Ownership consolidation and input market power: evidence from Chinese tobacco

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Abstract

This paper examines the effects of ownership consolidation among Chinese cigarette manufacturers on input market power, product market power and efficiency. I combine a structural model of production and input market competition with a natural experiment in which firms under certain production thresholds were forced to exit. I find that this consolidation led to an increase in tobacco leaf price mark-downs of 20%, while cigarette price markups and efficiency remained constant. This increase in input market power had important distributional consequences: the consolidation explains 30% of the increase in income inequality between farmers and manufacturing workers, and 75% of manufacturing profit growth after 2003.

Keywords: Concentration, Market Power, Monopsony, Inequality, China

JEL Codes: L13, J42, O25

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1 Introduction

Product markets are increasingly concentrated in the United States (Autor et al. 2017). In theory, this can have multiple consequences. First, market power could rise on product markets, as firms increase the markup of prices over marginal costs. Second, the same can happen on input markets, as firms increase the markdown between input prices and marginal products. Third, firms could become more efficient due to scale economies. In order to understand how ownership consolidation affects welfare, all three channels need to be examined jointly, as they can have very different distributional and efficiency effects. The usual way to study the effects of ownership consolidation has been to make assumptions about how firms compete on product and/or input markets and to estimate the price elasticity of product demand or input supply (Berry, Levinsohn, and Pakes 1995; Nevo 2001). This approach does not, however, allow separate identification of efficiency gains, and usually also imposes exogenous prices on either input or product markets.

In this paper, I examine the effects of a large-scale consolidation in the Chinese cigarette manufacturing industry on both cigarette price markups, and tobacco leaf price markdowns, and production efficiency. Chinese tobacco is an ideal case study to study this question, as cigarette firms producing under certain size thresholds were forced to close down in 2003, thereby generating quasi-experimental market structure variation. Moreover, tobacco leaf markets are isolated due to strict leaf trade regulations. It is, finally, also interesting in its own right: 40% of the world’s cigarettes are made in China, which generate annual revenues exceeding 7 billion USD.1

I start by discussing identification of markups, markdowns and efficiency in the production approach of Hall (1986) and De Loecker and Warzynski (2012), with the key distinction that not all inputs are mutually substitutable. When producing cigarettes, one cannot substitute raw tobacco leaf for either labor or capital, and many other industries have at least one such non-substitutable input. As shown in De Loecker and Scott (2016) for US beer brewers, this changes how markups are inferred, as firms cannot choose all inputs independently from each other when minimizing costs. In contrast to that paper, however, I allow both for product and input prices to be endogenous. I show that the combination of input and product market power with limited substitutability of at least one input leads to non-identification of markups and markdowns when using the production and cost approach only.

I solve this challenge by combining a model of how firms produce cigarettes with a model of how they compete on tobacco leaf markets, while still making no assumptions on how firms compete on cigarette markets.2 I infer markdowns by estimating the tobacco leaf supply function using productivity residuals from the production function. Manufacturing productivity shocks shift demand for tobacco leaf, but are presumably excluded from farmer utility. Next, I use both the estimated output

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1 Tobacco differs, obviously, from other industries because of its health externalities. I will abstract from these in this paper.
2 More structure on input market competition was also placed in Tortarolo and Zarate (2018), but with a very different identification strategy, and while still relying on substitutability between all inputs.
elasticities and markdowns to infer markups.

I find that markups of cigarette producers are not significantly different from zero, meaning that prices are equal to marginal costs. Markdowns were, however, much larger than zero: the average ratio of the tobacco leaf price farmers received compared to their marginal revenue product to cigarette manufacturing was 43%. This is much lower compared to prior papers that estimate the input supply curve, such as Syverson and Goolsbee (2019) for US university professors (83%) and Ransom and Oaxaca (2010) for US grocery clerks (0.70). This high degree of monopsony power is unsurprising: labor markets are highly frictional in rural China, as in many other transitioning and developing countries. The combination of low markups and high markdowns is also consistent with the fact that around 100 cigarette manufacturers buy tobacco leaf from 20 million farmers on isolated leaf markets, but sell their entire production to a single government-controlled buyer which operates a cartel.3

Having estimated both markups, markdowns and efficiency, I examine how all three were affected by the 2003 consolidation policy. I compare firms in markets with at least one firm below the exit threshold of 100,000 cases before 2003 (the treatment group) with firms in markets without such firms (the control group). I find that markdowns increased by on average 20% more in the treatment group relatively to the control group. This increase was largest in markets with low migration and high unemployment, for state-owned enterprises (SOEs) and for firms with high market shares. Markups did, in contrast, not evolve differently for both groups. Contrarily to the policy’s main objective, efficiency did not increase differently for the treatment group, which is consistent with the absence of scale economies found when estimating the production function.

Prior research on state-owned enterprise reform and ownership consolidation in China, such as Hsieh and Song (2015), came to the opposite conclusion that SOE consolidation increased aggregate TFP by 20% across all manufacturing industries. They did not allow for input market power, however. In a model which assumes substitutable inputs with exogenous prices, an increase in markdowns will be interpreted as productivity growth as intermediate inputs and quantities are usually not separately observed. Using such a model for the tobacco industry would lead to the erroneous conclusion that TFP increased by 30% for firms in the treatment group, while in reality input prices merely fell. This has important policy implications: large-scale consolidation policies such as the one in this paper are often used: in China alone, many important industries such as energy, transport utilities, telecommunication and defense industries have been, or are currently being, consolidated into industrial giants.4 Other countries, such as Indonesia, have mimicked these policies in various strategic industries. If these consolidations lead to markdown rather than productivity growth, their welfare costs can be large.

One particular adverse consequence of increasing markdowns is distributional: I show that the

3High markdowns are also consistent with widespread poverty among Chinese tobacco farmers, in contrast to most other tobacco-growing countries where tobacco ranks high among crops in terms of profitability (FAO 2003).
4These policies are known as “Grasping the large and letting the small go” (Naughton 2007)
consolidation explains 30% of the increase in income inequality between manufacturing workers and farmers. This surge in inequality was not in line with official policy objectives: tackling income inequality was a crucial feature of President Hu Jintao’s *Harmonious Society* program throughout the mid-2000s. The fact that the official publication of raw tobacco prices was discontinued in 2003, simultaneously with the reform, strongly suggests that the reform indeed did not square with official ‘equitable economic growth’ objectives. More recently, poverty among tobacco farmers has been addressed by targeted subsidies in the 13th five-year plan from 2017,\(^5\) which acknowledges the precarious state of tobacco farmers. Such transfer schemes may not have been necessary without the consolidation policy.

In this paper, I make three main contributions to the literature. First of all, this is the first paper that empirically examines the effects of ownership consolidation on both product market power, input market power and efficiency. There is a large empirical literature on market structure and product market power, such as Nevo (2001) and Miller and Weinberg (2017), but they assume exogenous input prices and cannot identify efficiency gains. A much smaller literature studies the efficiency effects of ownership consolidation (Braginsky et al. 2015; Blonigen and Pierce 2016), but rules out buying power as well and encounters the issue that ownership consolidation is likely to be endogenous. Finally, there is a literature about monopsony power on input markets, such as Card and Krueger (1994) for fast food workers, Naidu, Nyarko, and Wang (2016) for UAE migrant workers, Syverson and Goolsbee (2019) for academics and Wollmann (2019) for US dialysis nurses. None of these papers examine monopsony power together with product market power or efficiency. The monopsony literature also focuses mainly on labor, while I show that cigarette manufacturers rather had market power on intermediate input markets. In the tobacco industry, it is logical that tobacco farmers, rather than manufacturing workers, will be more vulnerable to monopsony power: their product is industry-specific, crop switching is very costly, and farmers can migrate less easily than urban manufacturing workers due to Hukou registration system. Given that the revenue share of intermediate inputs is ten times higher compared to labor across Chinese manufacturing, monopsony power over these input will also have much larger aggregate welfare consequences.

A second contribution concerns the identification of markups and markdowns using the production and cost approach when not all inputs are substitutable. Prior production and cost approaches to markdown estimation, such as Morlacco (2017), Dobbelrae and Wiersma (2019), and Brooks et al. (2019), hinge on the substitutability of all inputs. In many industries, however, a subset of inputs is not substitutable,\(^6\) examples include universities (professors), coffee roasting (coffee beans), beer breweries (hop), and consumer electronics (metallic ores). Once firms have buying power over any of these non-substitutable inputs, my approach become necessary. In fact, buying power seems even most likely when inputs are non-substitutable: if firms cannot economize on these inputs through

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\(^5\)https://www.tobaccoasia.com/features/china-aims-to-increase-tobacco-farmers-income/

\(^6\)At least in the short run
factor-biased technical change, the only remaining way to reduce costs is to gain buying power. I contribute by developing an alternative identification strategy which combines a model of how firms compete on input markets with a production and cost model. Another advantage of combining a production and input supply model is that the input supply function can be identified using estimated productivity shocks. Finding valid input demand shifters to estimate the input supply functions is, otherwise, typically hard. Finally, I also contribute methodologically by discussing the identification properties of the production function under various models of input market competition using simulated data.

A final contribution is to quantify the distributional consequences of the rise in buying power due to the consolidation policy, with a focus on rural-urban income inequality in China. Existing work on market power and inequality has mainly focused on product price markups (De Loecker and Eeckhout 2017, 2018), with input suppliers only being affected through general equilibrium channels. Input and product market power have, however, very different distributional implications. In the case of Chinese tobacco, for instance, rising markdowns on tobacco leaf markets led to income redistribution from farmers towards firm owners, while manufacturing workers remained unaffected. As farmers and manufacturing workers live mainly in rural and urban areas respectively, ownership consolidation contributed to a rise in the urban-rural income gap. This margin of inequality has risen sharply in China since the early 1990s (Yang 1999; Benjamin, Brandt, and Giles 2005; Chen and Ravallion 2009), and increasing markdowns have been an important driving factor for this rise, at least in the tobacco industry.

The remainder of this paper is structured as follows: in the next section, I briefly summarize the industry background, provide key motivating facts and discuss the data. Next, in section 3, I present the model and discuss identification of markups, markdowns and productivity. Section 4 contains the main empirical analysis. Distributional consequences are discussed in section 4.5 and are followed by conclusions.

2 Chinese tobacco: background and facts

2.1 Industry description

Ownership structure

Manufacturing of tobacco products, such as cigarettes and cigars, is mainly carried out by state-owned enterprises (SOEs) in China. These make up to 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 operates a cartel by buying the entire production of manufacturing firms through an entity called the ‘Chinese National Tobacco Trade Corporation’ (CNTTC) with which it shares most of its management\(^7\) (Wang 2013). Both CNTIC and CNTTC operate using long vertical command chains, as depicted in Figure 2. 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).

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 3, with red dots indicating counties with at least one tobacco factory. The tobacco industry is scattered across the country, but the most important centers of activity are located in the Southern provinces of Yunnan, Guizhou, Sichuan and Henan. 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.

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.\(^8\) 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*. A picture of the consecutive steps in the cigarette production process are in Figure 4.

\(^7\)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.

\(^8\)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. 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. Tobacco leaves are usually auctioned per quality grade multiple times a year. 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 RMB. This was around the median among the major crop types (FAO 2003). Ten years later, in 2006, tobacco had the lowest rate of return of all cash crops (Hu et al. 2006).

As cigarette manufacturing does not require specific worker skills, firms compete for labor with other industries as well. Raw tobacco leaf is, in contrast, only used as an input in the tobacco industry. Cigarette manufacturers hence only compete amongst each other on this market. Tobacco farmers can, of course, switch to an outside option, being other crops or employment outside of agriculture. Choosing this outside option is, however, costly. Crop substitution is widely known to be costly and difficult Li et al. (2012) and the rural Hukou registration system restrains rural labor mobility. Some sources even indicate that tobacco farmers are being coerced by local officials not to switch crops, in order to preserve an important source of local fiscal revenue Peng (1996).

2.2 Data

First, I use firm-level 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. I refer to Brandt, Van Biesebroeck, and Zhang (2012) for a comprehensive discussion on this dataset.

Second, I obtain product-firm-month level production quantities from the NBS as well, which are observed between 1999 and 2006. The availability of quantity and price data reduces the sample from 2,638 to 1,248 observations (58% of the total), but still covers 90% of total industry revenue, which means the firms for which quantity is unobserved are much smaller than the average. More details on this dataset are in Lu and Yu (2015). I deflate revenues, profits and input expenditures using the relevant input deflators, but the deflator is the same for all firms as I only focus on one industry.

Third, I retrieve county-level data from the 2000 population census through the Harvard Dataverse. This dataset covers 73% of the sample, or 1,924 observations. The population census contains many variables, of which I only use five. I use the county’s total population, the unemployed population, the labor force and the number of migrants, all in the year 2000.

Finally, I obtain brand-level information about cigarette characteristics from O’Connor et al. (2010). This dataset reports several product characteristics at the level of individual cigarette brands in 2009,
such as the weight of tobacco leaf per cigarette. This dataset is observed only for 13% of the observations, but covers 29% of observations by revenue. I only use this data in an extension, not in the main specification.

More details on the various data sources is in Appendix A. Summary statistics are in Table 1. The average factory-gate price of a cigarette case is USD 0.60 (in 1999 prices), with the most expensive pack costing USD 20. Conditional on quantities being observed, an average firm produced 340K cigarette cases per year, and the median firm only 153K cases. Prior to 2003, the average firm produced 294K cases per year, below the merger threshold, and the median firm 104K, which was just above the exit threshold of 100K. 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]

2.3 Key motivating facts

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

**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 5 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 100,000 cases per year to be closed, while firms with annual production below 300,000 cases were still encouraged to merge with larger firms. The bottom part of Figure 5 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 100K cases in 2000, generating a fifth of total industry revenue. As Figure 5 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.

9One case contains 50,000 sticks of cigarettes (Fang, Lee, and Sejpal 2017)
Fact 2. — Industry-level intermediate input revenue shares fell, labor revenue shares not

Figure 6 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%, 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 6 shows the exact opposite pattern has occurred in reality.

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.

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.

Fact 4. — The ratio of intermediate input expenditure over labor expenditure declined more rapidly for firms in consolidated markets after 2003

In Figure 7, I compare the ratio of intermediate input expenditure over the wage bill between two groups of firms. A first group of firms, called ‘control’ did not have any competitors in the same

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10This 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.
prefecture with annual production under the 100K cases 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 weighted averages yields a similar picture.

This pattern can be due to two reasons: first, it could be due to a factor-biased technology shock which made that less tobacco per worker was necessary to produce a cigarette. Given the nature of cigarette manufacturing, this seems very unlikely. Secondly, it could be due to a change in relative input prices, for instance, due to increased monopsony power on tobacco leafs markets, or decreased monopsony power on labor markets.

[Figure 7 here]

## 3 A model of production, markups and markdowns

### 3.1 Production and costs

I now present a model of how cigarette manufacturers produce, choose inputs and compete on tobacco leaf markets. While the model is tailored to the Chinese tobacco setting, it is applicable more generally to industries in which there is at least one non-substitutable input over which firms have buying power. I derive an expression for markups and markdowns which is general enough to nest markup and markdown expressions in prior work. Next, I discuss identification of markdowns and markups.

**Production**

Cigarette manufacturers $f$ produce $Q_{ft}$ cases of cigarettes using a quantity of tobacco leafs $M_{ft}$, labor $L_{ft}$ and fixed assets $K_{ft}$. I allow substitution between labor and capital, but not between tobacco leaf and labor or capital. For now, I take these substitution patterns as given, but I estimate the substitution elasticities between all inputs in section 4.4. Let the production function be given by the following gross output production function:

$$Q_{ft} = \min\left\{ \beta_{ft}^H M_{ft}, \Omega_{ft}^H H_t(L_{ft}, K_{ft}) \right\} \exp(\varepsilon_{ft}) \quad (1)$$

The unobservable shock $\varepsilon_{ft}$ captures i.i.d. unanticipated shocks to production. Firms differ in $\Omega_{ft}^H$, a scalar productivity shifter which is Hicks-neutral in capital and labor. This rules out any factor-biased technological change or labor-augmenting productivity\textsuperscript{11}. Again, I provide empirical evidence for this

\textsuperscript{11} Techniques to estimate factor-biased technical change, such as Doraszelski and Jaumandreu (2017), hinge on perfectly competitive input markets.
assumptions in section 4.4. Firms also differ and in the amount of tobacco leaf needed to produce a case of cigarettes, $\beta^M$. Firms do not differ in the function $H(\cdot)$, which parametrizes the substitution pattern between labor and capital. In other words, all firms use the same cigarette production technology. As is usual, I assume the function $H(\cdot)$ is twice differentiable in labor and capital.

I view both labor, capital and tobacco leaves as scalars, but the model generalizes to settings in which these three input types are vectors of variables. As such, this production function nests production functions in which all inputs are substitutable: in that case, the input requirement $\beta^M$ is zero, and the labor variable $L$ becomes a vector $L$ which contains both labor and intermediate inputs.

The model features single-product firms because the average firm in the sample earns more than 90\% of its revenue comes from selling cigarettes\footnote{Some firms also sell other tobacco products such as cigars or chewing tobacco, but I abstract from this.}. The model can be generalized to a multi-product setting, for which I refer to 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.

**Input markets**

I assume tobacco leaf and labor are variable and static inputs, while fixed assets are a dynamic fixed asset. This means that both tobacco leaf and labor can be adjusted fully flexibly during each period. The model can be easily adjusted to a setting in which labor is dynamic as well.

The prices for labor and tobacco leaf are denoted $W^L_{ft}$ and $W^M_{ft}$. The prices of these inputs $V \in \{M, L\}$ can depend on exogenous firm characteristics, of which the observables are collected in vector $Z_{ft}$ and the latent characteristics in $\zeta_{ft}$. Examples of these characteristics are the firm’s ownership structure (observed) or how close it is to a highway (latent). Input prices can potentially also depend on how many inputs the firm uses in a given year.

$$W^V_{ft} = W^V(Z_{ft}; \zeta_{ft}, V_{ft})$$

The price elasticity of input supply is defined as $\psi^V_{ft} - 1$ and can differ across firms and over time. If $\psi^V$ equals one, the input supply function is flat, which means that the price of input $V$ is given to the firm.

$$\psi^V_{ft} \equiv \frac{\partial W^V_{ft}}{\partial V^V_{ft}} \frac{V_{ft}}{W^V_{ft}} + 1 \geq 1 \quad \text{for} \quad V_{ft} \in \{M_{ft}, L_{ft}\}$$

I assume that firms are price takers on labor and capital markets, meaning that $\psi$ is one for these inputs, but I allow price-setting power (‘input market power’) on the market for tobacco leaf, so $\psi^M$ can be above one. This assumption is inspired by facts (2)-(4) in section 2, which suggested...
that if firms have buying power on input markets, they are most likely to have it on tobacco leaf markets. I will test this assumption empirically in section 4.4. In terms of generality, I could allow for substitutable inputs $L$ with upward-sloping input supply curves, but it is crucial that there is at least one substitutable variable input for which input prices are given to the firm.

I assume firms choose the price of the non-substitutable input $M$ every period in order to minimize per-period variable costs, taking the other input prices as given. In practice, firms may not always be cost-minimizing, especially state-owned enterprises (SOEs) in the Chinese context. The model can be extended to a certain extent to allow for different objective functions, which I discuss more in detail in Appendix B.5. The crucial assumption, as in all production and cost approaches to markups, is that firms minimize some linear combination of inputs.

**Assumption 1.** Firms choose input prices $W_{ft}^M$ annually to minimize a short-term cost function, taking the other input prices as given.

The associated Lagrangian of the cost minimization problem is given by equation (3), with marginal costs $\lambda_{ft}$:

$$W_{ft}^{M^*} = \arg\min L_{ft} = W_{ft}^M M_{ft} + W_{ft}^L L_{ft} + \lambda_{ft} \left( Q_{ft} - Q_t(M_{ft}, L_{ft}, K_{ft}, \Omega^H_{ft}, \beta^M_{ft}) \right)$$

This formulation of the cost minimization problem is different from prior approaches, such as in De Loecker and Warzynski (2012), in two ways. First, firms choose input prices rather than input quantities. As input prices are a function of input quantities, it does not matter at this stage whether prices or quantities are chosen by the firm. When a model of input market competition will be defined later, this distinction will matter though, and at that point I will impose a Nash-Bertrand model, meaning that firms choose input prices rather than quantities. Second, there is just one first-order condition, rather than one condition for each input. This is due to the Leontief production function. Firms cannot choose intermediate inputs conditional on labor and capital being fixed, and vice-versa. Hence, there is just one first order condition rather than one for each variable input.$^{13}$

### 3.2 Markups

**General case: endogenous input prices and non-substitutable inputs**

I start by deriving the expression for markups in this most general case, which applies to the Chinese tobacco industry. Next, I show how it relates to the prior markup literature.

The markup is defined as the price of output divided by marginal costs. From the Lagrangian in

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$^{13}$This also applied to the beer brewing production function in De Loecker and Scott (2016).
equation (3), we know that marginal costs are $\lambda_{ft}$. The markup $\mu$ is hence given by:

$$\mu_{ft} \equiv \frac{P_{ft}}{\lambda_{ft}}$$

Solving the first order condition in equation (3) for marginal costs yields the markup expression in equation (4d), the derivation of which is in Appendix B.1.

$$\mu_{ft} = \left( \frac{\alpha_L^{ft} \psi_L^{ft} + \alpha_M^{ft} \psi_M^{ft}}{\beta_L^{ft} \psi_M^{ft} + \alpha_M^{ft} \psi_M^{ft}} \right)^{-1}$$ (4a)

The revenue shares $\alpha$ on the right-hand side of equation (4a) are in principle observed, or can be estimated if there is measurement error, as in De Loecker and Warzynski (2012). An estimate of the output elasticity of labor, $\beta_L$, is obtained when estimating the production function. In the context of this paper, I assume labor wages are exogenous, meaning that $(\psi_L^{ft} - 1) = 0$. Even then, the right-hand side of equation (4a) still contains the input price elasticity of tobacco leaf, $\psi_M$, which is latent. Markups $\mu$ and the input price elasticity $(\psi - 1)$ are hence not separately identified when relying on the production function alone.

The intuition for the fact that markups depend on the input supply elasticity is that the slope of the input supply curve is part of marginal costs: if the firm increases output by one unit, costs increase by more the steeper the input supply function is, as input prices endogenously increase.

If the firm has more variable inputs, this does not solve this identification issue: it would merely add more observed or estimable terms linearly in the numerator of equation (4a). independent equations. The intuition behind this is simple: none of the variable substitutable inputs are substitutable with $M$. The input demand conditions for all these inputs hence incorporate the endogenous price effect of $M$ in the same way.

**Special case (i): Exogenous input prices and substitutable inputs**

Suppose all inputs have exogenous prices and are mutually substitutable. In that case, the non-substitutable input requirement is by definition zero, $\beta_M^{ft} = 0$, and all input price elasticities are zero: $(\psi_V - 1) = 0$. The markup $\mu$ becomes simply the output elasticity of a variable input divided by its revenue share. This corresponds to the original framework of Hall (1986) and De Loecker and Warzynski (2012).

$$\mu_{ft} = \frac{\beta_L^{ft}}{\alpha_L^{ft}}$$ (4b)

If there is only one variable input, the markup is exactly identified. In case there are multiple variable inputs, one can a markup expression for each variable input, and hence the markup is overidentified.
Special case (ii): Endogenous input prices and substitutable inputs

Now consider a setting in which all inputs are substitutable, but in which input prices are endogenous, that is, the input supply functions are upward-sloping. The markup is then expressed as the output elasticity of a variable input divided by its revenue share and divided by the input price elasticity of supply plus one. This corresponds to the expression from Morlacco (2017).

\[ \mu_{ft} = \frac{\beta_{ft}^{L}}{\alpha_{ft}^{L} \psi_{ft}^{L}} \]  \hspace{1cm} (4c)

If there is just one variable input, markups and markdowns are not separately identified. In case there is a vector of N variable inputs \( L \), markups are separately identified from markdowns in case there is at least one input of which the price is exogenous. In that case, equation (4c) becomes a system of N equations and N unknowns: (N-1) input supply elasticities and one markup.

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

A final special case holds when all input prices are exogenous, but when there is one input that cannot be substituted for any other input. In this case, \( \beta_{ft}^{M} > 0 \), but all input supply elasticities \( (\psi - 1) \) are zero. The markup is given by equation (4c), which corresponds to De Loecker and Scott (2016). It is identified even if there are is only one substitutable input.

\[ \mu_{ft} = \left( \frac{\alpha_{ft}^{L}}{\beta_{ft}^{M}} + \alpha_{ft}^{M} \right)^{-1} \]  \hspace{1cm} (4d)

Note that cases (ii) and (iii) can be blended: if there are the prices of the substitutable inputs are endogenous and the prices of the non-substitutable input is not, the markup is identified as long as there is at least one substitutable input with an exogenous price.

Possible approaches to achieve identification

Back to the general case in equation (4a), in which markups and the intermediate input supply elasticity are not separately identified. It is hence indispensable to impose additional structure on how firms compete either downstream or upstream. This leaves two possibilities to achieve identification. One could estimate markups \( \mu_{ft} \) by imposing a model of how firms compete on product markets and by estimating demand, as in a large literature in industrial organization. The input supply elasticity can then be backed out without further assumptions. I is also possible to take the opposite approach: imposing a model of how firms compete on input markets and then estimating the input supply elasticity.

There are three reasons why I opt for this second approach in this paper. First, tobacco leaf markets are much easier to define than cigarette markets in China as tobacco leaf trade across county bound-
aries is restricted by law, while cigarette trade is not. Second, leaf market competition is easier to model than cigarette market competition. Manufacturers buy from many small farmers in local static spot markets. They sell, however, to a cartel-enforcing government holding, which raises questions about conduct downstream. Also, the prices in the dataset are factory-gate prices rather than prices faced by consumers. Product demand for cigarettes would also have to incorporate all sorts of dynamics inherent to cigarette consumption, such as addiction, which is not the case for tobacco leaf supply.

3.3 Markdowns

Markdown interpretation of the input supply elasticity

The input price elasticity of supply, \((\psi - 1)\), is intimately related to the concept of ‘markdown’, that is, the wedge between an input’s marginal revenue product and its price. To see this, rewrite the cost minimization problem in equation (3) as a profit maximization problem. Using the derivation in appendix B.2, the following expression is obtained:

\[
\psi^M_{ft} W^M_{ft} = \frac{\partial(P_{ft} Q_{ft})}{\partial M_{ft}} - \frac{\partial M_{ft}}{\partial L_{ft}} \frac{\partial L_{ft}}{\partial Q_{ft}}
\]

\[\text{MRP leaves} - \text{Marginal labor cost}\]  

(5)

The right-hand side of this equation is the marginal revenue product of tobacco leafs minus the additional labor cost which needs to be paid when increasing tobacco leafs by an additional unit. This entire term can hence be thought of as the marginal profit gain from an additional unit of leaf, net of leaf costs. The term \(\psi^M\) can now be interpreted as a ‘markdown’: it is the ratio of the marginal benefit of leafs divided by the leaf price farmers receive. If the markdown is large, farmers only get paid a small fraction of their contribution to manufacturing profits.

Input competition model

Let there be \(I\), isolated leaf markets \(i\). Farmers \(j\) can sell tobacco leafs to manufacturing firms \(f \in F_{it}\), with \(f = 0\) indicating the outside option of not selling to any firm. I assume each firm operates in exactly one market and that farmers sell their entire production to a single firm, which makes sense as there were 20 million household-level farms producing tobacco leaf in 1997 (FAO 2003), selling to merely 350 firms. I follow Berry (1994) and the ensuing literature and let the utility function of an farmer \(j\) depend on the leaf price, manufacturer characteristics \(Z_{ft}\) and \(\zeta_{ft}\) and an i.i.d. type-I distributed manufacturer-farmer utility shock \(\nu_{jft}\):

\[U_{jft} = \gamma^W W^M_{ft} + \gamma^Z Z_{ft} + \zeta_{ft} + \nu_{jft}\]
As usually, I normalize the utility of the outside option to zero: \( U_{j0t} = 0 \). I explicitly rule out variation in supplier preferences for input prices or manufacturer characteristics, \( \gamma_W \) and \( \gamma_Z \). While richer substitution patterns could be introduced in principle, for instance a mixed logit as in Berry, Levinsohn, and Pakes (1995), I will show later that this requires a different identification strategy of the production function. I stick to the simple logit model as homogeneous preferences as this seems plausible for a static spot market such as tobacco leaf markets: farmers are likely to care mainly about the input price they receive, not so much about who they sell to. When applying the used methods to other input markets, such as labor markets, it seems more important to allow for heterogeneous supplier preferences and possibly also search frictions and persistence in buyer-supplier utility \( \nu_{jft} \). I leave this for further work.

For now, I assume the farmer-manufacturer utility shock \( \nu_{jft} \) is i.i.d. across firms, farmers and time, and make the usual logit distributional assumption. Hence, I assume that every period, there are random reasons why farmer \( j \) sells to firm \( f \), for instance, but these do not persist over time.

**Assumption 2.** — The farmer-manufacturer utility shock \( \nu_{jft} \) follows an extreme-value type-I distribution.

I already assumed that firms simultaneously choose tobacco leaf prices to minimize costs. As such, firms engage in a static Nash-Bertrand game on the tobacco leaf market. I denote the tobacco leaf market share as \( S_{ft} = \frac{M_{jft}}{\sum_{r \in F_i} M_{frt}} \).

The distributional assumption on \( \nu_{jft} \) allows to write the intermediate input share \( S_{ft} \) as:

\[
S_{ft} = \frac{\exp(\gamma_W M_{ft} + \gamma_Z Z_{ft} + \zeta_{ft})}{\sum_{r \in F_i} \exp(\gamma_W M_{rt} + \gamma_Z Z_{rt} + \zeta_{rt})}
\]

Dividing this share by the market share of the outside option \( S_{0t} \), whose utility is normalized to zero, and taking logs leads to equation 6, which will be estimated in the next section.

\[
s_{ft} - s_{0t} = \gamma_W W_{ft} + \gamma_Z Z_{ft} + \zeta_{ft}
\]

The markdown \( (\psi) \) can be expressed as equation (7).

\[
\psi_{jft}^M \equiv \left( \frac{\partial S_{ft}}{\partial M_{ft} \cdot S_{ft}} \right)^{-1} + 1 = \left( \gamma_W W_{ft}^M (1 - S_{ft}) \right)^{-1} + 1
\]

4 **Empirical analysis**

The empirical analysis consists of four main steps. I start by estimating the production function. Second, I estimate the input supply function in order to retrieve the markdown. Third, I combine the
output elasticity estimates from the first step with the markdown estimates from the second step to calculate markups. Finally, I examine how the 2003 consolidation policy affected both markdowns, markups and productivity.

4.1 Production function estimation

Why estimating the production function?

The production function needs to be estimated for three reasons. First, the output elasticity of labor is required to estimate the markup. Second, we want to evaluate the degree of scale economies and possible effects of the consolidation on productivity, for which we again need the production function. Finally, the productivity residuals will be used as input demand shifters when estimating the input price elasticity of leaf supply.

When estimating the production function, intermediate inputs can be ignored: only the \( H(.) \) function needs to be estimated.\(^{14}\) Denoting logs of variables in lowercases, the equation to be estimated is:

\[
q_{ft} = h(l_{ft}, k_{ft}) + \omega_{ft}^H
\]

\( q_{ft} \) = tobacco leaf demand
\( h(l_{ft}, k_{ft}) \) = production function of labor and capital
\( \omega_{ft}^H \) = productivity residual

The ownership consolidation, which will be defined later in more detail, is indicated by a dummy \( C_{ft} \in \{0, 1\} \). The consolidation could affect efficiency, as in Braguinsky et al. (2015), so I allow productivity to endogenously change due to the consolidation. I follow De Loecker (2013) by imposing an AR(1) process on the productivity residual in which the consolidation dummy enters. The productivity process is hence given by equation (9):

\[
\omega_{t}^H = g(\omega_{t-1}^H, C_{ft}) + \xi_{ft}
\]

Identification challenge

The usual approach to solve the endogeneity bias due to latent productivity in the literature is to invert an input demand function and express the productivity residual \( \omega^H \) as a function of observables only (Olley and Pakes 1996; Levinsohn and Petrin 2003; Ackerberg, Caves, and Frazer 2015). As derived in Appendix B.3, I can write tobacco leaf demand as equation (10). Input demand depends on several observable variables: cigarette prices, other inputs and their prices, ownership consolidation, and firm characteristics \( Z \) such as its export status or ownership structure. It also depends on three latent

\(^{14}\)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.
variables: markups $\mu$, markdowns $\psi^M$ and productivity $\omega_{ft}$.

$$m_{ft} = m(l_{ft}, k_{ft}, W^M_{ft}, W^L_{ft}, \omega_{ft}, \mu_{ft}, \psi^M_{ft})$$  \hspace{1cm} (10)$$

As soon as markups and/or markdowns are persistent, which they are almost certainly as market structure is persistent, this creates an identification problem as the input demand function (10) can no longer be inverted. The intuition for this is simple: low input usage could be due to low productivity, a high markup, and/or a high markdown.

**Solution 1: Input prices and market shares in input demand**

A first solution to this challenge is to stick to the inversion approach, but to insert drivers of markdown and markup variation across firms in the input demand function. A variation of this approach was used in De Loecker et al. (2016), but with only latent markups rather than markups and markdowns. In most models of supply and demand, markup and markdown variation across firms depends on prices and market shares. In the logit model outlined in section 3.3, for instance, markdown variation depends on the tobacco leaf price and leaf market share. If the same holds on the cigarette market, including leaf and cigarette prices and upstream and downstream market shares in the input demand function should solve the problem. Defining market shares downstream can be tricky and was one reason not to follow the demand estimation approach, but we can insert multiple market shares at different geographical levels (county, prefecture, province) in the demand function.

I expect this first approach to be suitable in the context of Chinese tobacco because (i) downstream markups are not expected to vary much across firms as they all sell to a single state-owned holding (ii) the static logit model of tobacco leaf markets is realistic because of reasons already highlighted in section 3.3.

When studying productivity, markups and markdowns in other industries, though, identifying the production function may be more problematic as markups and markdowns may depend on persistent variables other than market shares and prices. If there is, for instance, persistent heterogeneity in input supplier or consumer preferences across firms, that would be problematic as inversion of the input demand function would still not be achieved.

In Appendix D, I use simulated data to show that the production function can be consistently using this approach under the assumptions made, even if input prices are endogenous. I show, however, that the estimates can become seriously biased if (i) the input supply model is a mixed rather than standard logit, (ii) there is measurement error in input market definitions (iii) there is measurement error in input prices.
Solution 2: BLP instruments

An alternative solution that overcomes the challenges raised above is to step away entirely from the control function approach and to rely on an instrumental variables approach instead. The production function literature has stepped away from IV approaches because in the standard competitive input market model, few if any valid instruments are available for input usage.

Now that input markets are oligopsonic, however, it becomes possible to use instruments used in the literature on demand estimation in oligopoly. Berry, Levinsohn, and Pakes (1995), for instance, use exogenous product characteristics of competing products in the same market as instruments for product prices. Similarly, characteristics of competing cigarette manufacturers on the same leaf market should affect the leaf price a manufacturer sets, if these firm characteristics enter farmer utility, or if they are input demand shifters.

I discuss this alternative IV approach more in detail in appendix C.1 and again examine its consistency using Monte Carlo simulations. In the main text, I will follow the more traditional ACF approach as it is valid in the context of Chinese tobacco farmers.

Product differentiation

The log production function in equation (8) has both input and output quantities on both sides of the equation. Cigarettes are, however, differentiated products with various quality levels. As pointed out in De Loecker et al. (2016), this can result in bias as firms which produce high-quality, high-price cigarettes use more labor per unit of cigarette than low-quality producers. A second issue is that I observe the number of employees $\tilde{l}$ rather than the total amount of hours worked $l$. The unit wage $W^L_l$, which is the wage bill divided by the number of employees, captures variation in hours worked, though. I follow De Loecker et al. (2016) and solve both these issues by adding a function $a(\cdot)$ of both product prices (which proxy quality) and labor wages (which proxy hours worked) to the production function. The equation to be estimated hence becomes (11):

$$q_{ft} = h(\tilde{l}_{ft}, k_{ft}) + a(w^L_{ft}, p_{ft}) + \omega^H_{ft}$$

Estimation procedure

I follow the two-stage procedure of Ackerberg, Caves, and Frazer (2015). In a first stage, I build on the inversion of the input demand function mentioned earlier to net output from unobserved production shocks $\varepsilon$ using a function $\Phi(\cdot)$. This results in equation (12). The vector of demand shifters $z_{ft}$ includes all observables which may affect input demand: product and ownership types, export dummies and export shares of revenue in the vector of input demand shifters $z_{ft}$. I use a third-order polynomial in labor and capital in $\Phi(\cdot)$, and include the leaf price and input market share to proxy for...
markdown variation, as discussed in the previous section.

\[ q_{ft} = \Phi(\tilde{l}_{ft}, \tilde{k}_{ft}, w_{ft}^{L}, w_{ft}^{M}, z_{ft}, p_{ft}, s_{ft}) + \varepsilon_{ft} \]  

(12)

In the baseline model, I use a Cobb-Douglas function in labor and capital for \( H(\cdot) \), which is in equation (13). In order to allow for more flexible substitution patterns, I estimate a translog as well, for which the details are in appendix E.4.

\[ h(L_{ft}, K_{ft}) = \beta^{L}l_{ft} + \beta^{K}k_{ft} \]  

(13)

The second stage uses the following moment conditions to estimate the output elasticities, assuming all variables in \( L \) are variable and static while \( K \) is dynamic. The moment conditions for the Cobb-Douglas version are in (14).

\[ \mathbb{E}\left\{ \xi_{ft}(\beta^{L}, \beta^{K}) \left( \begin{array}{c} l_{ft-1} \\ k_{ft} \end{array} \right) \right\} = 0 \]  

(14)

**Results**

The estimates are in Table 3. The first column contains the estimates of the baseline estimation method, using ACF. The output elasticities of labor and capital are 0.319 and 0.783 respectively. The standard errors are very large, which is not unusual when using ACF on small samples (this was, for instance, also the case in the industry-by-industry estimates from De Loecker et al. (2016)). The scale parameter is slightly above one, but constant returns to scale cannot be rejected. The apparent absence of large returns to scale already casts doubt about the main motivation of the ownership consolidation, which was to increase efficiency by exploiting scale economies.

The second columns reports the estimates when using export participation and export shares of competing firms in the same leaf market as BLP instruments for labor and capital, as explained in Appendix C.1. The sample size is now larger as all time periods are used for estimation, while ACF does not use the first year of observation due to its use of lagged variables. The estimates are very similar to ACF, with output elasticities of 0.345 and 0.769, but with much smaller standard errors. During the remainder of the paper, I will continue using the ACF estimates, but as both estimates are very similar using the IV estimates would not lead to very different results.

[Table 3 here]
4.2 Markdown and markup estimation

Input supply estimation

I now estimate the input supply function, equation (6). If the unobservable manufacturer characteristics $\zeta$ are uncorrelated with input prices, this equation can be estimated using OLS. This is unlikely to hold: manufacturers that are attractive in some unobserved way, for instance because they are conveniently located, will pay a lower leaf price to farmers. This results in the same simultaneity bias as when estimating product demand. In order to separately identify input demand and supply, an instrument for input prices is hence needed. This has to be a shifter of input demand which does not enter input supply, i.e. does not enter farmer utility.

The productivity residual $\omega^H$, which was estimated in the previous section, is a good candidate to serve as such an instrument. It is certainly relevant, as productivity enters the input demand function. In order for the exclusion restriction to hold, productivity of the cigarette manufacturer cannot enter the utility function of the tobacco farmers. In other words, farmers do not care how efficient the manufacturing firms is they are selling to, which is plausible.

Once the input supply elasticity is estimated, markdowns $\psi^M$ can be calculated using equation (7). Together with the estimated output elasticity of labor, markups can be calculated as in equation (4a).

Measurement

As is usually the case in production and cost datasets, I do not observe leaf prices $W^M_{ft}$, but only leaf expenditure $M_{ft}W^M_{ft}$. Due to Leontief production function, I can, however, divide leaf expenditure by the number of cigarette cases produced. This results in the leaf price $W^M_{ft}$, up to the leaf requirement $\beta^M_{ft}$, which is the amount of tobacco leaf used per case of cigarettes.

$$\frac{M_{ft}W^M_{ft}}{Q_{ft}} = \frac{W^M_{ft}}{\beta^M_{ft}}$$

In the main text, I assume all cigarette producers have the same tobacco content per cigarette, $\beta^M$. In an extension, I will use additional brand-level information on tobacco concentrations to check this assumption. Tobacco concentrations are very similar across firms, and even if they are different, this will merely shift the markdown level. As long as firms did not adjust the tobacco content per cigarette in response to the consolidation, and there is no evidence they did, cigarette composition differences will not affect the results of interest.

For the vector of input demand shifters $Z$, I include cigarette prices (because of the quality differences measured before), an export dummy and the export share of revenue, as firms who operate internationally may have different quality standards or be different in other unobserved ways, county
dummies, ownership types (SOEs, private, ...) and a linear time trend.

**Market definitions**

In order to estimate leaf supply, input markets need to be defined. In principle, leaf markets are at the county-level, as the tobacco monopoly law forbids trade in raw tobacco across county boundaries without permission of the provincial STMA office.\(^\text{15}\) In practice, as was clear from the map in Figure 3, many counties ended up without a tobacco manufacturing firm while tobacco farming continued, so permissions by the provincial STMA office seem likely in that case. In the baseline approach, I define input markets at the province-level, but I use more narrow market definitions in Appendix E.2.

**Results**

The estimates of the leaf supply function, equation (6) are in table 4. The first column reports the OLS estimates, which yield a negative price elasticity, that is, a downward-sloping supply curve. This is as expected, as supply and demand are confounded due to simultaneity bias. The second reports the IV estimates, and these indicate an upward-sloping supply curve. Productivity residuals are a strong instrument, as the first stage F-statistic is 419.

[Table 4 here]

How to interpret the estimates? The dependent variable is in logs while the leaf price is in levels. An increase in the leaf price of 1 RMB results in an increase of the leaf market share of 312%.\(^\text{16}\) The median leaf price per box was 1.06 RMB. The best way to interpret the magnitude of these results is to look at the associated markdowns. Selected moments for both the markdown and markup are reported at the top of table 5. The average markdown is 2.91, which means that farmers receive 34% of their marginal contribution to firm profits, as explained earlier.

The ratio of prices over marginal costs is, on the contrary, around 1 both when using a Cobb-Douglas and Translog function in labor and capital. This means that cigarette manufacturers have no price-setting power when selling to the government-controlled CNTTC holding. Manufacturers only have pricing power on the tobacco leaf market, when buying from farmers.

As a comparison, I also report the markdown and markup estimates using the more conventional model with substitutable tobacco leaf, which is also used in Morlacco (2017). The bottom rows in table 5. Markups are now estimated to be very high, with prices being on average 7 to 10 times as high as marginal costs. This seems very unlikely, especially given that cigarette manufacturers can sell to just a single buyer. Markdowns are, in contrast, estimated to be below one by the Cobb-Douglas

\(^\text{15}\)http://www.npc.gov.cn/englishnpc/Law/2007-12/12/content-1383891.htm

\(^\text{16}\)= \(\exp(1.415) - 1\)
model (and above one by the Translog model). This would mean that farmers receive more than their marginal profit contribution, which is again very unlikely given the industry context.

The large standard errors in the second (wrong) model with substitutable tobacco leafs are logically explained. This approach relies only on output elasticities, which are imprecisely estimated, and revenue shares. The first approach, with Leontief tobacco leafs, relies on both output elasticities and input supply estimates to estimate markups and markdowns.

The distribution of markups and markdowns is plotted in Figure 8. Markups are centered around 1, with around half of the firms selling to the CNTTC at prices below their marginal costs, and half above marginal costs. Upstream, however, markdowns are well above unity. Only a small fraction of firms have markdowns above 3.

Comparison to prior literature

How large are the markdown estimates implied by this paper? Most prior studies of monopsony power estimate the input price elasticity of input supply. I convert these into markdown estimates into the input price over marginal revenue product ratio using equation 7 and compare them to my estimates in 6. If the share of the input price over the marginal revenue product of that input is lower, this implies higher input market power. Prior studies found ratios ranging from 0.83 for tenure-track professors in US academia (Syverson and Goolsbee 2019) to 0.70 for female grocery clerks in the Southern USA (Ransom and Oaxaca 2010). For Chinese farmers, I find a ratio of 0.43, which lies much below these prior studies.

Comparison to prior literature

4.3 Estimating the effects of the consolidation

Now that I have estimates of both markups, markdowns and productivity, I examine how these outcomes were affected by the ownership consolidation.

Treatment and control groups

Let the number of firms producing less than 100,000 cases per year in market \(i\) be denoted \(N_{i,t}\):

\[
N_{i,t} = \sum_{f \in i} (\mathbb{I}[Q_{f,t} < 100K])
\]

\(17\) Monopsony power was estimated to be higher for associate and full professors.
Firms producing less than 100,000 cases were forced to exit in 2003. I construct a consolidation treatment variable $C_f$ which is a dummy indicating whether there was at least one firm under the threshold before 2003.

$$C_f = \mathbb{I}[N_{i,2002} > 0]$$

Table 7 shows that before the policy was implemented in 2003, 52% of the firms produced less than 100,000 cases, and together earned 4.5% of total industry revenue. 18% of the firms had at least one competitor under the threshold in the same county. At the prefecture level, this was 45% of firms, and at the province-level 80%. The treated firms sold 10, 37 and 89% of total revenue when defined at the county, prefecture and province level.

[Table 7 here]

**Difference-in-differences model**

In order to assess the effects of the consolidation on markups and markdowns, I estimate the difference-in-differences model in equation (15). I compare markups, markdowns and productivity between firms with and without competitors below the exit threshold before and after 2003. The consolidation dummy $C_f$ itself is not included as it is part of the firm fixed effect $\theta_f$. The coefficient of interest that quantifies consolidation effects is $\gamma_2$.

$$\begin{pmatrix} \mu_{ft} \\ \psi_{ft}^M \\ \omega_{ft}^H \end{pmatrix} = \theta_0 + \theta_1 \mathbb{I}[t \geq 2003] + \theta_2 C_f \mathbb{I}[t \geq 2003] + \theta_3 t + \theta_f + \upsilon_{ft}$$ (15)

The main assumption that is required to interpret $\gamma_2$ as causal is that the error term $\nu_{ft}$ is conditionally independent from $C_f \mathbb{I}[t \geq 2003]$, then the estimate of $\gamma_2$:

**Assumption 3.** — $\mathbb{E}(\nu_{ft} C_f \mathbb{I}[t \geq 2003]) = 0$

This error term $\nu$ contains all time series variation variation in markups, markdowns or productivity (depending on the dependent variable) across firms that is not captured by the other control variables. A first element that could cause differences in markdowns is variations in the objective function across firms, as discussed in Appendix B.5. Including ownership dummies does, however, not change the estimates significantly. A second element driving both consolidation and markups/markdowns/productivity could be internationalization. The Chinese tobacco industry has, however, remained largely domestic and is shielded from foreign competition. Under 1% of industry revenue was exported during the sample period. 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.

**Pre-trend**

I start by comparing the treatment and control groups in terms of markup, markdown and productivity levels and trends before the consolidation was enforced. For the pre-trends, I estimate equation (16). 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 the outcomes of interest was parallel between both groups.

\[
\begin{pmatrix}
    \mu_{ft} \\
    \psi^M_{ft} \\
    \omega^H_{ft}
\end{pmatrix}
= \eta_1 C_f + \eta_2 C_f^* t + \eta_3 t + \nu_{ft} \quad \text{if } t < 2003 \tag{16}
\]

The first part of table 9 shows that the treatment and control groups were very similar in terms of markups and markdowns before the consolidation. Firms in the treatment group were much less efficient, though, and less profitable. The policy hence seems to have targeted low-productivity, low profit firms. As the second table shows, the trends in both markups, markdowns, TFP and profit margins were, however, not different before the policy was implemented.

[Table 9 here ]

**Consolidation treatment effects**

The treatment effect estimates from equation (15), defining the policy to take place at the county-level, are in table 8. The first column of shows that markdowns increased by 20\% 18 for firms subject to the consolidation compared to firms that were not. Markdowns fell for the other firms. The second column indicates a moderate decrease in markups for firms subject to the consolidation, but this fall was not statistically significant. The third column estimates indicate that productivity did not grow faster in firms subject to the consolidation. This is consistent with the absence of scale economies in the production function estimates. From these results, it becomes clear that the main effect of the consolidation was to increase buying power on tobacco leaf markets, while downstream market power and productivity of manufacturers remained unaffected. This is consistent with the industry setting, in which cigarette manufacturers buy from millions of farms, but sell to a single state-controlled holding.

[Table 8 here]

\[18 \exp(0.185) - 1\]
Heterogeneous effects

I interact the treatment indicator with firm and county characteristics, in order to examine where markdowns increased the most. Rather than taking firm fixed effects, as in equation 15, I now add county dummies instead. In column 1 of table 10, I interact the treatment effect variable with the share of the population that migrated from that county in 2000. Markdowns increased by less in response to the consolidation in counties with a higher migration rate. This is to be expected: when farmers are more mobile, manufacturers gain less buying power because lowering leaf prices would cause more farmers to exit the market.

In the second column, I find that the markdown increase is larger in counties with higher unemployment rates in 2000. If there is more unemployment, farmers have less attractive outside options, which allows manufacturers to increase their markdowns by more. In column 3, I compare the treatment effect with the market share of the manufacturers on the leaf market. As is expected, the firms who gain markdowns are the firms who command the largest market shares on the leaf market. Finally, in the fourth column, I compare state-owned enterprises (SOEs) to firms with other ownership structures. I find that SOEs were able to increase their markdowns by more than other firms. This may be an indication of collusion among SOEs on agricultural markets, but examining this would require a context in which there is more variation in ownership types than the tobacco industry, which is heavily dominated by SOEs.

Comparison to the substitutable inputs model

Does taking into account non-substitutability of tobacco leaf matter? In table 11, I re-estimate the difference-in-differences model using a standard Cobb-Douglas model with substitutable tobacco leaf, in which markups and markdowns are calculated as in Morlacco (2017), i.e., equation (4c). This model finds much larger effects of the consolidation on markdowns, at 33%, while markups are estimated to have dropped by 22%. Importantly, this model finds large productivity gains from the consolidation, of 30%. The reason for this is simple: in the substitutable inputs model, input prices and quantities are not separately identified. The drop in intermediate input prices will be interpreted as increased productivity, while in reality it is merely a consequence of higher buying power. Combining a wrong substitution pattern with the assumption of perfectly competitive input markets hence leads to very misleading conclusions about the productivity effects of ownership consolidation.

[Table 11 here]
4.4 Revisiting the assumptions

I now revisit four modelling assumptions. First, I revisit the assumption that the tobacco leaf content per cigarette is constant across firms using brand-level product characteristics on a subsample of firms. Second, I check whether tobacco leaf and labor are really non-substitutable when producing cigarettes. Third, I examine whether employee wages were really exogenous to manufacturers. Fourth, I revisit the assumption that the productivity shifter in labor and capital was Hicks-neutral.

Heterogeneous product characteristics

A first assumption was that the tobacco leaf per cigarette requirement $\beta_{M}$ is constant across firms. The product characteristics data show that in reality, there was limited variation in tobacco concentration and in other cigarette characteristics, such as ventilation (which is commonly used in ‘mild’ cigarettes) and paper quality. As long as these characteristics were similar between the control and treatment groups, however, there is no problem. Table 13 shows this is indeed the case: firms in the treatment and control groups did not differ significantly in terms of any product characteristic, except that they were less likely to be ‘ventilated’ cigarettes. Such cigarettes are also labeled as ‘mild’ or ‘light’ cigarettes.

The second table in table 13 shows, however, that markdowns did not correlate with any product characteristic. Hence, the observed markdown increase for the treatment group cannot be merely due to changes in cigarette design. Markups do correlate with product characteristics: cigarettes with higher filter densities and more tobacco content are sold at higher markups, as these are more likely to be of higher quality. The physical cost to produce cigarettes with different product characteristics is very similar as both TFP and the leaf price are not significantly different across cigarette product types.

[Table 13 here]

Buying power on the labor market

Throughout the paper, I have assumed that cigarette firms do not have monopsony power over manufacturing employees. Even though this assumption was motivated by the industry setting, with mobile urban labor without tobacco-specific skills and immobile rural labor with tobacco-specific skills, this assumption can be tested more formally. I apply the same input competition model used for tobacco leaf supply to manufacturing labor supply, and estimate the wage elasticity of labor supply using the same specification and instruments as for tobacco leaf. The results are in appendix table A4, with the first column reporting the OLS estimates and the second column the IV estimates. The estimated elasticity of labor supply is close to zero and statistically insignificant in both specifications. The productivity instrument is weaker for labor, with an F-stat of 15, but the magnitude and sign of the estimates confirm that buying power on manufacturing labor markets is not a concern in this industry.
**Substitutable tobacco leaf**

Second, I estimate the elasticity of substitution between labor and tobacco leaf, which was intuitively set to zero throughout the model. Let the cigarettes production function no longer be given by equation (1), but by the following CES production function:

\[
Q_{ft} = \left( \beta^M M_{ft}^{\sigma-1} + \beta^L L_{ft}^{\sigma-1} + \beta^K K_{ft}^{\sigma-1} \right)^{\frac{1}{\sigma}} \exp(\omega_{ft})
\]

Deriving the first order conditions using the same cost minimization problem as before results in equation (17). Firms use more labor vs. tobacco leaf if labor is relatively cheaper, if the output elasticity of labor is relatively higher and if firms have higher monopsony power over tobacco leaf. As \( W_M \) is now unobserved, the markdowns \( \psi^M \) is unobserved as well. The goal is to find an instrument for labor wages, which has to be exogenous from tobacco leaf prices and monopsony power on leaf markets. This can be used to estimate the elasticity of substitution \( \sigma \). If \( \sigma \) is zero or close to zero, then the Leontief function used throughout the main text is the right one.

\[
l_{ft} - m_{ft} = \sigma \left( \ln(W^M_{ft}) - \ln(W^L_{ft}) \right) - \sigma \left( \ln(\beta^M) - \ln(\beta^L) \right) + \sigma \ln(1 + \psi^M) \tag{17}
\]

How to find shocks that affect labor wages, but not tobacco farm revenues? The timing assumptions used in Doraszelski and Jaumandreu (2017) cannot be used because they hinge on exogenous input and output prices. I re-use the BLP instruments which were also used to estimate the Leontief production function. More specifically, I use export shares and export dummies of competitors in the same input market as shifters of the labor wage. The reasoning for this instrument to be valid is as follows: throughout the 2000s, WTO accession and foreign demand shocks led to increased wages at exporting firms, as workers got more productive Brandt et al. (2017). If you are located in the same market as exporters, you end up paying higher wages as well in order to retain workers. On tobacco input markets, however, this did not apply as tobacco farmers were shielded from international competition, and did not experience the same productivity gains as in manufacturing.

The results are in Table 12. The F-statistic of the first stage is 105, so these instruments are strong. The first column shows that the estimated elasticity of substitution between intermediate inputs and labor is not significantly different from zero, in line with the Leontief model. In column 2, I re-estimate equation (17), but with capital instead of tobacco leaf, just as a comparison. The elasticity of substitution between capital and labor is estimated to be 0.92 with a standard error of 0.367. I conclude from these estimates that it cannot be rejected that labor and tobacco leaf are not substitutable, while labor and capital have an elasticity of substitution close to one. This corresponds to the Leontief production function with Cobb-Douglas term in labor and capital which was used throughout the paper.

[Table 12 here]
Labor-augmenting productivity

The productivity shifter $\omega^H$ was assumed to be Hicks-neutral throughout the paper. Even though tobacco leaf and labor cannot be substituted, changes in the ratio of leaf expenditure to labor costs could be explained by substitution between labor and capital due to factor-biased technical change. As the industry-wide relative cost share of labor vs. leaf increased over time, this would mean that cigarette production became less capital-intensive, though, which goes against the general trend in Chinese manufacturing.

I now re-estimate factor-augmenting technical change and examine whether the consolidation affected it. I modify the $H(.)$ function in production function (1) to allow for labor-specific productivity $\Omega^L$:

$$H(L_{ft}, K_{ft}, \Omega^L_{ft}) = (L_{ft} \Omega^L_{ft})^{\beta_L} K^{\beta_K}_{ft}$$

Using the same derivation as for equation (17) and treating capital as a variable input, labor-augmenting productivity can be estimated as the residual of the following equation, in which $W^K$ is the interest rate:

$$k_{ft} - l_{ft} = \sigma (\ln(W^L) - \ln(W^K_{ft})) + \sigma (\ln(\beta^K) - \ln(\beta^L)) + (1 - \sigma)(\omega^L)$$

The estimates of this equation were already shown in table 12. The markup formula, (4a) can be rewritten as follows, using the same derivation as before:

$$\mu_{ft} = \left( \frac{\alpha^L_{ft} \psi^L_{ft}}{\beta^L \psi^L_{ft}} + \frac{\alpha^M_{ft} \psi^M_{ft}}{\beta^M \psi^M_{ft}} \right)^{-1}$$

Taking into account labor-augmenting productivity which is higher than one will hence lead to a higher markup estimate. The reason for this is that a fall in the labor share of revenue is now not merely interpreted as a rise in markups, but can also be interpreted as a rise in labor-augmenting technical change. Using this adapted markup expression, I find that the average markup level shifts from 0.93 in the Hicks-neutral model to 1.10 in the adapted model. The correlation between both markup estimates is 0.91.

I now check whether labor-augmenting productivity changed differently between the treatment and control group by re-estimating equation (15) using labor-augmenting productivity term and markups as the left-hand-side variables. The results are in table 14. The first column shows that labor-augmenting productivity evolved similarly for both groups. The second column confirms the original finding that the markup change was not significantly different between treatment and control groups.
The point estimate is different, though. Even if the original results in table 8 showed an insignificant drop in markups, this drop was still estimated to be 10%. When labor-augmenting productivity is taken into account, the estimated markup drop is reduced to merely 1%.

Equation (18) shows that labor-augmenting productivity and monopsony power are not separately identified using the production and cost approach only. This has implications outside this paper. In a paper about migration in China using the same data, Imbert et al. (2018) find that increased immigration led firms to produce at a higher labor intensity. I find, however, that monopsony power fell in counties with high migration rates. In a model which takes input prices as given, such a fall in monopsony power would be picked up as decreased capital intensity.

Further robustness checks

In appendix E, I carry out multiple other robustness checks: I compare exporting behavior across treatment and control groups, use different market definitions, different functional forms and include non-wage benefits as a variable labor cost. None of these extensions result in conclusions that are meaningfully different.

4.5 Distributional consequences

Income inequality in the Chinese tobacco industry

In this section, I quantify the distributional consequences of enforcing the exit thresholds in 2003. I focus on income inequality between manufacturing workers, which are mainly urban, and farmers, which are mainly rural. Rural-urban income inequality has risen sharply in China over the past two decades (Yang 1999; Benjamin, Brandt, and Giles 2005; Chen and Ravallion 2009). Table 15 shows this was also true in the Chinese tobacco industry. While wages of manufacturing workers grew on average by 17% per year between 1999 and 2006, tobacco leaf prices grew only by 3% per annum. Accounting profits increased by no less than 45% per year for cigarette manufacturers, more than three times the growth rate of cigarette prices, which was 13% per year. These patterns show that two margins of inequality increased: first, the income gap between manufacturing workers and farmers rose sharply, second, the gap between firm profits and employee wages rose.

Tobacco leaf prices are not the only determinant of income for farmers, production quantities and farm productivity are as well. Aggregate producer statistics from the Food and Agriculture Organization (FAO) show, however, that farm sizes remained constant and yields per acre grew by merely 1.8% per year during this time period (FAOstat), not enough to compensate the rising price differential.
**Consolidation and inequality**

To what extent was this rising inequality a consequence of the ownership consolidation? I recalculate average leaf prices in the absence of a consolidation. I assume that the markdown for firms in the treatment group would have evolved identically to the firms in the control group. Using notation from equation (15), counterfactual leaf prices $\tilde{W}^M$ become:

$$
\tilde{W}^M_{ft} = \begin{cases} 
W^M_{ft} & \text{if } t < 2003 \\
W^M_{ft} & \text{if } t \geq 2003 \& C_f = 0 \\
W^M_{ft}(1 + \theta_2) & \text{if } t \geq 2003 \& C_f = 1
\end{cases}
$$

Similarly, counterfactual manufacturing profits $\tilde{\Pi}_{ft}$ were actual profits $\Pi_{ft}$ before 2003 and after 2003 for the control group, but would have been lowered by the decreased markdown for firms in the treatment group after 2003:

$$
\tilde{\Pi}_{ft} = \begin{cases} 
\Pi_{ft} & \text{if } t < 2003 \\
\Pi_{ft} & \text{if } t \geq 2003 \& C_f = 0 \\
\Pi_{ft} - M_{ft}W^M_{ft}(1 + \theta_2) & \text{if } t \geq 2003 \& C_f = 1
\end{cases}
$$

**Results**

Figure 9 compares the evolution of leaf prices with manufacturing wages between 1999 and 2006, with both series being normalized at 100 in 2003, the start of the consolidation. Before 2003, manufacturing wages (blue line) already grew faster than leaf prices (red solid line). Between 2003 and 2006, wages doubled while leaf prices fell by 10%. The dashed red line shows that if the consolidation would not have taken place, leaf prices would have grown by 20% over this time period. The consolidation hence explains 30% of inequality growth between manufacturing workers and farmers in the tobacco industry.

[Figure 9 here]

**Who profited from the consolidation?**

The second graph in figure 9 shows the effects on profits. In reality, accounting profits increased by 300% between 2003 and 2006. Without consolidation, they would have doubled. The median profit-to-revenue margin was 6.9% after 2003 in reality, in the counterfactual it would have been 1.8%.

This analysis assumes that markups remained constant. When defining the treatment at the county-level, markups did remain constant between control and treatment groups, but at the province-level
they did not. It is therefore not certain that manufacturers were the main beneficiaries of the reform, although their profits did soar after 2003.

If manufacturers were not the main beneficiaries from the reform, two other groups could be. The centrally controlled CNTTC, which operates the cigarette cartel seems the most likely winner, as they were able to decrease farm-gate prices by increasing their own markdown on the cigarettes market. If this did not happen, cigarette consumers were the main beneficiaries through lower prices (or victims, if stepping away from the goods definition of cigarettes).

As I do not observe cigarette retail prices throughout the sample, I cannot conclude which group gained the most surplus. Given that the cigarettes cartel did not change, it seems very likely that most profit gains were achieved at the CNTTC, which was also the main enforcer of the consolidation through the STMA, its regulating twin.

Caveats

There are two important caveats to make. First, the analysis above is not a full-blown counterfactual as it ignores entry and exit. In reality, manufacturing firms would have closed down without a consolidation: the share of loss-making firms after 2003 was 10% in reality, but 34% in the counterfactual. Moreover, higher agricultural prices would also affect entry and exit of farmers, and hence equilibrium leaf prices. Only a more complete model with entry and exit of both farmers and manufacturers would therefore be able to answer the question what the counterfactual equilibrium leaf price would have been.

Second, the analysis is of a partial equilibrium nature. As tobacco represents a large share of economic activity in some provinces, consolidation of manufacturers would have affected both cigarette prices, manufacturing wages and prices and wages in other sectors, next to the leaf price.

What the counterfactual does show is that increased markdowns were an important, probably even the most important, channel of profit growth after 2003 in the Chinese tobacco industry, and contributed considerably to increased income inequality between 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 by a third. While the reform was meant to be productivity-enhancing, productivity of cigarette factories did not increase. The main beneficiary of the consolidation and its profits seems to be the STMA, the central government-controlled cartel enforcer, rather than local factories. The consolidation had important distributional consequences: it explains 30% of the rise in income inequality between tobacco farmers and manufacturing employees between 2003 and 2006. As these groups are predominantly live in rural and urban areas respec-
tively, the consolidation contributed to rising urban-rural income inequality. On the methodological front, this paper relaxes the assumption that all inputs are substitutable, and allows firms to have buying power on the non-substitutable input. This change in assumptions leads to important differences in evaluating the merger policy: when assuming perfectly substitutable inputs, the conclusion is that mergers largely increased productivity. In reality, productivity did not increase, but input prices merely fell due to increased buying power.
References


Figure 1: Tobacco value chain

Farmers

Tobacco leaf → input market power?

Cigarette manufacturers (observed)

Cigarettes → product market power?

CNTTC (operates cartel)

Retailers

Consumers

Notes: Factories belong to the CNTIC = ”Chinese National Tobacco Industrial Corporation”. The cartel-operating holding is called CNTTC = ”Chinese National Tobacco Trade Corporation”.
Figure 2: Organization of the Chinese tobacco industry
Figure 3: 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 100K cases per year.
Figure 4: Cigarette production process

Farming

Drying

Manufacturing: inputs

Manufacturing: output
Figure 5: 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 6: Industry factor shares of revenue

Weighted average

[Graph showing industry factor shares of revenue over years 1998 to 2008 for intermediate inputs and labor, with a downward trend for intermediate inputs and a flat trend for labor.]

Median

[Graph showing industry factor shares of revenue over years 1998 to 2008 for intermediate inputs and labor, with a downward trend for intermediate inputs and a flat trend for labor.]

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

43
Figure 7: Relative factor revenue shares, by consolidation treatment

Weighted average

Median
Figure 8: Markups and markdowns

Note: Censored at 5th and 95th percentiles
Figure 9: No consolidation counterfactual

Farmer-employee income inequality

[Graph showing trends in farmer-employee income inequality and manufacturing profits with notes on deflation and normalization.]

Note: All series are deflated and normalized, 1999=100
<table>
<thead>
<tr>
<th>Variable</th>
<th>Unit</th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>N</th>
</tr>
</thead>
<tbody>
<tr>
<td>Revenue</td>
<td>Million USD</td>
<td>78.26</td>
<td>217.52</td>
<td>2638</td>
</tr>
<tr>
<td>Profit</td>
<td>Million USD</td>
<td>9.35</td>
<td>43.25</td>
<td>2631</td>
</tr>
<tr>
<td>Wage bill</td>
<td>Million USD</td>
<td>2.56</td>
<td>6.27</td>
<td>2631</td>
</tr>
<tr>
<td>Employees</td>
<td>Thousands</td>
<td>0.86</td>
<td>1.13</td>
<td>2631</td>
</tr>
<tr>
<td>Material expenditure</td>
<td>Million USD</td>
<td>26.65</td>
<td>56.55</td>
<td>2486</td>
</tr>
<tr>
<td>Capital stock</td>
<td>Million USD</td>
<td>35.71</td>
<td>78.97</td>
<td>2498</td>
</tr>
<tr>
<td>Export status</td>
<td>Dummy</td>
<td>0.16</td>
<td>0.37</td>
<td>2638</td>
</tr>
<tr>
<td>Export share of revenue</td>
<td>Share</td>
<td>0.01</td>
<td>0.07</td>
<td>2486</td>
</tr>
<tr>
<td>Quantity</td>
<td>Million cases</td>
<td>0.34</td>
<td>0.50</td>
<td>1260</td>
</tr>
<tr>
<td>Price</td>
<td>USD</td>
<td>1.53</td>
<td>13.63</td>
<td>1190</td>
</tr>
<tr>
<td>County population</td>
<td>Millions</td>
<td>0.569</td>
<td>0.364</td>
<td>1924</td>
</tr>
<tr>
<td>Agricultural population</td>
<td>Share</td>
<td>0.64</td>
<td>0.27</td>
<td>1924</td>
</tr>
<tr>
<td>Migrant population</td>
<td>Share</td>
<td>0.04</td>
<td>0.04</td>
<td>1911</td>
</tr>
<tr>
<td>Registered population</td>
<td>Share</td>
<td>0.82</td>
<td>0.16</td>
<td>1924</td>
</tr>
<tr>
<td>Leaf weight</td>
<td>Mg</td>
<td>683.47</td>
<td>27.23</td>
<td>353</td>
</tr>
<tr>
<td>Filter density</td>
<td>Mg/ml</td>
<td>112.38</td>
<td>3.84</td>
<td>353</td>
</tr>
<tr>
<td>Rod density</td>
<td>Mg/ml</td>
<td>242.03</td>
<td>9.93</td>
<td>353</td>
</tr>
<tr>
<td>Paper permeability</td>
<td>CAPU*</td>
<td>54.09</td>
<td>9.25</td>
<td>353</td>
</tr>
<tr>
<td>Ventilation</td>
<td>%</td>
<td>2.86</td>
<td>5.46</td>
<td>353</td>
</tr>
</tbody>
</table>

Notes: * CORESTA air permeability unit
## Table 2: Market structure and input revenue shares

<table>
<thead>
<tr>
<th># firms</th>
<th>Tobacco leaf revenue share</th>
<th>Labor revenue share</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>-0.254 (0.0792)</td>
<td>0.136 (0.115)</td>
</tr>
<tr>
<td>2</td>
<td>-0.196 (0.0816)</td>
<td>0.0463 (0.117)</td>
</tr>
<tr>
<td>3</td>
<td>-0.0242 (0.0845)</td>
<td>0.177 (0.109)</td>
</tr>
</tbody>
</table>

Observations: 2,325
R-squared: 0.138 0.102

Notes: Markets defined at 4-digit (prefecture) level. Revenue shares measured in logs. Controls: export dummy, product type, time trend. Standard errors clustered at prefecture level.
### Table 3: Output elasticities

<table>
<thead>
<tr>
<th>Dependent variable</th>
<th>Output</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Model</td>
<td>ACF</td>
<td>IV</td>
</tr>
<tr>
<td>Labor</td>
<td></td>
<td>0.319</td>
<td>0.345</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.577)</td>
<td>(0.194)</td>
</tr>
<tr>
<td>Capital</td>
<td></td>
<td>0.783</td>
<td>0.769</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.442)</td>
<td>(0.097)</td>
</tr>
<tr>
<td>Returns to scale</td>
<td></td>
<td>1.102</td>
<td>1.114</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.286)</td>
<td>(0.232)</td>
</tr>
<tr>
<td>Observations</td>
<td>822</td>
<td>1,094</td>
<td></td>
</tr>
<tr>
<td>R-squared</td>
<td>0.989</td>
<td>0.887</td>
<td></td>
</tr>
<tr>
<td>1st stage F-stat</td>
<td></td>
<td>41.76</td>
<td></td>
</tr>
</tbody>
</table>

**Note:** Bootstrapped standard errors in parentheses
**Table 4: Input supply elasticity**

<table>
<thead>
<tr>
<th>Dep. var: log(leaf market share) - log(outside option share)</th>
<th>Model:</th>
<th>OLS</th>
<th>IV</th>
</tr>
</thead>
<tbody>
<tr>
<td>Leaf price</td>
<td>-0.092</td>
<td>1.415</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.037)</td>
<td>(0.595)</td>
<td></td>
</tr>
<tr>
<td>Observations</td>
<td>855</td>
<td>855</td>
<td></td>
</tr>
<tr>
<td>1st stage F-stat</td>
<td>418.5</td>
<td></td>
<td></td>
</tr>
<tr>
<td>R-squared</td>
<td>0.881</td>
<td>0.137</td>
<td></td>
</tr>
</tbody>
</table>

**Note:** Controls: export dummy and share of revenue, cigarette price, time trend, product type, prefecture dummy, ownership type. Market shares at province-level. Instrument: TFP.
Table 5: Markups and markdowns

Tobacco leaf *not* substitutable

<table>
<thead>
<tr>
<th></th>
<th>Markdown</th>
<th>Markup</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Cobb-Douglas</td>
</tr>
<tr>
<td>mean</td>
<td>2.91</td>
<td>0.86</td>
</tr>
<tr>
<td>median</td>
<td>2.87</td>
<td>0.92</td>
</tr>
<tr>
<td>standard error</td>
<td>(0.32)</td>
<td>(0.17)</td>
</tr>
</tbody>
</table>

Tobacco leaf substitutable

<table>
<thead>
<tr>
<th></th>
<th>Markdown</th>
<th>Markup</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Cobb-Douglas</td>
</tr>
<tr>
<td>mean</td>
<td>0.57</td>
<td>4.47</td>
</tr>
<tr>
<td>median</td>
<td>0.38</td>
<td>0.33</td>
</tr>
<tr>
<td>standard error</td>
<td>(1.04)</td>
<td>(5.27)</td>
</tr>
</tbody>
</table>

*Note: Bootstrapped standard errors in parentheses*
Table 6: Comparison to prior monopsony studies

<table>
<thead>
<tr>
<th>Paper</th>
<th>Country</th>
<th>Industry</th>
<th>Input</th>
<th>Input price / MRP</th>
</tr>
</thead>
<tbody>
<tr>
<td>Syverson and Goolsbee (2019)</td>
<td>USA</td>
<td>Universities</td>
<td>Professors</td>
<td>0.83</td>
</tr>
<tr>
<td>Ransom and Sims (2010)</td>
<td>USA</td>
<td>Schools</td>
<td>Teachers</td>
<td>0.82 (M) - 0.75 (F)</td>
</tr>
<tr>
<td>Hirsch, Schank, and Schnabel (2010)</td>
<td>Germany</td>
<td>All</td>
<td>Employees</td>
<td>0.78</td>
</tr>
<tr>
<td>Ransom and Oaxaca (2010)</td>
<td>USA</td>
<td>Grocery stores</td>
<td>Clerks</td>
<td>0.74 (M) - 0.70 (F)</td>
</tr>
<tr>
<td>This paper</td>
<td>China</td>
<td>Tobacco</td>
<td>Farmers</td>
<td>0.43</td>
</tr>
</tbody>
</table>

Note: I report the average price of an input over its marginal revenue product, which I calculate based on the reported labor supply elasticity using equation (7).
Table 7: Treatment and control groups before policy

<table>
<thead>
<tr>
<th></th>
<th>% of firms</th>
<th>% of revenue</th>
</tr>
</thead>
<tbody>
<tr>
<td>Firms producing less than 100K cases</td>
<td>51.6</td>
<td>4.5</td>
</tr>
<tr>
<td>Treatment (county-level)*</td>
<td>18.2</td>
<td>9.5</td>
</tr>
<tr>
<td>Treatment (prefecture-level)</td>
<td>44.9</td>
<td>36.9</td>
</tr>
<tr>
<td>Treatment (province-level)</td>
<td>79.8</td>
<td>88.8</td>
</tr>
</tbody>
</table>

*Firms with competitors producing less than 100K cases in same county/prefecture/province
Table 8: Consolidation treatment effects

<table>
<thead>
<tr>
<th>Dependent variable:</th>
<th>Markdown</th>
<th>Markup</th>
<th>Productivity</th>
</tr>
</thead>
<tbody>
<tr>
<td>Treatment * I(year ≥ 2003)</td>
<td>0.199 (0.0644)</td>
<td>-0.111 (0.0750)</td>
<td>0.0633 (0.120)</td>
</tr>
<tr>
<td>I(year ≥ 2003)</td>
<td>-0.138 (0.0421)</td>
<td>0.0970 (0.0418)</td>
<td>-0.138 (0.0610)</td>
</tr>
<tr>
<td>Observations</td>
<td>817</td>
<td>817</td>
<td>817</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.742</td>
<td>0.743</td>
<td>0.767</td>
</tr>
</tbody>
</table>

Notes: Cobb-Douglas function in labor and capital. Controls: time trend, ownership types, product type, export dummy, firm fixed effects. Bootstrapped standard errors in parentheses. Treatment uses prefecture-level market definition.
Table 9: Pre-trend comparison of control and treatment groups

Levels

<table>
<thead>
<tr>
<th>Dependent variables:</th>
<th>Markdown</th>
<th>Markup</th>
<th>TFP</th>
<th>Profit margin</th>
</tr>
</thead>
<tbody>
<tr>
<td>Treatment</td>
<td>-0.0653</td>
<td>0.00203</td>
<td>-0.456</td>
<td>-0.115</td>
</tr>
<tr>
<td></td>
<td>(0.0408)</td>
<td>(0.0353)</td>
<td>(0.0703)</td>
<td>(0.0215)</td>
</tr>
<tr>
<td>Observations</td>
<td>417</td>
<td>417</td>
<td>417</td>
<td>417</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.560</td>
<td>0.599</td>
<td>0.248</td>
<td>0.405</td>
</tr>
</tbody>
</table>

Trends

<table>
<thead>
<tr>
<th>Dependent variables:</th>
<th>Markdown</th>
<th>Markup</th>
<th>TFP</th>
<th>Profit margin</th>
</tr>
</thead>
<tbody>
<tr>
<td>Year</td>
<td>0.0456</td>
<td>0.0455</td>
<td>0.0573</td>
<td>-0.0122</td>
</tr>
<tr>
<td></td>
<td>(0.0366)</td>
<td>(0.0347)</td>
<td>(0.0284)</td>
<td>(0.0146)</td>
</tr>
<tr>
<td>Treatment</td>
<td>-68.94</td>
<td>53.05</td>
<td>167.6</td>
<td>74.48</td>
</tr>
<tr>
<td></td>
<td>(111.3)</td>
<td>(103.7)</td>
<td>(168.2)</td>
<td>(48.04)</td>
</tr>
<tr>
<td>Treatment * Year</td>
<td>0.0344</td>
<td>-0.0265</td>
<td>-0.0839</td>
<td>-0.0373</td>
</tr>
<tr>
<td></td>
<td>(0.0556)</td>
<td>(0.0519)</td>
<td>(0.0841)</td>
<td>(0.0240)</td>
</tr>
<tr>
<td>Observations</td>
<td>417</td>
<td>417</td>
<td>417</td>
<td>417</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.771</td>
<td>0.770</td>
<td>0.761</td>
<td>0.762</td>
</tr>
</tbody>
</table>

## Table 10: Heterogeneous treatment effects

<table>
<thead>
<tr>
<th>Dependent variable:</th>
<th>Markdown</th>
<th>Markdown</th>
<th>Markdown</th>
<th>Markdown</th>
</tr>
</thead>
<tbody>
<tr>
<td>Treatment * I(year ≥ 2003)</td>
<td>0.227</td>
<td>0.210</td>
<td>0.171</td>
<td>0.188</td>
</tr>
<tr>
<td></td>
<td>(0.135)</td>
<td>(0.128)</td>
<td>(0.105)</td>
<td>(0.103)</td>
</tr>
<tr>
<td>Treatment*I(year ≥ 2003)*migration rate</td>
<td>-0.108</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0363)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Treatment*I(year ≥ 2003)*unemployment rate</td>
<td>-0.109</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0340)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Treatment*I(year ≥ 2003)*leaf market share</td>
<td>0.233</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0828)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Treatment*I(year ≥ 2003)*SOE</td>
<td>0.213</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0771)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Observations</td>
<td>575</td>
<td>575</td>
<td>817</td>
<td>817</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.760</td>
<td>0.760</td>
<td>0.752</td>
<td>0.748</td>
</tr>
</tbody>
</table>

**Notes:** Controls include county dummies, a linear time trend, ownership dummies and an export dummy. Standard errors are clustered at the county level.
### Table 11: Model with substitutable tobacco leaf

<table>
<thead>
<tr>
<th>Dependent variable:</th>
<th>Markdown</th>
<th>Markup</th>
<th>Productivity</th>
</tr>
</thead>
<tbody>
<tr>
<td>Treatment * I(year ≥ 2003)</td>
<td>0.283</td>
<td>-0.193</td>
<td>0.280</td>
</tr>
<tr>
<td></td>
<td>(0.115)</td>
<td>(0.0790)</td>
<td>(0.0922)</td>
</tr>
<tr>
<td>I(year ≥ 2003)</td>
<td>0.0342</td>
<td>-0.0198</td>
<td>-0.212</td>
</tr>
<tr>
<td></td>
<td>(0.0555)</td>
<td>(0.0576)</td>
<td>(0.0561)</td>
</tr>
<tr>
<td>Observations</td>
<td>817</td>
<td>817</td>
<td>817</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.660</td>
<td>0.736</td>
<td>0.793</td>
</tr>
<tr>
<td>Model</td>
<td>Cobb-Douglas</td>
<td>Cobb-Douglas</td>
<td>Cobb-Douglas</td>
</tr>
</tbody>
</table>

Notes: I estimate markups, markdowns and productivity using a Cobb-Douglas production function in labor, tobacco leaf and capital. I use the same sample size as before, even though the markup and markdowns could be estimated on a large sample as quantities and prices do not need to be observed.
Table 12: Elasticity of substitution

<table>
<thead>
<tr>
<th>Dependent variable:</th>
<th>Log(Materials/Labor)</th>
<th>Log(Capital/Labor)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Log labor wage</td>
<td>0.211</td>
<td>0.919</td>
</tr>
<tr>
<td></td>
<td>(0.514)</td>
<td>(0.367)</td>
</tr>
<tr>
<td>Observations</td>
<td>2,430</td>
<td>2,430</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.598</td>
<td>0.476</td>
</tr>
<tr>
<td>1st stage F-stat</td>
<td>104.95</td>
<td>104.95</td>
</tr>
</tbody>
</table>

**Note:** Controls: ownership type, product type, time trend, prefecture dummy, export dummy, export revenue share. IVs: avg. export share of revenue, export participation, input and output tariffs in other industries in the same county.
### Table 13: Product characteristics

#### Treatment vs. control group

<table>
<thead>
<tr>
<th>Dependent variable:</th>
<th>Leaf weight</th>
<th>Filter density</th>
<th>Rod density</th>
<th>Paper permeability</th>
<th>Ventilation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Treatment</td>
<td>0.000107</td>
<td>0.00571</td>
<td>0.0142</td>
<td>0.0392</td>
<td>-1.067</td>
</tr>
<tr>
<td></td>
<td>(0.00685)</td>
<td>(0.0101)</td>
<td>(0.0181)</td>
<td>(0.0680)</td>
<td>(0.448)</td>
</tr>
<tr>
<td>Observations</td>
<td>353</td>
<td>353</td>
<td>353</td>
<td>353</td>
<td>353</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.804</td>
<td>0.702</td>
<td>0.550</td>
<td>0.586</td>
<td>0.848</td>
</tr>
</tbody>
</table>

#### Correlations with markups, markdowns and productivity

<table>
<thead>
<tr>
<th>Dependent variable:</th>
<th>Markup</th>
<th>Markdown</th>
<th>TFP</th>
<th>Leaf price</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ventilation</td>
<td>0.0149</td>
<td>0.0261</td>
<td>-0.00883</td>
<td>-0.00520</td>
</tr>
<tr>
<td></td>
<td>(0.0281)</td>
<td>(0.0303)</td>
<td>(0.0573)</td>
<td>(0.0631)</td>
</tr>
<tr>
<td>Rod density</td>
<td>4.685</td>
<td>-0.253</td>
<td>1.224</td>
<td>0.0983</td>
</tr>
<tr>
<td></td>
<td>(6.984)</td>
<td>(7.524)</td>
<td>(14.24)</td>
<td>(15.67)</td>
</tr>
<tr>
<td>Filter density</td>
<td>22.46</td>
<td>-8.990</td>
<td>-9.010</td>
<td>4.338</td>
</tr>
<tr>
<td>Leaf weight</td>
<td>11.66</td>
<td>-5.984</td>
<td>-9.399</td>
<td>-6.184</td>
</tr>
<tr>
<td></td>
<td>(3.651)</td>
<td>(3.933)</td>
<td>(7.441)</td>
<td>(8.193)</td>
</tr>
<tr>
<td>Paper permeability</td>
<td>1.981</td>
<td>-1.391</td>
<td>-0.786</td>
<td>2.931</td>
</tr>
<tr>
<td></td>
<td>(1.355)</td>
<td>(1.459)</td>
<td>(2.761)</td>
<td>(3.040)</td>
</tr>
<tr>
<td>Observations</td>
<td>137</td>
<td>137</td>
<td>137</td>
<td>137</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.687</td>
<td>0.700</td>
<td>0.488</td>
<td>0.501</td>
</tr>
</tbody>
</table>

**Notes:** Controls: province dummies. Standard errors clustered at the county level.
Table 14: Ownership consolidation and labor-augmenting productivity

<table>
<thead>
<tr>
<th>Dependent variable:</th>
<th>Labor-augmenting productivity</th>
<th>Markup</th>
</tr>
</thead>
<tbody>
<tr>
<td>Treatment * I(year ≥ 2003)</td>
<td>0.00150</td>
<td>-0.0287</td>
</tr>
<tr>
<td></td>
<td>(0.140)</td>
<td>(0.0677)</td>
</tr>
<tr>
<td>Treatment</td>
<td>-0.0438</td>
<td>0.0243</td>
</tr>
<tr>
<td></td>
<td>(0.0907)</td>
<td>(0.0709)</td>
</tr>
<tr>
<td>Observations</td>
<td>817</td>
<td>817</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.611</td>
<td>0.720</td>
</tr>
</tbody>
</table>

Notes: Dependent variables in logs. Markup re-calculated with labor-augmenting productivity taken into account.
Table 15: Input prices, product prices and profits

<table>
<thead>
<tr>
<th>Dependent variable:</th>
<th>Manufacturing wage</th>
<th>Leaf price</th>
<th>Cigarette price</th>
<th>Profits</th>
</tr>
</thead>
<tbody>
<tr>
<td>Year</td>
<td>0.170***</td>
<td>0.0316</td>
<td>0.126***</td>
<td>0.448***</td>
</tr>
<tr>
<td></td>
<td>(0.0121)</td>
<td>(0.0197)</td>
<td>(0.0169)</td>
<td>(0.0423)</td>
</tr>
<tr>
<td>Observations</td>
<td>1,118</td>
<td>1,118</td>
<td>1,118</td>
<td>896</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.151</td>
<td>0.002</td>
<td>0.048</td>
<td>0.111</td>
</tr>
</tbody>
</table>

Notes: Dependent variables in logs.

Table 16: Prices and consolidation

<table>
<thead>
<tr>
<th>Dependent variable:</th>
<th>Leaf price</th>
<th>Manufacturing wage</th>
</tr>
</thead>
<tbody>
<tr>
<td>Treatment * I(year ≥ 2003)</td>
<td>-0.476***</td>
<td>-0.0681</td>
</tr>
<tr>
<td></td>
<td>(0.137)</td>
<td>(0.120)</td>
</tr>
<tr>
<td>Observations</td>
<td>817</td>
<td>817</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.197</td>
<td>0.214</td>
</tr>
</tbody>
</table>

Notes: Dependent variables in logs.
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 2-digit codes HS 24, "Tobacco and Manufactured Tobacco Substitutes". I keep the observations between 1998 and 2007. I drop firms with negative intermediate input usage values, which 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.

Quantities and prices are given at the product-firm-year levels between 1999 and 2006. I only keep product codes that are measured in numbers. As firms usually produce just one product, cigarettes, I infer prices by dividing firm revenue by total quantity. Quantity data are available for just about half of the firms, which reduces the sample size to 1260. Units are defined as cigarette cases, but from 2004 onwards this definition slightly changes. Fortunately, both quantities in the present and previous years are systematically reported, so I scale quantities from 2004 onwards to be consistent with the previous years. As the treatment variables are defined based on quantity units in 2002, this does not affect how the treatment variable is constructed.

A.2 Product characteristics

I obtain brand-level product characteristics of 65 Chinese cigarette brands from O’Connor et al. (2010). Observed characteristics are tobacco weight in mg, filter and rod densities in mg/ml, paper permeability using the CORESTA index and ventilation in percents. Given that a standard cigarette weighs 1000mg, the fraction of tobacco per cigarette can be inferred. All these characteristics are important factors in the consumer experience of cigarettes (Talhout et al. 2018).

A.3 Population census data

I use county-level demographical data from the 2000 Chinese population census. I retrieved the data from the Harvard Dataverse web repository. I aggregated the data from the township to the county level and matched with the industry survey data using 6-digit NBS location codes.
B Derivations and proofs

B.1 Markups with endogenous Leontief input price

In this section, I derive the markup expression in equation (4a). I start with the cost minimization problem in equation (3). Firms choose input prices in order to minimize per-period costs. The shadow price $\lambda_{ft}$ is the marginal cost of increasing the input price (and hence, output) by one unit. The markup $\mu$ is, as always, defined as the ratio of the product price over this marginal cost:

$$\mu_{ft} \equiv \frac{P_{ft}}{\lambda_{ft}}$$

Solving the first order cost minimization condition gives the following expression for $\lambda$:

$$\lambda_{ft} = \frac{\alpha_{ft}^L P_{ft}}{\alpha_{ft}^M} + \frac{\alpha_{ft}^M P_{ft} \psi_{ft}^M}{\beta_{ft}}$$

with $\alpha_{ft}^V \equiv \frac{V_{ft} W_{ft}^V}{P_{ft} Q_{ft}}$ for $V \in \{L, M\}$ and $\beta_{ft}^L \equiv \frac{\partial Q_{ft}}{\partial L_{ft}} L_{ft} Q_{ft}$

Dividing the price $P$ by marginal cost $\lambda$ yields equation (4a).

B.2 Markdown interpretation of input supply elasticity

I now derive the markdown interpretation in equation (5). In contrast to the previous paragraph, I now assume that firms choose the leaf price to maximize profits rather than minimize costs (this will, of course, give the same result). The first order condition gives:

$$\frac{\partial P_{ft} Q_{ft}}{\partial M_{ft}} \frac{\partial M_{ft}}{\partial W_{ft}^M} - M_{ft} - W_{ft}^M \frac{\partial M_{ft}}{\partial W_{ft}^M} - W_{ft}^L \frac{\partial L_{ft}}{\partial Q_{ft}} \frac{\partial Q_{ft}}{\partial M_{ft}} \frac{\partial M_{ft}}{\partial W_{ft}^M} = 0$$

Dividing by $\frac{\partial M_{ft}}{\partial W_{ft}^M}$ and inserting $\Psi^M$ leads to equation (5).

B.3 Demand for substitutable inputs with endogenous prices

In this section, I derive input demand for tobacco leaf $M$. Rearranging the markdown formula in equation (5) and using the relationship between the markup and the product demand elasticity $\mu = \frac{\partial Q}{\partial P} + 1$, gives:

\[\frac{\partial Q}{\partial P} + 1 = \frac{\partial Q}{\partial P} + 1\]
\[ M_{ft} = \frac{Q_{ft}}{\psi_{ft} W_{ft}^M} \left( \frac{1}{\mu_{ft}} - W_{ft}^L \frac{\partial L_{ft}}{\partial Q_{ft}} \right) \]

The inverse marginal product of labor \( \frac{\partial L_{ft}}{\partial Q_{ft}} \) depends on the functional form used for \( H(.) \), but in general is a function of all labor \( L_{ft} \), capital \( K_{ft} \) and Hicks-neutral productivity \( \omega_{ft}^H \). Hence, leaf demand is given by equation (10):

\[ m_{ft} = m(l_{ft}, k_{ft}, w_{ft}^L, w_{ft}^M, \omega_{ft}^H, \mu_{ft}, \psi_{ft}) \]

### B.4 Input market equilibrium in oligopsony

In this section, I characterize the equilibrium conditions in an oligopsonic market for the non-substitutable input, \( M \). I need these conditions in the Monte Carlo simulations. Let product prices \( P \) be normalized to one and let firms \( f \) simultaneously choose input prices \( W_{ft}^M \) every period by solving a static cost minimization problem:

\[
W_{ft}^M = \arg \min \left( W_{ft}^L L_{ft} + W_{ft}^M M_{ft} - Q(.) \right)
\]

\[ \Leftrightarrow W_{ft}^L \frac{\partial L_{ft}}{\partial M_{ft}} \frac{\partial M_{ft}}{\partial W_{ft}^M} + W_{ft}^M \frac{\partial M_{ft}}{\partial W_{ft}^M} + M_{ft} - \frac{\partial Q_{ft}}{\partial L_{ft}} \frac{\partial L_{ft}}{\partial M_{ft}} \frac{\partial M_{ft}}{\partial W_{ft}^M} = 0 \]

\[ \Leftrightarrow M_{ft} + \frac{\partial M_{ft}}{\partial W_{ft}^M} \left( W_{ft}^M + \beta_{ft}^M \frac{W_{ft}^L \frac{\partial Q_{ft}}{\partial L_{ft}}}{\partial W_{ft}^M} - \beta_{ft}^M \right) = 0 \]

Dividing by market size \( \bar{M} \) and defining \( S_{ft} \equiv \frac{M_{ft}}{\bar{M}} \), this gives the following equilibrium condition, which is very similar to those in oligopoly demand models:

\[ S_{ft} + \frac{\partial S_{ft}}{\partial W_{ft}^M} \left( W_{ft}^M + \beta_{ft}^M \frac{W_{ft}^L \frac{\partial Q_{ft}}{\partial L_{ft}}}{\partial W_{ft}^M} - \beta_{ft}^M \right) = 0 \]

### B.5 Different objective functions

Throughout the main text, it was assumed that firms minimize costs, following assumption (1). This is not necessarily true, especially for State-Owned Enterprises. These firms may value large employment in order to fulfill ‘social stability’ objectives, as explained in (Li et al. 2012). If such objectives affect all inputs in the same way, this just shifts the Lagrangian multiplier: firms have a different quantity objective in the Lagrangian (3). This causes a level shift in the markup estimates, but does not affect markdown estimates. Firms differ in their Lagrange multiplier \( \tilde{\lambda} \), which depends on ownership types.
$O_{ft} \in \{\text{SOE, private, ...}\}$.

$$
\min_{L_{ft}} \left( W_{ft}^L L_{ft} + W_{ft}^M M_{ft} - \tilde{\lambda}_{ft}(O_{ft})\left(Q(L_{ft}, M_{ft}, K_{ft}, \Omega^H_{ft}, \beta^M_{ft}) - Q_{ft}\right) \right)
$$

I regress markup estimates on ownership type dummies and include firm fixed effects in Table A9. This documents how markups change when firms change their ownership type. When using the Leontief model, in the first two columns, I find that privatization indeed leads to lower markups, which is consistent with SOEs having a lower employment target compared to private firms. The $R^2$ is very low, however. When assuming all inputs are substitutable, in the last two columns, the coefficients flip or become insignificant.

As just a very small proportion of cigarette manufacturers is private, ownership type differences are not a first order concern in this industry. To be entirely sure, I include ownership types in all regressions containing markups, but omitting them barely makes a difference.

A second way in which SOEs could diverge from the cost minimization assumption is if they have implicit wages $\delta_{ft}$ on one of the inputs, e.g. if they favour high employment more compared to intermediate inputs. The cost minimization is hence given by:

$$
\min_{L_{ft}} \left( \delta_{ft} W_{ft}^L L_{ft} + W_{ft}^M M_{ft} - \lambda_{ft}\left(Q(L_{ft}, M_{ft}, K_{ft}, \Omega^H_{ft}, \beta^M_{ft}) - Q_{ft}\right) \right)
$$

If firms favour high labor employment compared to the other inputs, then $\delta_{ft} < 1$. The true labor revenue share is then smaller than the observed one, which means markups are higher. This prediction is again consistent with the evidence in table B.5.
C Estimation

C.1 BLP instruments

General discussion

The intermediate input demand function (10) is both dependent on latent productivity, markups and markdowns. A disadvantage of using the control function approaches used in most of the productivity literature, such as in Ackerberg, Caves, and Frazer (2015), is that this inversion requires imposing a model of how firms compete on input and product markets, which we would like to avoid in the first place. De Loecker et al. (2016) have shown that this can be done relatively flexibly, but still require defining product and input markets, and observing all relevant and persistent product and input characteristics.

An alternative to this approach is to step away from the control function approach, and use an instrumental variable approach instead. In the competitive input market setting, finding such instruments, which affect input choices but not productivity, is extremely difficult. As discussed in Ackerberg et al. (2007), this approach has not been used in practice because of three impediments. First, input prices are usually unobserved. When observed, unit wages usually reflect information on labor quality or working hours as well, which are correlated with productivity. Secondly, all input choices depend on all input prices, meaning that all inputs need to be instrumented for. Thirdly, actions which endogenously affect productivity, such as R&D investment or exporting, generally depend on input prices and affect productivity, and omitting violates the IV moment conditions.

Oligopsonic input markets do, however, cause meaningful variation in input prices across firms due to both markdowns and firm characteristics entering supplier utility. Frequently used instruments from the oligopoly demand estimation literature should therefore also work in the oligopsonic input market setting. Characteristics of rival firms, which are the input market equivalent of the ‘BLP instruments’ from Berry, Levinsohn, and Pakes (1995) are one such candidate. Using such instruments does not even require observing input prices.

BLP instruments

Consider manufacturer characteristics \((\tilde{Z}_{ft}, \hat{Z}_{ft}) \in Z_{ft}\) that enter the farmer utility function. The BLP instrument \(\tilde{X}_{ft}\), with input market \(i\) and a set of firms \(F_i\) (and similarly for \(\hat{X}\)), is:

\[
\tilde{X}_{ft} = \frac{1}{|F_{it}| - 1} \left( \sum_{r \in F_{it}} (\tilde{Z}_{rt}) - \tilde{Z}_{ft} \right)
\]

If there are as many suitable characteristics as coefficients for the substitutable inputs (in this paper,
2), the moment conditions are in (21).

\[ E \left\{ \omega_{jt}(\beta_l, \beta_k) \left( \tilde{z}_{jt}, \hat{z}_{jt} \right) \right\} = 0 \quad (21) \]

A firm characteristic which probably enters input supplier utility and which is fixed on the short run is, for instance, whether the firm is a SOE or a private enterprise. As long as a manufacturer’s productivity is not changed by the ownership structure of its competitors, and as long as input suppliers value selling to SOEs differently compared to private firms, the instrument is valid.

Another type of instrument would be to use input demand shifters at neighbouring firms. could be used as well. Most demand shifters, such as export shocks, are not excluded from productivity and therefore not to be used as instruments themselves. Demand shocks of competitors in the same market are, however, more likely to be excluded from the production function in the absence of ‘productivity spillovers’ from exporting to non-exporting firms. Ideally, one could use demand shifters of firms who operate in the same geographical input market, but in a very different product market. Apparel and tire producers in the same city both are likely to compete on the market for unskilled labor, but use very different production technologies and sell unrelated products. Export participation and tariff shocks of tire producers affect their unskilled labor demand, and therefore wages, but plausibly not productivity of apparel manufacturers.

In this paper, I use two variables to construct BLP instruments: the export share of revenue and an export dummy. The idea is that as competitors enter the international cigarettes market, this changes leaf prices of incumbent domestic firms, and hence their input decisions, but does not change their productivity level directly.

Monte Carlo simulations

In appendix D, use simulated data to compare the performance and consistency of both the BLP IV and regular ACF estimation strategies under various data generating processes.

C.2 Control function approach

Give details about specific functional forms used etc.
D Monte Carlo simulations

D.1 Estimation steps

In this section, I use simulated data to show the circumstances under which the identification approach outlined above works, and when it fails. To sum up, the estimation strategy consists of three steps:

(i) Estimate the production function, equation (8) \( \rightarrow \) retrieve \( (\hat{\omega}_{ft}, \hat{\beta}_{ft}) \)

(ii) Use productivity residuals \( \omega_{ft}^H \) to estimate markdowns by using re the input supply function and markdowns \( \rightarrow \) retrieve \( (\psi_{ft}^M) \)

(iii) Retrieve markups using \( \hat{\beta}_{ft} \) from (i) and \( \psi_{ft}^M \) from (ii).

D.2 Data generating process

I create a panel of 200 local intermediate input markets with exactly three firms in each market. All firms are observed during 3 periods and there is no entry or exit. The dataset hence contains 1800 observations. I impose a standard logit model for intermediate input supply, as in the model section. I simulate the dataset using 50 iterations.

Simulation procedure

In each iteration loop, the simulation procedure is as follows:

1. Draw \( \omega_{f1}^H, \xi_{f1}, \zeta_{f1}, K_{f1} \)

2. Find equilibrium wages \( W_{f1}^M \) using conditions in equation (20)

3. Calculate optimal investment \( I_f \)

4. Use transition equations to get \( \omega_{f2}, x_{f2}, K_{f2} \)

5. Repeat steps (2)-(4) until final period

I start by drawing initial productivity \( \omega^H \), productivity shocks \( \xi \), firm characteristics \( \zeta \) (which enter supplier utility) and capital \( K \) from their respective distributions, all in the first year. Next, I search for equilibrium input prices and intermediate input quantities for all firms in order to have an equilibrium in all input markets. Based on these equilibrium input prices, firms decide on investment, and optimal investment is calculated. In a fourth step, the capital stock is updated for the next year, using the capital accumulation equation and productivity is updated in the next period using the equation of motion for productivity. The next period, the draws and equilibrium calculation are repeated. Due to the upward-sloping intermediate supply curve, analytical expressions for labor usage no longer exist.
(in contrast with, for instance, Van Biesebroeck 2007). Equilibrium wages and employment levels are jointly obtained by solving the equilibrium conditions in equation (20) for each market in each year.

**Parametrization**

The parametrization of all coefficients and distributions are in Table A1. I let the output elasticity of labor and capital be 0.4 and 0.6. I use a lognormal distribution for TFP, with a serial correlation of 0.7 and a cross-sectional standard deviation of 0.5. Input market sizes are distributed uniformly between 0.5 and 1.5, meaning that the largest markets are three times larger than the smallest ones. Working conditions are drawn from a uniform distribution between 0 and 3. Valuation for wages and working conditions is 2.5 and 0.5 respectively, and in the second DGP there is a random coefficient on wages which varies 15% compared to the average wage valuation. Investment costs are normalized to one and the annual depreciation rate is 10%.

[Table A1 here]

**D.3 Results**

The estimated output elasticities using the simulated dataset are in table A2. The OLS estimates are, as usual, biased due to simultaneity. When not input prices and market shares do not feature in the first stage regression of ACF, the ACF estimates are as biased as OLS, which confirms the non-identification result in the theoretical model. When properly controlling for both market shares and input prices, in column 3, ACF delivers consistent estimates.

[Table A2 here]

Secondly, I use the productivity residuals as instrument for input prices in the supply estimation. In the simulated model, the wage valuation coefficient is 2.5. Column 1 of table ?? reports the OLS estimates of equation (??). These are evidently biased due to unobserved product characteristics $\zeta$. Column (2) reports the IV estimates. While these still seem to be slightly biased (which may be due to a small sample size), the estimates are still close to the truth, at 2.25. The true value of 2.50 lies within the 95\% confidence interval of the estimates. The first stage F-statistic is around 100, meaning that TFP is a strong instrument for endogenous input prices.

[Table ?? here]
Random coefficients

In the model, it was assumed that input supply follows a standard logit model. This implies that input suppliers all value input prices in the same way. It could, however, that there is unobserved heterogeneity in supplier preferences for input prices and other firm characteristics. In the case of labor, for instance, it seems likely that some workers prefer higher wages while others value working conditions or job security more. While estimating such a random coefficients input supply function is possible using mixed logit models, such as Berry, Levinsohn, and Pakes (1995), it poses problems for identifying the production function. Let the input supply elasticities be distributed across suppliers, and hence across firms with mean $\bar{\gamma}_W$ and $\sigma_\gamma$:

$$\gamma_{Wt} \sim \Gamma(\bar{\gamma}_W, \sigma_\gamma)$$

In this case, markdown variation across firms is not captured by observed input prices and market shares alone. Including these in the input demand function hence does not suffice to solve the problem of serially correlated unobservables which prevent inverting unobserved scalar productivity. Table A3, in the appendix, shows the simulated results for both production function estimators when input supply follows a random coefficients logit model. The estimates when using Ackerberg, Caves, and Frazer (2015) are almost as biased as the OLS results, even when including market shares and wages in the first stage regression.

Solving this problem is beyond the scope of this paper: for agricultural spot markets, it seems reasonable to assume that farmers all value input prices in the same way. For labor markets, this seems more problematic. I refer to another paper, Rubens (2019), for a discussion of this problem and for possible solutions.
E Robustness checks

E.1 Export participation

The Chinese economy globalized rapidly throughout the 1990s and 2000s, and the accession to WTO in 2003 affected total factor productivity and markup growth (Brandt et al. 2017; Li et al. 2012). As was already argued, the tobacco industry remained largely domestic: less than 1% of total industry revenue came from exports. For the 16% of firms who do export, exports represent merely 6% of their revenues on average. In table A5, I test whether exporting behavior changed through the consolidation, it turns out it did not.

E.2 Alternative market definitions

In Table A6, I re-estimate the effects of the consolidation on markdowns, markups and productivity using different market definitions. In the baseline specifications, input markets were defined at the 4-digit level, which correspond to prefectures and prefectural-size cities. In the first table, I narrow down the market definition to the county-level (6-digit location codes). In the second table, I enlarge it to the province level (2-digit codes). The markdown-increasing effects of the consolidation are similar in magnitude with the different market definitions. The markup-decreasing effect is not noticeable at the county level, but is at the province-level. Total factor productivity remains invariant to consolidation at the county-level, and slightly increases at the province-level. This effects is merely borderline significant, however.

E.3 Non-wage benefits

In the main text, I included non-wage benefits, such as social insurance, in variable labor costs. Table A7 re-estimates the effects of consolidation on markups when excluding these benefits from labor costs. The estimates are very similar to the baseline estimates. The markup level is estimated at 1.12 in the Leontief model with Cobb-Douglas term instead of 1.06, but the difference between both is not significant given the standard error of 0.17 on markup estimates in the baseline model.

E.4 Translog production function

Throughout the main text, I used a Cobb-Douglas specification for the labor-capital term $H(.)$ in the production function. As the elasticity of substitution estimate between labor and capital was not significantly different from one, this seems the correct production function. Nevertheless, I also use a translog specification for $H(.)$ as a robustness check. The corresponding functional form of $h(.)$ in
logarithms is given by:

\[ h(L_{ft}, K_{ft}) = \beta^L l_{ft} + \beta^K k_{ft} + \beta^{LK} l_{ft} k_{ft} + \beta^{L2} l_{ft}^2 + 2\beta^{2K} k_{ft}^2 \]

The moment conditions to estimate this translog production are given by:

\[ \mathbb{E}\left\{ \xi_{ft}(\beta^L, \beta^K, \beta^{LK}, \beta^{L2}, \beta^{K2}) \begin{pmatrix} l_{ft-1} \\ k_{ft} \\ l_{ft-1}^2 \\ k_{ft}^2 \end{pmatrix} \right\} = 0 \]

Table A8 compares the estimates for the main coefficients of interest and the markdown and markup averages between the Cobb-Douglas and Translog model. The estimates are very similar and never significantly different from each other.
### Table A1: Parametrization of Monte Carlo simulations

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Description</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\beta_l$</td>
<td>Output elasticity of labor</td>
<td>0.4</td>
</tr>
<tr>
<td>$\beta_k$</td>
<td>Output elasticity of capital</td>
<td>0.6</td>
</tr>
<tr>
<td>$\omega_{jt}^H$</td>
<td>TFP</td>
<td>$\sim \exp(N(0, 0.5))$</td>
</tr>
<tr>
<td>$\zeta_{jt}$</td>
<td>TFP shock</td>
<td>$\sim \exp(N(0, 0.5))$</td>
</tr>
<tr>
<td>$\rho$</td>
<td>TFP serial correlation</td>
<td>0.7</td>
</tr>
<tr>
<td>$\sigma^a$</td>
<td>TFP cross-sectional standard deviation</td>
<td>0.5</td>
</tr>
<tr>
<td>$\bar{M}_m$</td>
<td>Input market size</td>
<td>[0.5, 1.5]</td>
</tr>
<tr>
<td>$\xi_{jt}$</td>
<td>Working conditions</td>
<td>$\sim U[0, 3]$</td>
</tr>
<tr>
<td>$\alpha^c$</td>
<td>Working condition valuation</td>
<td>0.5</td>
</tr>
<tr>
<td>$\alpha^w$</td>
<td>Wage valuation</td>
<td>2.5</td>
</tr>
<tr>
<td>$\gamma^w$</td>
<td>Input price valuation by supplier (DGP 1)</td>
<td>0</td>
</tr>
<tr>
<td>$\gamma^w$</td>
<td>Input-price valuation by supplier (DGP 2)</td>
<td>$\sim U[-0.375, 0.375]$</td>
</tr>
<tr>
<td>$K_0$</td>
<td>Initial capital stock</td>
<td>$\sim \exp(N(0, 0.25))$</td>
</tr>
<tr>
<td>$\kappa$</td>
<td>Investment cost coefficient</td>
<td>1</td>
</tr>
<tr>
<td>$\delta$</td>
<td>Depreciation</td>
<td>0.1</td>
</tr>
</tbody>
</table>

Notes:
Table A2: Monte Carlo simulations

Output elasticities

<table>
<thead>
<tr>
<th>Dependent variable:</th>
<th>Truth</th>
<th>OLS</th>
<th>ACF</th>
<th>ACF bis*</th>
</tr>
</thead>
<tbody>
<tr>
<td>Log labor</td>
<td>0.400</td>
<td>0.544</td>
<td>0.582</td>
<td>0.401</td>
</tr>
<tr>
<td></td>
<td>( 0.028)</td>
<td>( 0.070)</td>
<td>( 0.113)</td>
<td></td>
</tr>
<tr>
<td>Log capital</td>
<td>0.600</td>
<td>0.555</td>
<td>0.543</td>
<td>0.600</td>
</tr>
<tr>
<td></td>
<td>(0.025)</td>
<td>(0.030)</td>
<td>(0.043)</td>
<td></td>
</tr>
</tbody>
</table>

Notes: *ACF with input market shares and input prices in first stage. Simulated using 50 iterations.

Input supply elasticity

<table>
<thead>
<tr>
<th>Dependent variable:</th>
<th>Log input market share</th>
</tr>
</thead>
<tbody>
<tr>
<td>Truth</td>
<td>OLS</td>
</tr>
<tr>
<td>Input price</td>
<td>2.500</td>
</tr>
<tr>
<td></td>
<td>(0.083)</td>
</tr>
<tr>
<td>First stage F-stat</td>
<td>97.949</td>
</tr>
</tbody>
</table>

Table A3: Monte Carlo: random coefficients logit supply

<table>
<thead>
<tr>
<th>Dependent variable:</th>
<th>Output</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>OLS</td>
</tr>
<tr>
<td>Labor</td>
<td>0.518</td>
</tr>
<tr>
<td></td>
<td>(0.029)</td>
</tr>
<tr>
<td>Capital</td>
<td>0.562</td>
</tr>
<tr>
<td></td>
<td>(0.024)</td>
</tr>
</tbody>
</table>

Notes:
Table A4: Labor supply elasticity

<table>
<thead>
<tr>
<th>Dep. var: log(labor market share) - log(outside option share)</th>
<th>Model:</th>
<th>OLS</th>
<th>IV</th>
</tr>
</thead>
<tbody>
<tr>
<td>Wage</td>
<td>-0.000414</td>
<td>-0.0623</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.00121)</td>
<td>(0.237)</td>
<td></td>
</tr>
<tr>
<td>Observations</td>
<td>830</td>
<td>830</td>
<td></td>
</tr>
<tr>
<td>1st stage F-stat</td>
<td>14.53</td>
<td></td>
<td></td>
</tr>
<tr>
<td>R-squared</td>
<td>0.915</td>
<td>0.372</td>
<td></td>
</tr>
</tbody>
</table>

**Note:** Controls: export dummy and share of revenue, cigarette price, time trend, product type, prefecture dummy, ownership type. Market shares at province-level. Instrument: TFP.
<table>
<thead>
<tr>
<th>Dependent variables:</th>
<th>Export dummy</th>
<th>Export share of revenue</th>
</tr>
</thead>
<tbody>
<tr>
<td>Treatment * I(year ≥ 2003)</td>
<td>-0.0476 (0.0426)</td>
<td>-0.0113 (0.00894)</td>
</tr>
<tr>
<td>Treatment</td>
<td>-0.0303 (0.0417)</td>
<td>-0.00554 (0.00951)</td>
</tr>
<tr>
<td>I(year ≥ 2003)</td>
<td>0.0756 (0.0252)</td>
<td>0.00787 (0.00347)</td>
</tr>
<tr>
<td>Observations</td>
<td>2,638</td>
<td>2,486</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.040</td>
<td>0.011</td>
</tr>
</tbody>
</table>

**Note:** Controls include a time trend, product type, ownership type and firm fixed effects.
Table A6: Consolidation effects, alternative market definitions

<table>
<thead>
<tr>
<th>Treatment effect estimate</th>
<th>County-level</th>
<th>Prefecture-level</th>
<th>Province-level</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dependent variables:</td>
<td>Markdown</td>
<td>Markup</td>
<td>TFP</td>
</tr>
<tr>
<td>County-level</td>
<td>0.199</td>
<td>-0.111</td>
<td>0.0633</td>
</tr>
<tr>
<td></td>
<td>(0.0644)</td>
<td>(0.0750)</td>
<td>(0.120)</td>
</tr>
<tr>
<td>Prefecture-level</td>
<td>0.126</td>
<td>-0.0307</td>
<td>0.0727</td>
</tr>
<tr>
<td></td>
<td>(0.0503)</td>
<td>(0.0521)</td>
<td>(0.0748)</td>
</tr>
<tr>
<td>Province-level</td>
<td>0.268</td>
<td>-0.320</td>
<td>0.0891</td>
</tr>
<tr>
<td></td>
<td>(0.0584)</td>
<td>(0.0653)</td>
<td>(0.0804)</td>
</tr>
</tbody>
</table>

Notes: Estimates of treatment effect in difference-in-differences regression reported. Same specification as before. Dependent variable in logs. Treatment and control groups calculated by defining input markets at different geographical levels.
Table A7: Consolidation effects on markups without non-wage benefits

<table>
<thead>
<tr>
<th>Dependent variables:</th>
<th>Markup</th>
</tr>
</thead>
<tbody>
<tr>
<td>Treatment * I(year≥2003)</td>
<td>-0.165 -0.0673</td>
</tr>
<tr>
<td></td>
<td>(0.101) (0.0960)</td>
</tr>
</tbody>
</table>

| Observations | 999 | 999 |
| R-squared    | 0.164 | 0.749 |
| Firm FE      | No | Yes |

Notes:
Table A8: Cobb-Douglas vs. Translog

<table>
<thead>
<tr>
<th>Model for $H(L, K)$:</th>
<th>Cobb-Douglas</th>
<th>Translog</th>
</tr>
</thead>
<tbody>
<tr>
<td>Leaf supply elasticity</td>
<td>1.415 (0.595)</td>
<td>1.655 (0.719)</td>
</tr>
<tr>
<td>Avg. markdown</td>
<td>2.354 (0.32)</td>
<td>2.157</td>
</tr>
<tr>
<td>Avg. markup</td>
<td>0.930 (0.17)</td>
<td>0.934 (0.21)</td>
</tr>
<tr>
<td>Treatment effect markdown</td>
<td>0.184 (0.065)</td>
<td>0.167 (0.061)</td>
</tr>
<tr>
<td>Treatment effect markup</td>
<td>-0.097 (0.075)</td>
<td>-0.087 (0.076)</td>
</tr>
<tr>
<td>Treatment effect TFP</td>
<td>0.048 (0.120)</td>
<td>0.072 (0.121)</td>
</tr>
<tr>
<td>Observations</td>
<td>830</td>
<td>830</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.751</td>
<td>0.785</td>
</tr>
</tbody>
</table>

**Notes:** Dependent variables in logs.
### Table A9: Log markups and ownership types

<table>
<thead>
<tr>
<th>Dependent variable:</th>
<th>Markup</th>
</tr>
</thead>
<tbody>
<tr>
<td>Private</td>
<td>-1.191 -1.308 1.139 -0.276</td>
</tr>
<tr>
<td></td>
<td>(0.459) (0.466) (0.466) (0.987)</td>
</tr>
<tr>
<td>Joint stock</td>
<td>-0.209 -0.206 0.0166 0.0528</td>
</tr>
<tr>
<td></td>
<td>(0.145) (0.148) (0.148) (0.254)</td>
</tr>
<tr>
<td>Stock shareholding</td>
<td>-0.412 -0.502 2.305 -0.294</td>
</tr>
<tr>
<td></td>
<td>(0.375) (0.381) (0.380) (1.396)</td>
</tr>
<tr>
<td>Observations</td>
<td>999 987 999 903</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.012 0.013 0.046 0.000</td>
</tr>
<tr>
<td>Firm FE</td>
<td>Yes Yes Yes Yes</td>
</tr>
<tr>
<td>M substitutable</td>
<td>No No Yes Yes</td>
</tr>
<tr>
<td>Model</td>
<td>Cobb-D Translog Cobb-D Translog</td>
</tr>
</tbody>
</table>

**Notes:** The reference ownership type is SOE