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Measuring returns to scale in nineteenth-century French industry[☆]

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Abstract

Were nineteenth-century French firms too small? Previous research has found either constant returns to scale throughout (Nye, 1987) or increasing returns to scale for most industries (Sicsic, 1994). This research sheds some light on these contradictory results by proposing and estimating a series of models that consider previously ignored econometric issues. My analysis of the 1839–1847 census suggests that there were increasing returns to scale for some industries and constant returns for others, while the analysis of the 1861–1865 census suggests constant returns to scale throughout. Assessing the economic implications of the estimated returns to scale, I argue that there were significant unexploited scale economies in the first half of the nineteenth century. In the second half of the nineteenth century, though, France had little to gain from scale economies.

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1. Introduction

Were nineteenth-century French firms too small? Opinions are divided on this matter. On the one hand, Landes (1949) and Gerschenkron (1962) contend that France suffered from an abnormal number of small firms; neither author doubts that small industry scale constituted an economic weakness. On the other hand, O'Brien

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and Keyder (1978) determine that the techniques of production as well as the scale and form of industrial organization were in most cases well adapted to the demands that confronted the industrialists in that country. Most research attempts to link cultural values to observed firm size in nineteenth-century France, but little has been done to determine whether size was in fact a drag on economic growth. Yet if French industry exhibited constant returns to scale, then firm size would be associated with neither gains nor losses.

Nye (1987) and Sicsic (1994) estimate returns to scale using French industrial censuses from the nineteenth century. Nye (1987) estimates cost functions and finds no evidence of economies of scale in the 1861–1865 industrial census. Sicsic (1994), in contrast, estimates production functions and reports increasing returns to scale using data from both the 1839–1847 and the 1861–1865 census. Looking at the size of French firms both absolutely and in comparison to their international counterparts, he finds that around the middle of the nineteenth century factories using the same kind of mechanical technology were not significantly smaller in France than in England. Similarly, in their study of the largest industrial firms, Kinghorn and Nye (1996) find that French plants at the beginning of the twentieth century were no smaller than US or British plants and considerably larger than German plants. Thus, from a comparative perspective there was no economic loss at this point in time, although from an absolute perspective there might well have been.

The question arises whether the different results are driven by differences in the econometric approaches. Three issues come to mind. (i) Cost and production function estimates require different exogeneity assumptions: cost function estimation assumes that output is exogenous, production function estimation assumes that inputs are exogenous (Christensen and Greene, 1976; Nerlove, 1963). The exogeneity of output underlying any cost function estimation is questionable in a competitive environment such as the one in nineteenth-century France. If firms determine how much output to produce, then output is likely to be correlated with the residual in the cost function equation, thereby leading to biased coefficient estimates. Yet Nye (1987) fails to provide a convincing argument for why firms act like cost-minimizers and take their output levels as given. A much more plausible model of French industry is one of profit maximization. Under some circumstances, however, profit maximization itself calls the assumption that inputs are exogenous into question, so that production function estimation yields biased coefficient estimates. (ii) The measures of returns to scale that are appropriate to answer the question of whether French firms were too small to fully exploit scale economies in their production technologies are defined in terms of gross-output production functions. The reason is that value-added production functions ignore the possibility that different firms combine labor and capital with materials in different ways. Yet Sicsic (1994) follows the latter route. Basu and Fernald (1997) show that estimates of returns to scale from gross-output data and value-added data differ. In general, increasing returns to scale in the value-added production function do not imply increasing returns to scale in the gross-output production function. (iii) As a peculiarity of the data sources, small firms have been aggregated into “collective” observations. Nye (1987) and Sicsic (1994) both use the average firm as their unit of observation. Unlike Nye (1987),

Sicsic (1994) attempts to correct for the heteroskedasticity induced by averaging and finds that his results are sensitive to this correction. However, the correction scheme he employs is not consistent with his model. Indeed, when taken literally, it induces a correlation between error term and regressors that causes the coefficient estimates to be biased.

This paper estimates production functions from gross-output data instead of value-added data, thus addressing the second issue. The third issue is addressed by employing a general heteroskedasticity correction and by using first aggregate and then average establishments as the unit of observation to probe the sensitivity of the results to collective observations. While I am unable to resolve the first issue, I at least assess the direction of the bias that arises in production function estimation if inputs are not exogenous. More specifically, a Monte Carlo experiment shows that the estimates tend to overstate the true degree of returns to scale. Finally, in addition to proposing and estimating a series of models that consider these previously ignored econometric issues, I investigate the sensitivity of the results to the choice of functional form (Cobb–Douglas versus translog) as well as the employed data source and industry classification (both the first and the second census come with various industry classifications).

2. Previous studies

There is no dispute that French industry consisted primarily of small firms. Kinghorn and Nye (1996), for example, find that 95% of all French establishments have 5 or fewer employees.¹ The question then is whether this was a function of the sectoral composition of industrial output or of a failure to achieve optimal scale. Below I review previous attempts to investigate this problem econometrically.

2.1. Data sources

The data available for the investigation of nineteenth-century French industry come from the two industrial censuses that were conducted during this period. The first census was launched in 1839, interrupted, and resumed in 1845. It did not cover Paris. The first census describes establishments (i.e., plants) and not firms. It reports the value of annual output and the number of employees broken down into men, women, and children and their wages, the number of engines and machines, the value of the tax paid (*patente*), and the tax base (*valeur locative*). The latter depends on the size of the building and on the engines and machines inside it, and thus serves as a measure of the capital stock. Only establishments employing more than 10 workers were to be included in the census, but the census in fact includes many small

¹ This compares to an estimate of 46% in the US. Because of differences in census-taking procedures, however, the share of US establishments with 5 or fewer employees may have been almost twice as large (Kinghorn and Nye, 1996, Table 4).

Table 1
Individual and collective observations

	French industrial census 1839–1847		French industrial census 1861–1865	
	Number of observations	Number of establishments	Number of observations	Number of establishments
Individual observations	12,560	12,560	2,642	2,642
Collective observations	1,569	58,164	5,579	119,931
Total	14,129	70,724	8,221	122,573

Notes. Individual and collective observations in the French industrial census 1839–1847 (left panel) and 1861–1865 (right panel).

establishments. Often these have been aggregated into so-called collective observations that describe several establishments by giving sums of the above variables rather than their individual values. In the case of collective observations, the number of establishments is recorded. As the left panel of Table 1 shows, there are 1569 collective observations that describe 58,164 establishments and 12,560 individual observations, each of which pertains to exactly one establishment.

The second census from 1861 to 1865 was designed to include all French industry. It reports output and inputs in values as well as the number of employees and their average wage separately for men, women, and children. Each observation also reports the length and season of unemployment. The capital stock is reported as *valeur vénale*, a measure of market value. Finally, the power of engines, broken down by animate power, wind, water, and steam, is recorded. The data consist largely of collective observations (see Table 1, right panel) and is broken down by industry classification and arrondissement.

In contrast to previous work (Nye, 1987; Sicsic, 1994) this paper uses the most comprehensive datasets available. A detailed description along with the datasets themselves can be found in Chanut et al. (2000).

2.2. Modeling approaches

In what size range did economies of scale exist? To answer this question, Nye (1987) proposes a model in which each industry employs a single technology. Owing to capital market imperfections, capital is a fixed factor of production. Technology and constraint can be described by a short-run variable cost function that has translog form (Braeutigam and Daughety, 1983; Christensen and Greene, 1976). Nye (1987) concentrates on the cotton, wool, and flour-milling industries using data from the second French industrial census.² The unit of observation is the average firm per industry and arrondissement. The results show no significant returns to scale.

² In contrast to the datasets published by Chanut et al. (2000), Nye's (1987) datasets include both value and quantity of inputs, thus allowing the recovery of input prices that are needed in the estimation of cost functions.

Given the dual nature of production, one could use either a cost or a production function to infer returns to scale. Which of the two approaches to use could be decided on statistical grounds. Cost function estimation assumes that output is exogenous, production function estimation assumes that inputs are exogenous (Christensen and Greene, 1976; Nerlove, 1963). The choice between cost and production functions is, however, more than a statistical issue because, for general functional forms such as the translog, the expansion paths along which returns-to-scale measures are computed may differ between the two approaches. Hence the two approaches may yield different estimates.

Sicsic (1994) assumes that each industry employs a single technology and estimates a value-added Cobb–Douglas production function. The data are taken from the first census and cover 23 industries. Of these 23 industries, 13 industries exhibit significant returns to scale. In particular, there are increasing returns to scale in cotton spinning, wool spinning, wool carding, wool hosiery, and wool weaving. Glass mills and paper mills also benefit from increasing returns to scale. Among the small-scale industries, tanneries, breweries, distilleries, oil mills, flour mills, and printing exhibit increasing returns to scale. Regressions based on data from the second census also provide evidence of increasing returns to scale in small-scale industries.

There are two potential problems with Sicsic's (1994) econometric approach. First, he estimates value-added production functions, whereas the appropriate measures of returns to scale are defined in terms of gross-output production functions. Moreover, gross-output data and value-added data lead to different estimates of returns to scale (Basu and Fernald, 1997). In general, increasing returns to scale in the value-added production function do not imply increasing returns to scale in the gross-output production function. While the Cobb–Douglas form Sicsic (1994) uses is an exception in that increasing returns in the value-added production function are equivalent to increasing returns in the gross-output production function, the choice between value-added and gross-output production function is nevertheless not innocuous for two reasons: (i) Returns to scale estimated from the value-added production function overstate (understate) the degree of returns to scale in the case of increasing (decreasing) returns.³ These differences between estimates can be substantial. In the first census, for example, if I estimate value-added production functions for tanneries, breweries, oil mills, flour mills, and printing, I obtain returns to scale of 1.01, 1.24, 1.30, 1.21, and 1.10, respectively. In contrast, if I estimate gross-output production functions, I obtain returns to scale of 0.99, 1.06, 1.00, 1.02, and 1.02, respectively. (ii) Given differences of such magnitude, a test for constant returns might be rejected for the value-added estimates but not for the gross-output estimates. In fact, I reject constant returns for breweries, oil mills, flour mills, and printing using the value-added estimates but just for flour mills using the gross-output estimates.

The presence of collective observations leads to a second problem. Nye (1987) and Sicsic (1994) both use the average establishment as the unit of observation. Unlike

³ An Appendix containing the derivation of this claim and others made in the paper is available from the author on request.

Nye (1987), Sicsic (1994) tries to correct for the heteroskedasticity due to averaging by weighting observations with the square root of the number of establishments. With this correction, he finds increasing returns to scale; without it, he finds constant returns to scale. Since his model is log-linear (as opposed to linear), however, it is not consistent with weighting observations by the square root of the number of establishments. Indeed, when taken literally, this correction induces a correlation between error term and regressors, thereby leading to biased coefficient estimates.⁴

The above problems can seriously distort the estimation results. In the remainder of this paper, I address these problems by estimating production functions from gross-output data instead of value-added production functions, by employing a general heteroskedasticity correction, and by using first aggregate and then average establishments as the unit of observation to explore the impact of collective observations.

While the notions of aggregate and average establishment coincide in individual observations, they differ in collective observations. If the unit of observation is the aggregate (average) establishment, the variables used in the estimation are calculated as the sums (averages) over the establishments that are described by a collective observation. Consequently, the resulting estimates differ depending on the chosen unit of observation.⁵ In particular, returns to scale estimated from average establishments overstate (understate) the degree of returns to scale in the case of increasing (decreasing) returns to scale. But if the aggregate establishment is used as the unit of observation, then the estimate tends to understate (overstate) the degree of returns to scale in the case of increasing (decreasing) returns to scale.⁶ Consequently, if the estimated returns to scale are similar irrespective of whether the average or the aggregate establishment is used as the unit of observation, the presence of collective observations likely does not seriously distort the results.

3. Econometric models

3.1. Functional form

The most commonly used specification for a production function is the Cobb–Douglas form,

$$y_i = e^{\beta_0} l_i^{\beta_l} m_i^{\beta_m} k_i^{\beta_k} e^{\epsilon_i},$$

where $i = 1, \dots, N$ enumerates observations within a given industry and y_i denotes output, l_i labor input, m_i materials input, and k_i capital input. Taking logs yields

$$\ln y_i = \beta_0 + \beta_l \ln l_i + \beta_m \ln m_i + \beta_k \ln k_i + \epsilon_i.$$

⁴ See the Appendix.

⁵ In the estimation itself I use establishments described by individual observations in addition to the aggregate or average establishments constructed from the collective observations.

⁶ See the Appendix.

Returns to scale are given by $\rho = \beta_l + \beta_m + \beta_k$, and testing for constant returns (i.e., $\rho = 1$) is straightforward.

The Cobb–Douglas specification is restrictive in that it exhibits a unitary elasticity of substitution between any two inputs. To probe the sensitivity of my results to the choice of functional form, I therefore also consider a translog production function (Christensen et al., 1971, 1973), which provides a second-order approximation to an arbitrary twice differentiable production function at a given input combination and can achieve an arbitrary elasticity of substitution at this point. The translog form belongs to the class of so-called flexible functional forms and is defined as

$$\ln y_i = \beta_0 + \beta_l \ln l_i + \beta_m \ln m_i + \beta_k \ln k_i + \beta_{ll} (\ln l_i)^2 + \beta_{mm} (\ln m_i)^2 \\ + \beta_{kk} (\ln k_i)^2 + \beta_{lm} \ln l_i \ln m_i + \beta_{lk} \ln l_i \ln k_i + \beta_{mk} \ln m_i \ln k_i + \epsilon_i.$$

The Cobb–Douglas form is obtained as a special case by setting $\beta_{ll} = \beta_{mm} = \beta_{kk} = \beta_{lm} = \beta_{lk} = \beta_{mk} = 0$. I have tested this restriction in preliminary work. It is rejected in the vast majority of cases.

In contrast to a Cobb–Douglas production function, where returns to scale are global, the translog production function may exhibit increasing returns for some input combinations and decreasing returns for others. For example, the degree of returns to scale may differ between small and large establishments or between capital-intensive and labor-intensive production processes. Thus, a local measure of returns to scale is needed. The scale elasticity measures the percentage increase in output due to a one percent increase in all inputs, i.e., due to an increase in the scale of operations. Let $f(l_i, m_i, k_i)$ denote the production function and t a positive scalar. Then the scale elasticity is given by

$$\rho_i = \frac{df(tl_i, tm_i, tk_i)}{dt} \frac{t}{f(tl_i, tm_i, tk_i)} \Big|_{t=1} \\ = \beta_l + \beta_m + \beta_k + 2\beta_{ll} \ln l_i + 2\beta_{mm} \ln m_i + 2\beta_{kk} \ln k_i + \beta_{lm} \ln m_i + \beta_{lk} \ln k_i \\ + \beta_{lm} \ln l_i + \beta_{mk} \ln k_i + \beta_{lk} \ln l_i + \beta_{mk} \ln m_i.$$

Since the scale elasticity ρ_i depends on the labor input l_i , materials input m_i , and capital input k_i , the translog functional form allows the estimated returns to scale to be different for each observation. To arrive at an assessment of the scale economies in a given industry, I compute the test statistic for a scale elasticity of unity at the sample mean.

3.2. Heteroskedasticity correction

An important issue that arises in the estimation of the above described production functions is the presence of heteroskedasticity. Although the OLS estimator is consistent in the presence of heteroskedasticity, its variance–covariance matrix changes. Hence a test for constant returns to scale based on the usual formula for the variance–covariance matrix fails to be consistent. To investigate the extent to which the models suffer from heteroskedasticity, I have conducted a series of tests of

$H_0 : \sigma_i^2 = \sigma^2$ versus $H_1 : \sigma_i^2 \neq \sigma^2$. I briefly discuss these tests and their results in what follows. Then I suggest a more general approach to correcting for heteroskedasticity.

There are two potential sources of heteroskedasticity: the number of establishments summarized by the i th observation and the level of labor, materials, and capital input. Previous research has focused on the former source but neglected the latter. In particular, Sicsic (1994) suggests that the variance of the error term is a function of n_i , the number of establishments summarized by the i th observation. I have carried out Breusch–Pagan tests as well as residual-based tests to assess this possibility. The results suggest that when heteroskedasticity is present it is of a fairly complicated form. In particular, the simple correction scheme employed by Sicsic (1994) is not supported by the data.

To test the hypothesis that the variance of the error term depends on labor, materials, and capital input, I again used a Breusch–Pagan test. The results indicate heteroskedasticity for most of the production function estimates. However, inspection of the squared residuals showed no discernible relationship with the explanatory variables.

In sum, there is heteroskedasticity in the number of establishments as well as in labor, materials, and capital inputs. To account for both sources of heteroskedasticity, I compute the heteroskedasticity-consistent variance–covariance matrix of the OLS estimator (Gallant and Nychka, 1987, pp. 125) in conjunction with a small-sample correction (MacKinnon and White, 1985). Using the heteroskedasticity-consistent variance–covariance matrix ensures that a test for constant returns to scale is consistent in the presence of heteroskedasticity. It also frees me of the need to specify the functional relationship between error variance, explanatory variables, and number of establishments, a task that seems daunting if not impossible in light of the above results.

3.3. Endogeneity bias

OLS fails to be consistent when regressors and error term are correlated. Hence, production function estimation assumes that inputs are exogenous. Under some circumstances, profit maximization itself calls this assumption into question. To assess the direction of the so-called endogeneity bias, consider the case of a Cobb–Douglas production function. Firm i 's profit maximization problem is given by

$$\max_{l_i, m_i, k_i} p e^{\beta_0} l_i^{\beta_l} m_i^{\beta_m} k_i^{\beta_k} e^{\epsilon_i} - w_l l_i - w_m m_i - w_k k_i,$$

where p is the price of output and w_l , w_m , and w_k are the input prices. Provided the firm knows the productivity shock ϵ_i when it chooses its inputs (Levinsohn and Petrin, 2003; Olley and Pakes, 1996), it sets

$$l_i = c \frac{\beta_l}{w_l} e^{\frac{\rho}{1-\rho}\epsilon_i}, \quad m_i = c \frac{\beta_m}{w_m} e^{\frac{\rho}{1-\rho}\epsilon_i}, \quad k_i = c \frac{\beta_k}{w_k} e^{\frac{\rho}{1-\rho}\epsilon_i},$$

where

$$c = e^{\frac{\beta_0}{1-\rho}} \left(\frac{\beta_l}{w_l} \right)^{\frac{\beta_l}{1-\rho}} \left(\frac{\beta_m}{w_m} \right)^{\frac{\beta_m}{1-\rho}} \left(\frac{\beta_k}{w_k} \right)^{\frac{\beta_k}{1-\rho}} p^{\frac{1}{1-\rho}},$$

in order to maximize its profits whenever $\rho = \beta_l + \beta_m + \beta_k < 1$. Hence, l_i , m_i , and k_i are positively correlated with ϵ_i . If $\rho > 1$, the firm maximizes profits by using an infinite amount of inputs, so that error term and regressors are uncorrelated. Yet if the firm is forced to choose a finite amount of inputs, say because of capital market constraints, then l_i , m_i , and k_i are again positively correlated with ϵ_i (assuming that $\beta_l + \beta_m < 1$). Intuitively one suspects that this causes overestimation of β_l , β_m , and β_k , and thus of the degree of returns to scale. However, this is not generally true, since the biases of the OLS estimators for β_l , β_m , and β_k also depend on the covariances of the regressors. To shed light on this issue, I conducted a Monte Carlo experiment based on the French industrial censuses. The Monte Carlo samples are generated such that the means, variances, and covariances of the simulated inputs equal their empirical counterparts and the variance of the productivity shock is set equal to the variance of the OLS residuals.⁷ The Monte Carlo experiment suggests that even small amounts of positive correlation between inputs and productivity shock cause the degree of returns to scale to be overstated.

While an instrumental variables approach could in principle be used to correct for endogeneity, the two industrial censuses do not contain variables that are suitable as instruments. I therefore interpret the OLS estimates as upper bounds on the true degree of returns to scale. It should also be noted that endogeneity is by no means ubiquitous. If the error term enters the production function additively (i.e., $y_i = e^{\beta_0} l_i^{\beta_l} m_i^{\beta_m} k_i^{\beta_k} + \epsilon_i$) instead of multiplicatively, for example, the first-order condition for firm i 's profit maximization problem is independent of ϵ_i , so that regressors and error term are uncorrelated.⁸ Similarly, endogeneity is not an issue provided the firm first learns about the productivity shock after it has chosen its inputs.

4. Empirical analysis

I estimate production functions separately for both censuses. In both censuses, the value of output, y_i , is recorded. Consistent with previous research, I use the tax base (*valeur locative*) as a measure for the value of capital stock, k_i , in the first census, and a measure of market value (*valeur venale*) in the second census.⁹ The value of materials, m_i , is reported as one measure in the first census, whereas in the second census it is broken down into two measures—one that represents material costs such as fuel, and one that represents the value of intermediate goods. I add the two values in the second census to obtain an aggregate measure for the value of material inputs.

⁷ See the Appendix.

⁸ While a multiplicative error is often assumed for convenience, on a priori grounds it is no more plausible than an additive error. On the contrary, measurement error suggests an additive error.

⁹ Unfortunately, I do not have a measure of working capital. Omitting working capital may bias returns-to-scale estimates unless working capital is proportional to capital stock. In this case it is easy to show that returns-to-scale estimates are the same even if working capital is omitted.

Both censuses include data on employment broken down into men, women, and children with corresponding salaries. Assuming that wages reflect productivities, I construct a composite labor figure as

$$l_i = l_{im} + \frac{w_{if}}{w_{im}} l_{if} + \frac{w_{ic}}{w_{im}} l_{ic},$$

where l_{im} , l_{if} , and l_{ic} are the number of males, females, and children employed and w_{im} , w_{if} , and w_{ic} are their respective wages (Nye, 1987; Sicsic, 1994). It is unclear whether the censuses take entrepreneurial labor into account. To ensure that my results do not hinge on the treatment of entrepreneurial labor, I added one to l_i (e.g., Sokoloff, 1984) and repeated the estimation. While this tends to inflate returns-to-scale estimates somewhat, overall the results appear to be reasonably robust.

Unfortunately, I do not have information on full-time versus part-time establishments. This may bias returns-to-scale estimates if large establishments were more likely to be full time than small establishments (Atack et al., 2002; Sokoloff, 1984).

The data come with various industry classifications. I estimate separate models for each industry using first a broad classification and then a narrow one. The broad classification divides the manufacturing sector into 16 industries, while the narrow one subdivides these 16 industries into 52 industries. The narrow classification is roughly comparable to the industry classifications Nye (1987) and Sicsic (1994) employ; the broad one is much less detailed. Because of the different industry classifications, the first round of estimates should suffer from aggregating over heterogeneous firms, while the second should suffer from a small number of observations per industry.

Tables 2 and 3 present descriptive statistics for the various industries in the first and second census, respectively. Both tables show the number of observations and the number of valid observations along with the number of establishments that the valid observations represent. Means and standard deviations are presented for the values of output and capital, the number of male-equivalent workers, and the value of materials. The tables first give the numbers for the broad industry classification and then for the narrow one. For example, textiles is subdivided into hosiery, wool processing, hemp processing, and so on.

Textiles and food processing are by far the largest industries in the first census, and they remain largest in the second census. Iron and other metals is a distant third. Flour mills make up the lions share of food processing. In textiles, wool, cotton, and silk processing are largest.

For the further analysis I drop industries with 15 or fewer valid observations.

4.1. Results

The fit for all models is generally excellent with R^2 s of above 0.9. Most coefficients estimates are economically meaningful. The returns-to-scale estimates are almost always plausible and lie well within the interval (0.5, 1.5). Detailed estimation results for all models are available upon request.

Table 2
Descriptive statistics

Broad	Narrow	Industry	Number of observations	Number of valid observations	Number of establishments	Output		Capital		Labor		Materials	
						Mean	SD	Mean	SD	Mean	SD	Mean	SD
1		Textiles	5,006	4,695	11,460	110,660	477,112	844	3,745	32	124	75,111	351,251
1	3068	Hosiery	194	179	370	46,024	165,935	345	1,451	20	65	25,509	89,182
1	3108	Wool processing	1,486	1,407	2,033	210,923	537,942	1,255	3,845	41	89	147,319	388,076
1	3280	Hemp processing	150	123	540	19,528	157,531	309	1,760	6	30	12,631	90,554
1	3283	Cotton processing	1,577	1,542	1,598	229,684	336,118	2,213	3,744	96	147	145,500	228,412
1	3288	Linen processing	308	276	5,206	14,902	466,620	217	6,172	6	121	9,485	316,844
1	3289	Silk processing	640	590	860	159,627	165,309	890	984	46	54	118,438	120,081
1	3407	Printing	99	97	97	870,893	803,795	4,404	4,429	151	156	591,445	584,925
1	3565	Small wares	62	23	72	58,155	231,550	337	1,088	26	28	35,449	149,855
1	3726	Dry cleaning and laundry	277	258	478	181,512	765,252	1,357	2,359	20	78	144,931	705,493
1	3727	Mixed or undetermined fibres	173	165	171	286,779	401,335	1,447	2,609	99	159	165,149	264,968
1	3901	Other textiles	40	35	35	154,764	132,656	1,233	1,969	25	23	109,503	108,650
2		Mining and quarrying	708	285	509	101,060	428,284	1,671	8,933	43	199	49,654	233,466
2	3266	Iron mines	128	103	103	154,127	497,369	1,952	2,939	23	42	98,735	310,270
2	3392	Fuel	142	26	44	272,399	802,743	3,647	10,243	186	601	112,825	287,955
2	3503	Clay and stones	408	140	342	48,420	143,802	655	1,543	31	81	21,414	93,399
2	3594	Non-ferrous metals	20	6	6	380,438	592,098	1,750	2,074	22	29	280,240	468,583
2	3683	Salt	10	10	14	338,327	509,678	18,188	40,076	52	86	81,053	165,979
3		Iron and other metals	907	879	909	279,339	526,201	4,600	6,418	51	104	182,677	317,975
3	3382	Iron foundries	872	845	875	256,921	472,649	4,585	6,317	51	105	163,473	259,800
3	3422	Non-ferrous metallurgy	35	34	34	856,279	1,138,882	4,980	8,666	54	89	676,902	838,090
4		Iron products	539	516	1,224	98,695	369,529	1,125	6,629	38	159	55,866	222,178
4	3029	Arms	8	7	55	65,472	402,467	1,095	13,139	74	535	16,414	141,128
4	3169	Nails	137	127	274	71,295	222,006	633	2,437	51	213	44,369	136,867
4	3192	Cutlery	23	21	262	5,426	86,763	254	1,045	2	27	3,742	58,527
4	3440	Machines	155	150	228	188,837	484,063	2,898	10,497	51	131	97,442	239,267
4	3691	Ironwork, hardware, tools	92	88	171	139,633	253,280	1,101	5,653	70	139	63,808	143,043
4	3904	Other iron products	124	123	234	125,272	380,324	974	2,292	19	64	90,648	300,842
5		Leather	809	775	1,327	45,364	108,635	535	944	6	14	32,667	78,613
6		Wood products	126	94	408	44,476	652,150	730	5,509	6	29	26,578	235,710
6	3676	Sawmills	90	64	71	201,537	767,730	2,234	4,461	13	19	118,264	259,933
6	3759	Woodwork	36	30	337	11,386	101,654	412	6,883	4	43	7,262	80,477

7		Glass	509	439	941	60,478	253,180	913	3,912	30	119	21,850	78,481
7	3260	Earthenware, porcelain, pottery	385	320	805	26,703	123,666	487	2,994	17	74	9,251	41,378
7	3797	Glass and crystal	124	119	136	260,394	377,811	3,436	4,898	110	171	96,425	103,638
8		Chemicals	412	374	457	243,257	644,597	2,164	7,583	19	60	163,748	431,739
9		Building materials	1,003	846	3,347	7,563	40,562	348	1,681	4	12	2,852	23,722
9	3355	Binding materials	281	233	498	13,211	37,032	517	1,906	6	13	4,585	17,348
9	3777	Bricks and tiles	721	613	2,849	6,576	41,488	318	1,580	4	12	2,549	25,691
9	3909	Other building materials	1	0									
10		Lighting	140	133	177	94,518	245,893	1,585	5,628	8	16	61,169	176,811
10	3163	Wax and candles	111	105	149	77,427	249,805	578	1,260	5	9	62,339	197,614
10	3365	Gas	29	28	28	185,472	212,235	6,940	10,650	25	24	54,942	48,680
11		Furniture	20	20	244	19,988	221,787	628	2,734	12	66	7,389	119,487
12		Clothing	209	185	803	27,829	156,759	286	1,199	20	118	14,608	103,707
12	3146	Hats	70	62	269	26,892	66,492	396	505	20	102	10,351	35,680
12	3154	Shoes	23	18	139	16,008	65,479	354	1,676	21	79	9,128	35,238
12	3362	Gloves	58	55	59	149,725	207,372	394	353	92	159	90,113	134,845
12	3912	Other clothing	58	50	336	12,066	133,781	151	1,937	8	47	7,026	104,352
13		Food processing	2,779	2,472	35,360	38,946	1,089,691	542	4,598	3	25	33,955	943,408
13	3082	Breweries	326	193	1,282	22,764	56,370	745	1,662	3	4	14,232	28,875
13	3225	Distilleries	228	223	1,328	35,251	207,505	418	1,397	2	6	28,441	82,090
13	3400	Oil mills	368	341	1,198	57,968	372,484	608	1,886	4	12	50,084	317,063
13	3504	Flour mills	1,281	1,219	30,725	34,273	1,414,083	499	5,358	2	9	30,782	1,223,222
13	3703	Sugar refining	341	322	329	437,054	1,072,053	3,491	4,545	52	37	347,773	965,122
13	3913	Other food products	235	174	498	70,042	324,600	889	5,595	11	28	49,100	218,614
14		Transport equipment	120	89	168	87,119	249,592	5,010	75,474	28	72	52,462	165,676
14	3078	Saddlery and carriage building	14	14	40	72,975	253,398	1,528	6,114	18	63	41,550	134,227
14	3183	Ship construction	106	75	128	91,539	250,319	6,098	82,212	31	73	55,872	171,440
15		Paper, printing, pens	881	816	1,281	46,658	134,084	1,075	2,778	15	36	23,179	75,179
15	3408	Printing	474	424	802	24,293	86,954	727	848	9	17	9,790	35,752
15	3550	Paper mills	356	344	412	87,586	161,988	1,855	4,032	26	42	47,443	91,522
15	3915	Watchmaking	51	48	67	62,690	169,189	445	894	27	71	34,244	130,304
16		Luxury items	64	60	141	335,009	5,470,792	452	1,055	5	16	326,714	5,468,619

Notes. Descriptive statistics for the various industries in the French industrial census 1839–1847. Equal weight is given to all establishments, irrespective of whether they are described by an individual or a collective observation.

Table 3
Descriptive statistics

Broad	Narrow	Industry	Number of observations	Number of valid observations	Number of establishments	Output		Capital		Labor		Materials	
						Mean	SD	Mean	SD	Mean	SD	Mean	SD
1		Textiles	1,306	567	7,009	288,578	1,265,028	70,474	376,124	53	192	207,386	1,041,357
1	3068	Hosiery	52	14	253	84,174	336,511	15,941	91,486	42	458	53,435	225,978
1	3108	Wool processing	443	164	1,782	385,091	1,827,856	76,633	328,617	47	136	284,798	1,563,561
1	3280	Hemp processing	105	23	86	268,000	555,453	99,628	210,706	53	107	191,058	400,681
1	3283	Cotton processing	205	131	1,903	292,524	917,417	97,347	538,026	76	222	195,614	658,367
1	3288	Linen processing	82	34	313	440,974	1,231,978	142,364	479,696	80	173	332,080	974,299
1	3289	Silk processing	116	81	1,455	234,151	921,660	33,346	187,791	34	121	191,164	748,251
1	3407	Printing	21	8	99	407,121	1,337,815	117,667	127,702	73	99	295,889	1,318,699
1	3565	Small wares	45	11	45	290,178	620,271	48,178	106,237	123	377	196,289	436,346
1	3726	Dry cleaning and laundry	107	53	404	112,886	255,932	49,973	174,757	19	82	53,483	144,618
1	3727	Mixed or undetermined fibres	77	32	637	237,063	1,259,807	48,080	392,634	51	242	152,794	949,205
1	3901	Other textiles	53	16	32	209,406	356,638	57,219	87,598	25	37	146,969	253,359
2		Mining and quarrying	590	20	97	67,299	168,869	79,990	194,299	18	44	34,835	81,360
2	3266	Iron mines	47	0									
2	3392	Fuel	94	1	1	168,000		600,000		135		110,000	
2	3503	Clay and stones	410	10	71	54,268	162,222	74,676	117,863	17	32	25,141	64,634
2	3594	Non-ferrous metals	17	1	2	358,500		150,000		86		27,000	
2	3683	Salt	22	8	23	77,826	125,715	67,696	209,273	11	21	62,174	91,445
3		Iron and other metals	340	261	990	403,222	1,654,682	219,240	1,236,156	90	396	293,844	923,861
3	3382	Iron foundries	280	213	860	390,648	1,708,723	234,298	1,345,910	96	429	279,171	844,028
3	3422	Non-ferrous metallurgy	60	48	130	486,408	1,397,973	119,631	500,724	49	183	390,915	1,215,846
4		Iron products	559	398	1,681	128,446	642,345	65,590	587,090	45	251	69,460	371,144
4	3029	Arms	8	5	5	1,436,200	1,355,804	1,110,000	855,102	1,295	1,161	327,600	231,677
4	3169	Nails	77	54	191	111,911	327,456	39,440	131,017	43	116	70,639	236,923
4	3192	Cutlery	45	30	403	29,122	190,972	12,873	147,760	30	213	11,139	73,586
4	3440	Machines	218	162	598	171,050	804,338	111,115	868,282	48	222	86,614	445,810
4	3691	Ironwork, hardware, tools	97	77	291	167,467	410,332	59,828	144,077	54	134	95,625	232,037
4	3904	Other iron products	114	70	193	127,482	519,850	42,114	139,905	22	67	90,782	435,420
5		Leather	487	101	924	93,019	336,840	25,174	81,951	9	35	70,113	260,911
6		Wood products	339	115	915	45,877	235,592	14,209	57,630	6	20	32,437	177,109
6	3676	Sawmills	205	96	801	47,404	253,728	14,700	57,564	5	19	33,975	192,327
6	3759	Woodwork	134	19	114	35,140	104,478	10,754	58,815	11	16	21,632	50,925

7		Glass	369	307	1,832	54,903	409,335	39,866	459,363	23	166	26,031	200,774
7	3260	Earthenware, porcelain, pottery	302	245	1,686	21,690	190,947	15,916	169,032	12	95	8,457	72,483
7	3797	Glass and crystal	67	62	146	438,452	558,649	316,438	863,313	153	240	228,966	272,201
8		Chemicals	465	306	1,152	234,672	705,193	67,115	296,814	14	56	176,877	544,664
9		Building materials	478	400	4,112	11,098	54,964	7,567	47,765	5	25	6,179	31,899
9	3355	binding materials	851	748	12,564	7,488	44,863	6,774	39,889	5	20	3,678	26,339
9	3777	Bricks and tiles	370	346	8,447	5,679	21,253	6,329	23,912	4	12	2,417	9,505
9	3909	Other building materials	3	2	5	96,000	147,885	104,800	169,429	11	11	78,000	119,586
10		Lighting	374	125	362	147,483	568,145	82,019	1,098,312	6	27	116,097	458,081
10	3163	Wax and candles	233	100	334	140,746	611,721	24,805	111,432	5	17	114,596	493,997
10	3365	Gas	141	25	28	227,857	340,572	764,500	2,364,807	27	47	134,000	277,705
11		Furniture	47	14	30	145,200	216,844	62,067	79,809	36	56	75,900	92,809
12		Clothing	335	108	596	108,228	416,412	22,886	113,936	31	140	60,773	232,741
12	3146	Hats	93	65	310	81,868	248,116	10,968	25,663	24	103	42,458	129,199
12	3154	Shoes	60	8	50	283,680	769,794	62,880	225,720	83	223	156,960	429,097
12	3362	Gloves	38	4	36	185,444	719,023	26,167	80,370	76	419	133,000	515,125
12	3912	Other clothing	144	31	200	91,325	479,176	30,770	166,735	21	98	52,115	249,895
13		Food processing	1,433	873	25,392	66,198	1,346,937	17,218	280,442	4	85	55,172	1,206,258
13	3082	Breweries	263	229	2,191	34,562	82,535	26,822	70,871	4	6	21,319	52,280
13	3225	Distilleries	226	181	4,109	27,649	484,764	10,377	157,689	4	62	20,246	388,736
13	3400	Oil mills	244	129	2,607	68,415	932,416	12,277	111,910	5	22	58,591	795,699
13	3504	Flour mills	357	110	15,220	64,996	822,717	13,019	167,580	2	12	56,146	727,457
13	3703	Sugar refining	39	38	354	728,743	5,619,730	243,669	1,022,191	120	127	610,655	5,135,079
13	3913	Other food products	304	186	911	72,434	335,546	21,261	63,287	8	21	52,233	230,176
14		Transport equipment	160	93	334	125,674	644,849	88,844	527,226	51	296	64,596	338,132
14	3078	Saddlery and carriage building	122	83	265	51,321	150,832	66,487	513,801	24	81	24,558	86,625
14	3183	Ship construction	38	10	69	411,232	1,804,294	174,710	604,106	155	854	218,362	933,755
15		Paper, printing, pens	460	224	862	591,189	23,803,669	93,986	386,458	36	115	460,487	20,656,231
15	3408	Printing	193	48	265	132,170	1,020,895	87,298	677,935	26	139	58,155	477,626
15	3550	Paper mills	197	145	491	156,098	349,350	103,853	222,171	35	72	97,405	225,155
15	3915	Watchmaking	70	31	106	3,754,113	64,570,193	65,000	385,029	66	199	3,148,142	56,053,034
16		Luxury items	66	15	89	92,258	372,005	32,753	72,436	31	102	50,180	317,063

Notes. Descriptive statistics for the various industries in the French industrial census 1861–1865. Equal weight is given to all establishments, irrespective of whether they are described by an individual or a collective observation.

For each estimate, I conduct two (two-sided) Wald tests for constant returns to scale, one using the usual variance–covariance matrix and another one using the heteroskedasticity-corrected variance–covariance matrix. Using the heteroskedasticity-corrected instead of the usual variance–covariance matrix tends to inflate the standard errors of the coefficient estimates. The null hypothesis of constant returns to scale is thus rejected less often. This is in line with results I obtained in preliminary work using a parametric correction for heteroskedasticity in the number of establishments. But, as I have argued before, there is also heteroskedasticity in labor, materials, and capital inputs that refutes a parametric correction. Since using the heteroskedasticity-consistent variance–covariance matrix guarantees a consistent test, I restrict attention to this more general heteroskedasticity correction in what follows. It is worth noting that correcting for heteroskedasticity does not change the results from constant to increasing returns to scale as in Sicsic (1994).

Tables 4 and 5 present the findings for the first and second census, respectively. The tables are organized as follows. On the top level, I distinguish between aggregate and average establishments as the unit of observation. On the bottom level, I first look at the Cobb–Douglas (CD) specification, then at the translog (TL) specification. For each of these, I report the returns-to-scale estimate and the result of a Wald test for constant returns to scale (symbolized by “+,” “0,” and “–”) using a significance level of 5%.

I start with the broad industry classification. In the first census (Table 4), textiles, mining, and quarrying, iron and other metals, chemicals, and lighting exhibit increasing returns to scale through all specifications; wood products, glass, clothing, transport equipment as well as paper, printing, pens exhibit constant returns to scale through all specifications. In contrast, iron products, leather, building materials, furniture, food processing, and luxury items exhibit either increasing or decreasing returns to scale for some specifications and constant returns for others. In the second census (Table 5), mining and quarrying, iron and other metals, iron products, leather, wood products, glass, chemicals, lighting, furniture, paper, printing, pens, and luxury items exhibit constant returns to scale through all specifications. The results for food processing range from increasing over constant to decreasing returns. The remaining industries occupy the middle ground in terms of stability, exhibiting either constant and decreasing or constant and increasing returns to scale depending on the specification.

The findings for the narrow industry classification are also shown in Tables 4 and 5. In the first (second) census, 31 (23) out of 43 (35) industries exhibit the same returns-to-scale measure through all specifications. Unlike the results for the broad industry classification, these stable industries range from increasing over constant to decreasing returns to scale in the first census. In the second census I always obtain constant returns to scale just as for the broad industry classification. The remaining industries in both censuses occupy the middle ground in terms of stability, exhibiting either constant and decreasing or constant and increasing returns to scale depending on the specification.

Table 4
Returns-to-scale estimates

Broad	Narrow	Industry	Aggregate establishment				Average establishment			
			CD		TL		CD		TL	
1		Textiles	1.02	+	1.02	+	1.03	+	1.03	+
1	3068	Hosiery	1.05	0	1.03	0	1.06	+	1.04	0
1	3108	Wool processing	1.01	0	1.01	0	1.02	+	1.02	+
1	3280	Hemp processing	1.00	0	1.00	0	1.02	0	0.99	0
1	3283	Cotton processing	1.03	+	1.03	+	1.03	+	1.03	+
1	3288	Linen processing	0.98	0	0.99	0	1.06	+	1.05	+
1	3289	Silk processing	1.03	+	1.04	+	1.04	+	1.04	+
1	3407	Printing	1.05	0	1.02	0	1.05	0	1.02	0
1	3565	Small wares	1.09	0	1.11	0	1.08	0	1.12	0
1	3726	Dry cleaning and laundry	1.04	0	1.02	0	1.07	+	1.04	+
1	3727	Mixed or undetermined fibres	1.00	0	0.99	0	0.99	0	0.99	0
1	3901	Other textiles	0.84	–	0.85	–	0.84	–	0.85	–
2		Mining and quarrying	1.09	+	1.09	+	1.09	+	1.08	+
2	3266	Iron mines	1.00	0	1.02	0	1.00	0	1.02	0
2	3392	Fuel	1.01	0	1.07	0	1.02	0	1.07	+
2	3503	Clay and stones	1.12	+	1.08	+	1.15	+	1.10	+
3		Iron and other metals	1.04	+	1.05	+	1.04	+	1.05	+
3	3382	Iron foundries	1.04	+	1.05	+	1.04	+	1.05	+
3	3422	Non-ferrous metallurgy	1.05	0	1.00	0	1.05	0	1.00	0
4		Iron products	1.01	0	1.02	+	1.02	0	1.03	+
4	3169	Nails	1.00	0	1.02	0	1.00	0	1.03	0
4	3192	Cutlery	0.95	0	1.05	0	1.11	0	1.27	0
4	3440	Machines	0.99	0	1.00	0	1.00	0	1.02	0
4	3691	Ironwork, hardware, tools	0.99	0	0.99	0	0.94	0	0.97	0
4	3904	Other iron products	1.01	0	1.03	0	1.03	0	1.05	+
5		Leather	0.97	–	0.98	–	0.99	0	0.99	0
6		Wood products	1.06	0	1.05	0	1.01	0	1.04	0
6	3676	Sawmills	1.01	0	1.04	0	1.01	0	1.04	0
6	3759	Woodwork	1.05	0	1.06	0	1.01	0	1.02	0
7		Glass	1.00	0	0.98	0	1.02	0	1.01	0
7	3260	Earthenware, porcelain, pottery	0.99	0	0.96	0	1.02	0	1.01	0
7	3797	Glass and crystal	1.03	0	0.97	0	1.01	0	0.96	0
8		Chemicals	1.10	+	1.08	+	1.12	+	1.09	+
9		Building materials	0.99	0	1.03	0	1.06	+	1.08	+
9	3355	Binding materials	1.07	+	1.07	+	1.10	+	1.12	+
9	3777	Bricks and tiles	0.96	0	1.00	0	1.03	0	1.05	0
10		Lighting	1.18	+	1.12	+	1.19	+	1.13	+
10	3163	Wax and candles	1.04	+	1.03	0	1.04	+	1.04	0
10	3365	Gas	0.97	0	0.91	0	0.97	0	0.91	0
11		Furniture	1.13	+	1.04	0	1.02	0	1.08	0

Table 4 (continued)

Broad	Narrow	Industry	Aggregate establishment				Average establishment			
			CD		TL		CD		TL	
12		Clothing	0.98	0	0.96	0	1.02	0	1.01	0
12	3146	Hats	1.04	0	1.02	0	1.04	0	1.02	0
12	3154	Shoes	0.94	0	0.98	0	0.96	0	0.93	0
12	3362	Gloves	0.87	–	0.87	–	0.89	–	0.90	–
12	3912	Other clothing	0.95	0	0.93	0	1.07	0	1.01	0
13		Food processing	1.00	0	1.02	+	1.08	+	1.05	+
13	3082	Breweries	0.96	–	0.99	0	1.06	0	1.05	0
13	3225	Distilleries	0.99	0	1.03	0	1.02	0	1.04	0
13	3400	Oil mills	0.99	0	0.98	–	1.00	0	1.00	0
13	3504	Flour mills	0.99	–	1.00	0	1.02	+	1.01	0
13	3703	Sugar refining	1.03	0	1.07	+	1.03	0	1.07	+
13	3913	Other food products	1.03	0	1.02	0	1.06	+	1.06	+
14		Transport equipment	0.99	0	1.02	0	1.00	0	1.03	0
14	3183	Ship construction	1.00	0	1.02	0	0.99	0	1.03	0
15		Paper, printing, pens	1.00	0	1.01	0	1.01	0	1.01	0
15	3408	Printing	0.98	0	0.98	0	1.02	0	1.00	0
15	3550	Paper mills	1.06	+	1.09	+	1.06	+	1.09	+
15	3915	Watchmaking	0.95	0	0.96	0	0.99	0	0.96	0
16		Luxury items	1.06	0	1.01	0	1.19	+	1.07	0

Notes. Returns-to-scale estimates for the French industrial census 1839–1847. The results of a Wald test for constant returns to scale are represented by “+,” “0,” and “–.” “+” (“–”) indicates that constant returns are rejected in favor of increasing (decreasing) returns; “0” indicates that constant returns cannot be rejected.

To facilitate the subsequent interpretation I have compiled the incidence of increasing, constant, and decreasing returns to scale for the various econometric specifications, industry classifications, and data sources in Table 6.

One of the objectives of this research is to investigate the sensitivity of the returns-to-scale estimates to the assumed functional form. Tables 4–6 show them to be rather robust. Holding everything else fixed, the use of the alternative translog form instead of the traditional Cobb–Douglas specification leads to little change in the returns-to-scale estimates themselves and, consequently, to little change in the results of the Wald tests for constant returns to scale. In fact, looking at the broad industry classification, the test results change for 3 (2) industries in the first census when the unit of observation is the aggregate (average) establishment and for 2 (3) industries in the second census (see Tables 4 and 5). A similar picture emerges for the narrow industry classification, where the results change for no more than 7 industries (see again Tables 4 and 5). Moreover, switches are either between increasing and constant or between decreasing and constant returns, never between increasing and decreasing returns.

Holding the functional form constant and comparing the estimates using aggregate establishments with those using average establishments shows that the incidence

Table 5
Returns-to-scale estimates

Broad	Narrow	Industry	Aggregate establishment		Average establishment					
			CD	TL	CD	TL				
1		Textiles	1.00	0	1.01	0	0.98	–	0.98	–
1	3108	Wool processing	1.01	0	1.01	0	0.99	0	0.98	0
1	3280	Hemp processing	0.98	0	0.83	0	1.01	0	0.99	0
1	3283	Cotton processing	1.00	0	0.99	0	0.98	0	0.98	0
1	3288	Linen processing	1.00	0	1.01	0	0.98	0	0.98	0
1	3289	Silk processing	0.98	0	0.98	0	1.00	0	1.03	0
1	3726	Dry cleaning and laundry	1.03	0	1.08	+	1.01	0	1.05	0
1	3727	Mixed or undetermined fibres	0.97	0	0.95	0	0.96	0	0.97	0
1	3901	Other textiles	1.06	0	1.04	0	1.06	+	1.03	0
2		Mining and quarrying	1.14	0	1.22	0	0.99	0	1.15	0
3		Iron and other metals	0.98	0	0.98	0	0.99	0	0.98	0
3	3382	Iron foundries	0.99	0	0.99	0	1.00	0	0.99	0
3	3422	Non-ferrous metallurgy	0.96	0	0.95	–	0.96	0	0.95	–
4		Iron products	1.00	0	1.01	0	1.00	0	1.01	0
4	3169	Nails	0.98	0	0.99	0	0.97	0	0.98	0
4	3192	Cutlery	1.09	0	1.10	0	1.06	0	1.07	0
4	3440	Machines	0.99	0	1.03	0	0.98	0	1.01	0
4	3691	Ironwork, hardware, tools	0.96	0	0.97	0	0.95	0	0.96	0
4	3904	Other iron products	1.00	0	1.02	0	1.00	0	1.00	0
5		Leather	1.02	0	1.01	0	0.99	0	0.99	0
6		Wood products	1.02	0	1.03	0	1.06	0	1.04	0
6	3676	Sawmills	1.04	+	1.03	0	1.04	0	1.04	0
6	3759	Woodwork	0.98	0	1.19	0	1.05	0	0.87	0
7		Glass	0.98	0	0.98	0	1.00	0	1.00	0
7	3260	Earthenware, porcelain, pottery	0.97	–	0.97	0	1.00	0	0.99	0
7	3797	Glass and crystal	1.01	0	1.03	0	1.02	0	1.01	0
8		Chemicals	1.01	0	1.01	0	1.00	0	1.01	0
9		Building materials	1.00	0	1.00	0	0.95	–	0.97	0
9	3355	Binding materials	0.98	0	0.99	0	0.94	–	0.93	–
9	3777	Bricks and tiles	1.01	0	1.01	0	1.01	0	1.01	0
10		Lighting	1.00	0	1.00	0	1.03	0	1.03	0
10	3163	Wax and candles	1.02	0	1.02	0	1.03	0	1.02	0
10	3365	Gas	0.90	–	0.90	0	0.91	–	0.91	0
11		Furniture	1.02	0	1.26	0	1.08	0	1.03	0
12		Clothing	1.03	0	1.05	+	1.03	0	1.02	0
12	3146	Hats	1.04	0	1.06	0	1.00	0	0.97	0
12	3912	Other clothing	1.08	+	1.07	0	1.10	+	1.07	+
13		Food processing	0.99	–	0.99	0	1.01	0	1.02	+

Table 5 (continued)

Broad	Narrow	Industry	Aggregate establishment		Average establishment					
			CD	TL	CD	TL				
13	3082	Breweries	0.98	–	0.99	0	1.00	0	1.03	0
13	3225	Distilleries	1.00	0	1.00	0	1.00	0	1.00	0
13	3400	Oil mills	0.98	0	0.98	0	0.98	–	0.98	0
13	3504	Flour mills	0.99	0	0.99	0	1.00	0	1.01	0
13	3703	Sugar refining	0.98	0	0.98	0	1.00	0	0.90	–
13	3913	Other food products	1.03	0	1.02	0	1.06	+	1.04	+
14		Transport equipment	0.96	0	0.97	0	0.95	–	1.00	0
14	3078	Saddlery and carriage building	0.93	0	0.96	0	0.93	0	1.00	0
15		Paper, printing, pens	1.02	0	1.01	0	1.02	0	1.01	0
15	3408	Printing	1.05	0	1.08	0	1.03	0	0.98	0
15	3550	Paper mills	0.99	0	1.00	0	1.02	0	1.02	0
15	3915	Watchmaking	1.08	0	1.07	0	1.03	0	1.06	0
16		Luxury items	1.04	0	1.11	0	1.04	0	1.05	0

Notes. Returns-to-scale estimates for the French industrial census 1861–1865. The results of a Wald test for constant returns to scale are represented by “+,” “0,” and “–.” “+” (“–”) indicates that constant returns are rejected in favor of increasing (decreasing) returns; “0” indicates that constant returns cannot be rejected.

Table 6
Summary of returns-to-scale estimates

	French industrial census 1839–1847			French industrial census 1861–1865		
	IRS (%)	CRS (%)	DRS (%)	IRS (%)	CRS (%)	DRS (%)
<i>Broad industry classification</i>						
<i>Aggregate establishment</i>						
Cobb–Douglas production function	38	56	6	0	94	6
Translog production function	44	50	6	6	94	0
<i>Average establishment</i>						
Cobb–Douglas production function	50	50	0	0	81	19
Translog production function	50	50	0	6	88	6
<i>Narrow industry classification</i>						
<i>Aggregate establishment</i>						
Cobb–Douglas production function	19	70	11	5	87	8
Translog production function	17	74	9	3	95	3
<i>Average establishment</i>						
Cobb–Douglas production function	32	64	4	8	84	8
Translog production function	30	66	4	5	87	8

Notes. Incidence of increasing, constant, and decreasing returns to scale for various econometric specifications in the French industrial census 1839–1847 (left panel) and 1861–1865 (right panel).

of increasing (constant) returns to scale is lower (higher) with aggregate establishments than with average establishments in both censuses. The incidence of decreasing returns to scale is higher (lower) with aggregate establishments than with average

establishments in the first (second) census. Turning from Table 6 to Tables 4 and 5, in the first (second) census no more than 5 (4) industries switch based on the broad industry classification. For the narrow industry classification, Tables 4 and 5 confirm these observations. In fact, in the first (second) census no more than 7 (7) industries switch.

Next I compare the estimates based on the broad industry classification with those based on the narrow one. In the first census, using broadly defined industries leads to a higher incidence of increasing returns to scale and to a correspondingly lower incidence of constant and decreasing returns. Put differently, returns-to-scale estimates are inflated by the less detailed industry classification in the first census, while the impact of the employed industry classification is unclear in the second census.

Finally, looking across data sources shows a higher (lower) incidence of increasing (constant) returns to scale in the first census than in the second census. The 1861–1865 census provides substantial evidence for constant returns to scale, with no more than 8% of increasing-returns industries. In the first census, in contrast, the share of increasing-returns industries reaches 50% while the share of constant-returns industries falls as low as 50%. In other words, there is evidence for increasing returns to scale in some industries and for constant returns in others.

4.2. Discussion

At first glance, the above results raise further questions rather than providing an unequivocal answer in the debate about nineteenth-century French industry. It appears that a definitive assessment is very difficult to come by through econometric analysis due to the complexity of the factors that affect it. Nevertheless, I am able to make some headway in sorting out the econometric issues. Three conclusions emerge.

(i) Using a broad instead of a narrow industry classification clearly inflates returns-to-scale estimates in the first census. This is consistent with Basu and Fernald's (1997) finding that aggregating over heterogeneous firms increases returns-to-scale estimates. Basu and Fernald (1997) argue that their finding is due to aggregation bias. In contrast, the overall effect of the employed industry classification is ambiguous in the second census.

While the aggregation issues appear to be serious, the above results already offer some clues. The point is that, as a closer look at Tables 4 and 5 shows, the broad industry classification to some extent lumps together the proverbial apples and oranges. The heterogeneity among the establishments within a broadly defined industry may lead to different conclusions depending on the exact specification. For example, the estimates for food processing in the second census range from decreasing over constant to increasing returns to scale; the estimates for its constituent industries (breweries, distilleries, and so on) are much more robust. This suggests that, despite the smaller sample sizes, returns-to-scale estimates using the narrow industry classification are more reliable than estimates using the broad industry classification.

(ii) Results based on data from the first census suggest increasing returns to scale for some industries and constant returns for others, while results based on data from the second census suggest constant returns to scale throughout. This is in line with the results obtained by Nye (1987), who uses data from the second census, but is at odds with Sicsic's (1994) finding of increasing returns to scale in both censuses.

There are a number of factors that may sway the mixed assessment for the first census in one way or another. On the one hand, I have argued before that it is likely that a firm's profit-maximizing behavior induces a positive correlation between inputs and productivity shock, which in turn causes the degree of returns to scale to be overstated. The estimated measures of returns to scale have therefore to be taken as upper bounds on the true degree of returns to scale. In light of this caveat, it seems possible that a more elaborate econometric analysis that succeeds in resolving the endogeneity problem would indicate constant returns to scale not only for the second but also for the first census.

On the other hand, there are two arguments in favor of increasing returns to scale. First, the behavior of the estimation results with respect to the unit of observation is consistent with increasing returns to scale. As I have pointed out in Section 2, returns to scale estimated from aggregate (average) establishments understate (overstate) the degree of returns to scale in the case of increasing returns to scale. The estimation results in Tables 4 and 6 follow this predicted pattern.¹⁰ Second, there is the incomplete coverage of the first census. In particular, the first census omits Paris, where average firm size was small (Sicsic, 1991, Appendix I). The likely omission of small establishments is reinforced by the selection effect that arises from the (partial) exclusion of establishments with fewer than 10 employees from the first census. Assuming that small establishments have not yet exhausted their scale economies, one thus expects the estimated returns to scale to be downward biased in the first census. In other words, the estimated returns to scale understate the extent of scale economies. Which one of the above three considerations dominates is an open question.

(iii) In contrast to the critical roles played by the industry classification and the data source, the functional form plays a secondary role. Nevertheless, as I have already mentioned, the data tend to reject the Cobb–Douglas specification in favor of the more general translog form. I therefore focus in the translog estimates in what follows.

5. Economic implications

Given that there are scale economies, the question is whether a failure to achieve optimal scale was at the root of sluggish economic growth in nineteenth-century France. To answer this question, it is essential to see if a significant portion of

¹⁰ In the second census, by contrast, the estimated returns to scale are much more similar irrespective of whether the average or the aggregate establishment is used as the unit of observation. This is consistent with constant returns to scale and suggests that the presence of collective observations does not seriously distort the results.

French industry was operating under increasing returns to scale and thus left potential scale economies unexploited.

To shed some light on this issue, I proceed as follows. Recall from Section 3 that the translog functional form allows the estimated returns to scale to differ across observations. Using the translog estimates for the narrow industry classification, I test each observation for constant returns to scale. Based on the outcome of the test, I classify the observation as increasing, constant, or decreasing returns to scale. Then I compute the fraction of observations with increasing, constant, or decreasing returns using either the number of establishments or the value of output as weight. This yields the share of establishments that operate under increasing returns to scale as well as the share of output produced with increasing returns.

Table 7 reports the results broken down by broadly defined industries. To better understand the table, consider textiles in the first census. When the aggregate establishment is used in the estimation of the production functions, the left panel of Table 7 shows that 14% of establishments operated under increasing returns and that these establishments produced 15% of the industry output. When the average establishment is used as the unit of observation in the estimation, the shares of establishments and output with increasing returns are 66% and 20%, respectively.

The percentages based on the aggregate establishment tend to be lower than those based on the average establishment in the first census. This parallels my earlier finding that the incidence of increasing returns to scale was lower for aggregate establishments than for average establishments. In the two largest industries, textiles and food processing, there was a strikingly high degree of increasing returns in textiles and a modest degree in food processing. In the third largest industry, iron and other metals, 56% of output was produced with increasing returns to scale. The scale economies in these three industries in turn drive the overall results: between 15% and 23% of total output was produced under increasing returns!

Turning to the second census (Table 7, right panel), it is apparent that the role of increasing returns diminished. In particular, the degree of scale economies in textiles was much lower than in the first census (between 6% and 9% of output in the second census, between 15% and 20% in the first census) and iron and other metals no longer exhibited any scale economies. The main exception is food processing, which continued to exhibit some degree of increasing returns. Nevertheless, in the entire manufacturing sector, between 6% and 9% of output was produced under increasing returns.

In sum, French industry had much less to gain from scale economies in the second half of the nineteenth century than in the first half. The most straightforward explanation that comes to mind is simply that a large part of the manufacturing sector had successfully exploited whatever scale economies were at its disposal by the later part of the century. In fact, as evident from Tables 2 and 3, average establishment size had increased considerably between censuses, notably in some of the large industries.¹¹ For example, the average establishment in textiles grew from 32 to 53 work-

¹¹ Since comparing value measures like output, capital, and materials across time is tricky, I focus on the number of male-equivalent workers.

Table 7
Economic implications

Broad Industry	French industrial census 1839–1847				French industrial census 1861–1865			
	Aggregate establishment		Average establishment		Aggregate establishment		Average establishment	
	Establ. with IRS (%)	Output with IRS (%)	Establ. with IRS (%)	Output with IRS (%)	Establ. with IRS (%)	Output with IRS (%)	Establ. with IRS (%)	Output with IRS (%)
1 Textiles	14	15	66	20	13	9	8	6
2 Mining and quarrying	27	25	33	30	0	0	0	0
3 Iron and other metals	62	56	62	56	0	0	0	0
4 Iron products	2	0	3	1	22	8	3	3
5 Leather	2	0	7	4	2	0	0	0
6 Wood products	0	1	0	1	2	2	19	5
7 Glass	4	39	3	29	3	14	8	6
8 Chemicals	50	94	43	86	3	3	2	2
9 Building materials	4	8	38	25	6	5	11	10
10 Lighting	13	4	18	3	2	1	0	0
11 Furniture	1	2	1	1	0	0	3	3
12 Clothing	1	2	24	2	4	1	20	9
13 Food processing	1	3	17	18	0	7	12	18
14 Transport equipment	0	0	0	0	0	0	4	1
15 Paper, printing, pens	19	16	24	27	0	0	6	3
16 Luxury items	0	0	52	0	2	2	0	0
All	6	15	28	23	4	6	10	9

Notes. Shares of establishments and shares of output with increasing returns to scale for the French industrial census 1839–1847 (left panel) and 1861–1865 (right panel). Based on translog production function estimates for narrow industry classification.

ers, and establishment size in iron and other metals nearly doubled from 51 to 90 workers. In contrast, establishment size in food processing remained largely unchanged (3 versus 4 workers), and this may be the reason why this industry still exhibited some degree of increasing returns in the second census.

6. Conclusions

Were nineteenth-century French firms too small? Previous research has found either constant returns to scale throughout (Nye, 1987) or increasing returns to scale for most industries (Sicsic, 1994). Since firm size is associated with neither gains nor losses if French industry exhibits constant returns to scale, the answer to the above question would be no according to Nye (1987), and yes according to Sicsic (1994). This research sheds some light on the driving forces behind these contradictory results.

Nye's (1987) cost function estimates assume exogeneity of output, which is not a plausible assumption in a competitive environment. Sicsic (1994) estimates returns to scale from value-added production functions, although the appropriate measures of returns to scale are defined in terms of gross-output production functions. Moreover, as I have pointed out, returns to scale estimated from a value-added Cobb–Douglas production function overstate (understate) the degree of returns to scale whenever the underlying gross-output production function is subject to increasing (decreasing) returns. I have addressed these issues by estimating production functions from gross output data. In addition, I have paid special attention to a number of previously ignored econometric issues, including heteroskedasticity correction, collective observations, functional form, and endogeneity bias.

Broadly speaking, my results are in line with those of Nye (1987) but cast some doubt on those of Sicsic (1994). Using data from the second industrial census of 1861–1865, Nye (1987) focuses on the cotton, wool, and flour-milling industries. The results in Table 5 confirm his finding of constant returns to scale in these industries. In contrast, my results, shown in Table 4, are manifestly inconsistent with Sicsic's (1994) finding of increasing returns to scale in glass mills, tanneries, breweries, distilleries, oil mills, and printing for the first industrial census of 1839–1847. His claim of increasing returns to scale in flour mills and paper mills, as well as wool spinning and weaving for the second census, also does not seem to hold up (Table 5). At the same time, my results illustrate that the estimated returns to scale in numerous industries are fairly sensitive to the econometric specification.

While an unequivocal answer in the debate about nineteenth-century French industry is very difficult to come by through econometric analysis because of the complexity of the factors that affect it, several conclusions emerge. In particular, I find that the estimated measures of returns to scale depend critically on the industry classification (broad versus narrow) and on the data source (first or second census).

(i) Using a broad instead of a narrow industry classification inflates returns-to-scale estimates in the first census. This is consistent with an aggregation bias, i.e., the general finding that aggregating over heterogeneous firms increases returns-

to-scale estimates (Basu and Fernald, 1997). In contrast, the impact of the employed industry classification is unclear in the second census.

(ii) Results based on data from the first census suggest increasing returns to scale for some industries and constant returns for others. Reinforcing this mixed assessment is the particular fashion in which alternative treatments of collective observations affect the estimated returns to scale and the selection bias induced by the incomplete coverage of the first census. But if there is an endogeneity bias, then the estimated measures of returns to scale have to be taken as upper bounds on the true degree of returns to scale. In contrast to the first census, results based on data from the second census suggest constant returns to scale throughout.

Assessing the economic implications of the estimated returns to scale, I argue that there were significant unexploited scale economies in the first half of the nineteenth century. But France had little to gain from scale economies in the second half of the nineteenth century. This casts some doubt on the notion that small firm size was at the root of sluggish economic growth, especially in the second half of the nineteenth century. Quite to the contrary, I conjecture that French industry had exhausted most of the scale economies that were at its disposal by the second half of the nineteenth century. This is in line with the fact that France slipped behind gradually, mostly during the later part of the nineteenth century. From this point of view, scale economies must be regarded as an engine of growth rather than a hurdle.

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