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

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Abstract

Market power can be present in both a firm's product and input markets, allowing for supranormal profits to the detriment of social welfare. However, identification is challenging because it requires unbiased estimates of production elasticities under the interwoven presence of monopsony power and non-neutral productivity. We propose a way to measure market power in the product market and several input markets of a firm that is robust to biased technological change. The inference can be checked by assessing how much each market contributes to the gross profits of the firm. We illustrate the method with data from the highly concentrated US meatpacking industry, which is often suspected of exploiting livestock farmers and immigrant workers. We conclude that the prices in the product and livestock input markets are competitive, 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 market power in several input markets of a firm, in addition to its product market power, while controlling for labor-augmenting productivity. Then, it applies the method to the meatpacking industry, a concentrated industry that is often suspected of monopsony power in the livestock and labor markets, as well monopoly power in the product market. Additionally, labor-augmenting productivity has been an issue in the meatpacking industry.

Market power can be present in both a firm's product and input markets, allowing for supranormal profits to the 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 firm products, and avoiding assumptions about the specific competition game that firms play.[1] Our paper proceeds along the same lines. The approach, at least as old as Bain's (1951) work, has been recently revived in an intense debate about 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 on the input markets of firms (monopsony power), and firms' ability to set markdowns (the proportional difference between the marginal product and the price paid for

[1] The production approach received a strong impulse 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 addressed problems of data measurements (Traina, 2018; Basu, 2019; Syverson, 2019), methodology (Doraszelski and Jaumandreu, 2019, 2021; Raval, 2022; Demirer, 2020; Bond, Hashemi, Kaplan and Zoch, 2020; Hashemi, Kirov and Traina, 2022), and outcomes (Jaumandreu, 2022).

a factor).[3] Some economists have even asserted that this kind of market power is prevalent, especially in the U.S.[4] In any case, output market power cannot be properly measured without accounting for input market power, if it exists, and conversely, input market power cannot be measured without considering output market power, so a joint approach is quickly developing. Our work is a contribution to the simultaneous estimation of input and output market power.[5]

However, a general recognition of the importance of biased technological change, in particular of labor-augmenting productivity, has triggered serious concerns about how productivity and markups are usually measured when productivity has non-neutral components.[6,7] For example, the fall of the labor costs in variable cost -determined

[3] A "production" approach to the simultaneous measurement of monopsony power and product market power starts with Dobbelaere and Mairesse (2013, 2018), although the exercise was previously tried with tightly specified models. The basic method is to compare the FOC of an input with market power to the FOC of another without. A series of papers adapt this to the DeLoecker and Warzynski (2012) framework: Morlacco (2019), Brooks, Kaboski, Li and Qian (2021) and notably Yeh, Macaluso and Hershbein (2022). Rubens (2021) considers nonsustituitability of the relevant input and adopts a model for supply (more on this later). This literature coexists with more tightly specified micromodels such as Lamadon, Mogstad and Setzler (2022) and Berger, Herkenhoff and Mongey (2022). A different thread of literature approaches 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] A recent paper which particularly stresses the need for simultaneous estimation, and finds it relevant in the US construction industry, is Kroft, Luo, Mogstad, and Setzler (2022). In this paper we provide an analytical framework for the joint profitability of market power.

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

[7] Yeh, Macaluso and Hershbein (2022) are aware that this is a pending topic: "Last, our econometric methodology does not explicitly allow for factor-biased technological change. While there are estimation methods that do account for labor-augmenting technological change, they do not allow for a generalized production function (...) and/or labor market power (...) We leave investigation of

by labor-augmenting productivity (see below)- can be interpreted as 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. To make consistent inferences, the production approach to market power measurement in output and input markets must address labor-augmenting productivity.

Production elasticities

The measurement of market power, defined as price over marginal cost, requires dealing with non-observable marginal cost. Under cost minimization, marginal cost can be recovered from observed data using production elasticities. For example, De Loecker and Warzynski (2012) proposed the popular current approach to estimating market power that compares the elasticity of a variable input with its share in revenue. In our paper, the fact that the short-run elasticity of scale (sum of elasticities of variable inputs) equals the ratio of marginal cost to average variable cost plays a prominent role. Since monopsony power and labor-augmenting productivity are the two factors recognized to impact the estimation of the elasticities, they need to be fully controlled for.

With monopsony power the firm restricts the use of a variable input, and the input elasticity shows a disproportionate gap with respect to the input share in variable cost. Estimated elasticities should reflect this gap, and this makes estimation challenging. On the one hand, the control for unobserved neutral productivity has to face the presence of (at least) an additional unobservable in the first order conditions

these themes for future research.."

(FOCs) that researchers typically use to control for productivity.[8] On the other hand, whatever the adopted solution to the problem of the new unobservable is, a traditional estimate to pick up the difference between elasticities seems problematic due to the well-known "collinearity" problem among the variable inputs of the production function.[9] This suggests explicitly accounting for the gap when elasticities are estimated, in the spirit of Dobbelaere and Mairesse (2013). In fact, it seems natural to estimate the gap at the same time that it is controlled for.

With labor-augmenting productivity, the production elasticity of the input in terms of efficiency and of the raw quantities is the same, but omission of the efficiency term introduces a correlated omitted variable in the regression (as it does in any input demand). In addition, the evolution of productivity brings down the elasticity of the input when the elasticity of substitution among variable factors is less than one.[10] To estimate the production function consistently, the researcher faces two challenges: specifying the varying elasticities and accounting for the evolving unobservable efficiency that modifies the quantity of labor that is relevant in estimating the production function.

[8] The demand for any variable input subject to market power contains a new unobservable violating the "scalar unobservable assumption" of the Olley and Pakes (1996)/Levisohn and Petrin (2003) method to control for productivity. Rubens (2022) recognizes this. In fact, the unobservable is also transmitted to non-conditional demands for other inputs.

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

[10] 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 almost everywhere. For US manufacturing plants see Kehrig and Vincent (2021). On all this see Jaumandreu (2022).

Market power and labor-augmenting productivity

We propose a method that simultaneously addresses these difficulties. It consists of estimating the elasticities of the production function including the relevant input market power parameters, 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, in combination 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 as the proportional monopsony markdowns of the relevant markets. Using these markdowns, in combination with production observables, we can compute market power in the product market and decompose the profitability of the firm into its components.

Hall (1988), to account for imperfect competition, was the first to write Solow's (1957) share approximation to elasticities in terms of the markup times the revenue shares. Klette (1999) used this specification to measure productivity and markups, and De Loecker and Warzynski (2012) proposed using Hall's identity to solve for the markup (note that this sidesteps how the elasticity is estimated). We deviate from this convention by instead using the short-run elasticity of scale times the cost shares to model the elasticities, and only then computing the markup from the estimated scale.

The meatpacking industry

We apply the method to the US meatpacking industry, which has been at the center of controversy and the object of intensive research. Dominated by a small number of firms (currently four) and a high concentration of slaughter capacity at the firm and plant level, the meatpacking industry has been suspected of exercising market power in the product market, monopsony power in the market for its livestock input, and poor working conditions for its workforce.[11] The latter suggests the presence of monopsony power in the labor market. In the absence of ready availability of firm-level data, we illustrate the model with industry data.[12] In part because of its simplicity, the model works remarkably well, and we are able to reject the hypothesis of non-competitive pricing in both the product and livestock markets but fail to do so in the labor market. Meatpacking workers are estimated to receive 60% of their marginal productivity.

Contributions

The paper makes six incremental contributions to the literature. First, it crafts a novel approach for the joint assessment of market power in the product and (possibly several) input markets in the context of the production framework to market power measurement, that is, measurement without specifying the demand for the firm's product or the supply for the inputs, and placing no restriction on the nature of competition in these markets. Second, the method constitutes an alternative to the classical approach by Hall (1988), Klette (1999) and De Loecker and Warzynski (2012) to the measurement of market power. It hinges on the measurement of the short-run elasticity of scale in production as the way to obtain the relationship between (unobserved) marginal cost and (observed) average variable cost. Third, the method is developed for an environment in which input-augmenting productivity is present and perhaps prevalent. To our knowledge, this is the first time a procedure has been developed that is consistent with biased technological change. Fourth, the

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

[12] Two of the authors are completing the application for the special sworn status which allows researchers to access confidential Census data subject to the usual nondisclosure rules.

paper shows the different effects on a firm's input demands of an exogenous variation in input-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. Fifth, 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 estimates and can be used as a natural test for checking the outcome of any alternative market power measurement. Sixth, it formally explores the labor market of the meatpacking industry and establishes that it is monopsonistic for the first time.

The rest of the paper is organized as follows. Section 2 presents the model and Section 3 discusses identification. The empirical application to 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

Production function

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 as

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

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

We stress that this approach to the production function allows the elasticities to be firm and time specific. Later, we impose equality across firms and time of (only) the long-run and short-run scale parameters (and implicitly of the fixed input capital).[13]

First order conditions

We remain agnostic with respect to the nature of competition in the product market, where we consider without loss of generality that the firm has an unspecified amount of market power (the 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). 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 the "markdown".[14] We write ρ and τ for the markdowns in the livestock and labor market,

[13] We also take the constant as a common parameter by including all deviations from the common constant in the residual.

[14] Markdowns are often interpreted as the inverse of the elasticity of supply of the factor. However, this only corresponds to a market with a supply of finite elasticity and Bertrand input demand behavior by the oligopsonists. We do not need to abide by any particular specification of monopsonistic behavior. On the other hand, the model is general enough to accommodate other possible imperfect market models and even different signs of the parameter as discussed in Dobbelaere and Mairesse (2018). For example, collective bargaining with powerful unions may result in rent sharing implying a negative gap between productivity and wages.

respectively. FOCs 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.[15]

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.[16] 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 production 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. This is an alternative to what Hall (1988) and Klette (1999) do. 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 is the (observed) share of input cost in revenue, but this would introduce two problems: the need to directly deal with the presumably

[15] The FOCs could be extended to account for adjustment costs. See the discussion in Dorazelski and Jaumandreu (2019).

[16] Note that, as mentioned before, the elasticity of labor and "efficient labor" are the same.

highly varying unobservable markup μ, and the presence in the expressions of the unobservable error ε in estimation. Instead, we deal with the short-run elasticity of scale parameter ν, which we assume can be safely taken as constant, and our expressions do not involve error.[17]

Markups and a bound for market power

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

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

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

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 across enough observations on average (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 the 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.

[17] It is not difficult to be more general. The short-run elasticity of scale is, for a generic production function, a function of the inputs and the unobservable labor-augmenting productivity $v = v(k, r, \omega_L + l, m)$. Under appropriate restrictions on the dependence of ω_L, it can be modelled as a varying function of observables across sample and time.

Notice that all terms in the decomposition are likely to be positive. Parameter ν is a short-run elasticity of scale that we expect to be less than one according to economic theory. The markup is expected to be non-negative in general because price below marginal cost can only be a short-run dynamic optimizing solution under cost of adjustment of prices.[18] Monopsonistic power implies non-negative markdowns. So the value $\ln \frac{R}{VC}$ sets an upper bound to the sum of market power profitability effects (markup and markdowns). Note that this upholds the approach that Bain (1951) used to measure market power $((R - VC)/R)$ from a new point of view.

Empirical specification

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 the production function to directly estimate 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.[19] 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

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

[18] See Jaumandreu and Lin (2018).

[19] Alternatively β_K could be modeled as a function of K and λ become a varying long-run elasticity of scale.

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 apply equation (6) to the data we need to decide how to treat unobserved productivity ω_{Ljt} and ω_{Hjt}, however 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, it only requires equality of the long-run and short-run elasticity of scale and the markdowns across firms. 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 the scale from the gaps in estimation.

The estimation of the short-run elasticity of scale allows us to estimate the (log of the) price-marginal cost ratio or markup for every firm and moment of time up to a zero-mean error. 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 is assessed in any number of input markets (but not all). No assumptions about the behavior of the firm in the product or input markets are needed, only cost minimization is assumed.

3. Identification

The model in equation (6), 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 like nonlinear GMM, which we do later. We need enough valid moments to identify the four parameters, and it is not difficult to determine them. In this section, we first briefly discuss these moments. Then we switch to three more complex identification questions: how to control for the productivity unobservables (and whether this modifies the need for instruments), how the absence of substitution of a relevant input can hinder identification, and how we can identify monopsony power separately from labor-augmenting productivity.

Moments

In the absence of a persistent neutral productivity term, it seems natural to suppose that ε may encompass transitory productivity shocks correlated with the inputs. Later we reintroduce the neutral productivity term, and incorporate these shocks to its nonpersistent part, and nothing important changes. Capital, under the usual assumption that it results from investment made 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.

The control for unobserved productivity

The decisions about how to treat unobserved productivity, and in particular labor-augmenting productivity, are likely to strongly impact the estimation of the elasticities and hence all inferences about market power. For example, labor-augmenting productivity, given relative prices, is expected to be negatively correlated with labor and positively correlated with material inputs (see below). If we do not control satisfactorily 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. Since ω_L is persistent, these correlations are likely to invalidate the instruments based on the lags of input quantities as well.

Hicksian productivity ω_H enters the equation additively and hence, assuming that it follows a linear Markov process, can in principle be controlled for by taking differences of the nonlinear model. The autoregressive parameter is estimated and the equation includes the innovations of the Markov process, which now picks up all transitory productivity shocks. Under the usual timing assumptions we do not need different instruments from those discussed in the previous subsection. 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 style of Olley and Pakes (1996) and Levinsohn and Petrin (2003), would be to replace ω_H with the inverted demand for an input. This seems more problematic in that it needs to yield a solution to the unobservability of marginal cost in the FOC or FOCs used to derive the input demand and, even more challenging, to the presence of the input market power unobservable or unobservables.

To date labor-augmenting productivity ω_L has typically been 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. Note that the presence of the parameter of labor monopsony power complicates the approximation a little. The use of this substitution makes the addition of some instruments particularly correlated with the input prices convenient.

In our empirical illustration, 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 apriori specification of the increase of labor efficiency.

A non-substitutable input

In the production function approach, monopsony power over one input is identified because the firm substitutes other inputs for it. If the input is nonsubstitutable, that is, the input has to be used in fixed proportions with the output, identification based on the gap between the input elasticity and share in cost evaporates. Rubens (2022) realizes this and warns about the effects: "...this class of models, which imposes only a model of production and input demand, fails to separately identify markups and markdowns as soon as a subset of inputs is non-substitutable."

The problem is in fact similar to what happens if the relevant production function has only one input (and hence substitution is not possible). Suppose that the production function is $Q = F(L)$, and hence $\beta_L = \frac{(1+\tau)}{MC}\frac{WL}{Q}$. It happens that $\frac{R}{WL} = \frac{1}{\beta_L}\mu(1+\tau)$ and, without more information, output market power cannot be separated from market power in the input market as a source of total profitability.

In a multi-input market problem, however, we can still assess market power for the substitutable inputs (subject to the condition of one market without monopsony power). But, without more information, we will not be able to assess input market power for the non-substitutable input or to separate, in our profitability decomposition, the relative roles of product market power and power in the market of the non-substitutable input.

It has been suggested that livestock is a non-substitutable input that enters the production of meat in fixed proportions. Researchers have contested this claim, and we later argue that it is a substitutable input. However, suppose for a moment that this is not the case, and that the production function should be specified as

$$Q = \min\{\beta_R R, H(K, L^*, M)\},$$

where β_R is a fixed coefficient and $H(\cdot)$ is the amount of the variable composite input made of the contribution of all other variable inputs (and fixed capital). $H(\cdot)$ constitutes a subfunction homogeneous of degree ν_H in the variable inputs, whose cost is minimized, and where all the relationships shown above hold. Since $MC = \frac{P_R}{\beta_R}(1+\rho) + \frac{AVC_H}{\nu_H}(1+S_L^H\tau)$, it is easy to see that

$$\ln\frac{R}{VC} \simeq S_H(\frac{1}{\nu_H} - 1) + \ln\mu + S_R\rho + S_L\tau.$$

We are able to assess the role of profitability of technology and the labor market, but we are not able to separate the contributions of market power in the product market and monopsony power in the livestock market.

Monopsony power and labor-augmenting productivity

An important question seems to linger. Can we identify monopsony power separately from labor-augmenting productivity? The question arises because labor-augmenting productivity introduces an unobservable in the FOC for labor 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 can we be 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 of an exogenous increase in labor-augmenting productivity and an exogenous increase in monopsony power on our cost minimizing firm. We assume, without loss of generality, that ω_L and τ increase from an initial zero value to a positive value. Ceteris paribus, both effects give incentives to the cost minimizing firm to reduce employment. To facilitate the comparison of results, we consider that the increase in labor-augmenting productivity and monopsony power are such that in each case the firm adopts the same new ratio of 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 labor proportionally more so. As a result, the share of labor in variable cost S_L is reduced. In addition, productivity improvement implies that MC decreases. On the contrary, an exogenous increase in monopsony power induces the firm to contract labor while it expands materials. If the firm adopts a proportion of material over labor that matches the case of an ω_L increase, the share of labor in variable cost S_L diminishes, but somewhat more than with the ω_L increase. 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 an increment in monopsony power, an expansion or contraction of both inputs in the same proportion.

4. An illustration from the meatpacking industry

We illustrate how the model works by applying it to the US meatpacking industry. Some background on this industry follows, in addition to 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 both allow 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 in combination 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 US 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 (generally poultry is not included). Activities are carried out in plants of various sizes, but the bulk of activities are concentrated in a few mega plants. For example, in 2021, there were 726 beef packing plants, of which 12 slaughtered more than one million head of cattle each, accounting for 50% of all cattle slaughter. Similarly, there were 645 plants dedicated to pork, of which 14 plants slaughtered more than 4 million head each, accounting for almost 60% of hogs. And there were 534 sheep and lamb plants, of which 13 plants slaughtered more than 25,000 head each, accounting for 65% of sheep slaughtered (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 lambs (USDA AMS 2020). Concentration increased sharply from 1960 to 1990, as plant size grew and plants moved from the Midwest and Northern Great Plains to the Southern Great

Plains. Afterwards concentration grew more slowly. The four-firm concentration ratio (CR4) in beef processing increased from 41% in 1982 to 79% in 2006 and has since 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 input markets: livestock and labor. The concentration in meatpacking, the complaints of the livestock producers and the proliferation of alternatives to the spot market (marketing and production contracts among others) have generated concerns about the competitiveness of the market.

The industry has a long history of controversial labor practices. Increasingly located in rural areas, the industry employs a workforce composed of low skilled workers including above average proportions of immigrants, refugees, and people of color who have fewer employment 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 when 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 almost exclusively on cattle and beef pricing, and the additional question is invariably if there is oligopsony in cattle markets.[20] 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

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

significant market power either in the market for "packed meat," or in the input market for livestock. On the contrary, Wohlgenant (2013) stresses the evidence for 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 been increasing during the period, which 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 processing by wholesalers and retailers. Processed products, cut, prepared, and packed, known as "boxed beef," accounted for 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, grew by slightly less than 40% during the almost fifty-year period. The livestock input, measured in pounds of liveweight, followed the evolution of output very closely. We next report the evolution of capital, which has outgrown the evolution of output, and labor (measured in total production hours), which has tended to stay remarkably stable. The materials, with slightly noisier data, follow next. The evolution of the indices for capital, livestock, and labor, detailed in Figure 1, suggests some substitution over time of capital for labor. This matches the reports on technological progress well and is likely to be one of the sources of labor-augmenting productivity. Based on this input-output behavior, below we test for the absence of Hicks-neutral productivity and confirm the importance of productivity that specifically affects the labor input.

The fifth line of Table 1 reports the industry hourly wage. Despite trailing the evolution of wages in the rest of manufacturing, it more than doubles during the period (in fact it quadrupled in value between the two extreme observations, from \$4.301 in 1971 to \$19.704 in 2018). This implies 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 Figure 2. Under an elasticity of substitution smaller than unity, the evolution of the relative prices should have implied an increase in the labor share in costs. The fact that this has not happened, strongly suggests that labor-augmenting productivity is pushing this labor share down (or moderating its increase). Additionally, the details concerning the labor share in Figure 3 suggest 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 of revenue over variable cost, reported in the last row of the table. This ratio shows a relatively significant increase in the profitability of the firms over time, from 7 to 15 percentage points. Figure 4 shows that an important part of this increase has taken place in the last 10 years.

Estimation of the production function for meatpacking

Our model is designed to be applied to firm-level data. However, we only have industry-level data, and we have to fit the production function assuming that a meaningful production function at the industry level exists. Although using such data can possibly induce biases, we do not anticipate any inference that would be particularly wrong on this account.

Much more worrying is the scarce number of observations that this makes available, just 49 yearly 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 on all the variation across them. Although we try to be very parsimonious in the specification, we are consciously estimating the model with a sample that is too small. The estimation results turn out to be very good, but efficiency is low and the power of tests mild. We have carried the exercise as far as possible as a preparation for applying the model to firm-level/establishment data when we can access it.

Before starting, it is worthy establishing that evidence suggests that livestock presents some substitutability, and we are going to correspondingly assume that this doesn't enter the production function in a fixed proportion. The idea is that, in principle, it is possible to combine different amounts of used capital and labor, as well as materials, with different liveweight livestock amounts to get the same quantity of (standarized) output. Wohlgenant (2013) makes the case for this, and there is plenty of evidence on elasticities of substitution for different ouputs and inputs (see, for example, MacDonald and Ollinger, 2001). Our current exercise supports substitutability well. But this is just one of the cases in which an aggregated result may be impacted by substitution across establishments.

On the other hand, the presence of contracts (see above) may raise concerns that some of the livestock input is chosen before it is slaughtered, and its price is predetermined. However, since a) livestock grows in weight between the time it is contracted and the time it is slaughtered; b) the contract price is tied to the current spot price; and c) processors, as buyers, have the discretion about when livestock is delivered to the plant, we assume the choice of the livestock input is reflected in the amount delivered to the plant for slaughter at the current spot price.[21]

We start estimating a conventional Cobb-Douglas production function using OLS. All variables are in logs. The quantity of processed meat, measured in pounds, is regressed on a constant, real capital, k, the quantity of livestock measured in pounds,

[21] One may wonder if the mechanism implies some significant adjustment costs. We ignore this extreme right now, but our model can be, as mentioned, extended to test for this.

r, the number of hours by production workers, l, and the deflated value of materials, m. We add a dummy variable that captures the upward and downward phases of the cattle cycle (8-12 years) which impacts the number of animals available for slaughter as a control. 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, so we drop it. The elasticities β_K, β_R, β_L and β_M are reported in column (2) in additions to 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.[22] 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 of corn, the major livestock feed. In the remainder of the exercise, we use eight instruments to estimate six parameters. These instruments are the constant, time trend, capital and livestock lagged, share of labor in variable cost lagged, price of corn lagged, the cattle cycle variable, and the share of production workers' wages in the total wage bill, lagged. The last instrument accounts for cyclical utilization of slaughter 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 in

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

column (4). None of the input market power parameters are statistically significant, but the short-run and long-run elasticity of scale increase significantly. The elasticities of all inputs except labor increase significantly. We infer 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 are missing is the effect of labor-augmenting productivity. The estimate of column (4) produces an strangely high elasticity of livestock and an elasticity of labor that is comparatively too low. This is exactly, as previously mentionned, the type of bias that one expects from the omission of labor-augmenting productivity. In addition, we have given reasons in the descriptive subsection to expect this type of productivity to be 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 on the FOCs of the variable inputs for the unobservable labor-augmenting productivity. However, we are at the limit of the number of parameters that can be reasonably estimated. So, we adopt an extremely simple procedure based on 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, which embodies labor-augmenting productivity and at the same time 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 to be 0.960 and 1.185 respectively, very reasonable numbers. The parameter of monopsony power in the livestock market is evaluated virtually 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 receive 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 non-existent 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 now has 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 throughout the whole period of almost 50 years is moderate, about 10%. An important part of this profitability comes from technology, more specifically from the fact that in equilibrium marginal cost lies about four 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 a contribution as important as technology's to profitability. The fact that production workers are paid only 60% of the value of their marginal productivity implies a contribution to profitability of a little more than 4 percentage points, even though the share of labor in variable cost is relatively small (an average of 6%).

The detail by periods shows that profitability has risen, in particular over the latest ten years, when it increased more than three percentage points (the same as in the previous almost 40 years). The decomposition reveals 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

A reader who has followed the derivations in section 3 in detail, is likely to ask a question. Would we draw the same conclusions if we applied the popular measurements of DeLoecker and Warzynski (2012), henceforth DLW, and Yeh, Macaluso and Hershbein (2022), henceforth YMH, for product and input market power respectively, with the elasticities estimated in column (6)? 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 their application to this particular market. However, this is not a proof of the validity of these two measures, rather an insight into their incompleteness: these measures are only able to give the same answer as ours if the production function is estimated in the way we did. Otherwise they may produce senseless measurements that are, in general, even incompatible between them.

First check the equality of results from the means reported in the tables.[23] Start with the DLW measurement of market power, which consists of the elasticity for a variable input divided by its revenue share β_X/S_X^R. [24] If you divide the elasticity of

[23]This a rough procedure. The right way to proceed would be averaging the measured values obtained with the un-averaged data.

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

livestock by its share in revenue you get an estimate of the markup equal to 1.015, and with the elasticity of materials divided by the share in revenue an estimate equal to 1.016. Finally, 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 1.016 -despite the rounding imprecisions, the numbers are very close.

YMH propose measuring 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, $\beta_X/B_Z/(S_X/S_Z)$.[25] 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, we estimate 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 on the unspecified 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 -11 percentage points. But, we can apply DLW and YMH with the elasticities estimated in column (3). This is a standard IV-estimated Cobb-Douglas production function as used in many applications. The livestock and labor elasticities give DLW markup estimates of 1.192 and 1.250 respectively, a large estimate of market power for a market that seems to have none, and an unrealistically negative market power when one uses materials. The YMH index, on the other hand, increases to a nonsensical value (5.671). The positive DLW estimates of the markup by themselves already

[25] Since the denominator is a ratio it doesn't matter if shares are in variable cost or revenue.

violate our profitability bound (recall that average profitability is about 10%), so there is no point in trying a precise calculation of the components.[26]

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 an estimate that is basically a measure of the imperfections/biases in the implicit estimate of the scale elasticity. The problem would disappear if we estimated an infinite parameter-dimensional (nonparametric) elasticity, but that is something we cannot do. A feasible alternative is to focus, as we do, on the estimation of a sensible elasticity of scale, and to let the shares complete the estimation of the elasticities.

6. Concluding Remarks

This paper derives a method to simultaneously measure product and input market power (possibly in several markets) that is robust to the presence of labor-augmenting unobserved productivity (or other biased variants of technological change). No assumptions about the demand for the products, competition in the product market, or competition among oligopsonists in input markets are used. The method specifies an approximation to the production function of each firm, in each moment of time, by fully exploiting the structure of the FOCs for cost minimization.

In practice, it amounts to estimating the long and short-run elasticities of scale as well as the degree of input market power in each market of interest. The baseline

[26] Estimates of market power recently offered by different papers for all US manufacturing, and even the economy, seem to be beyond what the data says. Suppose a standard short-run elasticity of scale $\nu = 0.95$, and share of labor in variable cost $S_L = 0.25$. Take the average manufacturing markdown of 1.53 estimated by YMH, and either their 1.21 markup or the 1.61 markup of DeLoecker, Eeckhout and Unger (2021). The implied gross profitabilities are 36% and 65% respectively. Even the smallest number is too large to be defended as compatible with the existing firm-level data.

version of the model requires the scale elasticities and degree of input market power to be constant across firms and over time, but the model can be easily generalized. Scale elasticities may be specified varying with the inputs, and power in the input markets modelled according to observed determinants.

The estimated elasticities are robust to input market power and labor-augmenting productivity because they are estimated including their gaps with respect to the shares in cost and, in addition, allowed to vary with any technologically biased increase in productivity. For example, the labor shares can fall according to Hicks (1932) prediction when the elasticity of substitution is less than unity. Estimation is simple, using nonlinear GMM and moments based on lagged quantities of the inputs and, perhaps, some exogenous shifters.

We carry on a preliminary application to the concentrated meatpacking industry, often suspected of exploiting livestock farmers and its labor force, as well as exercising product market power. Despite the scarcity of observations, the model works very well, and allows us to reject non-competitive pricing in the product and livestock markets while detecting significant monopsony power in the labor market. The decomposition of gross profitability shows that technology and the labor market have been the traditional sources of profits in meatpacking, although a recent trend upwards of product market power is detected.

Compared with other ways of measuring market power, this method has the advantage of providing measures that are both unbiased and theoretically and practically consistent among themselves, decomposing the observed gross profitability of the firm into its technological and market power sources.

Appendix A: The effects of an exogenous increase of labor-augmenting productivity and labor market power

Let us examine in turn, with the help of Figure A1, 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 in the labor market (you may think of this as a rotation of the supply curve around the equilibrium wage, the relevant elasticity moves from infinity to a finite value). We assume, without loss of generality, that ω_L and τ increase from an initial zero value to a positive value. Ceteris paribus, both effects give incentives to a 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 the same new ratio of materials to labor in each case.

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[27]

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

This implies that any of the prices divided by the marginal productivity of the input gives a unique value. Using the inverse function rule, it 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 it 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 also implies a reduction in materials. Both inputs are reduced and hence their marginal productivities increase. Note 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 one, 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

[27] Multiplying 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.

minimizes costs at point C, where the ratio $\frac{M}{L}$ is the same as in B To achieve the new relationship between marginal productivities the firm must expand materials and decreases the use of labor along the isoquant. Point C is on the same ray as B and, if observed input prices were the same as in B, the observed labor share would have fallen by the same amount as in B. However, the new finite-slope supply curve implies that the observed wage falls and hence the fall in the share will be larger. 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).[28] The data are available for the SIC code 2011 (Meatpacking Plants), which includes cattle, hogs, and lambs, for 49 years (1970-2018).[29] 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 (2022) and USDA NASS (2022) reports. We use the real capital variable (equipment plus plants in million $) as provided by the CES-NBER database. Labor is measured as the hours of production workers in millions, as given by the CES-NBER database as well. We separate materials into livestock and other (non-livestock) materials (merging the energy input into materials as it accounts for less than 2% of variable cost expenses on average).

[28] 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 been widely used in previous meatpacking studies, allowing for comparison of results.

[29] 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 twofold. First it is a better match with the definition of the meatpacking industry for our purposes (which was separated into three categories in the NAICS codes as industries were reclassified). Second, its SIC 2011 codes match the livestock data from the USDA NASS (while the NAICS codes do not).

To separate out materials into livestock and other materials, we estimate livestock 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 equal to the shares in expenses, and solve for the unknown deflator.

The cycle variable equals 1 for the years when the beef cows inventory trends upwards and zero otherwise. Data on the inventory was obtained from USDA NASS (2022). Details on the cycle can be found in Rosen, Murphy and Schinkman (1994).

The instrumental variables include the ratio of 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 for 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
Materials (Index, 1972=1)	1.529	1.479	0.868	1.365
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

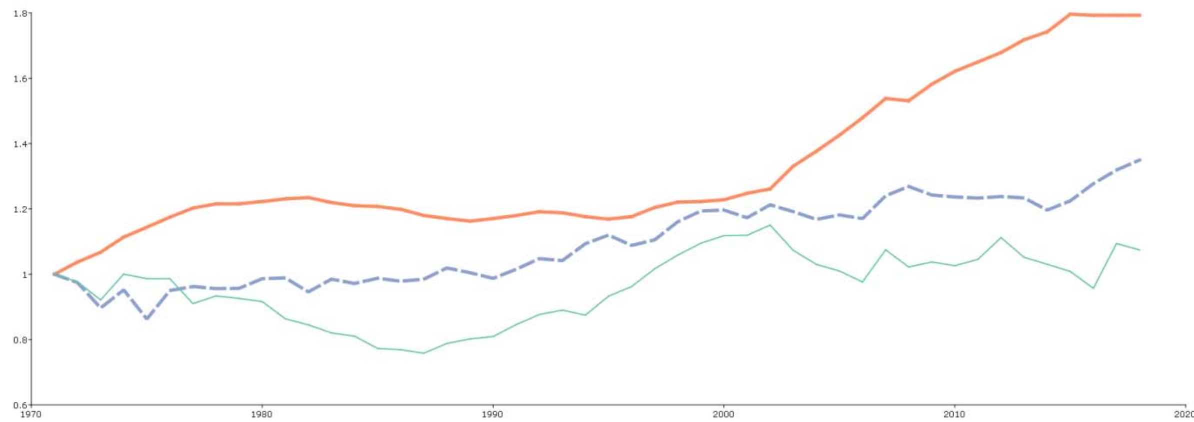
Table 2: Estimating the meatpacking production function 1970-2018

	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

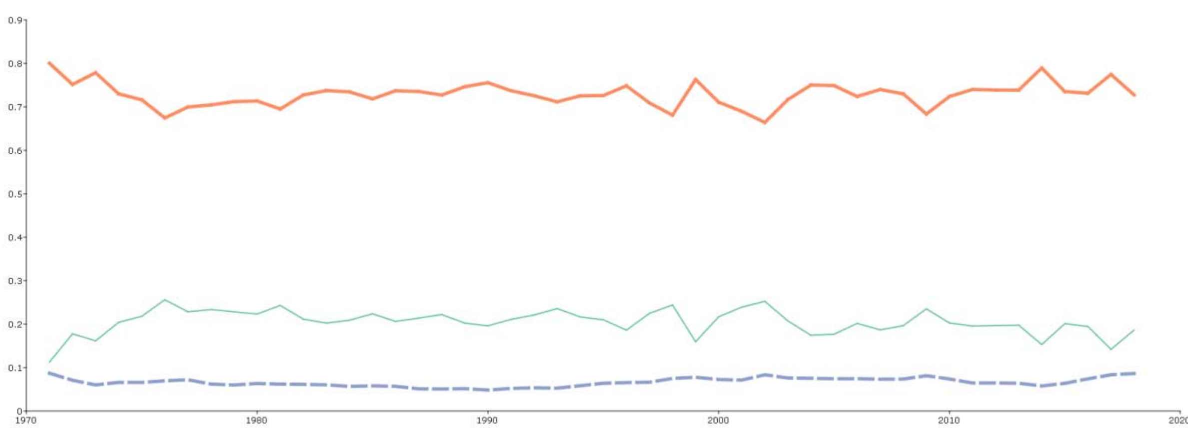
	1971-2018	1971-1989	1990-2007	2008-2018
Gross profit (%)	0.099	0.071	0.105	0.139
Technology	0.041	0.041	0.041	0.041
Product market power	0.015	-0.010	0.020	0.052
Labor market power	0.043	0.040	0.044	0.046

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

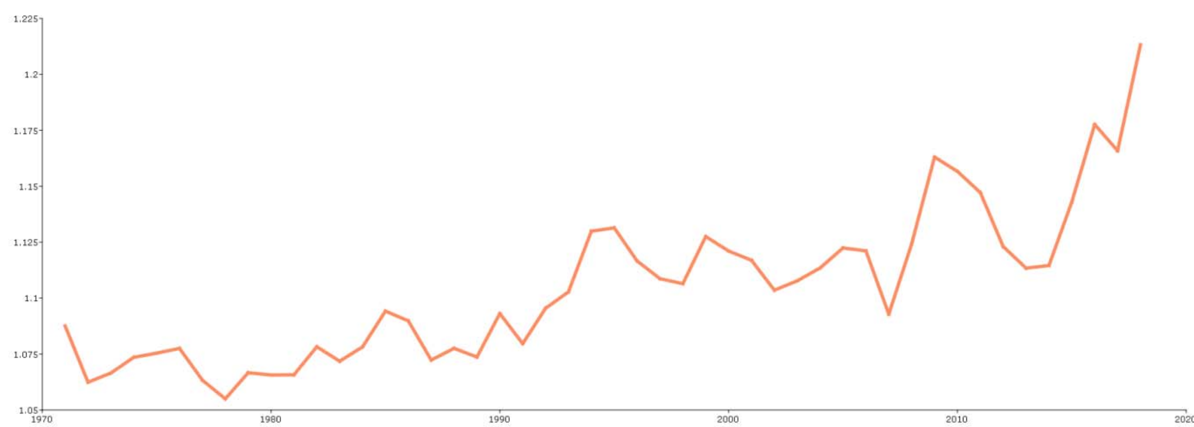
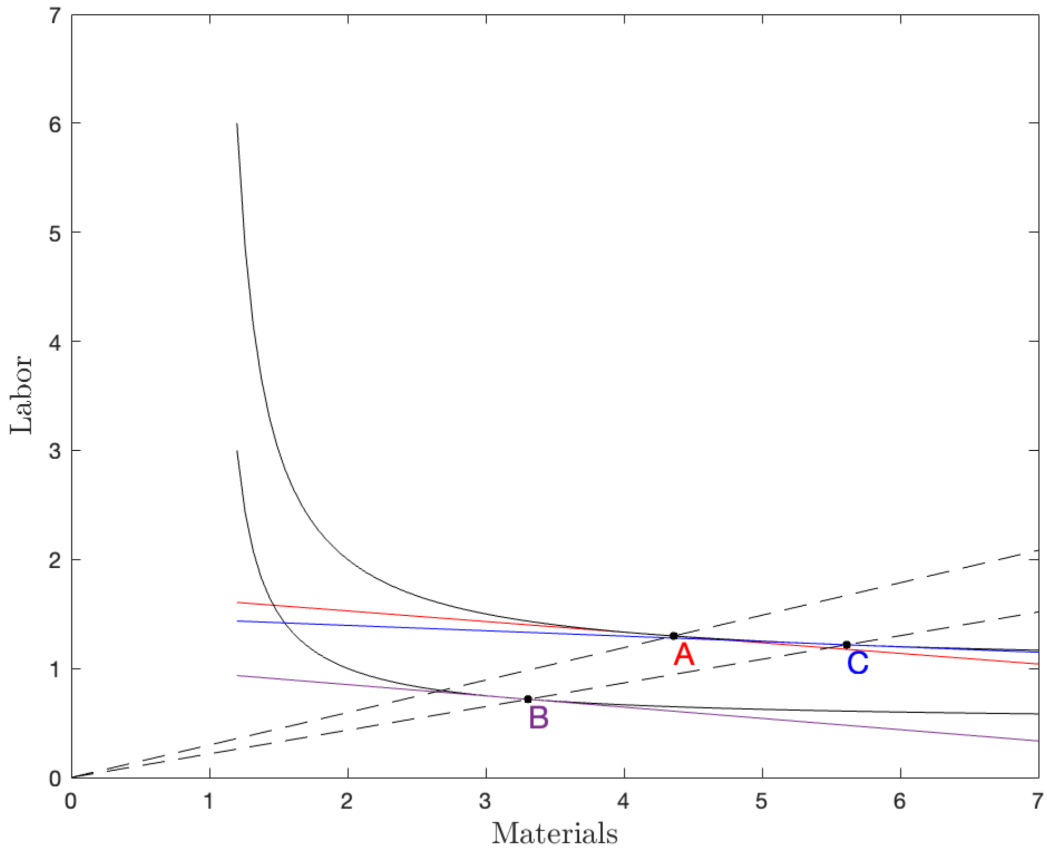


Figure A1: The effects of an exogenous increase of labor-augmenting productivity and labor market power



Labor-augmenting productivity (A to B): The isoquant moves closer to the Materials axis and the firm chooses an equilibrium on the new isoquant given prices.

Input market power (A to C): On the unique original isoquant, the firm chooses an equilibrium in which the slope equates the new (absolute) price ratio $P_M / W'(1+\tau)$ flattened by the increase in monopsony power.