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Measuring Markups from Revenue and Total Cost: An Application to Japanese Plant-Product Matched Data*

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Abstract

The evolution of product markups has important implications for macroeconomic dynamics. However, thus far, the trends and distributions of product markups have been very different, depending on how they are estimated. This paper uses plant-product matched data from Japan, and theoretically and empirically compares two alternative measures of product markups. One measure is De Loecker and Warzynski's (2012) state-of-the-art production approach that estimates production function parameters and computes markups from the output elasticities of an input divided by that input's revenue share. An alternative measure, which has been much less frequently applied empirically to micro data, is Diewert and Fox's (2008) approach that derived markups from the revenues divided by the total costs. Markups derived from the latter approach are consistent with the theoretical predictions: The markups increase as their market power increases and as their marginal costs decline.

Keywords: Markups, capital costs, output prices, plant-product matched data, Japanese manufacturing
JEL classification: D22, D24, E22, E25, F11, L11

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1 Introduction

The evolution of product markups has important implications for macroeconomic dynamics, including the inequality between capitalists and workers, the profitability of corporations, corporate tax revenue, and the exit and entry of firms. To examine the influence of markups on macroeconomic dynamics and find appropriate policy responses, it is crucial to measure markups accurately. However, thus far, the trends and distributions of markups have been very different, depending on how they are estimated. See, for example, De Loecker and Eackhout (2017), Karabarbounis and Nieman (2018), and Hall (2018) for the U.S. trends of markups during the past few decades.

To better understand which empirical approaches give us accurate measures of markups, this paper uses plant-product matched data from Japan, and empirically compares two approaches of estimating product markups. One approach is De Loecker and Warzynski's (2012) state-of-the-art production approach that estimates markups from the output elasticities of an input divided by that input's revenue shares. As an alternative approach (hereafter, the cost approach), building on Diewert and Fox's (2008) theoretical contributions, we derive markups from the revenues divided by the total costs, which is the cost share of an input divided by revenue share of that input. In principle, these two approaches are theoretically consistent; however, they are empirically different in how to estimate output elasticities. While the production approach assumes a certain form of production function and estimates output elasticities from production function parameters, the cost approach computes total cost and approximates output elasticities from cost shares of inputs without estimating production functions.

The cost approach has some advantages because it does not estimate production functions. To estimate production function parameters, the production approach requires that several econometric and data issues, including simultaneity and selection biases (Olley and Pakes, 1996), functional dependence problems (Ackerberg et al., 2015), and input allocation and price biases for multi-product firms (De Loecker et al., 2016), be resolved. Moreover, to obtain unbiased production function parameters, it is crucial to use product-level information about output prices and quantities (Lu and Yu, 2015; De Loecker et al., 2016).[1]

[1] Using the Annual Survey of Industrial Firms of China, Lu and Yu (2015) estimate a translog production function for two different measures of real outputs: one derived from product-level physical quantity for single-product firms; and the other from conventional method by using industry-level output deflators (i.e., firm-level revenue divided by industry-level output deflators). They find that the product markups computed from these two measures are very different, suggesting that the conventional practice to obtain revenue-based quantities from the revenue divided by

The cost approach has some disadvantages as well. First, to use the cost approach, "obtaining capital costs is usually the practical sticking point" (Syverson, 2011). To overcome this problem, we use Hall and Jorgenson's (1967) approach and impute capital costs from the opportunity costs of holding capital assets. Although this method is applied to national- or industry-level studies (Caballero and Lyons, 1992; Barkai, 2016; Karabarbounis and Neiman, 2018), it has rarely been applied to firm- or plant-level data. Once we compute capital costs at the plant level, a measure of product markup can be derived from the revenue divided by total cost. This measure is intuitive because the revenue divided by total cost is identical to the output price divided by marginal cost when scale elasticities are unity. Second, to theoretically derive markups from the cost approach, we need to impose all the first-order conditions. This implicitly assumes that producers optimize labor, capital, and intermediate inputs simultaneously for each year. This assumption could be inconsistent with the timing assumption that is traditionally presumed in the literature (Olley and Pakes, 1996). As discussed by Ackerberg et al (2015), it may take longer to hire labor and install capital than to purchase intermediate inputs. As such, we think that markups derived with the cost approach are appropriate in the medium to long run.

In this paper, we use plant-level data from the Census of Manufacture and compute markups from the cost approach, as well as various measures from the production approach. The Census of Manufacture is an annual survey conducted by the Ministry of Economy, Trade and Industry (METI). The advantage of this database is that we can combine plant-level production variables with product-level price and quantity variables over the relatively long period of 1986–2010. Our estimates of markups computed with the cost approach suggest that, on average, product markups increased over the period from 1.18 in 1988 to 1.33 in 2008. The markups computed with the cost approach are much smaller in levels and standard deviations than those computed with the production approach. For example, the standard deviation is 0.43 in 2008 for those estimated with the cost approach, and is 1.42 for those estimated with the production approach (i.e., the physical quantity-based Cobb-Douglas revenue production function).

We also examine the theoretical relationship implied in the duality problem (Hall, 1988; Roeger, 1995; Hall, 2018): Markups are related systematically to output prices, unit costs, production scale, and productivity. We perform this exercise for markups calculated based on the cost approach, as

industry-level deflators cannot identify markups accurately.

well as for four types of markup measures based on the production approach. Overall, the estimates computed with the cost approach are consistent with the theoretical predictions. Markups are positively related to output prices, production sizes, and productivity, and negatively related to unit costs, suggesting that product markups measured from the cost approach capture the evolution of markups arising from market power and marginal costs. The estimates from the production approach, however, do not strongly follow in the same manner: Some are positively related to unit costs, and others are negatively related to output prices. Among the markups computed with the production approach, those estimated from output elasticities of intermediate inputs are much more consistent with those estimated from output elasticities of labor.

Using data over the 1990s and 2000s, several studies (Klitgaard, 1999; Kiyota, Nakajima, and Nishimura, 2009; Obstfeld, 2009; Fukao and Nishioka, 2019) examine markup dynamics in Japan and show that markups declined over the period. Their findings are very different from our study. There are several potential reasons why we find increasing trends of markups and they find declining trends in markups. First, our plant-level data do not include data for headquarters for multi-plant firms. Therefore, we could underestimate total costs. Second, we use only the sample that covers all manufacturing plants that have 30 or more employees. The exclusion of small-size enterprises could overestimate markup trends of ours. Among these studies, Kiyota et al's (2009) theoretical and empirical contributions are closely related to those in the present study. However, we differ from their approach on several points. First, we use revenue production functions and do not use value added production functions. As shown in Basu and Fernald (1997), value added production functions are not valid when producers operate in imperfectly competitive markets. Second, we use Hall and Jorgenson's (1967) approach, and impute capital costs according to the opportunity costs of holding capital assets, whereas Kiyota et al (2009) use observed accounting values of depreciation as capital costs.

The rest of the paper proceeds as follows. In the second section, we explain our strategy for deriving the markup measure from the cost approach. In the third section, we discuss the development of data for capital costs. In the fourth section, we describe the data, and in the fifth section, we examine the evolution of product markups in the Japanese manufacturing sector. In the sixth section, we also examine how markups from various measures are related to market power and marginal costs. In the seventh section, we discuss our conclusions.

2 The Cost Approach of Measuring Markups

This follows Diewert and Fox (2008) and develops an approach that measures product markups without estimating production functions. We assume that a plant that produces a single product i at time t uses a production function that converts three inputs (labor L_{it}; capital K_{it}; and intermediate inputs M_{it}) into real output (Q_{it}). The corresponding input prices, w_{it}, r_{it}, and p_{it}, are strictly positive and exogenous for producers. There variables are plant-specific because each plant can choose distinct range and composition of each input (e.g., a different set of skill in labor). Following Basu and Fernald (1997) and Diewert and Fox (2008), we assume that scale elasticities (ρ_i) do not change over time. In particular, we use the following production function:

$$Q_{it} = \Omega_{it} \left[F_{it} \left(L_{it}, K_{it}, M_{it} \right) \right]^{\rho_i} \tag{1}$$

where we impose product-specific technique, $F_{it}(\cdot)$, is differentiable and homogeneous of degree one, but can evolve over time, and Ω_{it} is a Hicks-nuetral productivity measure that captures technological progress.

To derive a measure of markups for each product i, we use the following profit maximization problem:

$$\max_{L_{it}, K_{it}, M_{it}} P_{it} Q_{it} - \left[w_{it} L_{it} + r_{it} K_{it} + p_{it} M_{it} \right].$$

If all inputs are observable and optimally chosen, an expression of product markup can be derived from the first-order conditions and Euler's rule[2]:

$$\mu_{it} = \rho_i \frac{P_{it} Q_{it}}{w_{it} L_{it} + r_{it} K_{it} + p_{it} M_{it}} \tag{2}$$

To derive equation (2), we impose an assumption that all inputs are optimally chosen. As discussed in Ackerberg et al (2015), it may take longer time to hire labor and install capital than to purchase intermediate inputs. Therefore, our measure of product markup can be thought of the medium- to long-run values.

[2] For example, we have the following first order condition for labor: $\frac{\rho_i}{\mu_{it}} \frac{\partial F_{it}(\cdot)/F_{it}(\cdot)}{\partial L_{it}/L_{it}} = \frac{w_{it} L_{it}}{P_{it} Q_{it}}$. Using all the first order conditions and the property of homogeneous of degree one in $F_{it}(\cdot)$ for each time t, we can apply Euler's rule to obtain equation (2).

In this paper, we estimate markups from the revenue ($P_{it}Q_{it}$) divided by total cost ($w_{it}L_{it} + r_{it}K_{it} + p_{it}M_{it}$). Strictly speaking, the revenue divided by total cost is markup only if $\rho_i = 1$; however, as long as researchers are interested in the changes in markups, ρ_i would disappear with time differencing or would be captured by product-specific fixed effects. Intuitively, our measure of markups is straightforward. When constant returns to scale is assumed, product markup is the output price divided by marginal cost. When increasing (decreasing) returns to scale is estimated, the revenue divided by total cost would underestimate (overestimate) markup levels by ρ_i.

An alternative expression of equation (2) is the cost share of labor ($\alpha_{it}^L = w_{it}L_{it}/(w_{it}L_{it} + r_{it}K_{it} + p_{it}M_{it})$) divided by revenue share of labor ($\tilde{\alpha}_{it}^L = w_{it}L_{it}/P_{it}Q_{it}$) adjusted by scale elasticity:

$$\mu_{it} = \frac{\rho_i \alpha_{it}^L}{\tilde{\alpha}_{it}^L}. \tag{3}$$

Because output elasticity of labor is $\rho_i \alpha_{it}^L$, equation (3) corresponds to De Loecker and Warzynski's (2012) and De Loecker et al's (2016) production approach where product markup is derived from the output elasticity of an input (i.e., labor) divided by revenue share of that input. In principle, the two equations (2) and (3) are theoretically consistent. And, empirical discrepancies between these two measures depend solely on how well production function parameters or cost shares of inputs can approximate output elasticities.

To understand how market power and marginal costs can influence markups derived from equation (2), we use the following cost minimization problem similar to Roeger (1995), which is dual to the profit maximization problem above, and derive an alternative form of product markups:

$$\min_{L_{it},K_{it},M_{it}} w_{it}L_{it} + r_{it}K_{it} + p_{it}M_{it} - \lambda_{it}\left[Q_{it} - \bar{Q}_{it}\right].$$

Using all the first-order conditions, we can derive total cost c_{it} to produce a local target output level, $\bar{Q}_{it}$, as a function of input prices and productivity:

$$c_{it} = \Omega_{it}^{-1/\rho_i} \bar{Q}_{it}^{1/\rho_i} G_{it}\left(w_{it}, r_{it}, p_{it}\right) \tag{4}$$

where $G_{it}(\cdot)$ is unit cost function, which is a dual form of production function $F_{it}(\cdot)$.

Because $F_{it}(\cdot)$ is homogeneous of the first degree, $G_{it}(\cdot)$ is also homogeneous of the first degree. Moreover, the dual measure of markup (e.g., Hall, 2018) can be obtained from the output price

(P_{it}) divided by marginal cost (mc_{it}):

$$\mu_{it} = \rho_i \frac{P_{it}}{G_{it}(\cdot)} \bar{Q}_{it}^{1-1/\rho_i} \Omega_{it}^{1/\rho_i}. \tag{5}$$

Equation (5) suggests that product markup derived from equation (2) is positively related to output price (P_{it}) that reflects the market power and productivity (Ω_{it}) that reduce marginal costs, but negatively related to unit cost ($G_{it}(\cdot)$). Markup depends also on the scale of producing product i (Q_{it}); when scale elasticity is greater (less) than one, μ_{it} would increase (decrease) with Q_{it}.

3 Capital Costs

We estimate user costs of capital from opportunity costs of holding capital assets. This approach–the *ex-ante* approach–was proposed by Hall and Jorgenson (1967) and has applied to the country- or industry-level studied including Caballero and Lyons (1992), Barkai (2016), and Karabarbounis and Neiman (2018). The RIETI Japan Industrial Productivity (JIP) database (Fukao et al, 2007) also compute capital costs using the same approach.

Consider that K_{it}^k is the quantity of the kth capital service to product good i in time t, and r_t^k is its corresponding user cost. We also introduce the following notation: I_{it}^k is the quantity of the kth investment good newly acquired to produce good i in time t, and p_t^k is its corresponding price. Following the perpetual inventory method, the cumulated stock of past investments in the kth capital good has the following property:

$$K_{it}^k = (1-\delta^k) K_{i,t-1}^k + I_{it}^k \tag{6}$$

where δ^k is the depreciation rate of the kth investment good, which is derived from the RIETI JIP database.

Then, we can have the following equation:

$$r_t^k K_{it}^k = p_t^k K_{it}^k \left(i_t + \delta^k - \Delta p_t^k / p_t^k \right) \tag{7}$$

where i_t is the country-level risk free interest rates (i.e., government bond rate derived from the International Financial Statistics of the International Monetary Fund), and $\Delta p_t^k / p_t^k$ is the rate of capital gain or loss on the kth investment good from the RIETI JIP database.

By summing across all types of capital services, we can obtain capital costs to produce good i in time t:

$$\sum_k r_t^k K_{it}^k = \sum_k p_t^k K_{it}^k \left(i_t + \delta^k - \Delta p_t^k / p_t^k \right). \tag{8}$$

The primary problem to obtain capital costs from this approach is that we do not observe the capital stock data at the plant level. Therefore, we use the following strategy to estimate the initial capital stock.

First, we obtain the total capital stock for the three distinct types of capital assets: (1) non-residential buildings and structures; (2) machinery and equipment; and (3) transport equipment by using the following equation to obtain the initial values of capital stocks:

$$K_{t=1986}^k = \frac{I_{t=1986}^k}{\delta^k + g^k} \tag{9}$$

where $I_{t=1986}^k = \sum_i I_{i,t=1986}^k$, and g^k is the average annual growth rate in real investments over the period of 1986-2010.

By applying equation (6) at the aggregate level, we can create total capital stocks (K_t^k) in the manufacturing sector for each year. To allocate capital stocks to each plant, we use the plant-level book values for tangible assets (A_{it}) to allocate total real stocks of capital into each plant:

$$K_{it}^k = K_t^k \frac{A_{it}}{\sum_i A_{it}}. \tag{10}$$

Because each plant appears to the data in different date, the initial years differ across plants. After obtaining the initial values of capital stocks from equation (10), we use equation (6) to develop the plant-level stocks of real capital. When plants do not invest, their capital stocks decline with depreciation.

4 Data

4.1 The Census of Manufacture

We use plant-level data from the Census of Manufacture and compute product markups with various methods. The Census of Manufacture is an annual survey conducted by the METI. Plant-level variables, such as shipments, employment, wage bills, spending on intermediate inputs (materials, fuel, electricity, and domestic outsourcing), and investments are from the plant subset; and product-level variables, such as shipments and physical quantities, are from the product subset. In the analysis, we use only the sample that covers all manufacturing plants that have 30 or more employees. Although we do not include smaller plants, the data cover around 80% of Japanese plants in terms of total outputs. Over the period 1986–2010, we have 1,253,294 observations at the plant level. On average, we have around 50,000 plants for each year. The product-level data that include prices and quantities, however, are not rich. The information on products is reported in the Census of Manufacture's 6-digit classification system. There are approximately 2,000 products, of which quantity information is available for around 800 products. After we merge the product-level data with the plant-level data, we have 324,780 observations. The observations decrease further to 67,000 once we limit the sample to single-product plants.

Table 1 reports the summary statistics for the years 1988, 1998, and 2008. The data reported in this table do not include product-level information. One notable finding in the table is that the average size of Japanese manufacturing plants increases, whereas the number of plants decreases. There are 55,769 plants in 1988, but 44,198 plants in 2008. The decline is substantial over the 1998–2008 period. The average sale, however, increases by 58% from 4 billion Japanese Yen in 1988 to 6 billion Japanese Yen in 2008.

4.2 Cost Shares

The evolution of cost shares has important implications for the evolution of production techniques because the cost share represents the output elasticities when producers optimize all the production inputs. For example, if the underlying production technique is a Cobb-Douglas production function (i.e., the output elasticities are constant), the cost shares and the output elasticities are constant over time. Therefore, the cost shares of labor and capital do not change in the Cobb-Douglas production function. However, if the production techniques deviate from the Cobb-Douglas production function, then the cost shares could increase or decrease, depending on various factors, including changes in the composition of the inputs, substitutability and complementality between inputs (e.g., a CES or translog form), and structural changes in production techniques (e.g., an industry shifts to using a capital- or intermediate inputs–intensive technique).

Table 2 reports the summary statistics of cost shares for the years 1988, 1998, and 2008. The cost shares of labor are stable over the period: 27.9% in 1988, with a slight increase to 28.7% in 2008. Similar to the cost shares of labor, the labor shares–labor compensation divided by value added–are also stable, 52.7% in 1988, with a slight decrease to 51.4% in 2008. The results differ from global evidence of declining trends in labor shares. For example, Karabarbounis and Neiman (2014) show that labor shares decline because the cost of capital relative to labor decline over the 1980–2010 period. One notable finding is that the cost shares of capital decline and those of materials increase. The average cost share of capital is 13.7% in 1988, and decreases to 5.3% in 2008. This decline is offset by the increase in the cost shares of materials. The average cost share of materials increases from 45% in 1988 to 52% in 2008. Low inflation and interest rates after the asset bubble economy burst in 1992 could be responsible for the declining trend in the cost shares of capital. The cost shares of materials, however, increase due probably to increasing reliance on outsourcing after China's accession to the World Trade Organization.

5 Markup Estimates

In this paper, we use the revenue divided by total cost to approximate plant-level markups. To better understand how our estimates of product markups differ from those estimated with the production approach, we also estimate the constant returns to scale Cobb-Douglas production functions at the 2-digit industry level. Similar to Lu and Yu (2015), we estimate two sets of parameters: one derived from product-level physical quantities for single-product plants; and the other from the conventional method by using the revenues divided by industry-level output deflators from the RIETI JIP database (Fukao et al, 2007). To estimate all the parameters of the production function, we use Ackerberg et al's (2015) generalized method of moments (GMM) procedure. See the appendix for detailed discussions of our estimation strategy. Lu and Yu (2015) find that the output elasticities computed from these two different measures of prices are quite different. However, we find that the output elasticities appear to be similar although we do not estimate the translog forms.

5.1 Summary Statistics

Table 3 reports the summary statistics for the markup estimates based on the cost approach. In 1988, the markup estimates are centered on a mean of 1.18 and a median of 1.12 with a standard deviation of 0.31. Over the next 20 years, the mean shifts to 1.28 in 1998 and to 1.33 in 2008, and the standard deviation increases slightly to 0.37 in 1998 and to 0.43 in 2008. Using the production approach, we have a slightly larger mean around 1.5–1.9 and larger standard deviations ranging from 1.1 to 1.5. There are several reasons why the markup estimates from the cost approach have smaller standard deviations. First, even within the same industry, plants may use different production techniques. Thus, it is difficult to fit all plants within an industry into a one-size-fits-all production function. Second, we use the constant returns to scale Cobb-Douglas sectoral production functions for the production approach. This Cobb-Douglas form could be problematic because we do not take into account the interaction terms across the production inputs.

5.2 Cost Approach versus Production Approach

Figure 1 is a set of histograms of the markup estimates in the years 1988, 1998, and 2008. The histograms show that the shape of the distribution is remarkably stable over the years. Figure 2 shows the histograms of four kinds of markups in 1998 estimated based on the production approach. They differ by (1) whether the markups are estimated using elasticities of labor (panels A and B) or of intermediates (panels C and D) and (2) whether the production function is estimated using the revenue divided by industry-level deflators (panels A and C) or product-level physical quantities (panels B and D) as real outputs. Note that we refer to the output elasticities estimated from the revenues divided by industry-level deflators (product-level physical quantities) as revenue (quantity) elasticities. Our results suggest that the differences in the markup distributions by the revenue- and quantity-based production function estimates appear to be small. The mean of the markups based on the revenue elasticity of labor (intermediates) is 1.91 (1.53); that based on the quantity elasticity of labor (intermediates) is 1.81 (1.49). In addition, the standard deviation of markups based on the revenue elasticity of labor (intermediates) is 1.55 (1.33), which is slightly higher than that based on the quantity elasticity of labor (intermediates): 1.41 (1.28). These statistics suggest that the choice of output elasticity between labor versus intermediates seems to make somewhat larger differences in the shape of the markup distributions. In addition, judging from the histograms, the estimates based on the output elasticities of the intermediate inputs tend to have a longer upper tail compared to those that used the output elasticities of labor.

Figure 3 plots the mean and median of markups over years. Panel A plots those of markups based on the cost approach. Panels B and C show those of markups using quantity elasticities of labor and intermediates, respectively. The three kinds of markups have different trends. The time trend of the markups based on the cost approach is increasing overall, in terms of the mean and the median. However, the trend of markups based on quantity-based output elasticities of labor decreases in the 1990s and increases in the 2000s, and the trend of the markups based on quantity-based output elasticities of intermediates is the opposite.

Next, we examine correlations across various markup measures. In doing so, we regress the first difference of the log of the markup on the first difference of the log of another markup estimate. Table 4 reports the results. The standard errors are clustered at the industry level. Using the measure of markups based on the cost approach as a dependent variable, the coefficients of the measures of markups based on the production approach are all positive and statistically significant with the coefficients ranging from 0.40 to 0.53. Among them, the coefficients of the measures of markups that use output elasticities of intermediate inputs are larger than those that use output elasticities of labor. In other words, markups estimated from the cost approach are statistically close to those estimated from the production approach with intermediate inputs as a flexible input.

Interestingly, interchanging the dependent and independent variables results in larger coefficients. For example, regressing the markups from quantity elasticities of labor on those from the cost approach, the coefficient is 0.77. Similarly, using the markups from quantity elasticities of intermediates as a dependent variable results in a coefficient of 1.02. These results suggest that the markups from the revenue-cost ratios have fewer measurement errors than markups computed with the production approach.

Another noteworthy point in Table 4 is that the markups using revenue- and quantity-based production function estimations are highly correlated. The coefficient of the markup using quantity elasticities of labor (intermediates) is 0.97 (0.99) for the markup using revenue elasticities of labor (intermediates). This result may be surprising given the intuition in previous works that emphasizes the importance of quantity-based markup estimates (Lu and Yu, 2015).

5.3 Price Elasticities of Demands and Market Shares

Before exploring the determinants of markups, we examine the determinants of prices. In Table 5, we report the ordinary least squares (OLS) estimates of regressing the changes in the log of product prices on changes in the measures of market share. We use two measures of market share. One is to take the simple average of the product-wise share of the plant's shipments in the total shipments of all plants in the year. The other is to take the average of the same product-wise share weighted by the shipment value of a product. As for the measures of prices, in columns (1) and (3), we use the average product prices in the plant. The price data come from the product-level data of the Census of Manufacture, in which products are measured in 6-digit codes. Columns (2) and (4) restrict the samples to single-product plants and use the product prices. In all specifications, the coefficients of the market share are positive and statistically significant. The coefficient implies that an increase of 10 percentage points in the market share is associated with an increase of 3.0 to 4.6 percentage points in the product price. The findings suggest that producers with higher market shares (i.e., market power) tend to charge higher prices.

In this paper, we estimate markups from producer-side information. However, extant studies use demand-side information and examine markup dynamics; see, for example, Feenstra and Weinstein (2017). For the convenience of the analysis, we use the following inverse demand function:

$$P_{it} = P_{it}(Q_{it}) \tag{11}$$

and obtain the demand-side measure of product markups:

$$\mu_{it} = \frac{\epsilon_{it}(Q_{it})}{\epsilon_{it}(Q_{it}) - 1} \tag{12}$$

where price elasticity of demand is $\epsilon_{it}(Q_{it}) = -\left(\Delta Q_{it}/Q_{it}\right) / \left(\Delta P_{it}/P_{it}\right)$.[3]

In Table 6, we estimate the price elasticity of demand. In columns (1) and (2), we regress the changes in product-level price on changes in the log of physical quantity. We also include the log of unit cost as a control variable. To develop unit cost, we follow Hall (2018) and use the average of the normalized log input prices, weighted by the plant's cost shares. The price of intermediate

[3] Higher price elasticity of demand indicates higher competition, and perfect competition means $\epsilon_{it}(Q_{it})$ is close to ∞.

inputs is measured at the industry-year level and is obtained from the RIETI JIP database (Fukao et al., 2007). The results from the full sample is reported in column (1), and those from the sample of single-product plants is in column (2). In both specifications, the coefficients are negative and statistically significant: -0.38 for the full sample and -0.70 for the sample of single-product plants. The corresponding demand-side markups from equation (12) are bit too high: 1.61 and 3.33, respectively. For endogeneity concerns, we use Arellano-Bond's (1991) generalized method of moments (GMM) of estimating dynamic panel data by treating the growth of quantity as an endogenous variable.[4] The results from the sample of single-product plants are reported in columns (3) and (4) without or with the control variable of log unit cost. While we find that the coefficients of log quantity are still negative and statistically significant, the coefficients decline significantly to 0.07 and 0.19 after controlling for the endogeneity concerns. And, the corresponding demand-side markups are 1.08 and 1.23, much closer to the supply-side values. Lastly, we use an alternative measure of price, industry-level price deflators from the RIETI JIP database. The results are shown in columns (5) and (6) and indicate that the coefficient sign of price becomes positive and statistically significant.

5.4 Decomposition of the Markup Dynamics

In this section, we empirically examine the relationship implied in equation (5) that relates markups to output prices, unit costs, production scales, and productivities. We perform this exercise for the markups calculated from the cost approach, as well as for the four kinds of markup measures based on the production approach, as used above. As for the measure of prices, we have two alternatives. One is to use the product prices in product-level data by focusing on plants that produce a single product. The other is to use the industry deflators from the RIETI JIP database. Unit cost is measured in the same way as described above. Production scale is measured either by physical quantities focusing on single-product plants or by the total real revenues of the plants. Measures of TFP depend on production functions and measures of real outputs. For the analysis using the cost approach, we use the cost share of each input (labor, capital, and intermediates) to calculate the revenue-based TFP measure. For the analysis using the production approach, we use the estimated output elasticities to calculate the TFP measures. If the output elasticities are estimated using

[4] In this paper, we use two step approach for estimation and robust standard errors.

physical quantities, we use the quantity-based TFP measures.

Table 7 reports the results. Panel A shows the results for markups based on the cost approach. In columns (1) to (6), we use the simple OLS specification using the first differences for all variables. In this way, we eliminate any time-invariant unobserved component at the plant level, including scale elasticity (ρ_i). Standard errors are clustered at the industry level. In all of the equations, the coefficients of the log of price are positive and statistically significant for the product- and industry-level measures of prices. When we include all regressors, the coefficients are 0.34 and 0.54 for the product- and industry-level price measures, respectively.[5]

As predicted, the coefficients of the log of unit cost are all negative and statistically significant, ranging from –0.37 to –0.18 depending on the specifications. The coefficients of production scale, measured either by the log of quantity or the log of total real revenues, are positive and statistically significant in all equations, suggesting that scale matters for product markups. Finally, as our theory implies, the coefficients of TFP are positive and statistically significant in all equations. Overall, the results are consistent with the model prediction in equation (5).

For endogeneity concerns about price and quantity choice, in columns (7) to (12), we use the Arellano-Bond (1991) differenced GMM method for estimating dynamic panel data, again using the first difference for all variables. In column (7), we specify price as an endogenous variable without controlling for quantity and productivity. The coefficient of price is negative and not statistically significant. However, as in column (8), when we include the log of quantity as an endogenous variable, we have positive and statistically significant coefficients for price and quantity. In column (9), we include TFP as an exogenous variable. The coefficients for price (0.23), quantity (0.24), and TFP are all positive and statistically significant. The results are similar when we use the industry-level price deflators as shown in columns (10) to (12). In summary, the results are qualitatively unchanged with the differenced GMM method.

In panel B, we show the results for markups based on revenue elasticities of labor. Columns (1) through (6) are the results for the OLS of the first differences of the variables. The coefficients of the output price, scale effect, and TFP are all as predicted, but the coefficients of unit cost are positive and statistically significant in all regressions. This feature remains even in columns (7) to (12) when we use the differenced GMM method.

[5] Note that the samples also differ between these equations. In the regressions using establishment-level prices, we restrict the sample to single product producers.

Panel C reports the results for markups based on the quantity-based output elasticity of labor. The results share the same feature as those in panel B: The coefficients of unit cost are positive and statistically significant. In addition, the coefficients of (quantity-based) TFP are estimated to be negative when we use plant-level prices.

In panel D, we show the results for markups based on revenue elasticities of intermediate inputs. In columns (1) to (6), the results of OLS of the first differences are mostly reasonable as predicted, except that the coefficients of the log of industry-level price are either negative or close to zero, and the coefficients of unit cost are positive. In addition, even when we use the plant-level price, the estimated coefficients size of price and the log of unit cost are somewhat small, 0.13 and –0.18, respectively. In columns (7) to (12), the results of the GMM estimates are shown. The coefficients of price are either not statistically significant or are negative in all specifications. When we use product-level price, the coefficients of unit cost are negative and statistically significant, but the coefficients of quantity turn out to be negative and not statistically significant. Using industry-level price, the coefficients of unit cost are positive and statistically significant, and the coefficients of the scale are negative.

Panel E reports the results for markups based on the quantity elasticity of intermediate goods. The basic features of the results are the same as in panel D for markups based on the revenue elasticity of intermediate goods. In the OLS estimates, the coefficients of industry-level price and unit cost are inconsistent with the model prediction. In GMM, the coefficients of product- and industry-level prices are negative or close to zero.

Overall, only the results for the cost approach for markups appear to be robust and consistent with the theoretical predictions.

6 Conclusion

Researchers have documented that the evolution of product markups has important implications for macroeconomic dynamics, including inequality, profitability of corporations, and net entry of firms. However, thus far, the trends and distributions of markups have been very different, depending on how the markups are computed. This paper uses plant-product matched data from Japan and theoretically and empirically compares two alternative measures of product markups. One measure is De Loecker and Warzynski's (2012) state-of-the-art approach that estimates markups from the output elasticities of an input divided by that input's revenue share. An alternative measure we propose in this paper derives markups from the revenue divided by the total cost. The markups derived from the latter approach are consistent with theoretical predictions: The markups increase as their market power increases and as their marginal costs decline. Future research should improve our empirical measures of markups and apply these measures to examine what influences markup dynamics and its implications for macroeconomic dynamics in Japan.

Appendix

Production Function Estimations

In this paper, we follow the approach proposed by Ackerberg et al (2015) and estimate the Cobb-Douglas production function. Their approach examines firm-level dynamics of productivity innovations, which is based on the works by Olley and Pakes (1996) and Levinsohn and Petrin (2003).

The CRS Cobb-Douglas production function, $F\left[\ln(L_{it}), \ln(K_{it}), \ln(M_{it})\right]$, is estimated in two stages. In the first stage, we use the timing assumption that plants need more time to optimally hire labor and install capital than purchase intermediate inputs. Because of this timing assumption, a plant's demand for intermediate inputs depends on its productivity and the predetermined employment and the current stock of capital:

$$\ln(M_{it}) = h_t\left[\ln(A_{it}), \ln(L_{it}), \ln(K_{it})\right].$$

Following Ackerberg et al (2015), we assume that the above equation can be inverted:

$$\ln(A_{it}) = h^{-1}\left[\ln(L_{it}), \ln(K_{it}), \ln(M_{it})\right].$$

We then approximate $\ln(Q_{it})$ with the second-order polynomial function of the four variables in the first stage:

$$\begin{aligned}\ln(Q_{it}) &= h^{-1}\left[\ln(L_{it}), \ln(K_{it}), \ln(M_{it})\right] + \ln F(L_{it}, K_{it}, M_{it}) \\ &\approx \Phi\left[\ln(L_{it}), \ln(K_{it}), \ln(M_{it})\right] + \epsilon_{it}. \qquad (13)\end{aligned}$$

After the first stage equation is estimated, we obtain the fitted value of equation (13), $\hat{\Phi}$, and compute the corresponding value of productivity for any combination of parameters. When we estimate the CRS Cobb-Douglas production function, we need to identify two parameters: output elasticities of labor and capital.

This enables us to express the log of productivity $\ln(\bar{A}_{it})$ as the fitted log output from equation (14) minus the logged contribution of all three inputs in $\hat{F}[\ln(L_{it}), \ln(K_{it}), \ln(M_{it})]$:

$$\ln(\bar{A}_{it}) = \hat{\Phi}_t - \hat{F}[\ln(L_{it}), \ln(K_{it}), \ln(M_{it})]. \tag{14}$$

Our GMM procedure assumes that plant-level innovations to productivity, ζ_{it}, do not correlate with the predetermined choices of inputs. To recover ζ_{it}, productivity for any set of parameters, $\bar{A}_{it}$, follows a non-parametric first-order Markov process, and then we can approximate the productivity process with the third order polynomial:

$$\ln(\bar{A}_{it}) = \gamma_0 + \gamma_1 \ln(\bar{A}_{i,t-1}) + \gamma_2 \left[\ln(\bar{A}_{i,t-1})\right]^2 + \gamma_3 \left[\ln(\bar{A}_{i,t-1})\right]^3 + \zeta_{it}.$$

From this third order polynomial, the innovation to productivity, ζ_{it}, can be estimated for a given set of the parameters. Since the productivity term, $\ln(\bar{A}_{it})$, can be correlated with the current choices of flexible inputs, $\ln(L_{it})$ and $\ln(M_{it})$, but it is not correlated with the predetermined variable, $\ln(K_{it})$, the innovation to productivity, ζ_{it}, will not be correlated with $\ln(K_{it})$, $\ln(L_{i,t-1})$, and $\ln(M_{i,t-1})$. Thus, we create the moment condition and search for the optimal combination of the parameters by minimizing the sum of the moments using the weighting procedure proposed by Hansen (1982) for plausible combinations of parameters.

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Figures and Tables

Figure 1. Histogram of Markups based on Cost Approach

Panel A (1988)

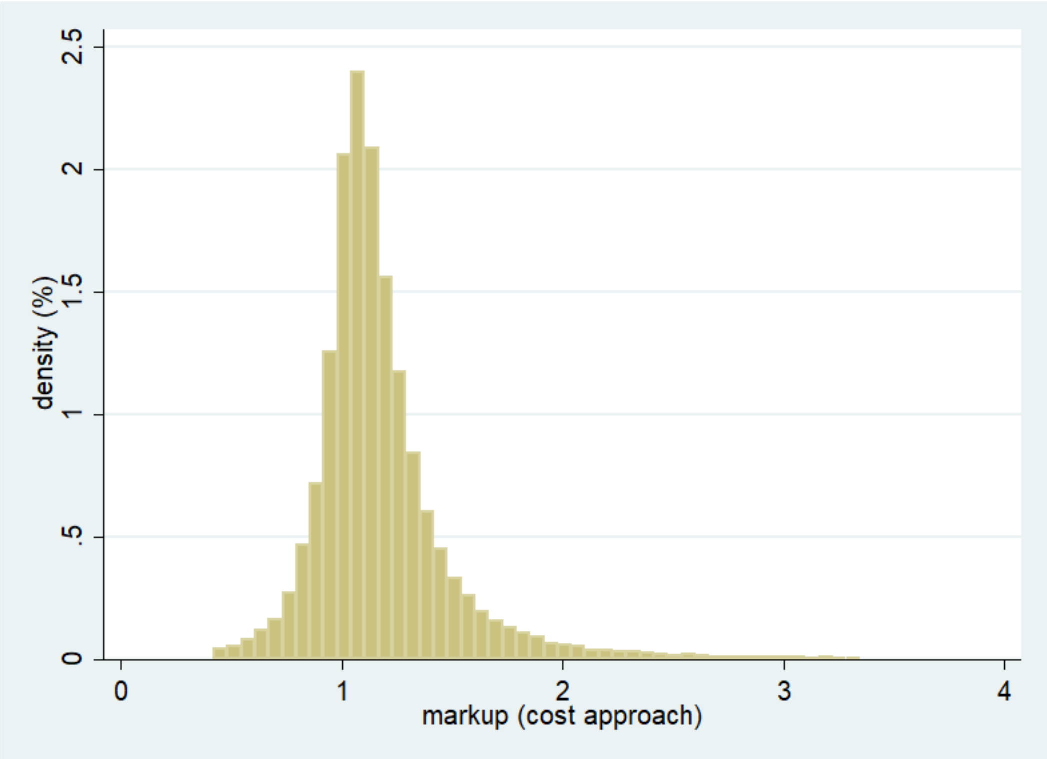

Figure 1. (cont.) Panel B (1998)

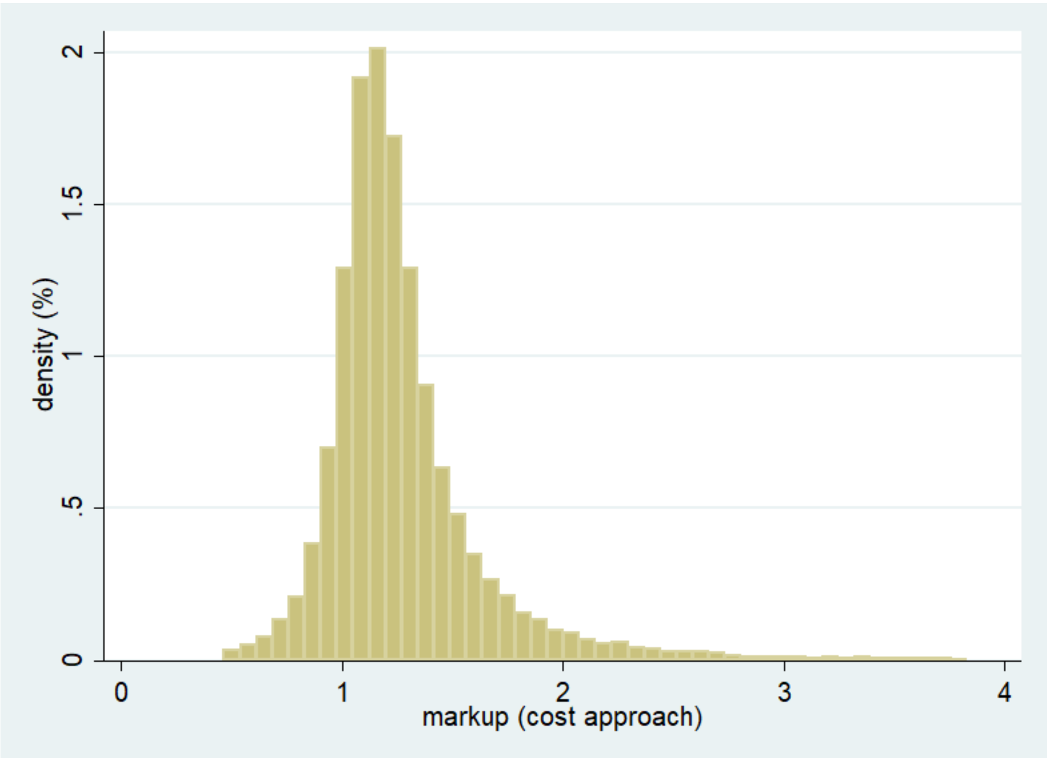

Figure 1. (cont.) Panel C (2008)

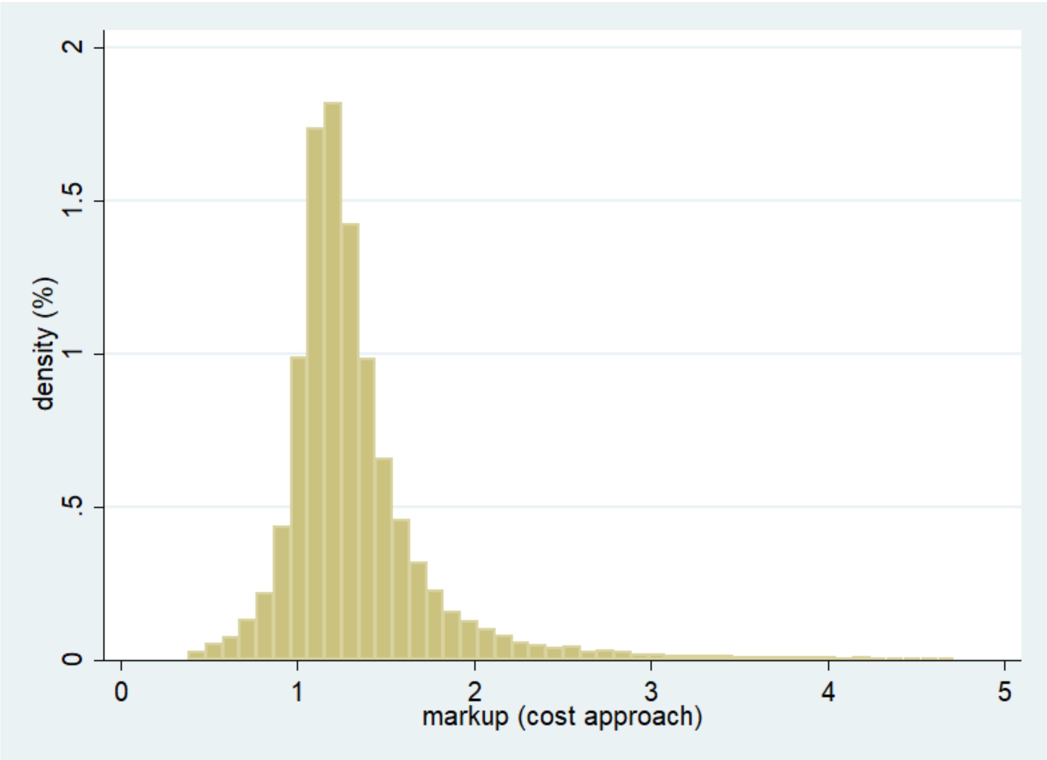

Figure 2. Histogram of Markups based on Production Function Approach
Panel A (1998). Labor, Revenue-based

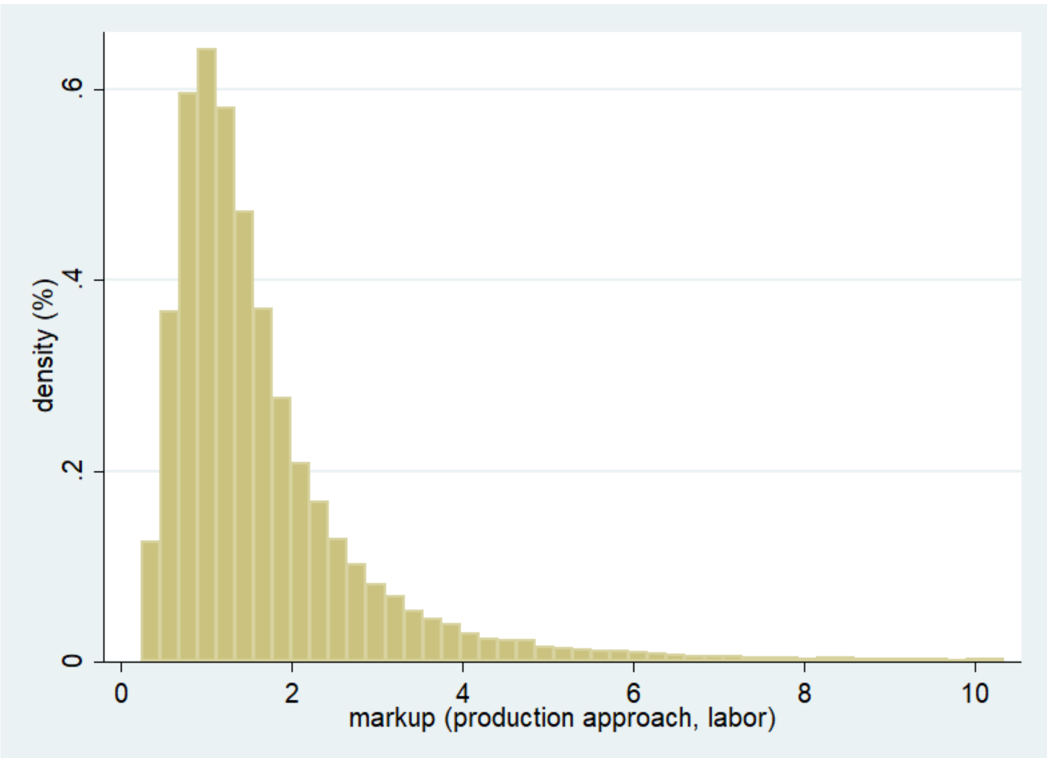

Figure 2. (cont.) Panel B (1998). Labor, Quantity-based

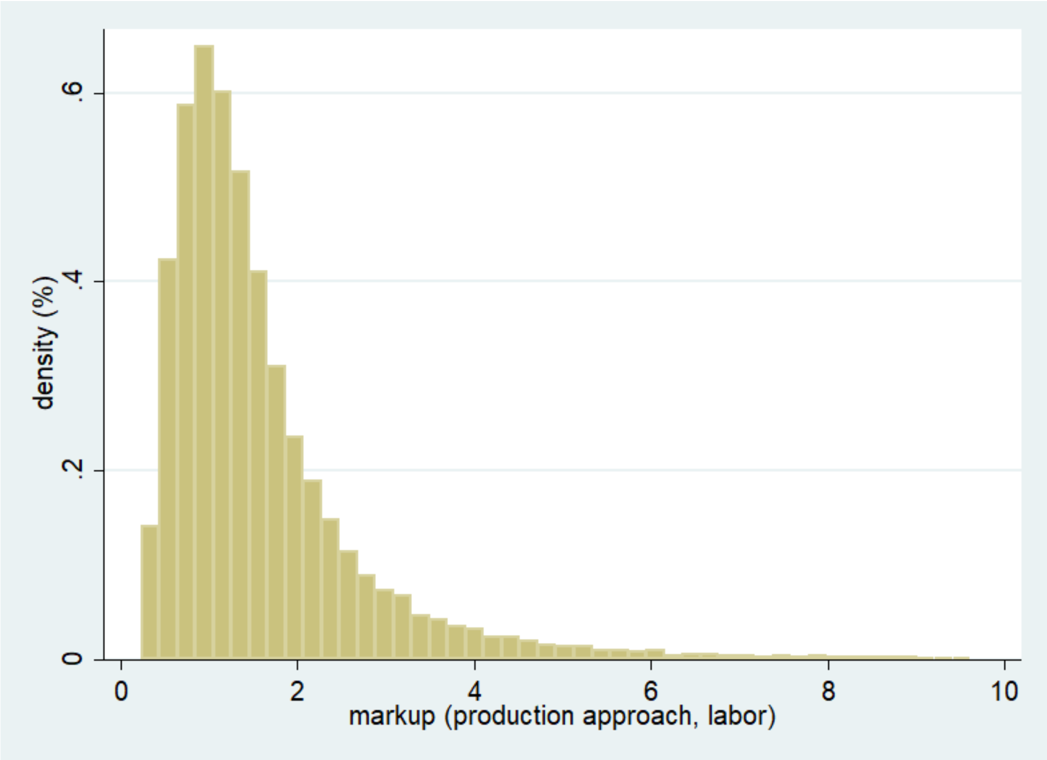

Figure 2. (cont.) Panel C (1998). Material, Revenue-based

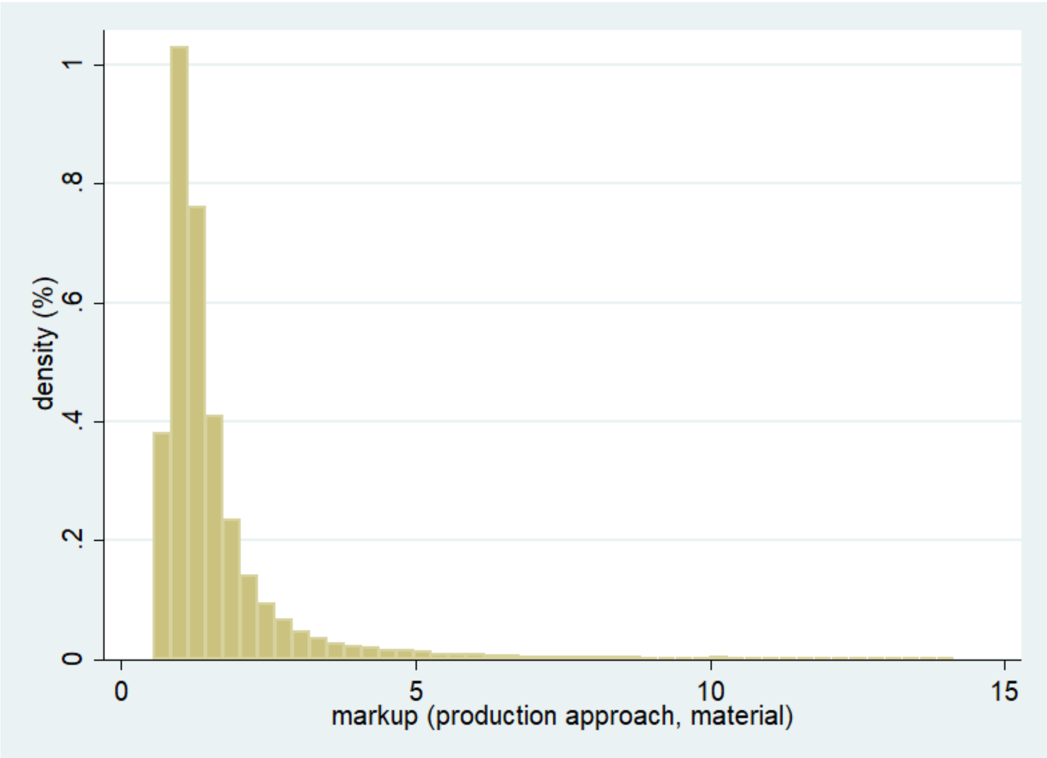

Figure 2. (cont.) Panel D (1998). Material, Quantity-based

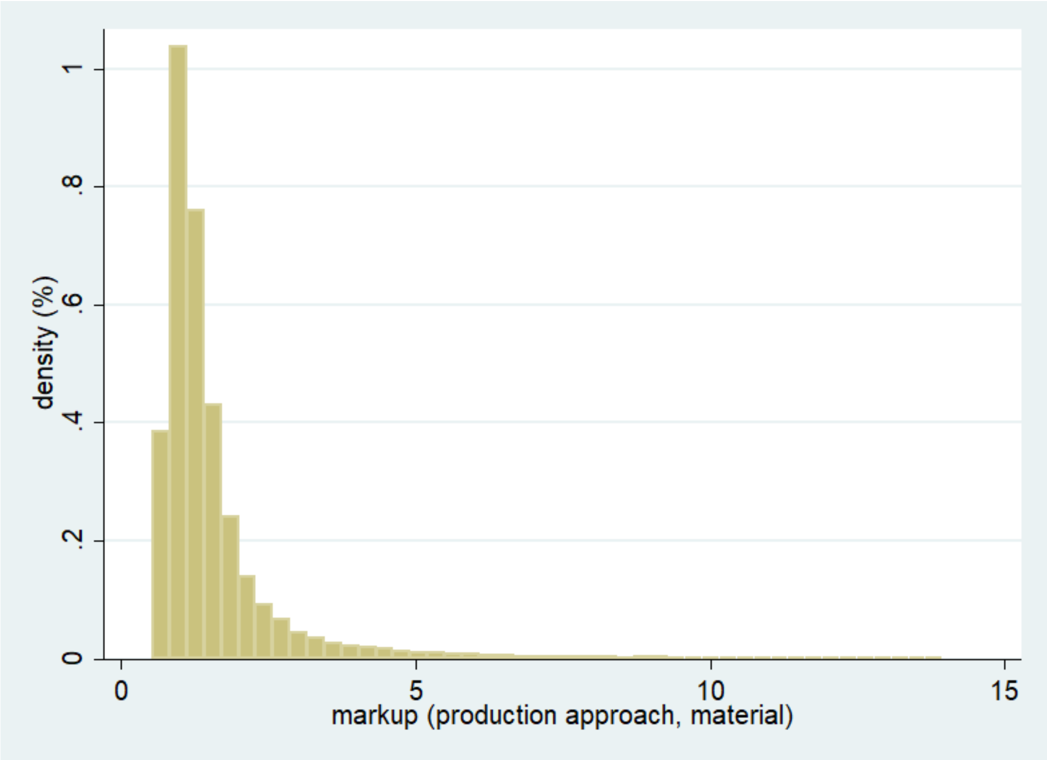

Figure 3. Time-trend of markups

Panel A. Cost approach

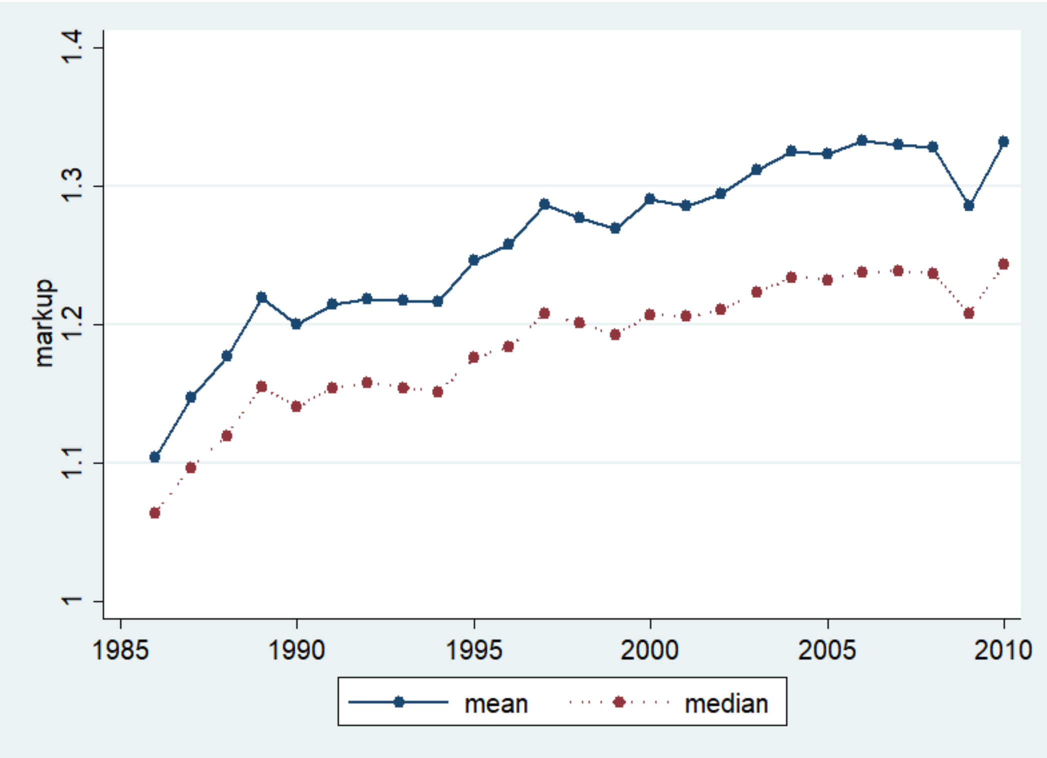

Figure 3. (cont.) Panel B. Production Function Approach (Labor, Quantity-based)

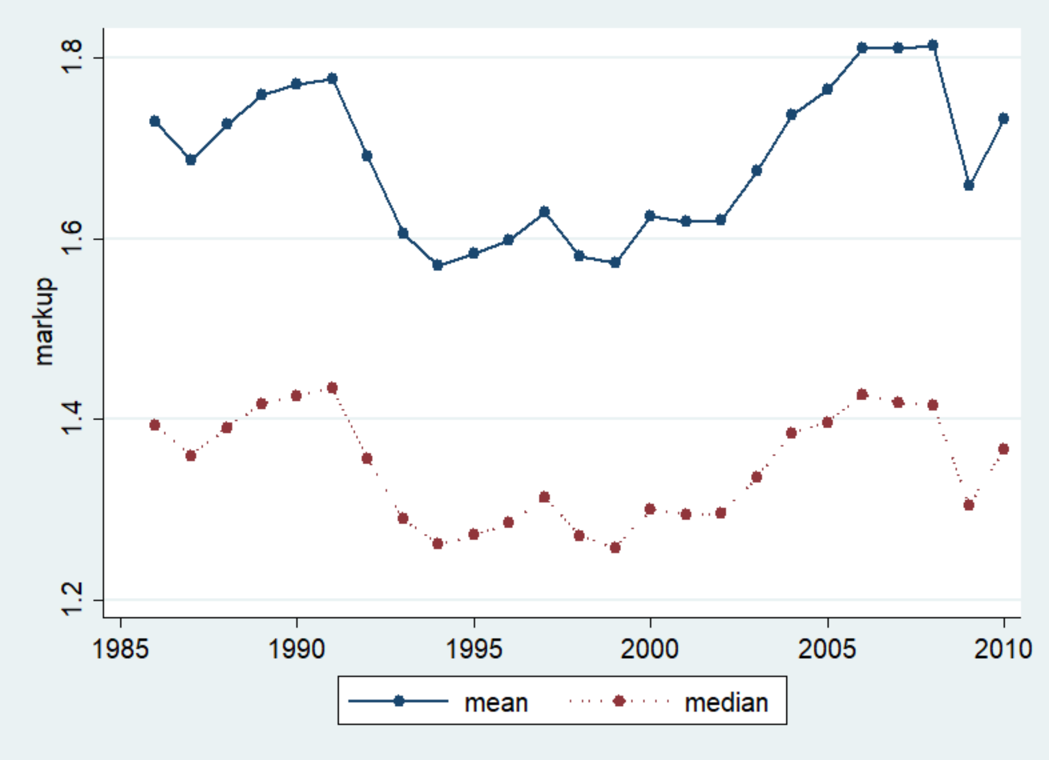

Figure 3. (cont.) Panel C. Production Function Approach (Material, Quantity-based)

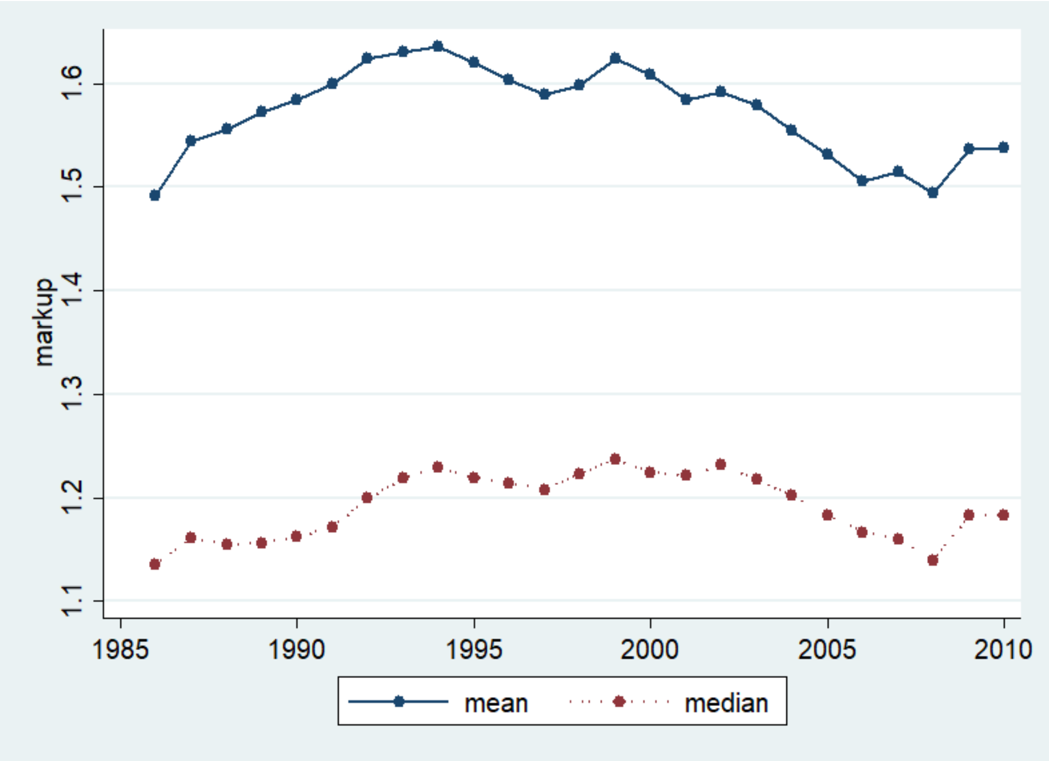

Table 1. Summary statistics

	obs		mean		total	
	unit	(1988=1)	unit	(1988=1)	unit	(1988=1)
1988						
sales (millions Yen)	55,769	1	3,989	1	222,451,108	1
value added (millions Yen)	55,769	1	1,629	1	90,844,020	1
employment (headcounts)	55,769	1	124	1	6,918,674	1
capital stock (millions Yen)	55,594	1	2,406	1	133,757,496	1
area (square meters)	55,758	1	237	1	13,229,466	1
1998						
sales (millions Yen)	51,735	0.93	4,881	1.22	252,530,331	1.14
value added (millions Yen)	51,735	0.93	2,049	1.26	106,009,412	1.17
employment (headcounts)	51,735	0.93	124	1.00	6,404,855	0.93
capital stock (millions Yen)	47,858	0.86	2,909	1.21	139,211,648	1.04
area (square meters)	51,735	0.93	158	0.67	8,198,994	0.62
2008						
sales (millions Yen)	44,198	0.79	6,291	1.58	278,032,513	1.25
value added (millions Yen)	44,198	0.79	2,243	1.38	99,132,313	1.09
employment (headcounts)	44,198	0.79	134	1.08	5,920,985	0.86
capital stock (millions Yen)	37,309	0.67	2,782	1.16	103,790,429	0.78
area (square meters)	44,198	0.79	174	0.73	7,695,698	0.58

Table 2. Cost shares

	1988			1998			2008		
	obs	mean	sd	obs	mean	sd	obs	mean	sd
cost shares									
employment	55,594	0.279	0.180	47,858	0.309	0.179	37,309	0.287	0.178
capital	55,594	0.137	0.112	47,858	0.089	0.078	37,309	0.053	0.057
intermediate inputs									
materials	55,594	0.450	0.243	47,858	0.464	0.238	37,309	0.521	0.238
fuel	55,594	0.010	0.017	47,858	0.009	0.018	37,309	0.017	0.036
electricity	55,594	0.019	0.024	47,858	0.021	0.025	37,309	0.024	0.029
outsourcing	55,594	0.106	0.136	47,858	0.108	0.141	37,309	0.098	0.138
labor share in value added	55,210	0.527	0.324	51,221	0.538	0.360	43,750	0.514	0.508

Table 3. Markup summary statistics

	1988			1998			2008		
	obs	mean	sd	obs	mean	std.dev	obs	mean	std.dev
Cost approach	55,091	1.177	0.310	47,413	1.276	0.365	36,970	1.328	0.431
Production approach									
Revenue-base									
Labor	55,005	1.825	1.338	47,352	1.679	1.235	36,914	1.913	1.550
Material	55,005	1.578	1.359	47,352	1.624	1.313	36,914	1.533	1.335
Quantity-base									
Labor	50,145	1.726	1.258	42,988	1.581	1.134	33,705	1.814	1.418
Material	50,145	1.557	1.348	42,988	1.599	1.292	33,705	1.495	1.285

Table 4. OLS regressions across markup measures

	Cost app	Revenue, Labor	Revenue, Material	Quantity, Labor	Quantity, Material
Cost approach					
Constant		-0.011 (0.001)	-0.004 (0.001)	-0.011 (0.001)	-0.004 (0.001)
ln(markup)		0.777 (0.013)	1.022 (0.009)	0.777 (0.014)	1.021 (0.009)
R-squiared		0.309	0.537	0.309	0.531
Revenue-base, Labor					
Constant	0.009 (0.001)		0.003 (0.001)	0.000 (0.001)	0.003 (0.001)
ln(markup)	0.398 (0.012)		0.057 (0.015)	0.967 (0.005)	0.049 (0.017)
R-squiared	0.309		0.003	0.941	0.003
Revenue-base, Material					
Constant	0.005 (0.000)	-0.006 (0.001)		-0.006 (0.001)	
ln(markup)	0.525 (0.026)	0.058 (0.017)		0.057 (0.018)	
R-squiared	0.537	0.003		0.003	
Quantity-base, Labor					
Constant	0.009 (0.001)	0.000 (0.001)	0.003 (0.001)		0.003 (0.001)
ln(markup)	0.397 (0.012)	0.973 (0.004)	0.055 (0.016)		0.064 (0.015)
R-squiared	0.309	0.941	0.003		0.004
Quantity-base, Material					
Constant	0.005 (0.000)	-0.006 (0.001)	0.000 (0.001)	-0.006 (0.001)	0.000 (0.001)
ln(markup)	0.521 (0.028)	0.050 (0.019)	0.993 (0.002)	0.065 (0.018)	0.999 (0.001)
R-squiared	0.531	0.003	0.992	0.004	0.992

Table 5. Price and market share

Devepndent variable = D. log price				
	(1)	(2)	(3)	(4)
	OLS	OLS	OLS	OLS
	Market share I		Market share II	
	Full sample	Single product	Full sample	Single product
D.Market share	0.466	0.392	0.339	0.300
	(0.168)	(0.125)	(0.129)	(0.115)
obs	291,223	72,958	291,223	72,958
R-squared	0.000	0.001	0.000	0.000

Table 6. Price elasticity of demand

Devepndent variable = D. log price						
	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	OLS	GMM	GMM	GMM	GMM
	Product-level price		Product-level price		Industry price deflator	
D.log quantity	-0.381	-0.700	-0.071	-0.186	0.118	0.052
	(0.022)	(0.028)	(0.020)	(0.022)	(0.002)	(0.002)
D.log unit cost				0.494		0.253
				(0.028)		(0.006)
obs	291,223	72,958	65,576	62,232	487,995	458,588
R-squared	0.221	0.602	-	-	-	-
# of IV	-	-	552	553	551	552

Table 7. Markup determinants

A. Cost approach

	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	OLS	OLS	OLS	OLS	OLS
	Product-level price			Industry price deflator		
log price	0.030	0.278	0.339	0.108	0.363	0.541
	(0.005)	(0.024)	(0.030)	(0.026)	(0.021)	(0.020)
log cost	-0.184	-0.343	-0.366	-0.261	-0.228	-0.275
	(0.054)	(0.044)	(0.040)	(0.030)	(0.040)	(0.043)
log scale		0.288	0.356		0.396	0.541
		(0.023)	(0.029)		(0.010)	(0.008)
log tfp		0.000	0.029		0.000	0.038
			(0.001)			(0.000)
obs	68,716	68,716	67,724	505,080	505,080	490,049
R-squared	0.007	0.214	0.332	0.003	0.296	0.481

A. Cost approach (cont.)

	(7)	(8)	(9)	(10)	(11)	(12)
	GMM	GMM	GMM	GMM	GMM	GMM
	Product-level price			Industry price deflator		
lagged markup	0.264	0.251	0.205	0.319	0.313	0.262
	(0.022)	(0.020)	(0.019)	(0.008)	(0.007)	(0.007)
log price	0.000	0.151	0.238	0.086	0.212	0.379
	(0.014)	(0.015)	(0.017)	(0.010)	(0.009)	(0.009)
log cost	-0.117	-0.311	-0.318	-0.195	-0.327	-0.426
	(0.021)	(0.021)	(0.022)	(0.014)	(0.011)	(0.011)
log scale		0.151	0.249		0.125	0.230
		(0.010)	(0.013)		(0.004)	(0.005)
log tfp			0.024			0.026
			(0.001)			(0.005)
obs	63,092	63,092	62,512	458,588	458,588	449,016
# of iv	553	829	830	552	828	829

B. Production approach (Revenue-base, Labor)

	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) OLS	(6) OLS
	Product-level price			Industry price deflator		
log price	0.042	0.432	0.447	0.061	0.468	0.501
	(0.007)	(0.033)	(0.036)	(0.033)	(0.053)	(0.056)
log cost	0.672	0.431	0.425	0.431	0.491	0.520
	(0.089)	(0.046)	(0.047)	(0.071)	(0.054)	(0.058)
log scale		0.450	0.467		0.643	0.703
		(0.033)	(0.036)		(0.010)	(0.006)
log tfp		0.000	0.004		0.000	0.010
			(0.001)			(0.000)
obs	67,700	67,700	66,763	498,215	498,215	483,695
R-squared	0.025	0.305	0.310	0.006	0.433	0.461

B. Production approach (Revenue-base, Labor) (cont.)

	(7) GMM	(8) GMM	(9) GMM	(10) GMM	(11) GMM	(12) GMM
	Product-level price			Industry price deflator		
lagged markup	0.481	0.359	0.349	0.518	0.423	0.418
	(0.019)	(0.018)	(0.016)	(0.007)	(.007)	(0.007)
log price	0.004	0.199	0.229	0.042	0.209	0.242
	(0.022)	(0.025)	(0.023)	(0.014)	(0.013)	(0.014)
log cost	0.556	0.324	0.311	0.354	0.076	0.056
	(0.034)	(0.031)	(0.030)	(0.019)	(0.015)	(0.015)
log scale		0.294	0.312		0.216	0.237
		(0.017)	(0.017)		(0.007)	(0.007)
log tfp			0.011			0.011
			(0.003)			(0.001)
obs	62,020	62,020	61,471	451,450	451,450	442,177
# of iv	553	829	1,100	552	828	1,100

C. Production approach (Quantity-base, Labor)

	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	OLS	OLS	OLS	OLS	OLS
	Product-level price			Industry price deflator		
log price	0.040	0.431	0.440	-0.012	0.379	0.241
	(0.007)	(0.034)	(0.037)	(0.044)	(0.059)	(0.083)
log cost	0.672	0.431	0.439	0.490	0.526	0.546
	(0.089)	(0.046)	(0.049)	(0.077)	(0.057)	(0.071)
log scale		0.452	0.465		0.641	0.732
		(0.033)	(0.036)		(0.010)	(0.015)
log tfp		0.000	-0.003		0.000	0.005
			(0.001)			(0.000)
obs	67,918	67,918	66,982	438,460	438,460	66,982
R-squared	0.025	0.309	0.312	0.250	0.439	0.480

C. Production approach (Quantity-base, Labor) (cont.)

	(7)	(8)	(9)	(10)	(11)	(12)
	GMM	GMM	GMM	GMM	GMM	GMM
	Product-level price			Industry price deflator		
lagged markup	0.473	0.359	0.359	0.571	0.501	0.432
	(0.019)	(.017)	(0.017)	(.005)	(0.005)	(0.009)
log price	0.004	0.204	0.221	0.029	0.234	0.288
	(0.022)	(0.025)	(0.027)	(0.010)	(0.009)	(0.021)
log cost	0.555	0.320	0.319	0.273	-0.057	0.102
	(0.034)	(0.031)	(0.032)	(0.014)	(0.012)	(0.022)
log scale		0.295	0.289		0.206	0.250
		(0.017)	(0.018)		(0.004)	(0.009)
log tfp			-0.007			0.001
			(0.001)			(0.000)
obs	62,248	62,248	61,702	874,677	874,677	250,282
# of iv	553	829	830	552	828	829

D. Production approach (Revenue-base, Material)

	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	OLS	OLS	OLS	OLS	OLS
	Product-level price			Industry price deflator		
log price	0.017	0.110	0.131	-0.088	-0.048	0.040
	(0.005)	(0.022)	(0.023)	(.038)	(0.036)	(0.038)
log cost	-0.066	-0.124	-0.180	0.122	0.127	0.060
	(0.059)	(0.073)	(0.072)	(0.081)	(0.086)	(0.081)
log scale		0.107	0.131		0.063	0.104
		(0.021)	(0.022)		(0.017)	(0.016)
log tfp		0.000	0.047		0.000	0.059
			(0.003)			(0.006)
obs	67,929	67,929	66,976	496,503	496,503	482,502
R-squared	0.001	0.021	0.112	0.000	0.004	0.107

D. Production approach (Revenue-base, Material) (cont.)

	(7)	(8)	(9)	(10)	(11)	(12)
	GMM	GMM	GMM	GMM	GMM	GMM
	Product-level price			Industry price deflator		
lagged markup	0.323	0.323	0.297	0.416	0.447	0.402
	(0.017)	(0.017)	(0.016)	(0.008)	(0.007)	(0.007)
log price	0.034	-0.011	0.011	-0.143	-0.168	-0.020
	(0.016)	(0.019)	(0.016)	(0.014)	(0.013)	(0.013)
log cost	-0.175	-0.144	-0.168	0.123	0.150	0.027
	(0.023)	(0.026)	(0.024)	(0.019)	(0.016)	(0.015)
log scale		-0.052	-0.028		-0.112	-0.032
		(0.013)	(0.011)		(0.006)	(0.006)
log tfp			0.026			0.056
			(0.003)			(0.000)
obs	62,158	62,158	61,596	449,445	449,445	440,622
# of iv	553	829	1,100	552	828	829

E. Production approach (Quantity-base, Material)

	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	OLS	OLS	OLS	OLS	OLS
	Product-level price			Industry price deflator		
log price	0.017	0.111	0.157	-0.121	-0.087	-0.313
	(0.005)	(0.022)	(0.024)	(0.040)	(0.037)	(0.065)
log cost	-0.071	-0.129	-0.194	0.077	0.080	0.040
	(0.058)	(0.072)	(0.071)	(0.081)	(0.085)	(0.070)
log scale		0.109	0.116		0.056	0.225
		(.021)	(0.023)		(0.017)	(0.027)
log tfp		0.000	0.044		0.000	0.042
			(0.003)			(0.003)
obs	68,135	68,135	67,177	436,796	436,796	67,177
R-squared	0.001	0.022	0.105	0.000	0.004	0.126

E. Production approach (Quantity-base, Material) (cont.)

	(7)	(8)	(9)	(10)	(11)	(12)
	GMM	GMM	GMM	GMM	GMM	GMM
	Product-level price			Industry price deflator		
lagged markup	0.319	0.321	0.297	0.424	0.476	0.372
	(0.017)	(0.016)	(0.016)	(0.006)	(0.005)	(.009)
log price	0.026	-0.013	0.061	-0.147	-0.172	-0.167
	(0.015)	(0.019)	(.019)	(0.010)	(0.009)	(0.017)
log cost	-0.176	-0.147	-0.231	0.088	0.148	0.034
	(0.024)	(0.026)	(0.026)	(0.013)	(0.011)	(0.018)
log scale		-0.052	0.003		-0.104	-0.072
		(.013)	(.012)		(0.003)	(.006)
log tfp			0.039			0.022
			(0.001)			(0.000)
obs	62,373	62,373	61,808	872,529	872,529	250,572
# of iv	553	829	830	552	828	829