Input and Output Market Power with Non-neutral Productivity: Livestock & Labor in Meatpacking*

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Abstract

Market power can be both present in a firm's product and input markets, allowing for supranormal profits in detriment of social welfare. Identification is challenging, however, because it requires to estimate unbiased production elasticities under the interwoven presence of monopsony power and non-neutral productivity. We propose to measure market power in the product market and (possibly) several input markets in a way that is robust to biased technological change and check the inference by assessing how much each market contributes to gross profits of the firm. We illustrate the method with data on the highly concentrated meatpacking industry, suspected of exploiting livestock farmers and immigrant workers. Our conclusion is the presence of competitive prices in the product market and livestock input market, but also that production workers receive only 60% of the value of their marginal productivity.

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1. Introduction

This paper proposes a method to estimate input market power, possibly in several markets, together with the market power in the product market, while controlling for labor-augmenting productivity. Then, it applies the method as an illustration to the meatpacking industry, a concentrated industry often suspected of monopsony power in the livestock and labor markets, as well as product market power, where labor-augmenting productivity has been an issue.

Market power can be both present in a firm's product and input markets, allowing for supranormal profits in detriment of social welfare. Economists seek to measure the degree of this market power in a simple and unequivocal way, and the production approach does so by using production data, without the need to specify and estimate the demand for the products of the firm, and avoiding assumptions on the specific competition game that firms play.[1] Our paper shares this way to proceed. It is an approach at least as old as Bain (1951), that has been recently revived in an intense debate on the evolution of markups and how to measure them in practice.[2]

Interest in the exercise of market power has recently tended to focus more and more the input markets of firms (monopsony power), and firms' ability to set markdowns (proportional difference between the marginal product and the price paid for a

[1] The production approach received a strong inpulse from the proposal for measuring markups contained in De Loecker and Warzynski (2012). An incomplete list of significant applications is: De Loecker, Goldberg, Khandelval and Pavcnik (2016), Brandt, Van Biesebroeck, Wang and Zhang (2017, 2019), De Loecker and Scott (2016), De Loecker, Eeckhout and Unger, (2021); Author, Dorn, Katz, Patterson and Van Reenen (2021).

[2] The debate has comprehended problems of data measurements (Traina, 2018; Basu, 2019; Syverson, 2019), methodology (Doraszelski and Jaumandreu, 2019, 2021; Raval, 2020; Demirer, 2020; Bond, Hashemi, Kaplan and Zoch, 2020; Hashemi, Kirov and Traina, 2022), and outcomes (Jaumandreu, 2022).

factor).[3] Some economists have even asserted that this kind of market power is prevalent, especially in the U.S.[4] Relationships between input and output market power, both in their measurement and effects have become evident, have implications, and a joint approach is quickly developing. Our work joins the simultaneous dealing with input and output market power.

However, a general recognition of the importance of biased technological change, in particular of labor-augmenting productivity, has triggered serious concerns on how productivity and markups are measured when productivity has non-neutral components.[5] For example, the fall of the labor costs in variable cost -determined by labor-augmenting productivity (see below)- can be mixed-up with an increase of revenue with respect to variable costs due to an increase in markups (an increase in prices with respect to costs). Or, since both monopsony power in the labor market and labor-augmenting productivity push down the share of labor costs in variable cost (and the use of labor relative to other variable factors), both phenomena are hard to disentangle raising the risk of misinterpretation and biases.

[3] A "production" approach to the measurement of monopsony power at the same time that product market power starts with Dobbelaere and Mairesse (2013, 2018), although the exercise was tried much before with tightly specified models. The basic method is to compare the FOCs of an input with market power and other without. A series of papers adapt this to the DLW framework: Morlacco (2019), Brooks (2021) and notably Yeh, Macaluso and Hershbein (2022). Rubens (2021) finds nonsustituitability of the affected input and adopts a model for the supply. This literature coexists with more tightly specified micromodels as Lamadon, Mogstad and Setzler (2022) and Berger, Herkenhoff and Mongey (2022). A different literature is approaching markdown modeling and estimation of the process of labor supply to the firms, with suitable microdata: Azar, Berry, and Marinescu (2022).

[4] Yeh, Macaluso and Hershbein (2022) claim that average markdown in wages in the US manufacturing is 53% (and that markups average 21%).

[5] See the discussions in Doraszelski and Jaumandreu (2019), Raval (2019, 2022), Demirer (2020) and Jaumandreu (2022).

The production approach to market power measurement in output and input markets has to address labor-augmenting productivity for consistent inferences. The measurement of market power, defined as price over marginal cost, requires to grasp the non-observable marginal cost. And, for this purpose, production elasticities of the inputs (under cost minimization) are key, because they allow to recover marginal cost from observed data. For example, De Loecker and Warzynski (2012) proposed the current popular approach to estimating market power that compares the elasticity of a variable input with its share in revenue. Or, in this paper, it plays a prominent role the fact that the short-run elasticity of scale (sum of elasticities of variable inputs) equals the ratio marginal cost to average variable cost. Since monopsony power and labor-augmenting productivity are the two factors that are recognized to impact the estimation of the elasticities, they need to be fully controlled for.

With monopsony power in an input market the firm restricts the use of the input, and the elasticity of the variable factor shows a disproportionate gap with respect to the share of the input in variable cost. Estimated elasticities should account for this gap, and this challenges estimation. The control for unobserved neutral productivity becomes more difficult,[6] and the "collinearity" problem traditionally associated with the variable inputs doesn't look as the adequate context for reaching in estimation this kind of precision.[7] This suggests rather to explicitly account for the gap when elasticities are estimated, in the spirit of Dobbelaere and Mairesse (2013). In fact, the researcher is likely to be interested as well in knowing the degree of input market power, and it seems natural to estimate the gap at the same time that is controlled

[6] As recognized by Rubens (2022), the demand for any variable input subject to market power contains a new unobservable violating the "scalar unobservable assumption" of an Olley and Pakes (1996)/Levisohn and Petrin (2003) method to control for productivity.

[7] See Ackerberg, Caves and Frazer (2015) for the collinearity or functional dependence problem. As it is well known, collinearity makes difficult to estimate separately the effects of the collinear variables See, for example, Goldberger (1991).

for.

With labor augmenting productivity, there is nothing special about the level of the elasticity -the production elasticity of the input in terms of efficiency is the same that the in terms of the raw quantities of the input-, but the evolution of productivity will bring down the elasticity of the input when the elasticity of substitution among variable factors is less than unit.[8] When labor-augmenting productivity is present, no elasticity can be consistently estimated without taking this into account. The researcher faces two challenges: specify the varying elasticities and account for the evolving unobservable efficiency that modifies the quantity of labor that is relevant in estimating the production function.

We propose a method that simultaneously addresses these difficulties. It consists of estimating the elasticities of the production function including the relevant market power parameters, possibly in several markets, while allowing these elasticities to change with labor-augmenting productivity. It is a straightforward method that simply considers the relationships that input and output market power, together with labor-augmenting productivity, induce among the expressions for the elasticities of the variable factors obtained from the FOCs. In practice we estimate the short-run elasticity of scale corresponding to such elasticities, at the same time that the monopsony proportional markdowns of the relevant markets. Using these markdowns, together with production observables, we can compute market power in the product market and decompose the profitability of the firms into its components.

Hall (1988) started the tradition of writing Solow's (1951) share approximation to

[8] With the elasticity of substitution less than unity the share of labor in variable costs is a negative function of labor-augmenting productivity (Hicks, 1932). For the elasticity to fall, it is sufficient that the short-run elasticity to scale is not increasing in labor augmenting productivity. In practice the labor shares are documented to be falling everywhere. For the US manufacturing plants see Kehrig and Vincent (2021). On all this see Jaumandreu (2022).

elasticities in terms of the markup times the revenue shares, to account for imperfect competition. Klette (1999) used this specification to measure productivity and markups, and De Loecker and Warzynski (2012) propose using Hall's identity to solve for the markup (this leaves apart how the elasticity is estimated). We depart from this tradition by using instead the short-run elasticity of scale times the cost shares, and only then computing the markup from the elasticity of scale.

We apply the method to the meatpacking industry. The industry has been the center of controversy and the object of intensive research. Dominated by a small number of firms (currently four), and with a high concentration of the productive activity at the plant level, it has been suspected of exercising market power in the product market, monopsony power in the market for its input livestock, and of keeping poor work conditions for its workforce.[9] The latter suggest the presence of monopsony power in the labor market. Waiting for the availability of firm-level data, we apply our model as an illustration to the industry data.[10] In part because of its simplicity, the model works remarkably well, and we are able both to reject the hypothesis of non-competitive pricing in the product and livestock markets, as fail to do so in the labor market. Workers are estimated to perceive 60% of their marginal productivity.

In whole, we think that the paper makes six incremental contributions to the literature. First, it crafts a novel proposal for the joint assessment of market power in the product and (possibly several) input markets in the context of the production approach to market power measurement, that is, measurement without specifying the demand for the product of the firms or the supply for the inputs, and no restriction about how competition is in these markets. Second, the method constitutes an alternative way to the classical approach by Hall (1988), Klette (1999) and De

[9] The effects of the Covid 19 pandemic raised concerns about the working conditions. See Congress of the United States (2021).

[10] Two of the authors are at the end of the process of application for the special sworn status that allows researchers to access the confidential Census data subjet to the usual nondisclosure rules.

Loecker and Warzynski (2012) for the measurement of market power. It hinges on the measurement of the short-run elasticity of scale in production as the way to get the relationship between (unobserved) marginal cost and (observed) average variable cost. Third, the method is developed for an environment in which labor augmenting productivity is present and maybe even prevalent. To our knowledge, it is the first time that a procedure is developed that is consistent with biased technological change. Fourth, the paper shows the different effects on the firm input demands of an exogenous variation in factor-augmenting productivity and in monopsony power for the same input, establishing how the corresponding unobservables map in different observed relative behaviors and hence can be identified. Five, it derives an observed profitability bound for the sum of market power contributions to profits in addition to the contribution of technology. This bound is met by the proposed estimates and can be used as a natural test for checking the coherency with the observed data of any alternative market power measurement. Six, it formally explores for the first time the labor market of the meatpacking industry and establishes that it is monopsonistic.

The rest of the paper is organized as follows. Section 2 presents the model and section 3 discusses identification. The empirical exercise in the meatpacking industry is carried out in section 4. Section 5 decomposes profitability and addresses the difference between our estimator and other estimators of market power in the product and labor markets. Section 6 concludes. Appendix A is dedicated to identification and a Data Appendix describes the construction of the variables and other details.

2. Model

Let us consider a first order approximation in logs to the unknown production function of each firm $Q = F(K, R, \exp(\omega_L)L, M)\exp(\omega_H)\exp(\varepsilon^*) = Q^*\exp(\varepsilon^*)$, where ω_L and ω_H are persistent unobservables representing labor-saving and Hicks-neutral productivity, respectively, and ε^* is a serially uncorrelated error. The approximation can be written

$$q = \beta_0 + \beta_K k + \beta_R r + \beta_L(\omega_L + l) + \beta_M m + \omega_H + \varepsilon, \quad (1)$$

where q is quantity of meat, β_X are the elasticities of the inputs K, R, L and M, representing in turn capital, livestock, labor and materials, and we write ε to acknowledge the expansion of the error ε^* with the residual of the approximation. We often write the model in terms of "efficient labor" $l^* = \omega_L + l$.

We want to stress that the approach to the production function allows the elasticities to be firm and time specific. We will impose later the equality across firms and time of (only) the long-run and short-run scale parameters (and implicitly of the fixed input capital).[11]

We stay agnostic with respect to how is competition in the product market, where we consider without loss of generality that the firm has an unspecified amount of market power (firm maximizes profits by equating marginal revenue and marginal cost). We assume that the firm minimizes costs in the short-run (cost of the variable factors R, L and M). It happens that two of the input markets, the markets for livestock and labor, are possibly monopsonistic, so we want to allow for the potential presence of input market power. We do this by specifying the presence of a percentage gap between the marginal productivity and the price of the corresponding input, popularly known as "markdown".[12] We write ρ and τ for the markdowns in the

[11] We will also take the costant as a comon parameter We can do this simply by including all deviations from the comon constant in the residual.

[12] Markdowns are often interpreted as the inverse of the elasticity of supply of the factor. However, this is only what corresponds to a market with non infinetely elastic supply of the input and Bertrand input demand behavior on the side of the oligopsonists. We do not need to abide for any particular specification of the monopsonistic behavior. On the other hand, the model is general enough to cope with all other possible contents and even different signs of the parameter as discussed in Dobbelaere and Mairesse (2018). For example, rent sharing because collective bargaining with powerful unions may result in a negative gap between productivity and wages.

livestock and labor market, respectively. First order conditions for cost minimization are then

$$\begin{aligned} MC\frac{\partial Q^*}{\partial R} &= (1+\rho)P_R, \\ MC\frac{\partial Q^*}{\partial L^*}\exp(\omega_L) &= (1+\tau)W, \\ MC\frac{\partial Q^*}{\partial M} &= P_M, \end{aligned}$$

where MC represents marginal cost and P_R, W and P_M are the prices of livestock, labor and materials respectively.

It is easy to see that, multiplying each equation by X/Q^* and re-arranging, they can be re-written as $\frac{X}{Q^*}\frac{\partial Q^*}{\partial X} = (1+a_X)\frac{AVC}{MC}S_X$, $a_X = \rho, \tau$ and 0, where $\frac{X}{Q^*}\frac{\partial Q^*}{\partial X} = \beta_X$, and S_X is the share of the input in variable cost. Notice that the elasticity of labor and "efficient labor" are the same. Define $\nu = \beta_R + \beta_L + \beta_M$, the sum of the elasticities of the variable inputs, as the short-run elasticity of scale. It happens that $\nu = \frac{AVC}{MC}(1 + S_R\rho + S_L\tau)$ and we can write $\frac{AVC}{MC} = \nu/(1 + S_R\rho + S_L\tau) = \nu^*$. Using this relationship and notation, cost minimization implies the following (nonlinear) expressions for the elasticities

$$\begin{aligned} \beta_R &= \nu^*(1+\rho)S_R, \\ \beta_L &= \nu^*(1+\tau)S_L, \\ \beta_M &= \nu^* S_M. \end{aligned} \tag{2}$$

We choose to express the production elasticities in terms of the (modified) elasticity of scale and shares in variable cost. We hence take an alternative route to Hall (1988), Klette (1999) or De Loecker and Warzynski (2012). As in these papers, we could use $\beta_X = \mu(1+a_X)S_X^R\exp(\varepsilon)$, where $\mu = \frac{P}{MC}$ is the markup and S_X^R the (observed) share of input cost in revenue. But this would introduce two problems: the need to directly cope in estimation with the presumably highly varying unobservable markup μ, and the presence in the expressions of the unobservable error ε. Instead, we deal with the short-run elasticity of scale parameter ν, that we assume it can be safely take as constant, and our expressions do not involve error.

Let R and VC denote revenue and variable cost. Notice that

$$\frac{R}{VC} = \frac{PQ}{AVCQ^*} = \frac{PQ}{\nu^* MCQ^*} = \frac{\mu}{\nu^*} \exp(\varepsilon^*), \tag{3}$$

where the second equality uses our above definition of ν^*.

Expression (3) has at least two important consequences. First, from this expression we can get the (log) markup in terms of ν^*, revenue and variable cost as

$$\ln \mu = \ln \nu^* + \ln \frac{R}{VC} - \varepsilon^*,$$

up to the production function error ε^*. The effect of the error will tend to cancel in mean across enough observations (consistency).

Second, observable gross profitability defined as $\ln \frac{R}{VC}$ (that is readable as a percentage) can be decomposed into the parts due to technology and market power of the firm, across the product and the input markets:

$$\ln \frac{R}{VC} = -\ln \nu + \ln \mu + \ln(1 + S_R\rho + S_L\tau) + \varepsilon^* \simeq -\ln \nu + \ln \mu + S_R\rho + S_L\tau + \varepsilon^*, \tag{4}$$

where in the second approximate equality we split the contributions of each input market power.

Notice that all terms in the decomposition are likely to be positive. Parameter ν is a short-run elasticity of scale that we expect by economic theory to be less than one. The markup is expected in general to be non-negative because price below marginal cost only can be a short-run dynamic optimizing solution under cost of adjustment of prices.[13] Monopsonistic power implies non-negative markdowns. So the value $\ln \frac{R}{VC}$

[13] See Jaumandreu and Lin (2018).

sets an upper bound to the sum of market power profitability effects (markup and markdowns). Note that this upholds, from a new point of view, the measure that Bain (1951) used to measure market power ($(R-VC)/R$).

Equations (2) mean that we can specify the approximation to the production function (1) in terms of a few parameters to be estimated. We do this rewriting first the production function to estimate directly the log-run parameter to scale $\lambda = \beta_K + \beta_R + \beta_L + \beta_M$. We take both parameters of scale λ and ν as constants, but note again that the individual elasticities β_R, β_L and β_M are not necessarily so. Model is

$$\begin{aligned} q &= \beta_0 + \lambda k + \beta_R(r-k) + \beta_L(l^* - k) + \beta_M(m-k) + \omega_H + \varepsilon, \\ &= \beta_0 + \lambda k + \nu^*[S_R(r-k) + S_L(l^*-k) + S_M(m-k)] \\ &\quad +\nu^* \rho S_R(r-k) + \nu^* \tau S_L(l^*-k) + \omega_H + \varepsilon. \end{aligned} \tag{5}$$

In terms of sample notation, indexing firms by j and time by t

$$q_{jt} = \beta_0 + \lambda k_{jt} + \nu^*_{jt} S_{SUMjt} + \nu^*_{jt} \rho S_{Rjt}(r_{jt} - k_{jt}) + \nu^*_{jt} \tau S_{Ljt}(l^*_{jt} - k_{jt}) + \omega_{Hjt} + \varepsilon_{jt}, \tag{6}$$

where

$$\begin{aligned} S_{SUMjt} &= S_{Rjt}(r_{jt} - k_{jt}) + S_{Ljt}(l^*_{jt} - k_{jt}) + S_{Mjt}(m_{jt} - k_{jt}), \\ l^*_{jt} &= \omega_{Ljt} + l_{jt}, \\ \nu^*_{jt} &= \nu/(1 + S_{Rjt}\rho + S_{Ljt}\tau). \end{aligned}$$

The parameters to estimate (in addition to the constant) are λ, ν, ρ and τ. In turn, we can use these parameters to estimate μ_{jt} and compute the profitability decomposition. Of course to take equation (5) to the data we need to decide how we treat unobserved productivity ω_{Ljt} and ω_{Hjt}. But this is a more standard problem that we leave for the next section.

The model is very general in that, given a sample of firms, only requires equality across firms of the long-run and short-run elasticity of scale and the markdowns. Individual elasticities of the variable inputs can change over time and across firms, in a useful generalization of the Cobb-Douglas specification.

The estimation of the production function identifies the scale elasticities and the gaps between marginal productivity and input prices in two markets. Identification of monopsony power is possible because the individual output elasticities are modified by the presence of market power in the input market. This requires, however the presence of at least one input market that is competitive. Intuitively, we need at least one market in which the elasticity equals the observed share times the scale parameter to disentangle in estimation the scale from the gaps.

The estimation of the short-run elasticity of scale allows us to estimate also, up to a zero-mean error, the (log of the) price-marginal cost ratio or markup for every firm and moment of time. Average product market power estimates are hence consistent, and the presence of market power in the product market is assessed at the same time that monopsony power has been assessed in any number of input markets (but not all). No assumptions on the behavior of the firm in the product or input markets are needed, only cost minimization is assumed.

3. Identification

The model in equation (5), even if the productivity unobservables ω_L and ω_H are zero, is nonlinear in parameters and variables. It must be estimated by a procedure as nonlinear GMM, that it is what we later do. When unobservable productivity is non-zero, the consistency of the estimation depends on the appropriate control for it. In fact, unobserved productivity, and in particular labor-augmenting productivity, are likely to strongly impact the estimation of the elasticities and hence all the inference about market power (recall that the monopsony power parameters are a component of the elasticity). For example, labor-augmenting productivity, given relative prices, is expected to be negatively correlated with labor and positively with material inputs (see below). If we do not control for ω_L, we are likely to get a positive bias in the estimation of the elasticities of materials and a negative bias in the elasticity of labor.

Hicksian productivity ω_H enters the equation additively and hence, assuming that it follows a linear Markov process, can in principle be estimated by using pseudo-differences of the nonlinear model. This sort of estimation is a generalization of what has been commonly applied in the estimation of production functions under the name of "dynamic panel".

Another method, in the tradition of Olley and Pakes (1996) and Levinsohn and Petrin (2003), would be replacing ω_H by the inverted demand for an input. This method seems more problematic in that it needs to give a solution to the unobservability of marginal cost in the FOC or FOCs used to derive the input demand, and to the presence of the input market power unobservables.

Labor-augmenting productivity ω_L has been typically replaced by expressions in terms of observables based on the ratio of the FOC for labor and a materials input. Given the unspecified form of the production function, the most adequate would be the use of the log linear approximation derived in Doraszelski and Jaumandreu (2018) for any function that is separable in capital. For example, assuming a zero constant, we could use

$$m - l = -\sigma(p_M - w) + \sigma\tau + (1-\sigma)\omega_L,$$

where σ is the elasticity of substitution implicit in the production function. Notice that the presence of the parameter of labor monopsony power complicates a little the approximation.

In what follows, given the scarcity of the data, we need to drastically limit ourselves. Fortunately for the exercise, neutral productivity seems virtually non-existent and we can test for this fact. Labor-augmenting productivity, however, seems to be very important and we adopt a simple procedure for testing its effect: an a-priori specification of the increase of the labor efficiency.

Leaving aside the question of how to control for the unobserved productivity, we need valid moments enough to identify the four parameters to be estimated from equation (4). In the absence of a persistent neutral productivity term, it seems natural to consider that inputs can be contemporaneously correlated with the productivity shocks encompassed by ε. Capital, under the usual assumption that it results from the investment decided in past years, can be taken as uncorrelated with the shocks. For livestock, labor, and materials, we can consider at least two types of instruments: lagged values of the input quantity, uncorrelated with the shocks given the absence of persistency, and input prices that can be considered exogenous for the firm. We continue this discussion in practical terms when we list the instruments that we use.

In any case, an important question seems to linger. Can we identify monopsony power separately from labor-augmenting productivity? The question shows up because labor-augmenting productivity introduces in the first order condition for labor an unobservable in a very similar way that monopsony power does (see the second expression of equations (2)). Even if we substitute an expression for the unobservable ω_L, separating it from the effects of the markdown ρ, how are we sure that these two effects can be neatly distinguished?

To consider the answer to this question, in Appendix A we look in detail at the effect in our cost minimizing firm of an exogenous increase in labor-augmenting productivity and an exogenous increase in monopsony power. We assume, without loss of generality, that ω_L and τ increase from an initial zero value to a positive value. Caeteris paribus, both effects give incentives to the cost minimizing firm to diminish employment. To facilitate the comparison of results, we consider that the increase in labor-augmenting productivity and monopsony power are such that the firm adopts in each case the same new ratio materials to labor.

The outcomes are as follows. An exogenous increase of labor-augmenting productivity induces the cost minimizing firm to reduce both labor and materials, but proportionally more labor. As a result, the share of labor in variable cost S_L is reduced. In addition, the productivity improvement implies that MC decreases. On the contrary, an exogenous increase in the monopsony power induces the firm to contract labor at the same time that it expands materials. If the firm adopts a proportion of material over labor that matches the case of an ω_L increase, it reaches the same share of labor in variable cost S_L. However, now MC increases. The different behavior of MC implies that the firm has incentives to further move in different directions: expanding output in the case of a productivity increase, and contracting output in the case of the increment in monopsony power, expanding or contracting both inputs in the same proportion.

4. An illustration from the meatpacking industry

We illustrate how the model works by applying it to the meatpacking industry. Some background on this industry follows, as well as a few descriptive statistics. Then, we estimate the production function and show how, in order to obtain the correct elasticities of the inputs, it is crucial to allow both for the possibility of monopsony power and to specify labor-augmenting productivity. Next, we infer the market power in the output market by using these estimated elasticities together with the observed data. Finally, we show how the profitability of firms decomposes in its sources: technology and market power in input and output markets.

The meatpacking industry

The meatpacking industry consists of the activities of slaughtering, processing, packaging, and distribution of meat from animals such as cattle, pigs, sheep and other livestock (poultry is in general not included). Activities are carried out in plants of very different size, but the bulk of those activities is concentrated in a few plants of huge size. For example, in 2021, there were 726 beefpacking plants of which 12 plants slaughtered more than 1 million heads each accounting for 50% of all cattle slaughter. Similarly, there were 645 plants dedicated to pork, from which 14 plants slaughtered more than 4 million heads each accounting for almost 60% of hogs slaughtering. And 534 sheep and lamb plants, from which 13 plants slaughtered more than 25,000 heads each, accounting for 65% of sheep slaughtering (USDA NASS 2022).

The activity is still more concentrated at the firm level, with a few companies operating several plants. In 2019, four big producers (Tyson, Cargill, JBS and National Beef) slaughtered 85% of all cattle, 67% of hogs and 53% of sheeps and lamb (USDA AMS 2020). Concentration increased sharply from 1960 to 1990, when plant size growth and plants moved from the Midwest and Northern Great Plains to the Southern Great Plains, and more slowly afterwards. The four-firm concentration ratio (CR4) in beef processing increased from 41% in 1982 to79% in 2006, and has since the remained more or less stable. Similarly, the CR4 for pork processing increased from 36% to 63% in the same period.

Packer conduct has been traditionally an object of concern in two markets, the market for livestock and the labor market. Cattle feeding is concentrated in specific areas: Great Plains, and parts of the Corn Belt, Southwest and Pacific Northwest regions. Cattle feeding operations are size heterogeneous, but far from unconcentrated. For example, feedlots with 1,000 head or greater are less than 5% but they market 80-85% of fed cattle, and feedlots with a capacity of 32,000 head or more market about 40% of fed cattle. The concentration in meatpackers, the complaints of the livestock producers and the proliferation of alternatives to the spot market (marketing and production contracts...) has induced worries about the competitiveness of the market. There have even been suggestions for treating the livestock market as a bilateral oligopoly.

The industry also has a long history of controversy over its labor practices. Increasingly located in rural areas, the industry exhibits a work force composed of low skilled workers including higher than average proportions of immigrants, refugees, and people of color with who have fewer options. Working conditions are famously known to be very poor. Controversy about the industry labor practices raged during the onset of the Covid-19 pandemic. At least 59,000 meatpacking workers were infected and 269 died (Congress of the United States, 2021).

The literature on competition in the industry is vast. Azzam (1998) reviews the literature from 1960s through the 1990s and Wohlgenant (2013) through the 2010s. The literature focuses exclusively on cattle and beef pricing, and the additional question is invariably if there is oligopsony in livestock markets.[14] To the authors' knowledge, there are no studies of oligopsony power in meatpacking labor markets. As summarized by Wohlgenant (2013), the takeaway from the existing literature is that, despite the different empirical approaches, there is no evidence of the exercise of significant market power either in the market for "packed meat," or in the input market for livestock. Wohlgenant (2013) stresses, on the contrary, on the evidence on lower processing and distribution costs due to cost savings from reorganization, technical innovation, and increased plant size.

The quality of the product (meat) may in fact have being increasing during the period, what can be seen as a part of technological progress that we cannot model properly with our limited data. At the beginning of our sample period, most meatpackers shipped carcasses for further fabrication by wholesalers and retailers. Pro-

[14] A first study by Schroeter (1988) finds no evidence of serious price distortions in the meatpacking industry; Azzam and Pagoulatos (1990), address simultaneously oligoply in meatpacking and oligopsony in livestock, concluding with moderate evidence of market power, greater in the input market; Morrison (2001) finds evidence of cost economies but not of market power.

cessed products, cut, prepared, and packed, known as "boxed beef," were only 10% of the shipments. Before 2000, they had already reached 50% (MacDonald and Ollinger, 2005).

Descriptive statistics

Table 1 reports a few descriptive statistics for the whole period 1970-2018 and selected subperiods. The industry output, measured in pounds of meat, has grown by slightly less than 40% in the almost fifty elapsed years. The livestock input, measured in pounds, has followed very closely the evolution of output. We next report the evolution of capital, that has outgrown the evolution of output, and labor (measured in total production hours), that has tended to stay remarkably stable. The output materials, with slightly noisier data, follows next. The evolution of the indices for capital, livestock, and labor, detailed in Graph 1, suggest some substitution over time of capital for labor, what matches well the reports on technological progress and is likely to be one of the sources of labor-augmenting productivity. Based on this input-output behavior we test below for the absence of Hicks-neutral productivity and confirm the importance of productivity that affects specifically the labor input.

The fifth line of Table 1 reports the industry hourly wage. Despite lagging on the evolution of wages in the rest of manufacturing, it more than doubles during the period (in fact it quadruplied its value between the two extreme observations, from \$4.301 in 1971 to \$19.704 in 2018). This implies a faster growth than the price of livestock and other materials, but the shares of all three variable inputs in total variable cost have been notably stable. This can also be checked in Graph 2. Under an elasticity of substitution smaller than unity, the evolution of the relative prices had to imply an increase in the labor share in costs. The fact that this has not happen, strongly suggests that labor-augmenting productivity is pushing this labor share down (or moderating its increase). The detail of the labor share in Graph 3 suggests in addition that labor-augmenting productivity could be particularly important in the first part of the period.

The bottom of Table 1 reports the input shares in revenue. In fact, they only diverge from the input shares in variable cost by the ratio revenue over variable cost, reported in the last row of the table. This ratio shows a relatively significant increase over time of the profitability of the firms, from 7 to 15 percentage points. Graph 4 shows that an important part of this increase takes place in the last 10 years.

Estimation of the production function for meatpacking

Our model is designed to be applied to firm-level data. It only requires the firms to have common long-run and short-run elasticities of scale and the same level of input monopsony power, allowing the elasticities of the non-capital inputs and market power to vary across firms and time. However, we only have industry-level data and the production function needs to be fitted assuming that there exists a meaningful production function at the industry level. Although this can possibly induce biases, we do not anticipate any inference that can be particularly wrong due to this motive.

Much more worrying is the scarce number of observations that this makes available, just 49 year observations from 1970 to 2018. If firm-level observations were available, we would be able to multiply the 49 years by the number of firms -or better, establishments- and rely in all the variation present across them. Although we try to be very parsimonious in the specification, we are consciously estimating the model with a too-small sample. Although estimation results turn out to be very good, efficiency is low and the power of tests mild. We have carried the exercise as far as possible as a preparation to apply the model to firm-level/establishment data when we can access them.

We start estimating a conventional Cobb-Douglas production function by OLS. All variables are in logs. The quantity of processed beef, measured in pounds, is regressed on a constant, real capital, k, the quantity of livestock measured in ponds, r, the number of hours by production workers, l, and the deflated value of materials, m. We add as a control the dummy variable called cycle (cattle has a known cycle, averaging 8-12 years, that impacts available quantity). The descriptive statistics do not indicate that there is any increase in the productivity of all factors simultaneously and, in fact, the inclusion of a time trend to account for such a neutral increase turns out to attract a zero coefficient and we drop it. The elasticities β_K, β_R, β_L and β_M are reported in column (2) together with their (robust) standard errors. The implicit short-run and long run parameters of scale are 0.862 and 0.988 respectively.

The absence of a persistent Hicks-neutral productivity term doesn't imply that input endogeneity is absent.[15] The current choices for the quantities of the variable inputs may be correlated with transitory productivity shocks embodied in the serially uncorrelated error term. To reach consistency in this eventuality we use instruments based on the lagged choices of the inputs and on a presumably exogenous price (corn). In all the rest of the exercise we use 8 instruments to estimate 6 parameters. These instruments are the constant, time trend, capital lagged, livestock lagged, share of labor in variable cost lagged, price of corn lagged, the cycle variable, and the proportion that wages of the production workers are of the total wage bill, lagged. The last instrument accounts for cyclical utilization of capacity. The IV estimation of the CD specification, reported in column (3), raises the elasticities of capital, labor, and materials. The implicit short-run and long run parameters of scale are now 0.903 and 1.075 respectively.

The generalization of the CD production function, allowing for varying coefficients and modeling the elasticities of livestock and labor as depending on a parameter measuring input market power, changes things quite radically. The results are reported

[15]The usual specification of the production functions includes the correlated transitory productivity shocks in the Markovian specification of unobserved productivity.

in column (4). None of the input market power parameters is statistically significant, but the short-run and long-run elasticity of scale increase significantly, with all elasticities except labor raising importantly. We interpret that we have advanced a step in a right direction but something remains underspecified. There is a clear sign that the estimation is biased: the implicit average markup is evaluated at 0.890, a negative percentage markup of about -11 percentage points.

Everything indicates that what we miss is the operation of labor-augmenting productivity. The estimate of column (4) produces an strangely high elasticity of livestock and a comparatively too low elasticity of labor. This is exactly the type of bias that one expects from the omission of labor-augmenting productivity. In addition, we have given reasons in the descriptive part for expecting this type of productivity being important: the stability of the labor share in variable cost when prices evolve in a way that should induce an increase.

With enough data observations, we would adopt a procedure to substitute an expression based in the FOC of the variable inputs for the unobservable labor-augmenting productivity. However, we are at the limit of the number of parameters that can be sensibly estimated. So, we adopt an extremely simple procedure based in what we observe in the data: we increase the observed labor by means of a trend that augments it yearly in "efficiency" terms by 2 percentage points. The resulting estimation, that embodies labor-augmenting productivity at the same time that allows for input monopsony power, is reported in column (5).

The results are very good. The short-run and long run parameters of scale are estimated 0.960 and 1.185 respectively, very sensible numbers. The parameter of monopsony power in the livestock market is virtually evaluated at zero, and the parameter of monopsony power in the labor market is significant with probability value of 6%. The markdown parameter value (0.666) implies that workers perceive 60% of the labor marginal productivity. The mean elasticities for the inputs look perfectly reasonable and market power in the product market is evaluated as virtually nonexistent (average percentage markup is 2.4 percentage points). A Sargan test of the specification strongly accepts it, giving a positive indication of validity of the instruments.

Since monopsony power seems inexistent in the livestock market, we reestimate the model imposing the restriction that the parameter of monopsony power of this market is zero. A Chi-square test strongly accepts the imposition of this restriction. If we similarly test the imposition of zero coefficient for the monopsony parameter in the labor market we tend to obtain a significant rejection. Column (6) reports the estimates of the parameters in the restricted model. Efficiency is slightly improved and the monopsony parameter estimate for the labor market has now a probability value of 4.6%. We use this estimate to draw our conclusions.

5. Decomposition of profitability and relation to other measures

The determinants of profitability

We use equation (4) to explore the determinants of profitability in Table 3. Mean profitability in the whole period of almost 50 years is moderated, about 10%. An important part of this profitability comes from technology, more specifically the fact that marginal cost lies in equilibrium about 4 percentage points above average variable cost. Market power in the product market adds very little to this, only 1.5 points, since the markup is very close to the unit value expected under perfect competition. The market power in the labor market adds to profitability, however, an amount so important as technology does. The fact that production workers are paid only 60% of the value of their marginal productivity implies, although the share of labor in variable cost is relatively small (an average of 6%), a contribution to profitability of a little more than 4 percentage points.

The detail by periods shows that profitability has risen, in particular in the latest ten years, where it increases more than 3 percentage points (the same than in the previous almost 40 years). The decomposition says that the origin of this increase is clearly the increase in the markup, that is, the prices charged by the firms in relation to marginal cost because of the exercise of more market power. The power in the labor input market, on the contrary, has tended to stay stable over the years.

Relationship with other measurements

The reader who has followed with detail the derivations in section 3, is likely to have a question. What the popular measurements of DeLoecker and Warzynski (2012) and Yeh, Macaluso and Hershbein (2022), for product and input market power respectively, would they give if applied to the estimated equation (6), were we draw the conclusions? Let's call them in this section DLW and YMH respectively. The short answer is that, if applied, they would give the same (numerical) results that we have obtained. So we are perfectly in agreement with the DLW and YMH measures in its application to this particular market. However, this is not a proof of the validity of these two measures but just of their incompleteness: these measures are only able to give the same answer that us if applied to the production function estimated in the way that we have done. Otherwise they produce senseless measurements that are in general incompatible between them.

A rough way to check the agreement is to compute these measures from the means reported in the tables (instead of the right way to do it, that would be averaging the values obtained with the un-averaged data). Take first equation (6). Start by the DLW measurement of market power, that consists of the elasticity for a variable input divided by its revenue share β_X/S_X^R. [16] If you divide the elasticity of livestock

[16] We put aside for simplicity the correction of the observed output with the estimated error for the equation. This is likely to determine only minor differences.

by its share in revenue you get an estimate of the markup equal to 1.015, with the elasticity of materials divided by the share in revenue an estimate equal to 1.016 and, with the elasticity of labor divided by the share in revenue and the markdown ratio estimated for the labor market, an estimate equal to 1.012. Our estimate for market power in column (6) is just 1.016. Despite the rounding imprecissions the numbers are always very close.

YMH propose to measure the markdown by dividing the ratio of elasticities of an input with monopsony power to an input without, by the ratio of shares in cost say, $\beta_X/B_Z/(S_X/S_Z)$ (since the denominator is a ratio it doesn't matter if shares are in variable cost or revenue). When we apply this measure to our average numbers for labor and materials we get 1.656, a number very close to our 1.663 estimate.

What is happening? It is quite subtle but simple to interpret. Our estimation imposes theoretical relations with which DLW and YMH are compatible. In fact, it estimates the elasticities from these theoretical restrictions as embodied in the FOCs of the problem. What differs from DLW and YMH is that their measures rely in the abstract estimation of an ideal elasticity that we do not have any way to carry out. Let us see in practice how and why they fail.

There is no point in repeating the above calculations with the estimates in column (4) because we know that the measures are going to coincide, and we have diagnosed that there is something wrong that determines a negative average markup of of -11 percentage points. But, we can apply DLW and YMH to equation (5). This is a standard IV-estimated CD production function as are used in many exercises. The livestock and labor elasticities give DLW markup estimates of 1.192 and 1.250 respectively, a huge estimate of market power for a market that seems not to have none, and a ridiculously negative market power when one uses materials. The YMH index, on the other hand, skyrockets to a nonsensical value (5.671). The positive DLW estimates of the markup already violate by themselves our profitability bound (recall that average profitability is about 10%), so there is no point in trying a precise calculation of the components.

The problem, in a nutshell, is the following. If you divide a parametrically estimated elasticity by a share that is in fact an observable component of this elasticity, you are likely to get something that is basically a measure of your imperfections in measuring the scale elasticity. The problem would disappear if we estimated an infinite parameter-dimensional (nonparametric) elasticity, that is something that we cannot do. A feasible alternative is to focus, as we do, in the estimation of a sensible elasticity of scale, and let the shares to complete the estimation of the elasticities.

6. Concluding Remarks

Model can be seen a little restrictive in that it considers the equality across firms of the main parameters that are estimated: long and short-run elasticity of scale and markdowns. In fact, the model can be easily generalized to account for variation of these values. First, the elasticity of capital can be specified as varying acros the sample, and hence the long-run elasticity of scale left unrestricted regardless of what is the specification for the short-run elasticity of scale. Second, the markdowns can be estimated as a function of firm or market-level observables that are likely to impact the labor supply elasticity in the labor market or any other relevant variable in other cases. Third, the short-run elasticity of scale is a function of the inputs and the unobservable labor-augmenting productivity. Under appropriate restrictions of the latter dependence, it can be modelled as a varying function across the sample and time.

Appendix A

Let us examine in turn, with the help of the Figure, what happens to the equilibrium of a short-run cost minimizing firm that experiences: 1) an increase in its labor-augmenting productivity, and 2) an increase of its monopsony power. We assume, without loss of generality, that ω_L and τ increase from an initial zero value to a positive value. Caeteris paribus, both effects give incentives to the cost minimizing firm to diminish employment. To facilitate the comparison of results, we consider that the increase in labor-augmenting productivity and monopsony power are such that the firm adopts in each case the same new ratio materials to labor.

Consider the production function of the model, dropping R and e^* to simplify the reasoning: $Q = F(K, \exp(\omega_L)L, M)\exp(\omega_H)$. Under standard regularity conditions we can invert it for effective labor

$$\exp(\omega_L)L = G(K, M, Q/\exp(\omega_H)),$$

and, for given K and ω_H, the slope of an isoquant in the plane (M, L) is

$$\frac{\partial L}{\partial M} = \frac{1}{\exp(\omega_L)}\frac{\partial G}{\partial M}.$$

The starting equilibrium A is the minimization of short-run cost $WL + P_M M$ for producing an output $\overline{Q}$, given input prices and subject to the technical feasibility condition given by the production function. As it is well known, the condition for cost minimization to produce $\overline{Q}$ is the choice of the quantities of M and L such that the ratio of their marginal productivities equals the relation of input prices[17]

$$\frac{\partial Q/\partial M}{\partial Q/\partial L} = \frac{P_M}{W}$$

[17] Multiplying conveniently both sides of the equality, the condition can also be written as

$$\frac{\beta_M}{\beta_L} = \frac{1 - S_L}{S_L},$$

where S_L is the share of labor cost on variable cost.

This implies that any of the prices divided by the marginal productivity of the input gives a unique value. Using the inverse function rule is easy to see that this ratio coincides with the definition of marginal cost (e.g. $W/\partial Q/\partial L = \partial(WL)/\partial Q = \partial VC/\partial Q = MC$).

An increase in ω_L is easily represented by a displacement of the isoquant corresponding to $\overline{Q}$ towards the $M-$axis. An increase in τ will be accommodated without any change in the isoquant. Let us compare the new minimization point under the two situations.

When labor-augmenting productivity increases, the new relevant isoquant shows a slope that is smaller in absolute value for each value of M. The firm realizes that now can produce quantity $\overline{Q}$ with much less labor, but since prices have not changed and the slope of the isoquant is consistently lower in absolute value, the new equilibrium B implies also to reduce some materials. Both inputs are reduced and hence their marginal productivities increase. Notice that greater marginal productivities with the same input prices imply a fall in MC.

The effects of this movement on the ratio M/L and the share S_L depend on the properties of the production function, as represented by the curvature of the isoquant. If the elasticity of substitution σ is less than unit, the ratio M/L rises and the share S_L falls.

With a positive τ, the relevant relative prices become $P_M/W(1+\tau)$, and point A is no longer an equilibrium. Assume that the change in τ is such that the firm minimizes costs at point C, where the ratio $\frac{M}{L}$ is the same as in B To meet the new relationship between marginal productivities the firm has to expand materials and decreases the use of labor along the isoquant. Point C is on the same ray that B and observed input prices are the same as in B, so the observed labor share falls exactly by the same amount as in B. With the same price, marginal productivity of materials is now lower, it follows that MC increases.

Data Appendix

The main data source is the CES-NBER Manufacturing Industry Database (available at https://www.nber.org/research/data/nber-ces-manufacturing-industry-database), which has been recently updated to 2018 (see Becker, Gray, and Marvakov, 2021).[18] The data are available at the SIC code 2011 (Meatpacking Plants), which includes cattle, hogs, and lambs, for 49 years (1970-2018).[19] It is a public dataset that contains yearly observations on nominal value of shipments (sales) and nominal expenditures on inputs. It also contains the real value of fixed assets, which includes plants, machinery and equipment as well as price deflators for the value of shipments, materials, energy, and investment.

We compute output in million pounds of meat from USDA ERS and USDA NASS reports. We use the real capital variable (equipment plus plants in million $) as provided by the CES-NBER data base. Labor is the hours of production workers in millions, as given as well by the CES-NBER database. We separate materials into livestock and other (non-livestock) materials (merging the energy input into materials as it accounts on average for less than two percent of variable cost expenses).

To separate out materials into livestock and other materials, we estimate livestock

[18] Like its predecessor, the updated CES-NBER database aggregates results from the Annual Survey of Manufacturers and the quintennial Census of Manufacturers, bridging the inter-Census years with the Annual Survey of Manufacturers data. The database has widely been used in previous meatpacking studies, allowing for comparison of results.

[19] The NBER-CES data is available in two versions: SIC (Standard Industrial Classification) codes prior to 1997, which contained 459 industries in 1987, and NAICS (North American Industrial Classification System) codes, which contained 473 industries in 1997. The reason to choose SIC over NAICS codes is that, first it is a better match of the definition of the meatpacking industry for our purposes, (which was separated into three categories in the NAICS codes as industries were reclassified), and second, its SIC 2011 codes match the livestock data from the USDA NASS (while the NAICS codes do not).

expenses in million $ and quantity in million pounds of meat from USDA ERS and USDA NASS reports. We subtract livestock expenses from the CES-NBER total cost of materials to compute the cost of other materials, and divide livestock expenses by livestock quantity to obtain the price per pound of meat. To obtain a deflator for the other materials we assume that (the log of) the CES-NBER deflator for materials (PIMAT) is a weighted average of the log of the prices of livestock and other materials, with weights the shares in expenses, and solve for the unknown deflator.

The cycle variable equals 1 for the years when the number of beef cows trends upwards and zero otherwise. Data on the number of cows was obtained from USDA NASS. Details on the cycle can be found in Rosen, Murphy and Schinkman (1994).

The instrumental variables include the ratio wages of production workers to total pay, both variables as provided by CES-NBER, and the price of corn, obtained from USDA NASS.

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Table 1: Descriptive statistics in the meatpacking industry

	1971-2018	1971-1989	1990-2007	2008-2018
Output (Index, 1971=1)	1.118	0.992	1.145	1.290
Capital (Index, 1971=1)	1.327	1.169	1.266	1.700
Livestock (Index, 1971=1)	1.095	0.967	1.133	1.256
Labor (Index, 1971=1)	0.962	0.884	0.995	1.042
Wage per hour ($)	10.357	7.229	10.259	15.919
Input shares in cost:				
Livestock	0.729	0.728	0.724	0.738
Labor	0.066	0.062	0.067	0.071
Materials	0.205	0.209	0.209	0.191
Input shares in revenue:				
Livestock	0.660	0.679	0.652	0.642
Labor	0.060	0.058	0.061	0.062
Materials	0.186	0.195	0.188	0.186
$\frac{R}{VC}$	1.105	1.073	1.111	1,149

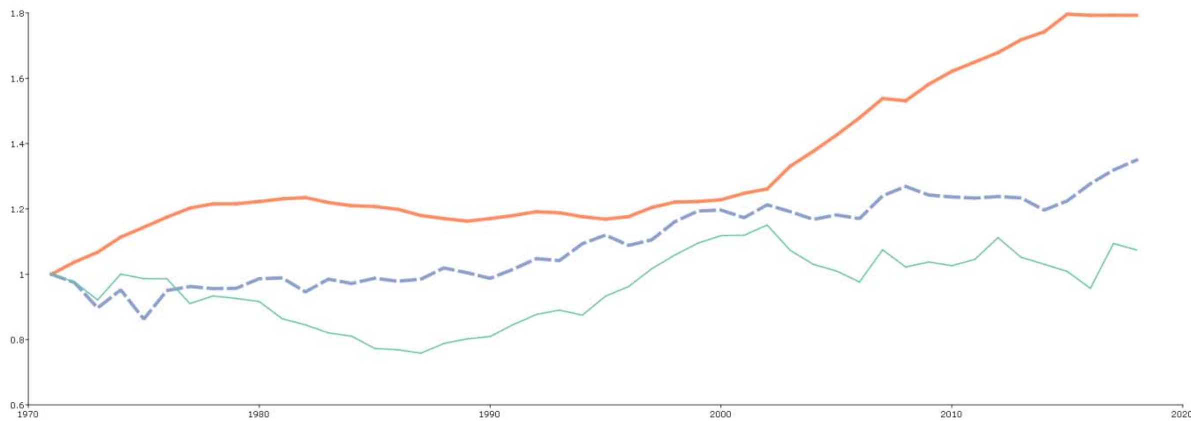
Table 2: Estimating the meatpacking production function 1970-2018

	Model				
	CD	CD	GCD Monopsony	GCD LAP+ Monopsony	GCD LAP+ Monopsony (restricted)
(1)	(2)	(3)	(4)	(5)	(6)
λ			1.378	1.185	1.183
$(s.e)$			(0.245)	(0.100)	(0.071)
ν			1.153	0.960	0.960
$(s.e)$			(0.210)	(0.097)	(0.093)
ρ			0.588	-0.012	-
$(s.e)$			(0.736)	(0.460)	
τ			0.043	0.666	0.663
$(s.e)$			(0.223)	(0.426)	(0.392)
μ			0.890	1.024	1.016
$(s.d.)$			(0.029)	(0.029)	(0.029)
β_K	0.127	0.172	0.225	0.225	0.223
$(s.e.)$	(0.022)	(0.044)	(0.079)	(0.066)	(0.056)
β_R	0.802	0.787	0.932	0.668	0.670
$(s.e/s.d.)$	(0.053)	(0.082)	(0.025)	(0.026)	(0.026)
β_L	0.052	0.075	0.056	0.102	0.101
$(s.e/s.d.)$	(0.028)	(0.080)	(0.008)	(0.015)	(0.015)
β_M	0.008	0.041	0.165	0.190	0.189
$(s.e/s.d)$	(0.004)	(0.021)	(0.025)	(0.027)	(0.026)
$Test$				$\chi^2(2)$=0.384	$\chi^2(1)$=0.068
$(P-value)$				(0.825)	(0.794)

Table 3: Decomposition of profitability in the meatpacking industry

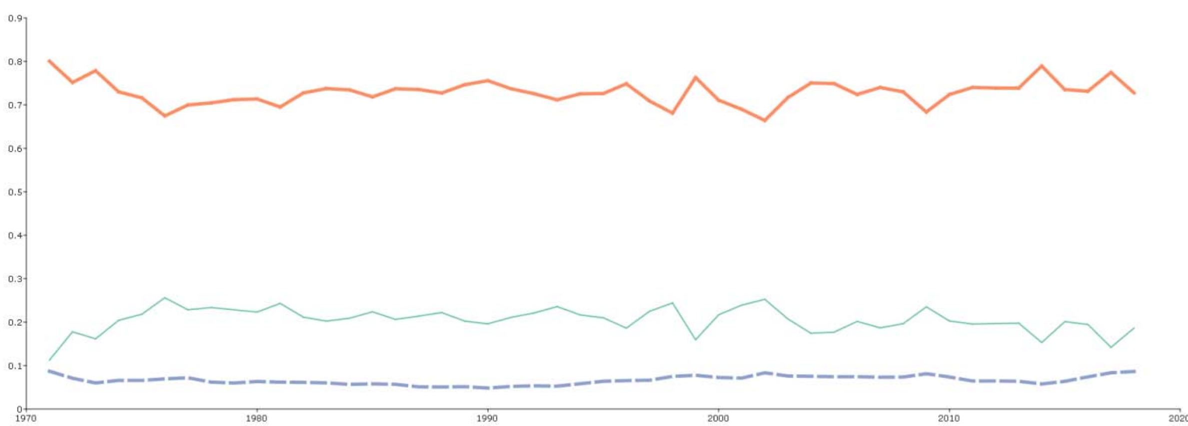
	1971-2018	1971-1989	1990-2007	2008-2018
Gross profit (%)	0.099	0.071	0.105	0.139
Technology	0.041	0.041	0.041	0.041
Product market power	0.015	-0.010	0.020	0.052
Labor market power	0.043	0.040	0.044	0.046

Figure 1.: The evolution of three meatpacking inputs: capital, livestock and labor, 1971-2018.



Thick solid line: Capital; Dashed line: Livestock; Thin solid line: Labor

Figure 2: Livestock, labor and materials share in variable cost, 1971-2018



Thick solid line: Livestock; Dashed line: Labor; Thin solid line: Materials

Figure 3: The share of labor in variable cost, 1971-2018

Figure 4: Evolution of the ratio revenue to variable cost, 1971-2018