22	8.45	1.13
Professional	1.25	8.61	1.16
Public/Education	1.44	8.35	1.28
Textiles	1.25	7.49	1.07
Unknown	1.41	8.98	1.29

G Civil engineering appendix

This appendix provides some additional detail supporting the analysis of civil engineering in Section 6. Figure 9 describes the number of major infrastructure projects on Skempton's list in each decade as well as the estimated cost (in current dollars) of those works. We can see from this graph that, while there was some growth in the number of projects in the first half of the 18th century, the major increase started between 1750 and 1770. While it is difficult to determine the direction of causality, it seems likely that the increase in the demand for civil engineering work described in Figure 9 provided an increase in market size that was sufficient to allow individuals to begin specializing as civil engineers.

Table 40 provides a breakdown of the main types of infrastructure projects that took place in each period. From 1500-1700, the most important types of projects, in terms of numbers or cost, related to harbors and drainage works. The large expenditures on drainage in the first half of the 17th century reflects the Great Level drainage project of the Fen marshlands. River navigation improvements were also important during this period, as were occasional bridge and water supply construction projects.

Figure 9: Number and cost of major civil engineering works, 1500-1830



Source: Skempton *et al.* (2002) Appendix II.

From 1750-1799, however, the pattern changed due to the enormous canal building boom that took place. Canal building continued after 1800, but at a slower pace, while we can begin to see the start of the railway boom that gathered steam after 1830.

Figure 10 describes the share of major British civil engineering projects that were the first major project undertaken by the chief engineer (open diamond symbols). From 1600-1760, roughly 75% of major engineering projects were overseen by someone who had not previously overseen another major project. The only major exception to this is in 1640-1659, when the Dutchman, Cornelius Vermeyden, oversaw several important drainage works. It is notable that this pattern persists into the 18th century despite the substantial increase in the number of projects available after 1690. After 1760, however, the pattern changes. From that point until 1830, roughly 35% of all major projects were overseen by a chief engineer who had not already overseen a major project. The second series in Figure 10 (filled circles) shows the number of first time project by individuals who had not previously trained under a more experienced engineer.[60] After 1760, we can see that very few projects were

[60]This data set is generated through a laborious manual review of the biographies of every engineer that oversaw a major project in the data. I begin the graph in 1680 because before that point I am not confidant that the available biographical information is detailed enough to identify the training

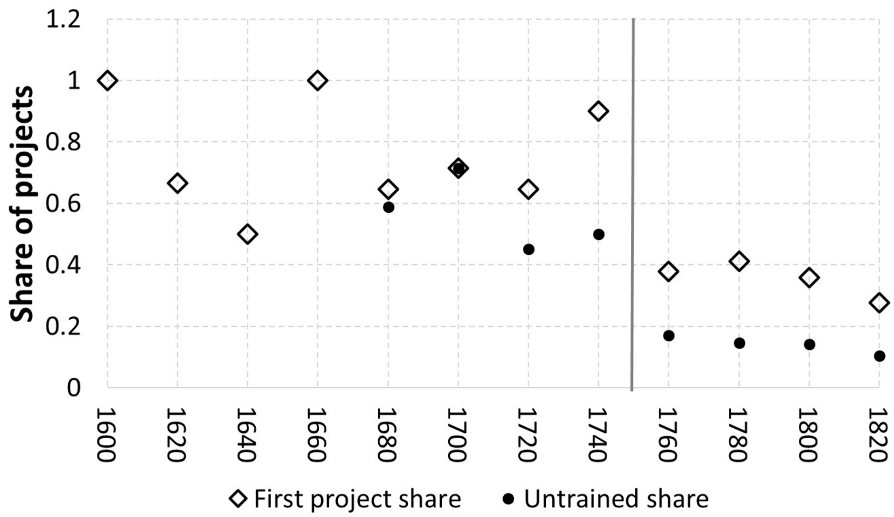
Table 40: Share of major civil engineering projects, by type and period

Period	Canals	River Nav.	Drainage	Harbors	Railways	Water supply	Bridges	Other
				Share of projects				
1500-1549	0.00	0.20	0.00	0.60	0.00	0.00	0.20	0.00
1550-1599	0.20	0.00	0.20	0.40	0.00	0.20	0.00	0.00
1600-1649	0.00	0.25	0.50	0.00	0.00	0.08	0.17	0.00
1650-1699	0.13	0.17	0.17	0.26	0.00	0.22	0.00	0.00
1700-1749	0.08	0.17	0.11	0.28	0.03	0.06	0.11	0.08
1750-1799	0.41	0.12	0.09	0.12	0.03	0.00	0.18	0.04
1800-1830	0.17	0.04	0.04	0.29	0.10	0.00	0.25	0.04
				Share by cost (where cost estimates are available)				
Period	Canals	River Nav.	Drainage	Harbors	Railways	Water supply	Bridges	Other
1500-1549	0.00	0.02	0.00	0.82	0.00	0.00	0.16	0.00
1550-1599	0.11	0.00	0.18	0.70	0.00	0.01	0.00	0.00
1600-1649	0.00	0.15	0.73	0.00	0.00	0.06	0.06	0.00
1650-1699	0.09	0.07	0.36	0.48	0.00	0.00	0.00	0.00
1700-1749	0.14	0.17	0.04	0.26	0.01	0.00	0.31	0.02
1750-1799	0.84	0.04	0.03	0.05	0.03	0.00	0.04	0.00
1800-1830	0.24	0.03	0.03	0.43	0.06	0.00	0.11	0.04

Source: Skempton *et al.* (2002) Appendix II.

overseen by engineers who did not either have prior experience or training under a more experienced engineer. Thus, the engineers chosen to oversee major projects were becoming a more experienced group.

Figure 10: Changes in the structure of the civil engineering profession



Source: Author's calculations using data from Skempton *et al.* (2002) Appendix II. Engineers are identified as having trained under a more experienced engineer if they had either worked for an engineer who had previously overseen one of the major projects on Skempton's list or were partnered with such an engineer on their first major project.

Table 41 lists the top three individuals in each period and the number of projects they oversaw for each half-century from 1500. Below the top three, I also provide the mean number of major projects across all individuals in each period as well as the ratio of the number of projects done by the top individual and the top three individuals to the mean. These statistics provide a sense of the extent to which the distribution of projects across individuals was becoming skewed.

for most engineers.

Table 41: Leading civil engineers by period and their share of projects

1500-1549		
Top individuals:	John Thompson	1
	Richard Cavendish	1
	Thomas Franche	1
Mean projects per individual (all)		1
Ratio of top/mean		1
Ratio of top three/mean		3

1550-1599		
Top individuals:	Jacopo Aconcio	1
	John Trew	1
	Joas Johnson	1
Mean projects per individual (all)		1
Ratio of top/mean		1
Ratio of top three/mean		3

1600-1649		
Top individuals:	Cornelius Vermuyde	3
	John Liens	2
	Hugh Myddleton	1
Mean projects per individual (all)		1.33
Ratio of top/mean		2.25
Ratio of top three/mean		4.5

1650-1699		
Top individuals:	John Hadley	3
	Thomas Fitch	2
	Edmund Dummer	2
Mean projects per individual (all)		1.26
Ratio of top/mean		2.38
Ratio of top three/mean		5.55

1700-1749		
Top individuals:	John Reynolds	4
	Thomas Steers	4
	Humphrey Smith	3
Mean projects per individual (all)		1.45
Ratio of top/mean		2.76
Ratio of top three/mean		7.6

1750-1799		
Top individuals:	John Smeaton	18
	William Jessop	15
	John Rennie	9
Mean projects per individual (all)		2.2
Ratio of top/mean		8.19
Ratio of top three/mean		19.1

1800-1830		
Top individuals:	Thomas Telford	26
	John Rennie	17
	John Rennie Jr.	9
Mean projects per engineer		2.62
Ratio of top/mean		9.94
Ratio of top three/mean		19.9

Source: Author's calculations using data from Skempton *et al.* (2002) Appendix II.

H Government and the engineering profession

The government never played the central role in the British engineering profession that it in other countries, most notably France. There, (military) engineers were deeply embedded in the state, which also oversaw the leading engineering schools, and as a result the engineers that they produced directed their attention first and foremost at solving the problems of importance to the military or the state.[61]

Addis (2007) contrasts the role of government in France and Britain in the development of civil and building engineering (p. 237):

> *The civil engineering profession in Britain developed very differently from its counterpart in France. In Britain, there were formal systems for educating and training military engineers, but the state played no part in establishing similar systems for civil engineers until the late nineteenth century. There was also very little state patronage of civil engineering works...By contrast, the scope of the civil engineer's role in France was defined largely by the king and his government's plans for establishing the French nation.*

The main way that government influenced the development of the engineering profession was as a source of demand for engineering services. Here the Royal Navy was particularly important. The most famous example is the Portsmouth Dockyard, where Henry Maudslay gained experience building machinery designed by Mark Isambard Brunel under the direction of Samuel Bentham.[62] Even this influence, however, was relatively modest compared the the enormous demand coming from private works, ranging from canal and railway companies to coal mines and textile factories.

[61]See Lundgreen (1990) and Alder (1997), particularly p. 9-11.

[62]While both Maudslay and Brunel appear in the patent record as engineers, Samuel Bentham, brother of the more famous Jeremy, appears as an esquire in the majority of his seven patents.