Ownership consolidation, buying and selling power: evidence from Chinese tobacco

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Abstract

This paper examines the effects of ownership consolidation on both upstream buying power and downstream market power when not all inputs are substitutable. In this case, which applies to many manufacturing industries, markups, markdowns and the production function cannot be identified using the production and cost approach. I propose an alternative identification strategy and use it to estimate both markups, agricultural markdowns and productivity in the Chinese cigarette manufacturing industry. A natural experiment in which factories under certain production thresholds were forced to exit or merge allows estimating the causal effects of ownership consolidation on markups, markdowns and productivity. The policy led to an increase in combined market power of 20%, but its effects were very different up- and downstream: while markdowns rose by almost 90%, markups *fell* by 60%. This increase in buying power caused income inequality between rural farmers and urban workers to double during the three years following the consolidation.

Keywords: Mergers, Buying power, Markdowns, Markups, Inequality, China
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1 Introduction

Firms in concentrated industries can exert market power both downstream, charging consumers more than the marginal cost of production, or upstream, paying suppliers less than their marginal revenue product. Prior research on mergers and acquisitions mostly focused on their competitive effects on product markets, while assuming perfectly competitive factor markets. While this assumption seems strong in many industries and countries, it is especially likely to be violated in developing countries with their frictional factor markets. Recent large-scale consolidation waves in important industries such as energy, telecom and mining in China and Indonesia hence raise questions about their competitive effects on both product and factor markets. In this paper, I fill this gap by examining how an important consolidation wave in the Chinese cigarette manufacturing industry affected markups, markdowns and productivity, and its distributional consequences.

This paper makes three main contributions. A first key contribution concerns the identification of markups and markdowns when factor markets are imperfectly competitive and when there is at least one non-substitutable input. The production and cost approach to markup identification of De Loecker and Warzynski (2012) has been used to identify markdowns as well by Morlacco (2017), but requires all inputs in the production function to be substitutable. In most manufacturing industries, there is at least one input which is proportional to output, usually intermediate inputs. As soon as the market for this input is imperfectly competitive, markups, markdowns and the production function are non-identified using the production and cost approach. I extend De Loecker and Scott (2016b), which identifies markups using a gross output production function for beer brewers, to allow for imperfect factor market competition. I impose more structure on upstream competition, and adjust the input demand functions when estimating the production function to be consistent with firms having buying power, while remaining agnostic about how firms compete downstream.

A second contribution of this paper is to examine the effects of ownership consolidation on both markups, markdowns and productivity, without assuming any of these three to remain constant. Prior work on merger evaluation has usually assumed either perfectly competitive input markets (Blonigen and Pierce 2016) and/or constant marginal costs (Nevo 2001). Very few papers exist on the upstream consequences of mergers and acquisitions[1]. I make use of a natural experiment in the Chinese tobacco industry, where firms producing less than 100M cigarettes per year were forced to exit in 2003, to obtain causal estimates of how ownership consolidation affected markups, markdowns and productivity. The objective of this policy was to increase industry productivity by closing small unproductive state-owned plants, and was enacted in many industries. I find that these small plants were indeed less productive, but that closing them led to a sharp increase in buying power. As this effect is large, taking

[1]A part of the financial economics literature addresses this, such as Fee and Thomas (2004) and Bhattacharyya and Nain (2011), without formally estimating markdowns, nor addressing the endogeneity of being subject to ownership consolidation

it into account is of first-order importance when evaluating similar reforms in other industries.

A third contribution is to examine the distributional consequences of this increased buying power. Existing work on the distributional effects of market power has mainly focussed on downstream market power De Loecker and Eeckhout (2017, 2018). Buying power has different distributional consequences, though: as markdowns increased, wealth redistributed from farmers towards consumers and firm shareholders. As manufacturing workers were not affected by this increase in buying power, inequality rose between (rural) tobacco farmers and (urban) factory workers. This margin of inequality has grown sharply in China since the early 1990s (Yang 1999; Benjamin, Brandt, and Giles 2005; Chen and Ravallion 2009), and elucidating the effects of buying power and mergers on it is novel. Tackling income inequality has been a crucial feature of President Hu Jintao's *Harmonious Society* throughout the mid-2000s, and the effects of the tobacco reform were hence likely non-desired. The fact that the Chinese government stopped providing raw tobacco price data after 2003 suggests, indeed, that the 2003 reform did not fit into the government's 'equitable economic growth' goals. Poverty among tobacco farmers has more recently been tackled by targeted subsidies in the 13th five-year plan (in 2017)[2], but such transfer schemes may not have been necessary if the industry would not have been consolidated.

The Chinese tobacco industry is perfectly suited for the questions raised in this paper: it was among the first Chinese SOE-dominated industries to be consolidated, has a simple production process in which non-substitutability of tobacco leafs and labor is obvious, and has been shielded from import competition even after China's WTO accession in 2001, avoiding an important confounding factor. While cigarette manufacturers compete upstream, product markets have been cartellized by the Chinese central government since 1982, so the 2003 consolidation should mainly affect competition upstream. Chinese tobacco is also interesting in its own right because of its size: 40% of the world's cigarettes are made in China, generating an annual revenue of more than 7 billion USD and being very important for fiscal revenue in China. The combination of buying power on a non-substitutable intermediate input applies, however, to many other industries. To give just a few examples, smartphone and tablet producers hold high market shares on markets for certain minerals, which are non-substitutable for labor or capital. Large brewers have dominant positions on hop markets, coffee producers on coffee bean markets, etc. This is also the setting in which buying power is most harmful: in contrast to labor, firms cannot substitute expensive inputs for capital, which makes gaining buying power the only possible business strategy to lower costs. The methods applied are not only important when examining markups or markdowns, but also when only examining production efficiency: the production function itself is non-identified if firms have buying power over their non-substitutable inputs using existing techniques. Tobacco is, of course, different from other industries because of its public health externalities. I will abstract from these considerations in this paper.

[2] https://www.tobaccoasia.com/features/china-aims-to-increase-tobacco-farmers-income/

The structure of the analysis is as follows. I start with a general model of production with imperfect factor markets and a non-substitutable input. I discuss identification of the production function, markups and markdowns in theory and demonstrate non-identification when the non-substitutable input market is imperfectly competitive. Next, I propose an alternative estimation routine. I first estimate markdowns by imposing a model of upstream competition and next include these markdown estimates in the input demand conditions for the competitive inputs in the Ackerberg, Caves, and Frazer (2015) model. I apply the first proposed technique on the Chinese tobacco manufacturing industry. I find that the gross output production approach yields median markup and markdown estimates of resp. 1.21 and 1.92 meaning that prices are 21% above marginal costs (which includes markdowns), while farmers receive 52% of their marginal revenue product. A conventional Cobb-Douglas approach, as in Morlacco (2017), estimates these medians at 3.39 and 0.40, meaning that farmers are paid 2.5 times *more* than their revenue product, is in stark contrast with economic intuition. I also find that adjusting the input demand conditions to imperfect competition matters a great deal in the output elasticity estimates, with unreasonable estimates when not doing so.

Next, I find that being subject to the consolidation policy increased markdowns by 90%, while markups fell by 60%. This is logical given that cigarette producers compete on input markets, but all sell there entire output to a single buyer which is controlled by the Chinese government. While markups should therefore not depend on market structure, markdowns should. I find that this increase in buying power led to increased inequality between rural farmers and urban manufacturing workers. The difference between factory worker and farm wages doubled between 2002-2005, while it would have remained constant in the counterfactual scenario without ownership consolidation.

The existing literature on monopsony power, such as Ashenfelter, Farber, and Ransom (2010), Naidu, Nyarko, and Wang (2016) and Naidu, Posner, and Weyl (2018), usually focuses on labor, rather than intermediate inputs. This distinction is, however, largely artifial: intermediate input suppliers obviously employ labor as well, and are quantitively much more important than labor that is directly employed by manufacturing firms: the revenue share of intermediate inputs is ten times higher compared to labor in Chinese manufacturing, as it is in most other industrialized countries. Buying power is also more likely on certain intermediate input markets because they are often much more industry-specific than labor, especially in the tobacco case: raw tobacco leaf is not used in no other industry than tobacco manufacturing, while manufacturing workers barely have any skills specific to cigarette manufacturing. The relevant set of buyers is hence much more narrow for tobacco leaf than for cigarette factory workers, and hence buying power is more likely there.

The remainder of this paper is structured as follows. I start with a model of production and input demand in imperfect factor markets, and discuss identification and estimation in section 2. In section 3, I discuss the institutional background, some salient facts and the data. In this section, I also apply the model to the Chinese tobacco industry and estimate the causal effects of the consolidation. Section 4 discusses the distributional consequences of the consolidation, and is followed by conclusions.

2 Model and identification

2.1 Production and markets

Production

Firms f produce Q_{ft} physical units of output using a variable intermediate input M_{ft}, a set of variable substitutable inputs $\mathbf{L}_{ft}$ and fixed assets K_{ft}. The production function is a gross output function, meaning that firms cannot substitute between M and either $\mathbf{L}$ or K, but can substitute between $\mathbf{L}$ and K. For ease of exposition, I restrict the function to cases with at most one input M, but generalizations are possible. Firms differ in their Hicks-neutral productivity term Ω_{ft}, in an intermediate input per output ratio β^M_{ft} and potentially in their functional form for $H(.)$. Let the production function be given by equation (1). This is a general formulation: functions without a fixed proportion between any input, such as a Cobb-Douglas or translog function, are a special case of function (1), in which $\beta^M_{ft} = 0$. In this case, intermediate inputs are just part of the vector $\mathbf{L}$.

$$Q_{ft} = \min\left\{\beta^M_{ft} M_{ft}, \Omega^H_{ft} H_{ft}(\mathbf{L}_{ft}, K_{ft})\right\} \tag{1}$$

For ease of exposition, I model single-product firms because multi-product firms are not a first-order concern in the Chinese tobacco tobacco industry, but the model can be generalized using the techniques from, e.g., De Loecker et al. (2016). Firms sell a differentiated product at price P_{ft}. Product markets are allowed to be imperfectly competitive, meaning that firms have some price-setting power on the product market.

***Assumption 1.* —** The productivity term Ω^H_{ft} is a scalar and enters the function $H(.)$ log-additively.

The productivity term Ω^H_{ft} is a scalar and enters the production function log-additively, as is usual in the literature.

Input markets

***Assumption 2.* —** The non-substitutable input M and at least one substitutable input in $\mathbf{L}_{ft}$ are variable and static.

This assumption means that both intermediate inputs and at least one other input can be adjusted fully flexibly each period. The assumption that M is variable is easily satisfied given the nature of intermediate inputs. The model can in principle be generalized to settings in which M is dynamic, for instance due to inventories, but this is beyond the aim of this paper. The requirement that at least one substitutable input is variable and static is crucial.

Assumption 3. — At least one static variable input in $\mathbf{L}_{ft}$ is perfectly competitive, and $H_{ft}(.)$ is twice differentiable in this input.

The market for at least one of the static variables in $H(.)$ needs to be perfectly competitive. For ease of exposition, I will consider the case when all variables in $H(.)$ are competitive, but all methods used generalize to settings with imperfectly competitive variables in $H(.)$, as will be shown in the next section. The added value of this paper consists in the fact that firms can have buying power on the non-substitutable input M. I restrict the model to cases when there is just one element M, without loss of generality.

Firms operate in input markets i. Input prices are denoted $\mathbf{W_{ft}} = (W_{ft}^M, \mathbf{W_{ft}^L})$. Prices of all inputs differ across firms depend on firm characteristics $\mathbf{Z_{ft}}$, part of which are observed and part of which are not. Input prices also depend on input quantities if the market for that input is imperfectly competitive. The price on any variable input $V \in \{M, \mathbf{L}\}$ is given by:

$$W_{ft}^V = W^V(\mathbf{Z}_{ft}, V_{ft})$$

The 'markdown' on input V is denoted ψ_{ft}^V and is defined as one plus the price elasticity of supply of that input. It quantifies the extent to which the marginal revenue product of that input exceeds its price. Markdowns are defined as follows:

$$\Psi_{ft}^V \equiv \frac{\partial W_{ft}^V}{\partial V_{ft}} \frac{V_{ft}}{W_{ft}^V} + 1 \geq 1 \qquad \text{for} \qquad V_{ft} \in \{M_{ft}, \mathbf{L_{ft}}\} \tag{2}$$

If input V is perfectly competitive, then $\psi_{ft}^V = 1$, otherwise $\psi_{ft}^V > 1$. Following Assumption 2, the markdown on the intermediate input M is greater or equal to one, while the markdowns on labor are one.

Assumption 4. — Firms minimize a short-term cost function taking output quantity and input prices of the competitive inputs as given.

The Lagrangian is given by equation (3), with marginal costs λ_{ft}.

$$\mathcal{L}_{ft} = \mathbf{W_{ft}}\mathbf{V_{ft}} + \lambda_{ft}\Big(Q_{ft} - Q_t(\mathbf{V_{ft}}, K_{ft}, \Omega_{ft}^H, \beta_{ft}^M)\Big) \qquad V \in \{\mathbf{L}, M\} \tag{3}$$

I assume firms choose their variable inputs every period to minimize current variable costs and taking both quantities and input prices for the competitive inputs $\mathbf{L}$ as given. In practice, firms may not always be cost-minimizing, especially state-owned enterprises (SOEs) in the Chinese context. I extend the model to allow for different objective functions in appendix B.

Assumption 5. — The state variables are given by $\{K_{ft}, Z_{ft}, \beta_{ft}^M, \Omega_{ft}^H, \psi_{ft}\}$

Demand for variable inputs

As stated in assumption 2, the intermediate input market is imperfectly competitive. When firms use one additional unit of M, the price hence increases by $\Psi^M_{ft} - 1$ units. The key issue underlying all identification problems in this paper is that this endogenous wage response is not only taken into account when choosing M, but also when choosing all variables in $\boldsymbol{L}_{ft}$. When firms choose labor, they take into account that increasing labor requires increasing intermediate inputs as well, which raises the price of intermediate inputs. The markdown on intermediate input markets hence affects labor demand as well. As derived more formally in appendix B, input demand for labor can be written as a function of the state variables, of input prices and of the slope of the intermediate input supply curve:

$$l_{ft} = l_t(\omega^H_{ft}, k_{ft}, z_{ft}, \mathbf{w_{ft}}, \Psi^M_{ft}) \tag{4}$$

2.2 Markup and markdown identification

I now discuss prior approaches to identify markups and markdowns using the production and cost approach. The main objective is to identify both upstream markdowns and downstream markups. The production and cost approach allows to impose less structure on how firms compete upstream and downstream, while requiring more assumptions on how firms produce and choose inputs[3]. I briefly discuss identification in the existing literature, and show why the more general framework of this paper leads to non-identification of markups and markdowns when uniquely relying on the production and cost approach. Denote the output elasticity and revenue share of any variable input V as α^V_{ft} and β^V_{ft}:

$$\begin{cases} \alpha^V_{ft} & \equiv \frac{W^V_{ft} V_{ft}}{P_{ft} Q_{ft}} \\ \beta^V_{ft} & \equiv \frac{\partial Q_{ft}}{\partial V_{ft}} \frac{V_{ft}}{Q_{ft}} \end{cases}$$

Case (i): Perfect input markets and substitutable inputs

This case corresponds to De Loecker and Warzynski (2012): there is no non-substitutable input M, so $\beta^M_{ft} = 0$. Let there be N variable inputs in vector $\boldsymbol{L}_{ft} = (L^1_{ft}, ..., L^N_{ft})$. The cost minimization problem in (3) yields N linearly independent first order conditions: demand for each input in $\boldsymbol{L}_{ft}$ can be chosen optimally keeping all other input quantities fixed. The markup can be expressed as

$$\mu_{ft} = \mu^{L^n}_{ft} \equiv \frac{\beta^{L^n}_{ft}}{\alpha^{L^n}_{ft}} \tag{5a}$$

[3] A comparison of both approaches and their assumptions is in De Loecker and Scott (2016b)

Assuming $\alpha_{ft}^{L^n}$ is observable and $\beta_{ft}^{L^n}$ can be identified, (5a) delivers an overidentified system of N equations in just one unknown, μ_{ft}.

Case (ii): Imperfect input markets and substitutable inputs

In this second case, there is still no Leontief input M, but there are $C < N$ perfectly competitive and $N - C$ imperfectly competitive inputs. This setting corresponds to Morlacco (2017). Write the variable inputs as $\boldsymbol{L}_{ft} = (L_{ft}^1, ..., L_{ft}^C, ..., L_{ft}^N)$, with the first C elements being perfectly competitive.

$$\begin{cases} \mu_{ft} = \mu_{ft}^{L^n} \equiv \beta_{ft}^{L^n} (\alpha_{ft}^{L^n})^{-1} & \text{if} \quad n \leq C \\ \mu_{ft} = \mu_{ft}^{L^n} \equiv \beta_{ft}^{L^n} (\alpha_{ft}^{L^n} \Psi_{ft}^{L^n})^{-1} & \text{if} \quad n > C \end{cases} \tag{5b}$$

There are now N-C+1 unknowns (the markup and all C markdowns) and N first order conditions, so as long as there is at least one competitive input, $C \geq 1$, the system (5b) is identified.

Case (iii): Perfect input markets and a non-substitutable input

In a third scenario, input markets are perfectly competitive but there is an input that cannot be substituted for any other input, so $\beta_{ft}^M > 0$. This scenario corresponds to De Loecker and Scott (2016a). There are now N+1 first order conditions for input demand, but just N are linearly independent, as M and L have to be changed jointly. Markups are given as

$$\mu_{ft} = \left((\mu_{ft}^{L^n})^{-1} + \alpha_{ft}^M \right)^{-1} \tag{5c}$$

Note that equation (5c) simplifies to equation (5a) if $\beta_{ft}^M = 0$, as this would imply $\alpha_{ft}^M = 0$

As soon as $N \geq 1$, markups are identified. If there are imperfectly competitive variable in $\boldsymbol{L}_{ft}$, than this is just a more general version of case equation (5b), and markups and markdowns can again be identified as long as $C \geq 1$.

Case (iv): Imperfect input markets and a non-substitutable input

This is the most general case, which nests all three previous cases, and is studied in this paper. The non-substitutable input M is now allowed to be imperfectly competitive. The markup is expressed in equation (5d), which is derived in appendix B. If there are N inputs in $\boldsymbol{L}_{ft}$, there are N markup expressions (5d) and two unknowns, the markup μ_{ft} and the markdown Ψ_{ft}^M. As none of the variable inputs in $\boldsymbol{L}_{ft}$ are substitutable with M, they are incorporate the markdown in their input demand condition in the same way, which is why markups and markdowns are not identified from each other from the cost minimization conditions for any number of variable competitive inputs N.

$$\mu_{ft} = \left((\mu_{ft}^{L^n})^{-1} + \alpha_{ft}^{M}\Psi_{ft}^{M}\right)^{-1} \tag{5d}$$

As imposing a production and cost model with cost minimization does not suffice to separately identify both markups and markdowns, more structure has to be imposed. This leaves us with two possibilities: either one has to impose a model of downstream competition and estimate markups μ_{ft} in order to recover markdowns Ψ_{ft}^{M} without explicitly modelling upstream competition, or the other way around.

2.3 Production function identification

Throughout the previous section, it has been implicitly assumed that the production function is identified. In all four cases outlined above, identification of the output elasticities is a necessary condition to identify markups and/or markdowns. In this section I show, however, that the production function is not identified using existing techniques in the most general case when there is an imperfectly competitive non-substitutable input.

Non-identification without prior markdown estimate

To estimate the gross output production function 1, intermediate inputs can be ignored: only the $H(.)$ function needs to be estimated[4].. Denoting logs of variables in lowercases, the equation to be estimated is given by:

$$q_{ft} = h_{ft}(\mathbf{l_{ft}}, k_{ft}) + \omega_{ft}^{H} \tag{6}$$

I follow De Loecker (2013) by imposing an AR(1) process on Hicks-neutral productivity in which ownership consolidation is allowed to endogenously affect productivity. Denoting an ownership consolidation indicator as $C_{ft} \in \{0, 1\}$, the productivity process is given by:

$$\omega_{ft}^{H} = g(\omega_{ft-1}^{H}, C_{ft}) + \xi_{ft} \tag{7}$$

Most of the production function literature estimates $h_{ft}(.)$ by recovering the productivity change ξ_{ft} from inverting an input demand function, and then imposing timing restrictions on the input choices (Olley and Pakes 1996; Levinsohn and Petrin 2003; Ackerberg, Caves, and Frazer 2015). If input markets are perfectly competitive, this is feasible under the scalar productivity assumption. Input

[4] In general, it could be optimal for firms to diverge from the Leontief 'first order condition' of intermediate inputs equalling the $H(.)$ function in labor and capital, as argued in Ghandi, Navarro, and Rivers (2018). The assumption that intermediate inputs enter the production function linearly solves this problem, however.

demand for the intermediate input is then given by (8a).

$$m_{ft} = m_t(\omega_{ft}^H, k_{ft}, z_{ft}, \mathbf{w_{ft}}) \tag{8a}$$

When intermediate inputs are imperfectly competitive, (8a) is violated as soon as firms differ in their markdown Ψ_{ft}^M, the correct input demand function is (8b). A shock to productivity ω_{ft}^H affects both the equilibrium input price W_{ft}^M and the input quantity m_{ft}, and how much each is affected depends on the size of the slope of the input supply curve $\Psi_{ft}^M - 1$. Inverting equation (8b) to get productivity as a function of known variables is hence impossible due to the latent markdown.

$$m_{ft} = m_t(\omega_{ft}^H, k_{ft}, z_{ft}, \mathbf{w_{ft}}, \psi_{ft}^M) \tag{8b}$$

An alternative proposed in Morlacco (2017) is to use a competitive input in $\mathbf{L_{ft}}$ for the inversion. Conditionally on the input quantity of the imperfectly competitive input, equation (8c) can be inverted for productivity. This, however, again works only if M and L are substitutable: otherwise, labor cannot change conditional on intermediate inputs (and fixed assets) being fixed.

$$l_{ft} = l_t(\omega_{ft}^H, k_{ft}, z_{ft}, \mathbf{w_{ft}}, m_{ft}) \tag{8c}$$

In the more general context of this paper, input demand for the competitive input can only be written unconditionally from the imperfectly competitive input M, as in (8d). In order to invert this equation and estimate the production function, knowledge of ψ_{ft}^M is again necessary.

$$l_{ft} = l_t(\omega_{ft}^H, k_{ft}, z_{ft}, \mathbf{w_{ft}}, \psi_{ft}^M) \tag{8d}$$

Estimation

Suppose now we have a consistent estimate of the log markdown $\hat{\psi}_{ft}^M$. Equation (8d) can now be inverted to back out productivity, as usual:

$$\omega_{ft}^H = h_t(l_{ft}, k_{ft}, z_{ft}, \mathbf{w_{ft}}, \hat{\psi}_{ft}^M)$$

I follow the two-stage procedure of Ackerberg, Caves, and Frazer (2015) by first netting quantities from measurement error ϵ_{ft}:

$$q_{ft} = \Psi(l_{ft}, k_{ft}, \mathbf{w_{ft}}, p_{ft}, z_{ft}, \psi_{ft}) + \epsilon_{ft}$$

For the practical setting of this paper, I impose a Cobb-Douglas function for $H(.)$, but more flexible substitution patterns could be allowed in general:

$$H_{ft}(L_{ft}, K_{ft} = L_{ft}^{\beta^L} K_{ft}^{\beta^K}$$

In a second stage, assuming all variables in L are variable and static while K is dynamic, the following moment conditions are formed to estimate the output elasticities:

$$\mathbb{E}\Big\{\xi_{ft}(\beta^l, \beta^k) \begin{pmatrix} l_{ft-1} \\ k_{ft} \end{pmatrix} \Big\} = 0$$

2.4 Input competition model

Motivation

The section on markup identification concluded that either a model of upstream or downstream competition needs to be imposed. As markdowns are necessary to identify the production function when using the control function approach, imposing a model of how firms compete on the market for intermediate inputs M is the only viable possibility left. The good news is that intermediate inputs are often sold on static spot markets, which should ease concerns about dynamic demand, search frictions and adjustment costs which are often present both in product and/or labor markets (although they will be ruled out for labor in the concrete setting of this paper). A similar strategy was used by Tortarolo and Zarate (2018), but for labor instead.

Theory

Let there be I_t markets i in which firms f purchase input M from input suppliers j. Let utility of a supplier j be parametrized as:

$$U_{jft} = \gamma^W W_{ft}^M + \zeta_{ft} + \nu_{jft}$$

with ν_{jft} being an i.i.d. type-I extreme value demand shock. Denote the intermediate input share of firm f in market i in year t as

$$S_{ft} = \frac{M_{fjt}}{\sum_{r \in i} M_{frt}}$$

***Assumption 6.* —** Firms engage in a static Nash-Bertrand game on the intermediate input market, simultaneously choosing input prices.

It is possible to allow for more flexible substitution patterns of farmers between firms, and/or to impose more complicated behavioral assumptions on how firms compete on input markets. Given the relative simplicity of how agricultural spot markets function, especially in the case of this paper, I stick to the simple logit model. The distributional assumption on ν_{jft} allows writing the intermediate input share S_{ft} as:

$$S_{ft} = \frac{\exp(\gamma^W W_{ft}^M + \zeta_{ft} + \xi_{ft})}{\sum_{r \in i} \exp(\gamma^W W_{rt}^M + \zeta_{rt} + \xi_{rt})}$$

The log input share s_{ft} is then

$$s_{ft} = \gamma^W W_{ft}^M + \xi_{ft} + D_{it} \tag{9}$$

with market-year dummies D_{it} controlling for the denominator.

The markdown is given by equation (10).

$$\psi_{ft} \equiv \Big(\frac{\partial S_{ft}}{\partial M_{ft}} \frac{M_{ft}}{S_{ft}} \Big)^{-1} = \Big(\gamma^W W_{ft}^M (1 - S_{ft}) \Big)^{-1} \tag{10}$$

Estimation

In general, input prices M are unobserved in production and cost datasets. The Leontief assumption does, however, contain information about input prices. Dividing input expenditure by output quantity identifies input prices up to the input requirement β^M:

$$\frac{M_{ft} W_{ft}^M}{Q_{ft}} = \frac{W_{ft}^M}{\beta_{ft}^M}$$

The above model can thus be estimated either if (i) firms do not differ in their intermediate input requirement $\beta_{ft}^M = \beta^M$ (ii) the researcher can obtain additional data on firm-level input prices W_{ft}^M (iii) additional data are obtained on the input requirements β_{ft}^M (e.g. the tobacco concentration per cigarette, or grams of hop in a beer bottle).

3 Consolidation and buying power in Chinese tobacco

3.1 Industry background and data

Ownership structure

Manufacturing of tobacco products such as cigarettes and cigars is controlled by SOEs in China, which generate 98% of industry revenues. While all tobacco manufacturing firms are formally subsidiaries of a single SOE, the Chinese National Tobacco Industrial Corporation (CNTIC), they are in reality controlled by local governments at the province, prefecture and county levels (Wang 2013).

Cigarette product markets are regulated by the State Tobacco Monopoly Administration (STMA), which in fact operates a cartel by buying the entire produce of manufaturing firms through an entity called the 'Chinese National Tobacco Trade Corporation' (CNTTC), with which it shares most of its management[5](Wang 2013). Both CNTIC and CNTTC operate using long vertical command chains, as depicted in Figure 1. While the STMA and CNTTC are highly centralized, with limited powers for local branches, manufacturing firms under the CNTIC have a large degree of autonomy in how they operate, and compete against each other on input markets and probably also, to a lower extent, on the product market (Peng 1996; Wang 2013).

[Figure 1 here]

Production process

This paper focuses on the manufacturing of tobacco products such as cigarettes and cigars. Intermediate inputs make up for the bulk of input expenditure, with a median revenue share of 49% (compared to 8% for labor). Tobacco leaves are by far the most important intermediate input[6]. Manufacturers generally buy the leaves directly from farmers, treat, shred and compress them, and finally insert them into cigarettes, cigars or other tobacco products. Contracts with tobacco farmers are negotiated locally (FAO 2003). Trade in both tobacco leaf and cigarettes across county boundaries requires explicit approval of the local STMA bureau under the *China Tobacco Monopoly Law*.

[5]While the formal distinction between CNTTC and CNTIC was made only in 2003, the combination of regulated wholesaling but autonomous manufacturing has been at the core of the STMA system since its inception in the early 1980s.

[6]The Chinese data do not break down intermediate inputs into more detailed categories, but US census data from 1997 show that tobacco leaves make up for for 60% of all intermediate input costs in tobacco manufacturing firms (U.S. Census Bureau 1997)

Input markets

Tobacco plants are grown, harvested and dried at farms that are predominantly, but not uniquely, located in the Southern provinces of Yunnan, Guizhou, Sichuan and Henan. Most farms are owned by individual households and are operated on a very small scale, on plots of 0.3-0.4 ha (FAO 2003). After sorting the leaves into quality and size grades, farmers sell them to manufacturers. In contrast to some other countries, tobacco farming is not a particularly profitable activity in China. In 1997,before the consolidation started, farm labor income per workday was 14.7 RMBn. This was around the median among the major crop types (FAO 2003).

As cigarette manufacturing does not require specific worker skills, firms compete for labor with other industries as well. Raw tobacco leaf is, on the contrary, only used as an input in the tobacco industry. Cigarette manufacturers hence only compete amongst each other on this market. Tobacco leaf markets are frictional: crop substitution is costly, rural labor mobility constrained due to the rural Hukou registration system, and some tobacco farmers are coerced not to switch crops by local officials who are dependent on tobacco as an important source of fiscal revenue Peng (1996).

Tobacco manufacturing employees do not live in the same places: counties with tobacco manufacturing firms are 30% more urbanized compared to other counties in the same prefecture.

Data sources

I obtain production and cost data from the above-scale annual survey of the National Bureau for Statistics (NBS) between 1998 and 2007. I retain all firms with HS 2-digit product codes 24, "Tobacco and Manufactured Tobacco Substitutes", resulting in 508 unique firms and 2638 observations. The above-scale survey includes non-SOEs with sales exceeding 5 million RMB and all SOEs irrespective of their size. As SOEs account for 98% of industry revenue, the survey includes nearly all tobacco manufacturing firms. I refer to Brandt, Van Biesebroeck, and Zhang (2012) for a comprehensive discussion on this dataset. Secondly, product-firm-month level quantities and values are obtained from the NBS as well, between June 2000 and December 2006. I observe prices and quantities for 58% of firms, but they produce 90% of total revenue. More details on this dataset are in Lu and Yu (2015). I only use prices to calculate annual production quantities, in order to know whether firms produced more or less than 100M and 300M packs per year before 2003. I deflate revenues, profits and input expenditures using the relevant input deflators. Finally, I use county-level demographic data from the 2000 Chinese population census. More information on all data sources is in Appendix A.

Summary statistics are in Table 1. The average cigarette pack costs 0.12 US dollar, with the most expensive pack costing 25 US dollar. Conditional on quantities being observed, an average firm produced 731M cigarettes per year. The median firm produced only 176M cigarettes per year. Prior to 2003, the average firm produced 311M cigarettes, and the median firm 68 M cigarettes, which was below the exit threshold of 100M. There is some selection in whether quantities are observed. Firms for which quantities are observed are around twice as large in terms of revenue than firms with unobserved quantities.

[Table 1 here]

In 1998, the market leader was Yuxi Hongta Tobacco Co., Ltd. with a nation-wide market share of 14.8%. A map of tobacco manufacturing locations in China is in Figure 2, with red dots indicating counties with at least one tobacco factory. The first map shows the tobacco manufacturing counties in 1998, the second map in 2007. The number of counties with a manufacturing factory clearly decreased substantially.

[Figure 2 here]

3.2 Motivating facts

In this section, I present three stylized facts which motivate the concrete modelling choices and identification strategy used.

***Fact 1.* —** The consolidation was size-dependent and led to increased industry concentration

The number of tobacco manufacturing firms fell from 351 in 1998 to 148 in 2007. The STMA central bureau stated in its annual report in 2000 that "to form competitive large enterprise groups, we must enforce the incorporation of inter-provincial tobacco groups" (Wang 2013). The top graph in Figure 3 shows that the number of tobacco firms indeed started to decline in that year. Initially, mergers were encouraged but not strictly enforced. This changed in 2003, when the STMA ordered all firms producing less than 100 million packs per year to be closed, while firms with annual production below 300 million packs were still encouraged to merge with larger firms. The bottom part of Figure 3 shows this size-dependent policy. The number of firms under the threshold dropped sharply between 2002 and 2004, from 130 to 50, while the number of firms above the thresholds remained fairly constant. These smaller firms were economically meaningful: 56% of firms produced less than 100M packs in 2000, generating a fifth of total industry revenue. As Figure 3 shows, average market shares of the provincial market leaders increased sharply from 2003 onwards, from below 50 to nearly 70%. For the two largest firms in each province, joint market shares increased from 70 to 85% between 2003 and 2007.

[Figure 3 here]

***Fact 2.* —** Industry-level intermediate input revenue shares fell, labor revenue shares not

Figure 4 plots the evolution of the industry-wide revenue shares for labor and intermediate inputs, that is, total input expenditure divided by total industry revenues (all deflated). While the labor share of revenue fluctuated around 3%[7], the material share of revenue fell from 40% to 25%. This drop started around 2000, when the industry started to consolidate.

Changes in relative input expenditure can be due to various reasons other than buying power, such as technical change. Mechanization replaces labor by machines, but should not affect the amount of tobacco used per cigarette, so it should lead to a falling labor share but a constant material share. Figure 4 shows the exact opposite pattern has occured in reality.

[Figure 4 here]

***Fact 3.* —** Intermediate input revenue shares covary negatively with market structure, labor revenue shares not

Next, I take a more disaggregated look at variation in labor and intermediate input revenue shares across geographical markets. Table 2 shows a simple OLS regression of firm-level factor revenue shares on the number of firms present in a prefecture. If there is only market power downstream, revenue shares for different variable inputs should react symmetrically to variation in market structure. Table 2 shows this is not the case: intermediate input revenue shares are 30% lower in markets with one firm and 20% lower when there are two firms. The labor share does, in contrast, not vary with local market structure. This suggests firms have buying power over intermediate inputs, but not over labor. This is consistent with the industry background.

[Table 2 here]

Caution is, however, required to interpret table 2 as causal: market structure is endogenous, and it is not merely the number of firms that matters. In Figure 5, I compare the relative revenue shares of intermediate inputs vs. labor between two groups of firms. A first group of firms‘, called ‘control’ did not have any competitors in the same prefecture with annual production under the 100M threshold in 2002. This group of firms should not have been affected by the consolidation. A second group of firms, denoted ‘treatment’, did have at least one competitors under the exit threshold. The intermediate input to labor revenue share fell from 6 to below 1 for this group of firms between 2003 and 2007. For the ‘control’ group, it fell from 7 to 6, so by much less. Taking the medians instead of the

[7] This is much smaller compared to the median labor share of 8% because it is weighted by firm labor usage. Smaller firms are less capital-intensive than large firms.

weighted averages yields a similar picture.

[Figure 5 here]

3.3 Estimation

I now use the model from section 2 to the estimate markups, markdowns and productivity in the Chinese tobacco industry.

Markdown estimation

I assume cigarette producers do not differ in their tobacco input requirement per cigarette, which is reasonable as cigarettes are not differentiated in terms of tobacco quantities, but rather in terms of quality and branding. This allows recovering raw tobacco prices.

$\beta^M_{ft} = \beta^M$

I start by estimating the input supply function using equation (9). Unobserved firm characteristics ζ_{ft} which enter utility of input suppliers, such as location, lead to endogeneity bias if they are correlated with tobacco leaf prices. I add firm fixed effects to control for cross-sectional variation in ζ_{ft}, such a fixed effects model is still inconsistent if the changes in ζ_{ft} over time are correlated with changes in input prices. I therefore adopt a third specification in which I instrument tobacco leaf prices with cigarette prices and export shares. As I control for location dummies, I instrument the changes in input prices with the changes in product prices and exporting, which affect input demand but plausibly not input supply. The estimates are in Table 3. The OLS specification in the first column reports a positive slope of the input supply curve, and implies that if the input quantity doubles, the tobacco leaf price increases by 32%. Adding firm fixed effects, in the second column, doubles this effect to 65%, as is expected due to endogenous firm characteristics. The IV model in column 3 estimates that doubling the market share results in twice as high input prices. These estimates are consistent with tobacco leaf markets being imperfectly competitive.

[Table 3 here]

Next, I calculate markdowns using equation (10). The mean and quantiles are in Table 5. Markdowns are on average 3.94, meaning that farmers receive merely a quarter of marginal product. For the median firm, the markdown is much lower, at 1.92, these farmers receive slightly more than half their marginal product. In contrast, I also included the markup and markdown estimates when estimating a Cobb-Douglas production function using the identification approach of Morlacco (2017). This approach yields much smaller markdown estimates, averaging at 0.70 which implies that farmers receive 42% *more* than their marginal product. For the median firm, this is even 0.40. It is clear that these estimates would not be realistic for most industries, and especially not in a concentrated and frictional one such as tobacco in China. The intuition behind this bias is simple: the Cobb-Douglas model assumes tobacco leafs are substitutable for labor and capital, and therefore estimates an output elasticity of tobacco leafs of around 0.5. The average firm has a much higher revenue share of tobacco leafs, around 0.6. The Cobb-Douglas therefore, wrongly, implies markdowns below one for tobacco leafs compared to the setting where tobacco leafs are proportional to output.

[Table 5 here]

The entire distribution of markdowns (and markups, which are discussed below) is depicted in Figure 6. The dispersion in markups is smaller than for markdowns, which is logical as input markets are narrower than product markets, and competition hence differs more upstream. There is a long tail in both markups and markdowns.

[Figure 6 here]

Production function estimation

Next, I estimate the production function as outlined in Section 2.3. Firms produce Q_{ft} numbers of cigarettes using labor L, raw tobacco M and capital K. Tobacco leafs are not substitutable for either labor or capital, while labor can be substituted for capital. As in the general model, and as motivated by the stylized facts, tobacco leaf markets are imperfectly competitive while labor markets are perfectly competitive. The log production function in labor and capital, equation (6), cannot be estimated directly as labor and capital quantities are unobserved. I observe the average number of employees (not accounting for skill differences, working days, etc.) $\tilde{l}$ and the capital stock $\tilde{k}$ instead. I follow De Loecker et al. (2016) to account for unobserved input quality differences by adding a function $A(.)$ to equation (6), which takes into account differences in labor unit wages and product quality. I also control for observable firm characteristics which may affect productivity, such as product types, ownership and an export dummy, collected in z. I hence estimate equation (11).

$$q_{ft} = \tilde{h}_{ft}(\tilde{\mathbf{l}}_{\mathbf{ft}}, \tilde{k}_{ft}) + A(w^L_{ft}, p_{ft}, z_{ft}) + \omega^H_{ft} \tag{11}$$

I follow the estimation routine from Section 2.3, with the markdown estimates entering the input demand function. I include cigarette prices, prices for all inputs, export status, product types, markdowns and consolidation treatment dummies in the first-stage input demand function. I bootstrap with 100 iterations to obtain the correct standard errors.

The estimates are in Table 4. Column (1) uses OLS, column (2) the ACF GMM approach without including markdowns in the input demand function, while (3) does include markdowns in this function. The OLS specification estimates large increasing returns to scale and a very high labor coefficient of 0.62, compared to the average labor revenue share of 0.11. When using ACF without including markdowns in the input demand function, the labor elasticity falls to zero while the capital coefficient grows to 0.82. Controlling for markdowns in the input demand function delivers an output elasticity of labor of 0.33 and a capital coefficient of 0.78. 0.78. Returns to scale are now not significantly different from one. The difference in the capital coefficient between the model with inclusion of the markdown is not significantly different from the model without doing so, because capital is a fixed asset anyway. The labor coefficient is very different, though, which makes sense as variable inputs adjust immediately to changes in markdowns on the intermediate input market.

[Table 4 here]

Markup estimation

With both output elasticities and markdowns being estimated, I can finally estimate markups without imposing a model of how firms compete on product markets using equation (5d). The markup distribution and some moments are in standard errors Figure 6 and Table 5. The average markup is 1.88, meaning that prices are 88% above marginal costs. Marginal costs include, however, also markdowns as explained in the model in section 2. The median markup is 1.21. Following a Cobb-Douglas model results in markups being estimated much higher, on average at 3.94 and with a median of 3.39. The degree of total market power is measured as the product of markups and markdowns. The Leontief model estimates market power at 2.48 on average and 2.15 at the median, as compared to 1.72 and 1.31 for the Cobb-Douglas model. The Cobb-Douglas model hence overestimates markups, but underestimates total market power. This is again due to the wrong output elasticities on intermediate inputs and the wrong markup formula being imposed on tobacco production.

The second rows in table (5) report the standard error around the mean of the markup and markdown distributions. These are not the standard deviations of the entire distribution, but rather the uncertainty around the output elasticity of labor for the markups, and uncertainty around the slope of the input supply curve for markdowns. The Leontief and Cobb-Douglas estimates of both markups and markdowns are significantly different from each other.

3.4 Estimating the effects of consolidation

Treatment and control groups

Let the number of firms producing less than 100M units per year in market i be denoted F_{it}:

$$F_{it} = \sum_{f \in i} (\mathbb{I}[Q_{ft} < 100M])$$

Firms producing less than 100M units were forced to exit in 2003. This group of firms represented 8% of industry revenue and a third of the number of firms before the consolidation started. Eight firms survived despite being under the exit threshold, I remove them from the sample.

I construct a consolidation treatment variable C_f which is a dummy indicating whether there was more than one firm under the threshold before 2003. In theory, the treatment would be a dummy indicating whether there was any firm under the threshold, but the presence of just one firm below the threshold does not have any meaningful effects in practice (probably because these firms are so small anyway).

$$C_f = \mathbb{I}[F_{i,2002} > 1]$$

In 2002, 38% of firms producing more than 100M units were in the treatment group, and table 6 shows they were smaller in terms of revenue than the control group, accounting for roughly a third of industry revenues.

[Table 6 here] In order to assess the effects of the consolidation on markdowns and markdowns, I estimate the following difference-in-differences model:

$$\begin{pmatrix} \mu_{ft} \\ \psi_{ft} \\ \omega_{ft}^{H} \end{pmatrix} = \gamma_0 + \gamma_1 \mathbb{I}[t \geq 2003] + \gamma_2 C_f \mathbb{I}[t \geq 2003] + \gamma_3 t + \gamma_f + \varepsilon_{ft} \tag{12}$$

The coefficient γ_2 estimates the causal effect of the consolidation on intermediate input markdowns if the time series variation of the error term ε_{ft} is conditionally independent from being subject to the merger reform. I only estimate equation (12) on firms which produce more than 100M cigarettes: these are the firms which are not targeted for consolidation but are exposed to its effects through changing upstream competition, if exposed to the treatment. The firms producing less than 100M which still survived the consolidation wave are probably operating due to some endogenous reason, which is why I exclude them from the analysis.

Identifying assumptions

The main identifying assumption of the difference-in-differences model (12) is that the error term ε_{ft} was not growing differently between firms with and without competitors under the threshold before and after 2003.

Assumption 7. **—** $\mathbb{E}\big(\Delta\varepsilon_{ft}C_f\mathbb{I}[t \geq 2003]\big) = 0$

The error term ε_{ft} contains all variation in markups or markdowns across firms that is not captured by the model. A first element that could be in ε_{ft} is differences in the objective function, that is, in the weights placed on employment in the cost function. Such differences could arise due to variation in ownership structure: SOEs value high employment more than private firms, for instance (Li et al. 2012). Including ownership dummies does not change the estimates significantly, though, so this does not seem to threaten assumption 7. A second element driving both consolidation and markups/-markdowns could be internationalization. The Chinese tobacco industry has, however, remained very domestically focussed and shielded from competition. The average firm in the sample sells merely 1% of its revenues abroad. Just to be sure, I include both export dummies and exports as a share of revenue as an additional control in the difference-in-differences regression.

Some further supporting evidence for assumption 7 consists in estimating parallel trends in markups and markdowns between both groups before 2003, using equation (13). The coefficient of interest here is the interaction term between the treatment variable and time: if this coefficient is not significantly different from zero, the trend in upstream markdowns between both groups was parallel.

$$\begin{pmatrix}\mu_{ft}\\ \psi_{ft}\end{pmatrix} = \eta_1 C_f + \eta_2 C_f * t + \eta_3 t + \nu_{ft} \qquad \text{if } t < 2003 \quad (13)$$

Market definitions

In principle, input markets should be defined at the county-level, as the tobacco monopoly law forbids trade in raw tobacco across county boundaries without permission of the local STMA office[8]. In practice, as was clear from the map in Figure 2, many counties ended up without a tobacco manufacturing firm while tobacco farming most likely continued. Tobacco trade across county boundaries is therefore likely, and I define input markets at the prefecture/prefectural city level (which includes several counties). This corresponds to the 4-digit level of the NBS administrative division codes[9].

[8]http://www.npc.gov.cn/englishnpc/Law/2007-12/12/content-1383891.htm

[9]In large cities, the administrative division into Province-Prefecture-County becomes less clear-cut. The counties in the data are, however, predominantly rural where this is not a problem.

Results

The estimates of equation (12) are in Table 7. The first two columns report the effects on total market power, both upstream and downstream. The third and fourth columns estimate the effects of consolidation on markdowns, while the final two columns do the same for markups. The even columns control for firm fixed effects, while the odd columns do not. The estimates show that the consolidation caused an increase in market power of 22.5%. A sole focus on total market power reveals, however, very different effects up- and downstrema. While markdowns increased by a hefty 90% for the firms in consolidated markets compared to other firms, markups *decreased* by 50%. Increasingly concentrated input markets hence mainly led to lower tobacco leaf prices, while cigarette prices fell as well. Consumers and firm shareholders were hence better off, while surplus of farmers fell sharply. I quantify the distributional effects of the consolidation in the next section.

It was expected that the consolidation increased markdowns by more than markups: input markets are much more localized and frictional in the Chinese tobacco setting than product markets are. It remains odd on first sight, however, that markups *decreased* during the consolidation. As markups are defined as prices over marginal costs, and as marginal costs include the markdown, this is not so strange. What table 7 actually says is that the increase in buying power was not entirely passed through towards shareholders, but that product prices fell slightly as well, hence leading to a smaller wedge between marginal costs and prices, but a larger wedge between input and output prices.

[Table 7 here]

I test whether treatment and control groups had a different markdowns trend before the exit thresholds were enforced in 2003, using the regression in equation (13). Table 8 shows this was not the case.

[Table 8 here]

Alternative explanations

I end this section by revisiting some of the modelling assumptions. First of all, I assumed the consolidation did not change substitution between labor and capital. In the first column of Table 10, I re-estimate the difference-in-differences regression, but using the log employment-to-capital ratio as a dependent variable. The evolution of capital intensity is not significantly different between the treatment and control group. Secondly, I check whether exporting behavior systematically changed for firms in consolidated markets. The second and third columns confirm that the exporting behavior did not differ between treatment and control groups at either the extensive or intensive margin.

[Table 10 here]

4 Distributional consequences

4.1 Overview

In this section, I use the estimates from the previous section to quantify the distributional consequences of enforcing the exit thresholds in 2003. Four different groups were affected by this consolidation: shareholders of cigarette manufacturers, which is mainly local and central governments, cigarette consumers, manufacturing workers and farmers. I will focus on income inequality between manufacturing workers and farmers: as factories lie mainly in urban areas, these two groups represent the urban and rural population. Rising income inequality between these groups has sharply increased in China over the past two decades, which motivates to study how consolidation affected them differently.

4.2 Income inequality measurement

As I do not observe farm- or firm-level intermediate input prices, I rely on average raw tobacco prices $\bar{W}_t^M$ as provided by the Producer Price statistics of the Food and Agriculture Organization (FAO). Income of tobacco farmers do not merely dependent on raw tobacco prices, but also on farm productivity and on input prices (such as fertilizers). I account for farm productivity by multiplying raw tobacco prices with average farm yields per acre, and assume farm input markets are perfectly competitive. I denote the product of average raw tobacco prices with average farm yields as $\bar{Y}_t$.

Counterfactual: no size-dependent exit policy

The income of tobacco farmers selling to firms in the control group was not effected by the 2003 exit policy. I denote income of this group as Y_t^0. Income of tobacco farmers supplying to firms in the treatmenet group did fall because of the increase in markdowns. I calculate how much farm income would have been for this group if markdowns had evolved as they did for the control group. Farm income of these farmers is denoted Y_t^1, and evolved as in equation (14). After the policy change in 2003, income of farmers selling to treated firms would have increased to the same extent as markdowns went down in reality. In other words, I let income of these farmers increase such that markdowns of treated firms grew at the same rate as markdowns of untreated firms did.

$$Y_t^1 = \begin{cases} Y_t \frac{E_t(\psi_{ft}|C_f=1)}{E_t(\psi_{ft}|C_f=0)} & \text{if} \quad t > 2003 \\ Y_t & \text{if} \quad t \leq 2003 \end{cases} \tag{14}$$

In order to know total farmer income in the counterfactual, I weight both groups by their relative intermediate input usage. Counterfactual average farm income is then defined as the weighted average of farm income of the treatment and control groups, with weight $\rho_t = \frac{\sum_f (M_{ft} C_f)}{\sum_f (M_{ft})}$. Let this weighted average be denoted $\hat{Y}_t$:

$$\hat{Y}_t = \rho_t Y_t^1 + (1 - \rho_t) Y_t^0$$

Results

Figure 7 plots the evolution of average raw tobacco prices (red short dashed line), actual farm income (the red solid line), counterfactual farm income without consolidation in 2003 (red long-dashed line) and manufacturing wages (in blue). Farm productivity increased after 2003, which means that raw tobacco prices underestimate actual farm income growth. Real wages of manufacturing workers almost quadrupled between 1998 and 2007, while farm incomes merely doubled. The income gap between both groups of workers therefore grew steeply over this period. As the dashed line shows, farm income would have grown at around the same rate as manufacturing wages without the 2003 exit policy, as markdowns would not have depressed farm income growth as much. In reality, inequality between farm and manufacturing wages doubled between 2003 and 2005.

[Figure 7 here]

Caveats

The partial equilibrium nature of this analysis comes with a number of caveats. First of all, market structure on the farming market is assumed to be exogenous. Higher farm income due to less downstream consolidation does hence not lead to more entrants in farming (or less exits). Secondly, changing labor migration between farms and manufacturing firms in the counterfactual worlds are assumed away. The results should therefore be seen as a back-of-the envelope calculation, which could be improved with a more complete model of occupational and location choices by both farmers and manufacturing workers.

5 Conclusion

In this paper, I find that a large-scale ownership consolidation in the Chinese tobacco industry increased buying power on the market for raw tobacco leaf. This rise in buying power had important distributional consequences: income inequality between tobacco farmers and manufacturing employees would have been a third lower without the 2003 consolidation. By increasing the income gap between rural farmers and urban manufacturing employees, the consolidation contributed to rising urban-rural income inequality. The finding that ownership consolidation only affected upstream, not downstream, competition may, of course, be specific to the Chinese tobacco industry. The methodology used can, however, be flexibly used in settings with both imperfectly competitive input and output markets. The frictions on Chinese agricultural input markets, as described in this paper, are present in many other factor markets throughout the developing world. Because of this, it is likely that the buying power effects of ownership consolidation generalize to other industry and country settings as well.

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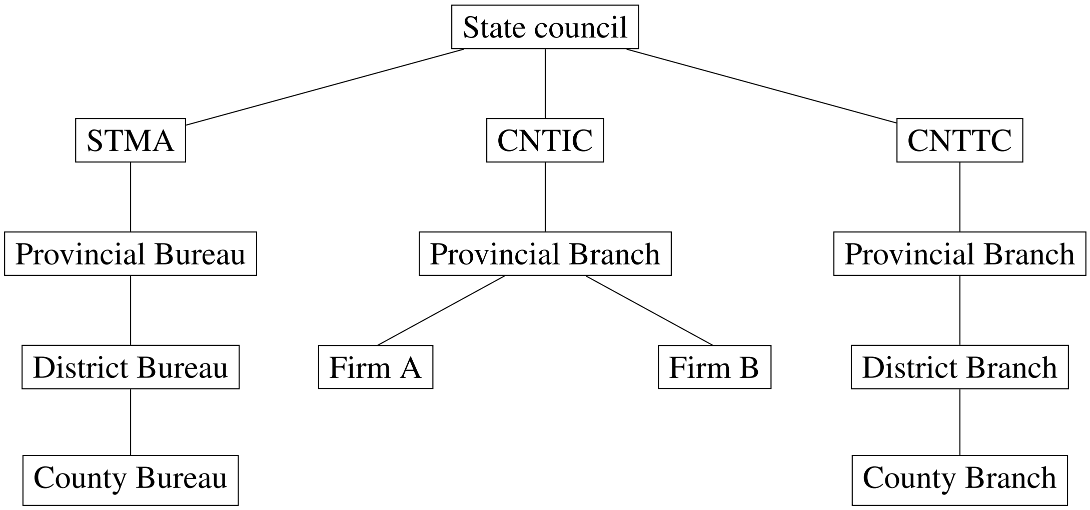
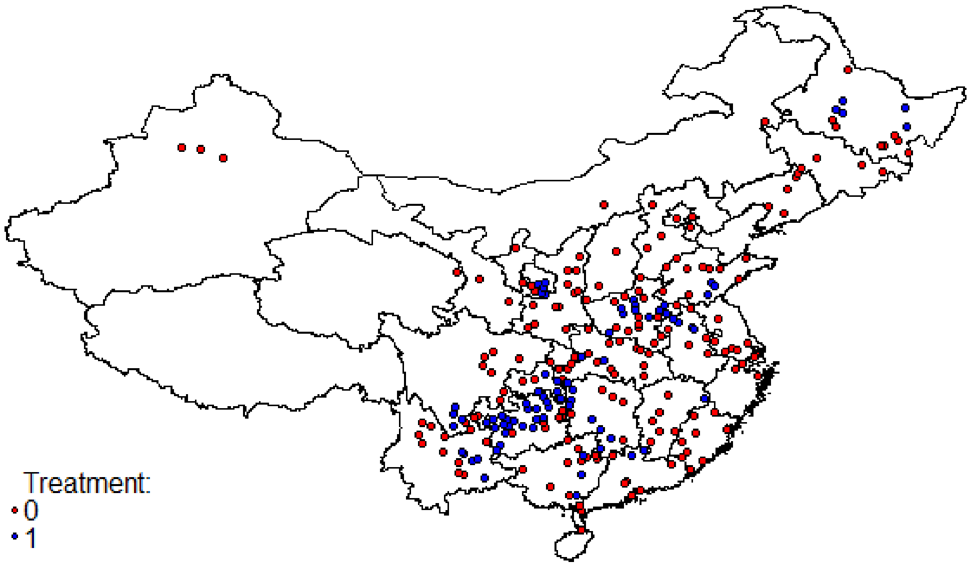
Figure 1: Organization of the Chinese tobacco industry



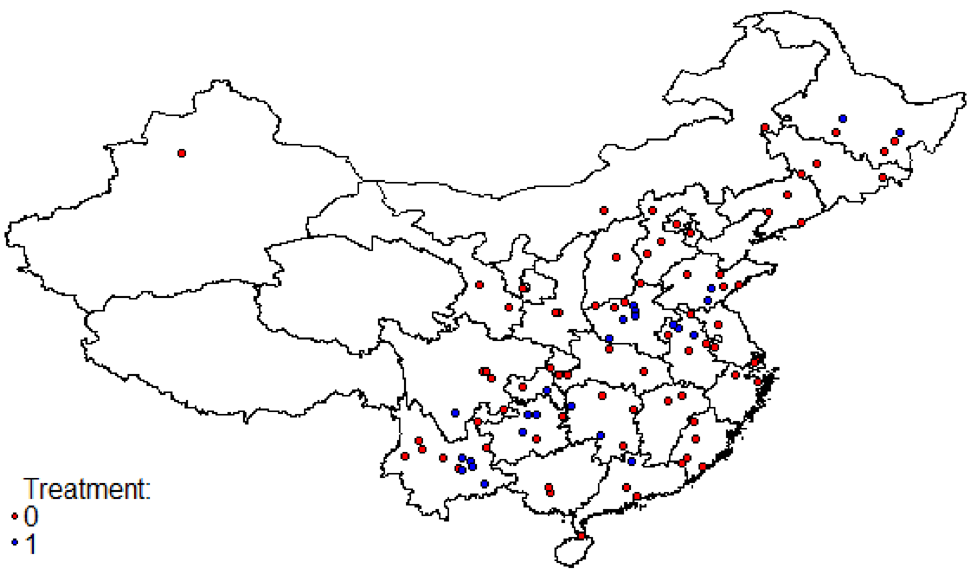
Source: Wang (2013)

Figure 2: Tobacco manufacturing locations

1998



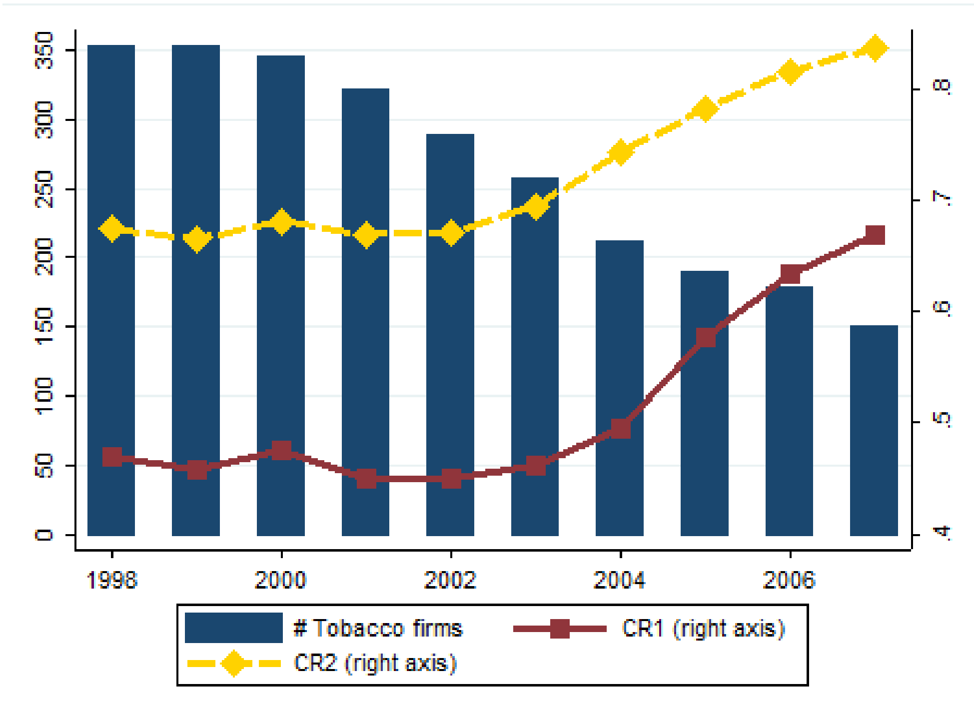
2007



Note: Dots indicate counties with at least one tobacco manufacturing firm.
Blue dots are counties with at least one firm producing less than 100M packs per year.

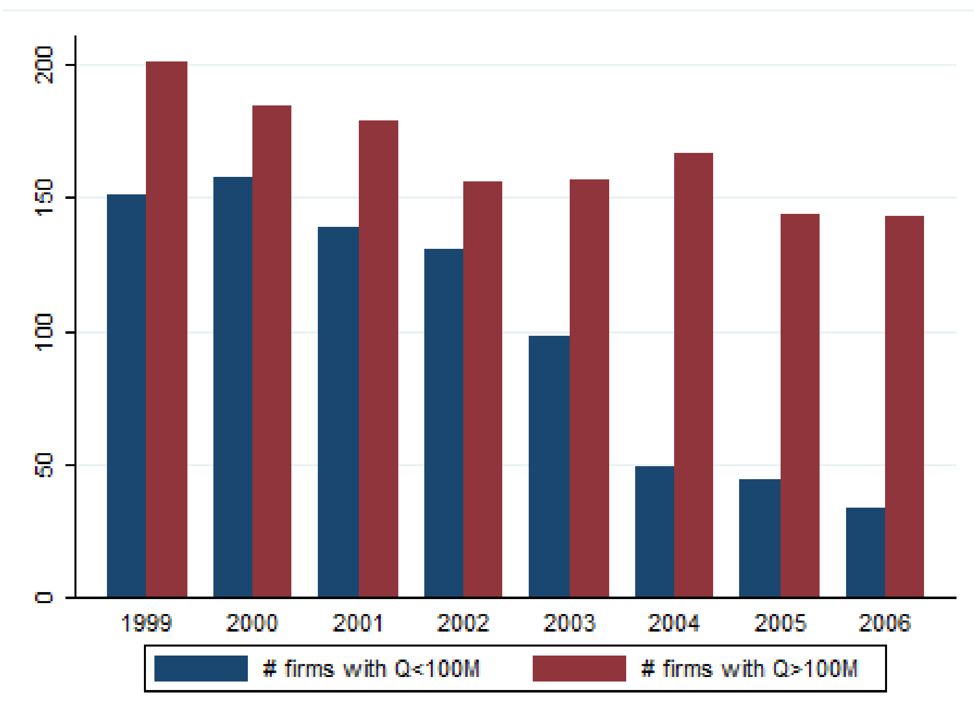
Figure 3: Market structure

No. firms and market shares



Note: Revenue shares are calculated at the province-year level.

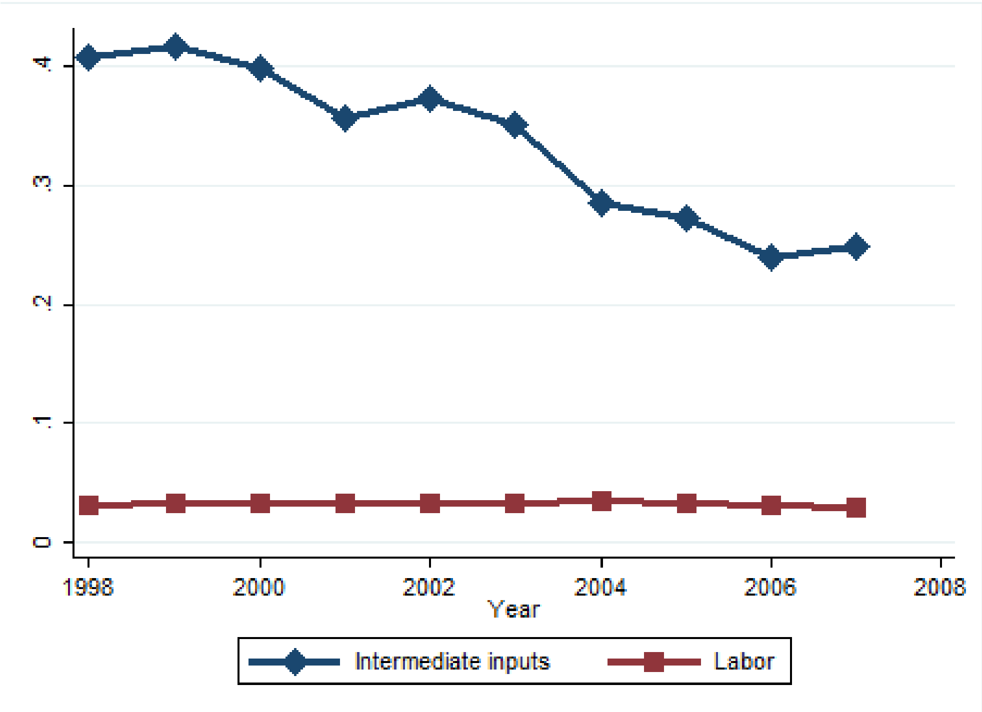
No. firms by annual production



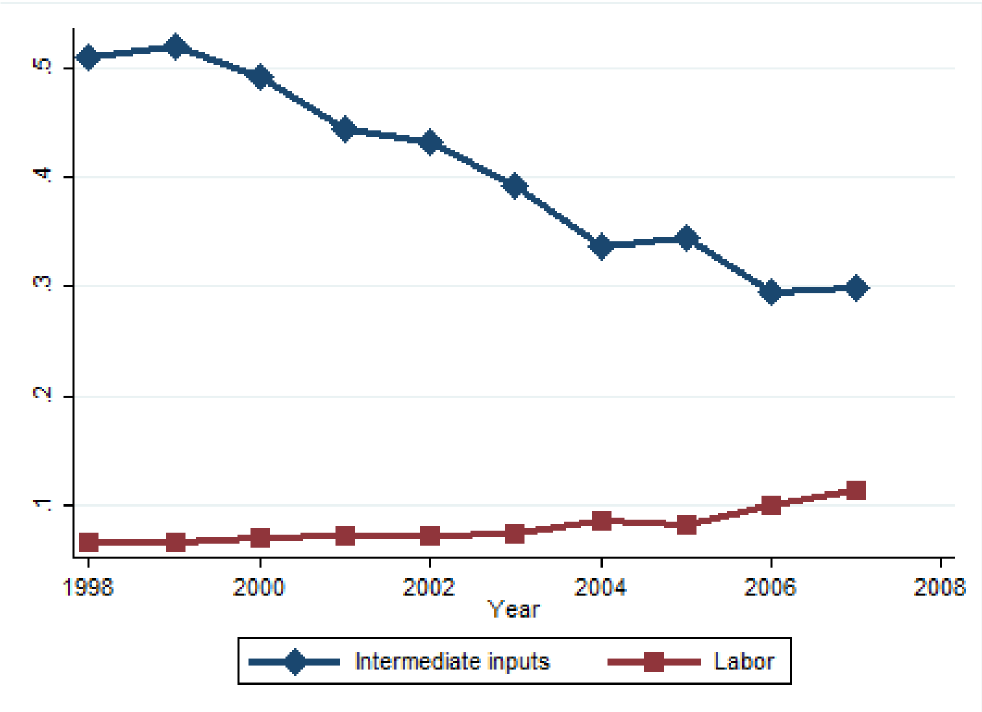
Note: This graph excludes firms for which quantities are unknown.
Prices and production quantities are observed only between 2000 and 2006.

Figure 4: Industry factor shares of revenue

Weighted average



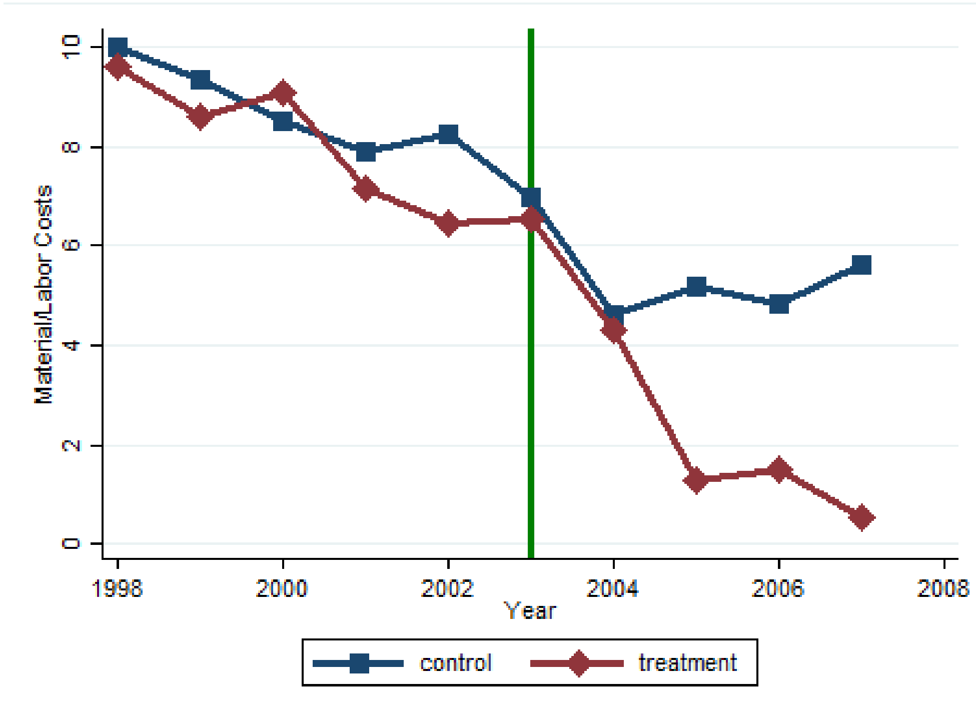
Median



Note: Factor shares are weighted by relative factor expenditures, i.e. the sum of input expenditures divided by the sum of revenues.

Figure 5: Relative factor revenue shares, by consolidation treatment

Aggregate



Median

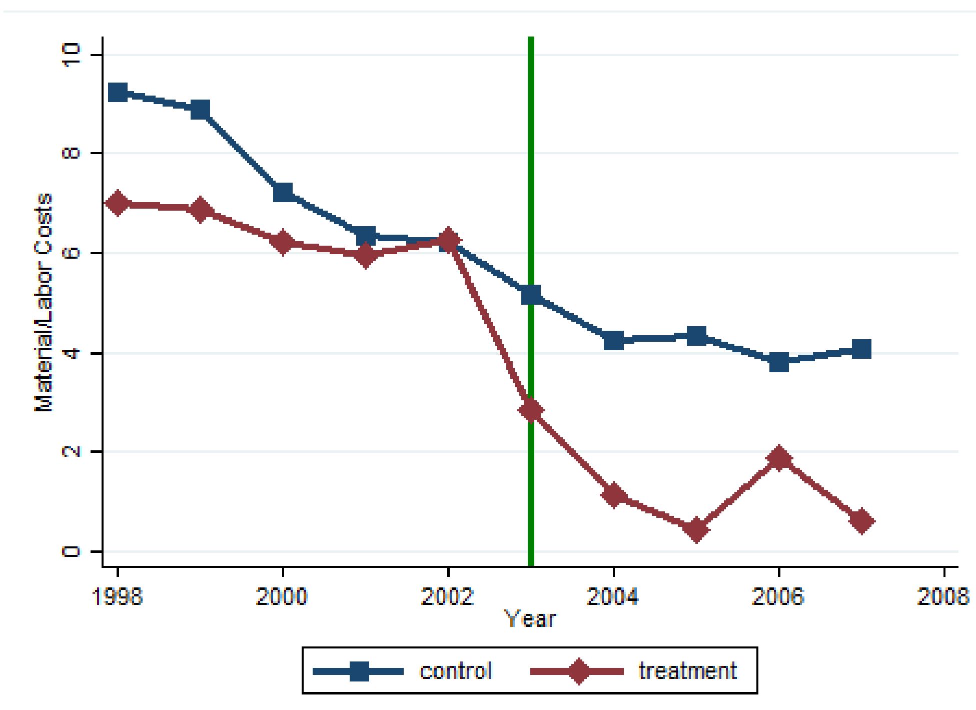
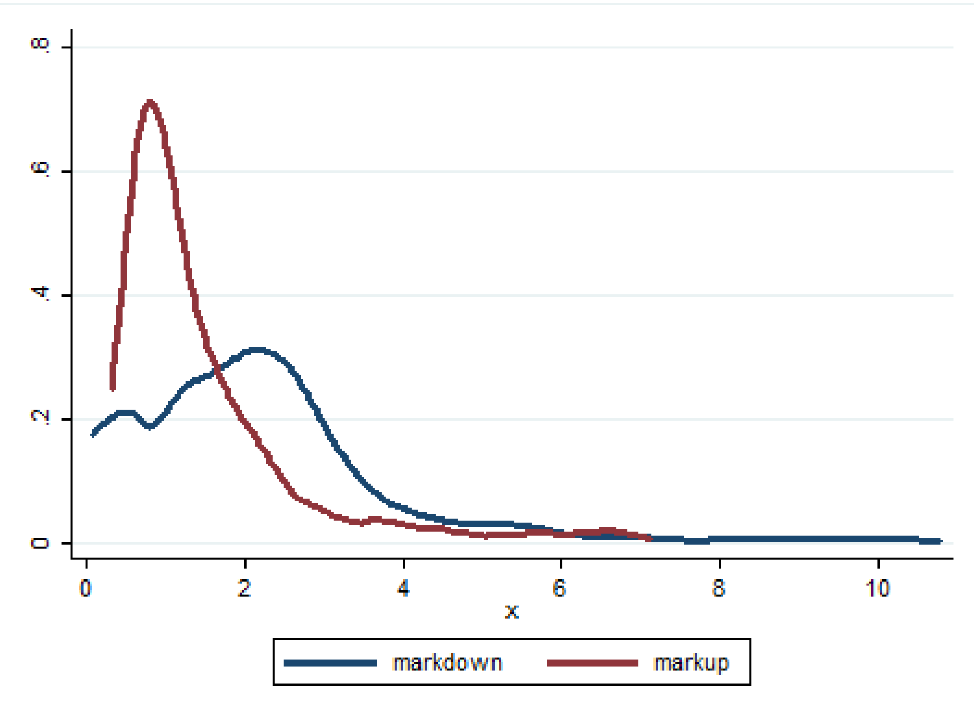
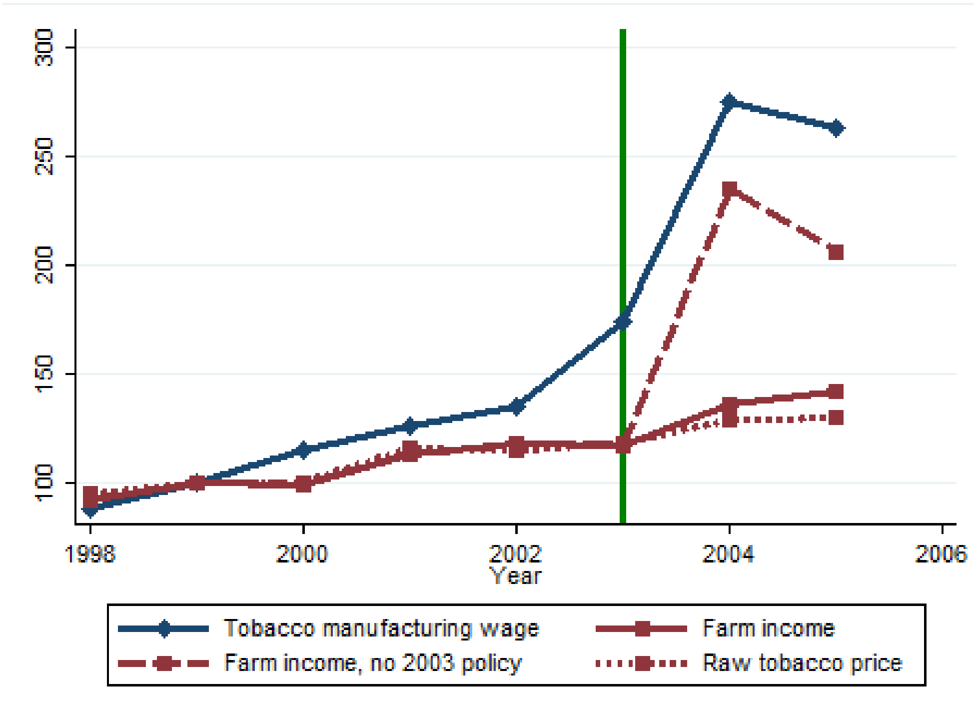


Figure 6: Markdowns



Note: Factor shares are weighted by relative factor expenditures, i.e. the sum of input expenditures divided by the sum of revenues.

Figure 7: Rural-urban income inequality



Note: All series are deflated and normalized compared to 1998 values

Table 1: Summary statistics

Variable	Mean	Std. Dev.	N
Revenue (million USD)	5.36	14.9	2638
Quantity (billion)	0.73	1.23	1080
Price (USD)	0.12	1.11	1031
Profit (million USD)	0.64	2.96	2631
Wage bill (million USD)	0.18	0.43	2631
Employees (thousand)	0.86	1.13	2631
Material expenditure (million USD)	1.83	3.87	2486
Capital stock (million USD)	2.45	5.41	2498
Export dummy	0.16	0.37	2638
Export share of revenue	0.01	0.08	2486

Table 2: Market structure and input revenue shares

Cost share:	**Intermediate inputs**	**Labor**
# firms = 1	-0.254***	0.136
	(0.0792)	(0.115)
# firms = 2	-0.196**	0.0463
	(0.0816)	(0.117)
# firms = 3	-0.0242	0.177
	(0.0845)	(0.109)
Constant	181.6***	-89.26***
	(21.03)	(20.20)
Observations	2,325	2,325
R-squared	0.138	0.102
Controls+	Yes	Yes

Standard errors in parentheses, *** $p<0.01$, ** $p<0.05$, * $p<0.1$

+Controls: export dummy, ownership type, product category

Note: The number of firms is calculated at the prefecture (4 digit) level.

Table 3: Intermediate input supply elasticity

Dependent variable:	Input price	Input price	Input price
Input market share	0.318***	0.648***	0.938***
	(0.0244)	(0.0594)	(0.0942)
Constant	-65.75**	-95.17***	3.370***
	(30.46)	(26.60)	(0.241)
Observations	1,122	1,122	919
R-squared	0.387	0.472	0.076
Model	OLS	FE	IV

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Controls: firm type, product type, export status
Instruments: product price changes and export changes

Table 4: Production function

Dependent variable:	**Output**	**Output**	**Output**
Labor	0.597***	0.0434	0.333***
	(0.0442)	(0.0765)	(0.0517)
Capital	0.616***	0.823***	0.782***
	(0.0302)	(0.0528)	(0.0374)
Observations	860	860	860
Method	OLS	GMM	GMM
Markdown control	No	No	Yes

Standard errors in parentheses

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 5: **Markup and markdowns**

Leontief:

	Markup	**Markdown**	**Market power**
mean	1.88	3.47	2.48
se(mean)	0.08	0.12	0.10
sd	2.33	10.06	2.33
p25	0.80	0.99	1.75
p50	1.21	1.92	2.15
p75	1.96	2.85	2.75

Cobb-Douglas:

	Markup	**Markdown**	**Market power**
mean	3.94	0.70	1.72
se(mean)	0.04	0.02	0.03
sd	0.70	2.42	2.92
p25	2.30	0.26	1.07
p50	3.39	0.40	1.31
p75	4.86	0.58	1.66

Table 6: Treatment and control groups

	Pre-2003:			Post-2003:		
	# obs	*% obs*	*% rev*	*# obs*	*% obs*	*% rev*
Control	640	62	69	490	67	68
Treatment	396	38	31	241	33	32

Table 7: Markups, markdowns and consolidation

Dependent variable	Market power	Market power	Markup	Markup	Markdown	Markdown
Treatment * I(year≥2003)	0.101	0.203**	-0.403**	-0.402***	0.646**	0.658***
	(0.110)	(0.0657)	(0.139)	(0.0933)	(0.205)	(0.126)
Treatment	-0.192***	-0.00522	0.193**		-0.493***	
	(0.0575)	(0.144)	(0.0719)		(0.103)	
I(year≥2003)	-0.104	-0.101*	0.249	0.222***	-0.357*	-0.340***
	(0.0914)	(0.0466)	(0.130)	(0.0642)	(0.171)	(0.0774)
Year	0.0642**	0.0510***	0.0591*	0.0431**	0.00886	0.0118
	(0.0209)	(0.0109)	(0.0275)	(0.0154)	(0.0377)	(0.0180)
Constant	-128.0**	-101.6***	-117.5*	-88.24**	-18.26	-21.26
	(41.81)	(21.90)	(54.92)	(30.75)	(75.40)	(36.00)
Observations	1,031	1,031	1,031	1,031	1,097	1,097
R-squared	0.051	0.805	0.219	0.847	0.234	0.872
Firm FE	No	Yes	No	Yes	No	Yes

Robust standard errors in parentheses

*** p<0.001, ** p<0.01, * p<0.05

Table 8: Markdown pre-trends

Dependent variable:	Markdown	Markup
Year	0.0296	-0.0138
	(0.0276)	(0.0194)
Year*treatment	4.52e-05	-0.000134*
	(0.000191)	(7.46e-05)
Constant	-60.85	30.61
	(55.48)	(38.81)
Observations	679	679
R-squared	0.044	0.062
Number of firms	241	241
Firm FE	Yes	Yes

Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table 9: Heterogeneous effects

Dependent variable:	**Markdown**	**Markdown**	**Markdown**	**Markdown**
Treatment * I(year≥2003)	1.778***	-0.0952	0.340***	0.746***
	(0.652)	(0.308)	(0.124)	(0.189)
Treatment*I(year≥2003)*log revenue	-0.111**			
	(0.0496)			
Treatment*I(year≥2003)*agri. pop. share		0.971**		
		(0.484)		
Treatment*I(year≥2003)*ethnic minorities			0.932***	
			(0.294)	
Treatment*I(year≥2003)*high emigration				-0.469**
				(0.238)
Constant	-241.2***	-300.4***	-209.4***	-205.4***
	(31.92)	(39.88)	(33.36)	(33.35)
Observations	1,880	1,316	1,880	1,880
R-squared	0.265	0.223	0.182	0.174
Firm FE	No	No	No	No
Province FE	Yes	Yes	Yes	Yes

Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table 10: Alternative explanations

Dependent variable:	**Capital intensity**	**Export dummy**	**Export/revenues**
Treatment*I(year≥2003)	0.0679	-0.0476	-0.0113
	(0.0972)	(0.0426)	(0.00894)
Treatment	-0.0429	-0.0303	-0.00554
	(0.175)	(0.0417)	(0.00951)
I(year≥2003)	0.0423	0.0756***	0.00787**
	(0.0573)	(0.0252)	(0.00347)
Year	-0.0777***	0.00539	-0.00129*
	(0.00985)	(0.00383)	(0.000767)
Constant	150.7***	-10.70	2.585*
	(19.70)	(7.660)	(1.535)
Observations	2,493	2,638	2,486
R-squared	0.091	0.040	0.011
Firm FE	Yes	Yes	Yes

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Appendices

A Data sources

A.1 Production and cost data

I use firm-level production and cost data from the Annual Survey of Above-Scale Industrial Firms, which is collected by the National Bureau of Statistics of China. I keep firms with HS 2-digit codes 24, ”Tobacco and Manufactured Tobacco Substitutes”. I calculate firm-level prices by dividing revenues with quantities. I drop observations with prices in the 1st and 99th percentile, as these are outliers. I also drop firms with negative intermediate input usage. This reduces the number of firms from 508 to 486 and the number of observations from 2638 to 2385.

I follow Brandt et al. (2017) by dividing firms into seven ownership types: state-owned , collective, private, foreign (incl. Hong-Kong, Macao and Taiwan), joint stock and stock shareholding enterprises. I obtain tariff and trade protection data from Brandt et al. (2017) as well. I calculate county-level average tariffs and the distribution of ownership types per county both for the tobacco industry and for all other manufacturing industries.

I geocode firms using the coordinates of the principal city in their 4-digit zipcode (which is the prefecture/prefectural city level). There are 340 such prefectures in the dataset, and around two thirds of the prefectures has only one tobacco firm.

A.2 Price data

Quantities and prices are given at the product-firm-year levels between 1999 and 2006. I calculate average prices (unit values) for the entire firm, all products combined (I only keep product codes in numbers). I also keep an indicator for the product with the highest revenue share for each firm. As product codes change over time in the original dataset, I keep the earliest product code with the highest annual revenue share. As some firms enter later than others, it is possible that some firms producing the same product have a different product code, but this should not be a large problem as entry was low anyway.

B Derivations and proofs

B.1 Input demand

I derive demand for the competitive input, henceforth L, in the gross output production function, with M being the imperfectly competitive input. When increasing L, firms take into account that M has to proportionally increase as well, which increases the price of M as well.

Let the first order condition on the competitive input be given as:

$$\min_{L_{ft}} \Big(W^L_{ft}L_{ft} + W^M_{ft}M_{ft} - \lambda_{ft}\big(Q(L_{ft}, M_{ft}, K_{ft}, \Omega^H_{ft}, \beta^M_{ft}) - Q_{ft}\big)\Big)$$

$$\Rightarrow W^L_{ft} + \frac{\partial W^M_{ft}}{\partial M_{ft}}\frac{\partial M_{ft}}{\partial Q_{ft}}\frac{\partial Q_{ft}}{\partial L_{ft}}M_{ft} + W^M_{ft}\frac{\partial M_{ft}}{\partial Q_{ft}}\frac{\partial Q_{ft}}{\partial L_{ft}} - \lambda_{ft}\frac{\partial Q_{ft}}{\partial L_{ft}} = 0$$

Assuming a Cobb-Douglas function for $H(.)$, we obtain:

$$\Rightarrow L_{ft} = \left(\frac{\big(\frac{P_{ft}}{\mu_{ft}} - \frac{W^M_{ft}\psi_{ft}}{\beta^M_{ft}}\big)\beta^L K^{\beta^K}_{ft}\Omega^H_{ft}}{W^L_{ft}}\right)^{\frac{1}{1-\beta^L}}$$

$$\Leftrightarrow l_{ft} = \Big(\frac{1}{1-\beta^{L_{ft}}}\Big)\Big(\log\big(\frac{P_{ft}}{\mu_{ft}} - \frac{W^M_{ft}\psi_{ft}}{\beta^M_{ft}}\big) + \omega^H_{ft} - w^L_{ft} + \beta^K k_{ft}\Big)$$

The markdown ψ_{ft} hence needs to enter the input demand formula.

B.2 Markup expressions

Leontief input is imperfectly competitive

Unlike with production functions in which the variable inputs are substitutable, there is no first order condition for each variable input in the gross output production function. Firms automatically choose both variable inputs together. Hence, there is just one first order condition:

$$\frac{\partial \mathcal{L}_{ft}}{\partial Q_{ft}} = 0$$

Marginal costs are given by:

$$
\begin{aligned}
\lambda_{ft} &= \frac{\partial(W^L_{ft}L_{ft})}{\partial Q_{ft}} + \frac{\partial(M_{ft}W^M_{ft})}{\partial Q_{ft}} \\
&= \frac{W_{ft}L_{ft}}{Q_{ft}\beta^L} + \frac{\partial(W^M_{ft})}{\partial Q_{ft}}M_{ft} + W^M_{ft}\frac{\partial(\frac{Q_{ft}}{\beta^M_{ft}})}{\partial Q_{ft}} \\
&= \frac{W^L_{ft}L_{ft}}{Q_{ft}\beta^L} + \frac{W^M_{ft}}{\Omega^M_{ft}}\Big(\frac{\partial W^M_{ft}}{\partial Q_{ft}}\frac{Q_{ft}}{W^M_{ft}} + 1\Big)
\end{aligned}
$$

Denote $\alpha^V_{ft} \equiv \frac{V_{ft}W^V_{ft}}{P_{ft}Q_{ft}}$ and $\beta^V_{ft} \equiv \frac{\partial Q_{ft}}{V_{ft}}\frac{V_{ft}}{Q_{ft}}$

To get the downstream markup, we now have to divide prices by marginal costs, which results in the following expression:

$$
\mu_{ft} \equiv \frac{P_{ft}}{\lambda_{ft}} = \frac{1}{(\mu^L_{ft})^{-1} + \alpha^M_{ft}\psi_{ft}} \tag{15}
$$

with $\mu^L_{ft} \equiv \frac{\beta^L_{ft}}{\alpha^L_{ft}}$ and $\psi_{ft} \equiv \frac{\partial W^M_{ft}}{\partial Q_{ft}}\frac{Q_{ft}}{W^M_{ft}}$ the slope of the intermediate input supply curve, as defined before.

This expression is very similar to the one in De Loecker and Scott (2016a), except for the fact that marginal costs now also include the endogenous wage reaction due to the upward slope of the intermediate input supply curve.

The gross output functional form impedes easy identification of buying power ψ. In models where intermediate inputs and labor are substitutable, such as in Morlacco (2017), monopsony power is obtained by simply dividing the total markup on the variable oligopsonic input by the markup on the variable competitive input. Buying power is identified in this setting because there are two first order conditions and two unobservables (markups and markdowns).

Leontief input is perfectly competitive

In this case, costs are given by:

$$
\mathcal{L}_{ft} = \arg\min(L^C_{ft}W^C_{ft} + L^{IC}_{ft}W^{IC}_{ft} + M_{ft}W^M_{ft} - \lambda_{ft}(Q(.)) - Q_{ft})
$$

There are two linearly independent first order conditions, for L^C and L^{IC}. Both take into account price effects on M:

$$\begin{cases} W^C_{ft} + \frac{\partial M_{ft}}{\partial L^C_{ft}} W^M_{ft} = \lambda_{ft} \frac{\partial Q_{ft}}{\partial L^C_{ft}} \\ W^{IC}_{ft} + \frac{\partial M_{ft}}{\partial L^{IC}_{ft}} W^M_{ft} + \frac{\partial W^{IC}}{\partial L^{IC}} L^{IC} = \lambda_{ft} \frac{\partial Q_{ft}}{\partial L^{IC}_{ft}} \end{cases}$$

Solving this system of equations yields the same expression for the markdown ψ as in Morlacco (2017):

$$\psi_{ft} = \frac{\mu^{IC}}{\mu^C}$$

The markup, however, is different from Morlacco (2017). Marginal costs λ are given by:

$$\lambda_{ft} = \frac{\partial(W^C_{ft} L^C_{ft})}{\partial Q_{ft}} + \frac{\partial(W^{IC}_{ft} L^{IC}_{ft})}{\partial Q_{ft}} + \frac{\partial(M_{ft} W^M_{ft})}{\partial Q_{ft}}$$

The markup is hence:

$$\mu_{ft} = ((\mu^{IC}_{ft})^{-1} \psi_{ft} + \mu^C_{ft} + \alpha^M)^{-1}$$

Using the markdown formula from above, the markup expression simplifies to:

$$\mu_{ft} = (2(\mu^{IC}_{ft})^{-1} + \mu^C_{ft} + \alpha^M)^{-1}$$