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Measuring Markups: Revisiting the Cost Accounting Approach

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Abstract

Among the ways to measure market power, special attention has always been given to the wedge between marginal cost and price: the markup. This paper investigates the validity of firm-level markup estimation techniques, focusing on the cost accounting (CA) approach—a straightforward, transparent, and data-thrifty alternative that, despite its origins in early industrial organization literature, has seen little modern application. While the production function (PF) approach has quickly become the workhorse method in macroeconomic applications, several high-profile criticisms have brought its validity into question. My findings show that the rise in U.S. markups is robust to CA, suggesting that the trend is not driven by PF's biases. In fact, variation in PF estimates is driven almost entirely by variation in its "accounting component", rather than its "production function component", which contains all well-known biases. For validation, I develop a novel test based on Dorfman-Steiner's (1954) advertising equation, concluding that the cost accounting approach has a higher signal-to-noise ratio, while both measures retain some signal of underlying markups. The data-thrifty nature of CA makes it feasible for a broader range of applications. To highlight this, I conclude with several examples that play into CA's strengths. Collectively, these results suggest that practitioners can confidently implement CA, particularly in contexts where alternative methods are infeasible.

Keywords: Markups, Market Power, Cost Accounting, Advertising

JEL Codes: D2, D4, L1, L2, M3, M4

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1 Introduction

Competition–and its opposite, market power–have been central to economics since the field's inception. Among the ways to measure market power, special attention has always been given to the wedge between marginal cost and price, the markup. In perfect competition, firms compete directly and prices are driven down to marginal cost, leading to a zero markup (or a markup *ratio* of price over marginal cost equal to one). When facing less ferocious competition firms can raise profits by setting prices above costs–a positive markup. High quality markup data, representative at a macro-economic level are extremely valuable both as a means to answer important economic questions directly, and to test and calibrate many key models in economics.

This paper investigates the validity of firm-level markup estimation techniques. Of particular interest is the production function (PF) approach, which has been used to document a rise in aggregate markups in the United States. While PF has quickly become the workhorse method in macroeconomic applications, several high-profile criticisms have brought its validity into question. Despite its origins in early industrial organization literature, the cost accounting (CA) approach–a straightforward, transparent, and data-thrifty alternative– has received comparatively minimal attention. To my knowledge, this is the first paper to directly compare the performance of the approaches of markup estimation, and the first systematic evaluation of CA of any sort.

My findings show that the rise in U.S. markups is robust to CA, suggesting that the trend is not driven by PF's biases. The production function estimates can be decomposed into an "accounting component" constructed directly from accounting data as the ratio of revenue to expenditures in one variable input, and a "production function component" an estimated output elasticity which all well-known biases of PF. I show that variation in PF estimates are driven almost entirely from the accounting component, while the literature has been primarily concerned with noise and bias in the "production function component" it simply does not contain any signal. Behind the complexity of PF, near identical results can be attained with use of a accounting esq measure that lacks micro foundation. CA on the other hand can be micro founded explicitly, and can be implemented directly from accounting data without the need to estimate production function parameters.

For validation, I develop a novel test based on the Dorfman and Steiner [1954] advertising equation, and find that both measures contain some signal of underlying markups, but CA outperforms PF in terms of its signal-to-noise ratio. CA dramatically outperforms PF in the sector and time cross sections, the dimensions in which the production function componet of PF varies. Collectively these results suggest both approaches produce markups that have a substantial signal of true underlying markups, though they have different errors (and different error variances). I argue that on balance the evidence should motivate more widespread use of the cost accounting approach. And, indeed, because it is less data-intensive than the other two methods, there are contexts in which only the cost accounting method can be used. I focus on three applications that play into the strengths of CA: a case study of the markups of tech giants, an investigation of markups over the firm life cycle, and an investigation of the cyclically of markups with respect to aggregate supply and demand shocks.

1.1 Background

Markups matter for central considerations of economics. High quality markup data representative of the macro-economy is invaluable both to directly answer important questions, and to test and calibrate many models in economics.

In static models, markups drive a wedge between marginal cost of production and marginal benefit of consumption, mechanically leading to inefficiency. Wedges of this sort erode the efficiency of general equilibrium in the Arrow-Debreu sense[1], moving the economy away from the optimality results of the first and second theorem of welfare economics.[2] As such aggregate movements in and of them selves are an important measure of the static efficiency of the economy, and policy makers and economists alike ought to be aware of their level and trend.

In the long run, the relation between markups and efficiency is more complex. Pursuit of future profits can lead to innovation, so imperfect competition is integral to endogenous technological growth.[3] Such models are founded on increasing returns to scale and monopolistic competition, with revenue generated from markups driving research and human capital investment, leading to knowledge spillovers and (under the right conditions) improvements in long-run dynamic efficiency. Markups are therefore at the core of the conflict between static and dynamic efficiency. Thus, discussions of this trade-off depend on a robust understanding of markups. Known since the dawn of endogenous growth theory, the centrality of markups features prominently in recent growth theory.[4]

The link between returns to scale and markups is not merely an artifact of endogenous growth models. Returns to scale and markups are determined simultaneously, and under free entry with no sunk costs, symmetric firms will equate their markup ratios to their returns to scale in equilibrium.[5] With heterogeneous

[1] Arrow and Debreu [1954]

[2] Arrow [1951]

[3] For canonical examples see Romer [1990] and Aghion and Howitt [1992]

[4] In the schumpeterian framework: Aghion et al. [2019], De Ridder [2024]. In the Endogenous technological change framework: Boucekkine et al. [2017] , Latzer et al. [2019], Etro [2020]

[5] See Zhelobodko et al. [2012] for a fairly general example of this phenomenon. Intuition with respect to the generality can be seen by noting the markup ratio is given by $\mu \equiv \frac{P}{MC}$, while degree of returns to scale are given by $\gamma \equiv \frac{\partial log Y(X)}{\partial log X} = \frac{Y' X}{Y} = \frac{P_X X}{Y} \frac{Y'}{P_X} = \frac{AVC}{MC}$. Then with free entry profits equal 0, ie $AVC = P$, thus $\gamma = \frac{AVC}{MC} = \frac{P}{MC} = \mu$. Where Y denotes output, X

firms à la Melitz an equivalent relation holds with the "marginal" firm, an important mechanism in canonical trade models. Sunk entry costs or entry restrictions of any type push the markup ratio above the degree of returns to scale. In absence of increasing returns to scale by one of these means firms would continue to enter until markups are fully eroded, and one is left with the perfect competition benchmark of a zero markup (and a markup ratio of one).

In the short run, markups and imperfect competition also play a pivotal role in sticky price models. Indeed, sticky prices require price-setting firms, and only firms with market power are price setters. Additionally, the strategic interactions that can prevent firms from adjusting prices directly to the long run equilibrium, slowing down *aggregate* price adjustment depends too on market power.[6]

Perhaps the most important prediction of sticky price models is that of counter cyclical markups. This phenomena is both one of the key insight into the mechanism that drives business cycles, and one of the most salient falsifiable predictions of the model. As such, empirical investigations have a history nearly as long as that of sticky price models[7]. Despite the long history, there is little consensus of the truth of the matter, with examples of evidence supporting counter cyclical markups[8] as well evidence to the contrary.[9] Much of this disagreement seems to come down to how movements of markups are inferred. Historically, the need to infer rather than observe firm level markups represents the most sever challenge to this literature.[10] Markups variation is often inferred from proxies[11], sector aggregates[12], or theoretically correlated variables. The later being possibly the most relevant to this discussion, with Rotemberg and Woodford [1999] showing that joint movements in ratio of sales to inventories and the discounted growth rate of output prices, and Hall [2012] leveraging the link between markups and advertising.

The connection between markups and advertising is a fundamental one, as has been understood by economists as early as Chamberlain [1933][13] who used the existence of advertising as the key piece of evidence in favor of the need to explicitly model market power. The key to this connection comes down to the effect of advertising; what is common to all theories of advertising is that advertising allows firms to increase sales *holding prices constant*. Then, since firms must still produce additional goods that they need to sell, the return to an additional sale generated by increases advertising is given by difference of price and marginal

inputs, P_X the price of inputs, P the price of output, AVC average variable cost, and MC marginal cost.

[6]See Kimball [1995] for a further discussion of the importance of imperfect competition and returns to scale in this class of models. For details on *real rigidities*, the strategic interactions that prevent prices from jumping directly to their long run equilibrium see Ball and Romer [1990].

[7]Gordon [1981] is earliest example of a sticky price macroeconomic model that this author is aware of is, while Domowitz et al. [1986], published 5 years later is the earliest example of an investigation of the cyclicality of markups that this author is aware of.

[8]Ex: Galeotti and Schiantarelli [1998], Rotemberg and Woodford [1999], and Bils and Kahn [2000].

[9]Ex: Domowitz et al. [1986], Hall [2012] and Nekarada and Ramey [2020].

[10]See Nekarada and Ramey [2020] for a more in depth discussion of the challenge of measuring markups in this context, as well as a more thorough history of though and literature review.

[11]Ex: labor share, as used by Nekarada and Ramey [2020].

[12]Ex: Galeotti and Schiantarelli [1998] and Domowitz et al. [1986]

[13]See Bagwell [2007] for a thorough history of thought regarding the economics of advertising and marketing.

cost: the markup. Chamberlain's observation was then that under perfect competition there is no incentive to advertise. That is, when marginal costs are equal to prices there are no profits to be gained by increasing sales, and if firms are price takers by assumption there is no gain on the price front either. More generally the optimal level of advertising expenditure is proportional to the markup[14], thus one simply cannot think critically about advertising without care for markups and marker power.

Lastly, over the past decade, macro-economists have taken special interest in the evolution of competition at an aggregate level, claiming there has been a "decline of business dynamism": a rise in market concentration, a rise in profit's share, a decline in labor's share of income[15] and preeminently, the potential of a rise in aggregate markups.

1.2 Markup Estimation Techniques

Markups are central to many topics and questions economists care deeply about. Given their importance, Macroeconomics and Researchers in Industrial Organization alike have long traditions of markup measurement.

On the industrial organization front, the rise of structural estimation methods under what has been dubbed the the new empirical industrial organization (NEIO) has embodied researchers with a tool kit to measure markups. A major aspect of the NEIO was the re-centering of focus of the field to intra-industries studies, as pointed out by Bresnahan [1989]. It is unsurprising then that fallowing the NEIO, measuring markup in an industrial organizational context has primary done so within sectors, and at the product level. These goals have motivated the development of the tools of industrial organization, and since in these contexts economists often have much better data on the demand side than they do on the supply side, these tools are designed to leverage that demand side, product level data. A key example begin that of Rosse [1970] where markups are estimated entirely from the demand side, without any supply side data. As such the most powerful tools of markup estimation in the industrial organization tool kit is the "demand estimation" approaches to markup measures, which rose to prominence following the seminal works of Berry et al. [1995] (henceforth BLP) and Nevo [2000]. As the name suggests, the demand estimation or BLP approach as its often called, relies on demand estimation in a discrete choice framework, for this reason it is neither feasible nor reliable at a macro economic level, as it requires consumer side data and the discrete choice assumption that may be unsavory in certain sectors. These limitations have not fully closed the door to macro-esq investigations using demand estimation techniques. Motivated by the discussion of the decline of business dynamism, Döpper et al. [2021] departs from the trend of intra-industry centered questions and uses

[14] See Dorfman and Steiner [1954]. This the result leveraged by Hall [2012].

[15] On the rise of market concentration: Autor et al. [2017a] Autor et al. [2017b]; On the rise of the profit share of GDP Gutiérrez and Philippon [2016]; On the declining labor share: Karabarbounis and Neiman [2013], Elsby et al. [2013], Lawrence [2015]

a demand estimation approach to estimate markups using a plausibly representative sample of consumer products, documenting a substantial rise coinciding with many of the macroeconomic results.

On the macroeconomic front, a seminal paper by Hall [1988] was among the first to provide clear evidence that the perfect competition benchmark may not an accurate snapshot of the US economy at the macro level. Thus far, markups representative at this level has been considered a non trivial endeavor, as markups are generally not observed directly and econometricians lack the macro level data needed to implement the canonical demand estimation techniques of the industrial organization literature. To over come this, modern results on markups at a representative level tend to rely on the "Production function approach" to markup estimation.[16] This agenda, spearheaded by De Loecker et al. [2020] (Henceforth DEU) documents a substantial rise in market power between the 1980s and 2016.

DEU builds off tools of Hall [1988] to circumvent the limitations of the BLP approach by developing what has been dubbed the production function approach. The production function approach of markup estimation begins by relating the markup to the output elasticity of a variable input, which is then estimated following Ackerberg et al. [2015] (henceforth ACF). In recent years the production function approach has faced a high degree of criticism. While issues will be discussed more in depth in subsequent sections, the crux of the major critics related directly to production function estimation. A primary point of contention is analogous to a classic critic of production function estimation owed to Klette and Griliches [1996], that is production function estimation should in principle utilize quantity data, but due to data limitations is typically estimated using output as measured by revenue.[17] Additionally there is the issue of unobserved input utilization[18] which further threatens identification of the production function parameters. As is known to the literature, the direction and magnitude of these biases is unclear, furthermore they cannot be properly controlled or instrumented away with the available data.[19] Ex-ante there is also no reason to believe that the sum of these biases' is constant over time, making it unclear what conclusions can be drawn regarding the trend in markups.

Aside from the line of literature in the NEIO or BLP tradition, and the line of literature following Hall and DEU, there is a third lesser used approach to markup estimation, the cost accounting approach. Despite its lack of use, the cost accounting method has the longest tradition, with use in macro dating back a least to Domowitz et al. [1986], with a much larger tradition in the industrial organization literature as one of the major tools of the Structure-Conduct-Performance paradigm (SCPP)[20]. The cost accounting approach

[16] See Hall [1988], Loecker and Warzynski [2012] , De Loecker and Scott [2016], De Loecker et al. [2020]

[17] See also Bond et al. [2021] and Ridder et al. [2022]

[18] See Basu [1996], Basu and Kimball [1997], and Basu et al. [2006]

[19] In the case of the error induced by using revenue data, Bond et al. [2021] no sufficient instrument could exist, as satisfying the relevance condition implies violating the orthogonality condition.

[20] See Bresnahan [1989] for an overview of the history of thought on this front.

fell out of favor in industrial organization with the NEIO in favor of approaches better suited to the data demands of the field's goals. It is important to note that this transition was motivated almost purely by pragmatic considerations. Though there has been some level of theoretical criticisms, owed largely to its simplicity, this author is not aware of any prior empirical tests of the cost accounting approach of markup estimation[21], or of any systematic comparison relative to alternative methods.

The cost accounting approach effectively operates by assuming constant marginal costs, which implies marginal cost equal to average variable costs, allowing the markup ratio to be estimated as $\mu \equiv \frac{P}{MC} = \frac{Revenue}{Total\ Variable\ Cost}$. While imperfect, the advantages to this approach are apparent; it is highly transparent leaving little question of potential pitfalls and relevant dimensions for robustness tests, and it is simple and data thrifty allowing for implementation in many cases where alternative methods are infeasible.

This paper argues that the lack of attention surrounding the cost accounting approach is unwarranted. This is motivated by several factors; first, given the value of evidence regarding markup and more broadly market power, researchers should pursue all possible angles in pursuit of a robust and clear understanding. Second, the data-thrifty nature of CA means it can be implemented in situations where the others cannot, and in contexts where PF and CA are both feasible, CA seems to perform better. Furthermore, none of the three methods are without faults, and limiting methods can only serve to bias our understanding in the direction of the pitfalls of said methods.

1.3 Organization

The organization of this paper is as follows: Section 2 introduces the main data set and outlines the cost accounting (CA), and production function (PF) approaches to markup estimation. Section 3 compares the predictions of the two approaches. Section 4 discusses the pitfalls and mechanical similarities between the two measures. Section 5 formalizes the connection between advertising and markups and develops a test based on the Dorfman and Steiner [1954] advertising equation. Section 6 considers several applications that leverage the strengths of the cost accounting approach. Finally, section 7 concludes with a brief discussion.

2 Markup Estimation

2.1 Data

There are two considerations with respect to data selection, the first is that of coverage, and the second is that of comparison to the literature. With these in mind, COMPUSTAT Fundamentals Annual is the clear

[21] See Bresnahan [1989] for a discussion of this criticism

choice, offering annual accounting data for all publicly traded firms in the United States since 1950. This data set has been widely used in the macroeconomics, accounting, and finance literatures. Additionally it is the mostly widely used data set in the macroeconomic markup estimation literature.

Although COMPUSTAT is not a direct analog for the universe of firms in the US, it is the closest feasible alternative. It offers coverage across all 2 digits NAICS industry codes, and collectively covering around thirty percent of employment[22] and forty percent of revenue[23] in the United States. Relative to the universe of firms, publicly traded firms are disproportionately older, larger and employ more capital. Since the question of performance of a given measure across sectors is central to the analysis, the coverage of COMPUSTAT makes it the obvious data choice.

COMPUSTAT offers hundreds of lines of firm level accounting data, but implementation of the cost accounting and production function methods will specifically require data on revenue, input costs, and capital stock, and later we will make use of advertisement spending. Total revenue is reported as Net Sales/Turnover (SALE). Generally Accepted Accounting Principles (GAAP) divides total expenses (XOPR) into two broad categories, Cost of Goods Sold (COGS) and Selling, General and Administrative Costs (SGA). It is standard in the literature to take SGA as a measure of total fixed costs, and COGS as a measure of variable costs. The capital stock is taken as the level of reported gross property plants and equipment (PPEGT), as is standard in the literature.

The sample used in the preceding section is limited to all firms that report nonegative values for COGS, XSGA, PPEGT and SALES. Further more, the sample is trimmed by 1% at the top and bottom of the ratio of COGS/SALES, and the ratio of XSGA/SALES. Summary Statistics are provided in appendix C.1.

2.2 Cost Accounting Approach

The primary hurdle to observing markups in economic data, is that of measuring marginal costs. All three methods of markup estimation must face this problem, but each does so in a different manner. The cost accounting process approaches this issue by assuming constant marginal cost, then markups are equal to the ratio of total revenue to total variable cost. Beyond this restriction, the cost accounting approach is general, and not reliant on any additional assumptions regarding the functional form of firm's production functions. Consider an arbitrary production function $Y = Y(X)$, where X is a vector of inputs. Denoting the vector of

[22] Davis et al. [2006]
[23] Asker et al. [2015]

input prices by P^X, cost minimization implies a cost function C given as[24]:

$$C(\bar{Y}) \equiv \min_{X \in \left\{Z | Y(Z) = \bar{Y}\right\}} P^X \cdot X$$

By letting $F_c = C(0)$, without loss of generality we can decompose the cost function as:

$$C(Y) = F_c + V_c(Y)$$

Then variable cost V_c is such that $V_c(0) = 0$, and F_c denotes any and all fixed cost. Average variable cost is given by $AVC = \frac{V(Y)}{Y}$, and marginal cost is given by $MC = \frac{\partial C(Y)}{\partial Y} = \frac{\partial V(Y)}{\partial Y}$. Then if we assume a constant marginal cost $V(Y) = MC \times Q$ we have $MC = AVC$. Under this assumption, marginal costs are observed so long as variable costs are observed.

To match to the data I take total variable costs as $V_c = COGS + PPEGT \times r$, where COGS and PPEGT come directly from the data, and r denotes the user cost of capital. The standard procedure from De Loecker et al. [2020] is followed to attain a measure of the user cost of capital, that is $r_t = I_t - \Pi_t + \triangle$, where I_t denotes the interest rate taken to be federal funds rate, Π_t denotes the inflation rate, taken from CPI, and $\triangle$ is the sum of depreciation and risk premium, taken as 12%. Then the cost accounting markup ratio is given as[25]:

$$\tilde{\mu}_{CA} \equiv \frac{PY}{V} = \frac{SALE}{COGS + PPEGT \times r} \tag{1}$$

2.3 Production Function Approach

The production function approach, inspired by Hall [1988] and pioneered by Loecker and Warzynski [2012], De Loecker and Scott [2016], and DEU infers marginal cost from the firms cost minimization problem for a variable input. The key to this approach is the realization that under cost minimization, the markup is equal to the product of the output elasticity of a given input and the revenue share of that input. This insight is owed to Hall, and allows a markup estimation from a combination of a production estimation component and an accounting component.

Consider a firm that produces a quantity of output Y given a variable input V and a vector of technology

[24]Strictly speaking the existence of a cost function does not requite cost minimization. The existence of any injective mapping from desired output to inputs will suffice, and does not need to be observed by the economist. For example consider a case where when selecting inputs producers misperceive input costs as $P^{\tilde{X}}$ and act inline with some spurious constraint $F(X) = 0$, then the cost function is given as $C(\bar{Y}) = P^X \cdot \left(arg \min_{X \in \{Z'\}} P^{\tilde{X}} \cdot X \right)$, where $Z' = \left\{Z | Y(Z) = \bar{Y}\right\} \cap \{Z | F(Z) = 0\}$

[25]Throughout I will refer to the markup ratio $(\frac{P}{MC})$ as μ, and the markup $(\frac{P-MC}{MC})$ as $\mu - 1$. The lerner index $\left(\frac{P-MC}{P}\right)$ can then be denoted as $1 - \frac{1}{\mu}$.

and all other inputs X^{-V} from the production function:

$$Y = F(V, X^{-V})$$

Then taking all other inputs as given (or at their optimal level), and given a price P^V for the variable input, the optimization sub-problem for the variable input V is summarized by the Lagrangian:

$$\mathcal{L}(V, \lambda) = P^V V - \lambda(F(V, X^{-V}) - Y^*)$$

λ is the key object of interest, it represents the shadow cost of an additional unit of output, ie the marginal cost, which can be seen directly from the envelope theorem. To back out the value of λ, first consider the first order condition for V:

$$\frac{\partial \mathcal{L}}{\partial V} = P^V - \lambda \frac{\partial F(V, X^{-V})}{\partial V} = 0 \tag{2}$$

Then (2) can be rearranged to solve for λ as:

$$\lambda = \frac{\partial V}{\partial F(V, X^{-V})} P^V = \frac{V P^V}{Y} \frac{1}{\theta_V}$$

Where $\theta_V \equiv \frac{\partial F(V, X^{-V})}{\partial V} \frac{V}{Y}$ is the output elasticity with respect to the variable input V. Then, given an output price of P, the markup ratio is given by:

$$\tilde{\mu}_{PF} = \frac{P}{\lambda} = \theta_V \frac{PY}{VP^V} \tag{3}$$

Taking COGS as the variable input, the second term on the right hand side is observed in the data as:

$$\frac{PY}{VP^V} = \frac{SALE}{COGS}$$

I will refer to this term as the "accounting component" of the production function markup. The remaining ingredient is a measure of the output elasticity θ_V, which I refer to as the "production estimation component". As we will see, the later component is the primary point of discussion of the production function approach, both in terms of implementation and of its criticisms. The accounting component, and its influence on the other hand gets much less attention, which will be a primary focus of section 4.

2.3.1 Production Function Estimation

In practice, to attain an estimate $\hat{\theta}_V$ econometricians typically follow an modified version[26] of the ACF two step production function estimation method. I follow the version of this method developed in Loecker and Warzynski [2012] and extended in De Loecker and Scott [2016] and De Loecker et al. [2020] to allow for first and second stage controls.

The first step is to choose a functional form of the production function, and select a level at which the parameters are estimated. Below I will follow the main estimate of DEU and estimate at the two digit NAICS sector level in 5-year rolling windows with a Cobb-Douglas structure.[27] That is, within a given sector, and 5 year rolling pool log output is given by:

$$y_{it} = \theta_{v,s,t} v_{it} + \theta_{k,s,t} k_{it} + \omega_{it} + \epsilon_{it} + g_{it} \tag{4}$$

Where $log(Sales) = y$, $log(COGS) = v$, $log(PPEGT) = k$. Furthermore ω denotes firm level hicks-neutral productivity term, and ϵ denotes a firm specific measurement error. Because inputs are measured in units of cost, rather than raw inputs, there is also the error term g which captures unobserved variation in raw inputs. Following DEU, I assume that the unobserved variation in raw inputs is given as a function of market share z_{it}, and the product of the market share with each input, ie:

$$g_{it} = g(z_{it}, k_{it} \times z_{it}, v_{it} \times z_{it})$$

The first stage in the two stage approach serves to purge the measurement error term ϵ, which can be done by estimating the non-parametric function function:

$$y_{it} = \phi(v_{it}, k_{it}, z_{it}) + \epsilon_{it} \tag{5}$$

The key assumption that allows for the construction of (5) lies in the assumption that the flexible input v is a function of ω in equilibrium, that is:

$$v_{it} = f(\omega_{it}, k_{it}, z_{it})$$

[26]It is worth noting that the microfoundations of ACF relies on a value added production function, while in practice those estimating markups typically assume a gross output production function, see Gandhi et al. [2020] for a discussion of the issue and associated bias.

[27]In addition DEU (2020) includes several alternative specifications, including a translog specification, though none of the produces meaningfully different estimates. It is worth noting that attempts to estimate the parameters more granularly (either with smaller rolling windows, or more narrow sector definitions) leads to poorly behaved estimates. Given that COMPUSTAT is the largest data set with coverage across all sectors this issue is unavoidable.

Then if we assume that f is invertible in ω, and denoting that inverse as f^{-1} we have:

$$y_{it} = \theta_{v,s,t} v_{it} + \theta_{k,s,t} k_{it} + \omega_{it} + f^{-1}(v_{it}, k_{it}, z_{it}) + \epsilon_{it} + g_{it}$$

Then letting $\phi(v_{it}, k_{it}, z_{it}) = \theta_{v,s,t} v_{it} + \theta_{k,s,t} k_{it} + \omega_{it} + f^{-1}(v_{it}, k_{it}, z_{it}) + g_{it}$ yields (5), and $\hat{\phi}$ asymptotically approaches y_{it} and is assumed to be free of measurment error. The variable of interest θ_V is not identified in this first stage, however in the second stage it is estimated by assuming an $AR1$ process on ω, ie $\omega_{i,t} = \rho \omega_{i,t-1} + \xi_{it}$. Given a level of $\theta = \{\theta_{v,s,t}, \theta_{k,s,t}\}$ and g_{it} we can attain a measure of ω and ξ respectively as:

$$\begin{aligned}
\hat{\omega}_{it}(\theta; g) =& \hat{\phi}_{it} - \theta_{k,s,t} k_{it} - \theta_{v,s,t} v_{it} - \hat{g}_{it} \\
\xi_{it}(\theta; g) =& \hat{\omega}_{it}(\theta; g) - \rho \hat{\omega}_{i,t-1}(\theta; g)
\end{aligned}$$

Where g is flexible function of controls, and the product of the controls and the inputs, which controls for unobserved input prices[28], and ρ is attained by projecting ω on its lag, given $\{\theta, g\}$[29]. Then estimates of θ (and the flexible function of g) are attained from numerically solving the moment condition:

$$\mathbb{E}\left(\xi_{it} \begin{bmatrix} v_{it-1} \\ k_{it} \\ Z_{it-1} \end{bmatrix}\right) = 0 \tag{6}$$

Where Z_{it-1} is a vector that contains the collection of polynomial terms of the set $\{z_{it-1}, k_{it-1} \times z_{it-1}, v_{it-1} \times z_{it}\}$.[30]

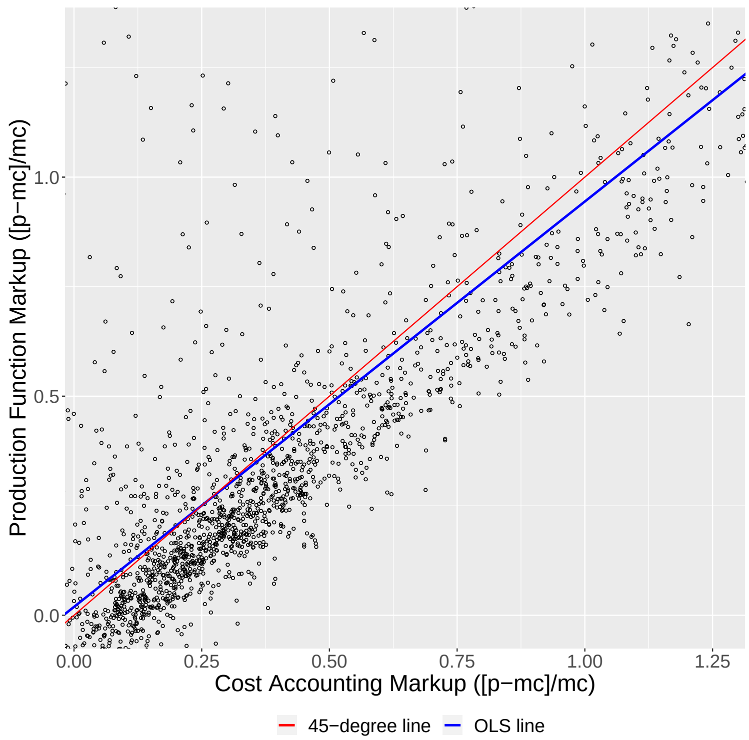
3 Comparing Markup Estimates

Despite its simplicity, this author is not aware of any attempt to compare the predicted markups of the cost accounting approach to that of the production function approach. On one hand, we might expect a strong relation between the two, the production function approach still relies on accounting data, both in estimation of the production estimation component, and directly in the form of the accounting component. On the other-hand, the underlying assumptions of each approach differ substantially, as do the criticisms, and the is not a clear mechanism by which the two feed off of some underlying biases. Seeing substantial agreement

[28] See De Loecker and Scott [2016] for discussion of identification in the presence of second stage controls.
[29] That is ρ is calculated at each step of the optimization routine to solve for $\{\theta, g\}$.
[30] See De Loecker and Scott [2016] for derivation of the moment condition.

between the two markups then provides at least suggestive evidence that both estimates are fairly consistent with true underlying markups, with at most minor effects of bias.

Figure 1: Markup Comparison: Scatter Plot with 1000 Sample Points



Notes: Cost accounting (CA) and production function (PF) markup estimates for a random sample of 1,000 firms. The OLS line is fitted from the full sample. Full sample correlation coefficient: 0.877.

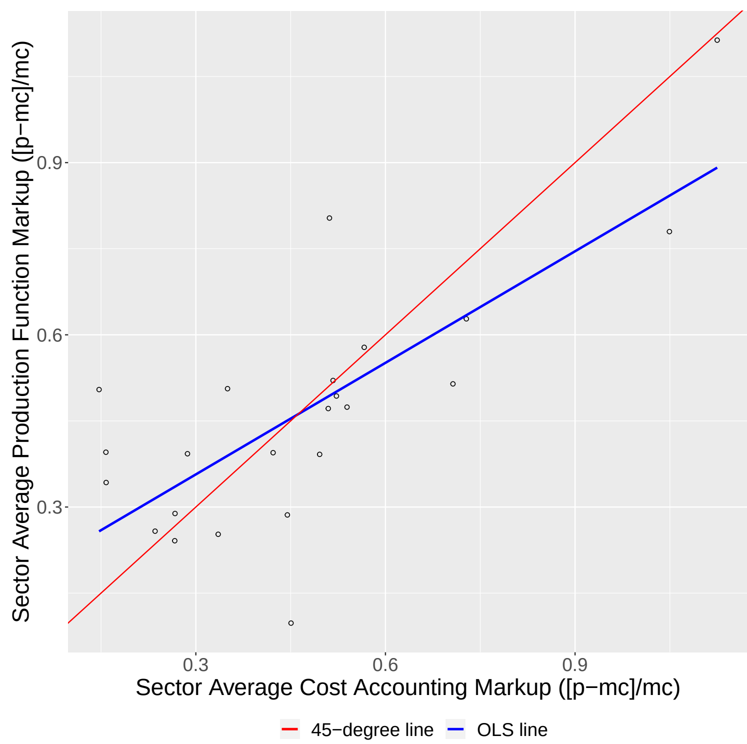
Figure 1 presents a scatter plot of the two markup measures with 1000 sample points, as as well as an OLS trend line estimated on the full sample. Several things jump out visually from the plot. First off the measures the estimates are highly correlated, with a correlation coefficient of 0.877. The OLS trend line has a slope statistically indistinguishable from 1, and intercept statistically indistinguishable from 0, thus in a sense the two markups are equal on average. That being said, a large cluster of points lie below the 45 degree line. Visually, there is an apparent lower bound on the ratio of the two markups, which in part drives the fact that the production function markups are higher on average. For a firm in sector s, denoting the production function markup estimate, and corresponding out put elasticity estimate as as $\mu_{P,it}$, and $\hat{\theta}_{v,s,t}$[31] respectively, it is straight forward to deduce the relation between the two estimates as:

$$\frac{\tilde{\mu}_{PF,i,t}}{\tilde{\mu}_{CA,it}} = \hat{\theta}_{v,s,t} \left(\frac{COGS_{it} + PPEGT_{it} \times r_t}{COGS_{it}} \right) \tag{7}$$

[31] Recall that $\hat{\theta}_{v,s,t}$ is estimated at the sector time level in 5 year rolling windows, the s, and t subscripts are included to make this clear.

It is then clear that the ratio $\frac{\tilde{\mu}_{PF,i,t}}{\tilde{\mu}_{CA,it}}$ is unbounded above, but bounded below. From (7) note that the ratio tends to infinity as the ratio $\frac{PPEGT_{it} \times r_t}{COGS_{it}}$ tends to infinity, that is a firm with a relatively high level of capital expenditures will admit a substantially higher measure under the production function approach. Additionally from (7) note that as the capital expenditure share tends to 0 we attain a lower bound, ie: $\frac{\tilde{\mu}_{PF,i,t}}{\tilde{\mu}_{CA,it}} \geq \hat{\theta}_{v,s,t}$. Note that while this lower bound technically varies at the sector time level (since output elasticises vary at this level), it does not vary much as the range of the elasticity estimates is quite tight.

Figure 2: Markup Comparison: Scatter Plot



Notes: Sector averages are constructed at the 2 digit NAICS level. Correlation coefficient: 0.630.

Figure 2 presents the scatter plot of sector averages according to each markup measure, with sectors again defined at the two digit NAICS level. The correlation coefficient is much lower in this case, at just 0.630. Additionally the OLS line is quite far from the 45 degree line when compared to that of figure 1. This suggests that the variation in the difference between markup measures is largely driven by variation across sectors, or equivalently that the correlation is largely driven by variation within sector.

Figure 3 compares the average markup by year across the two markup measures. The two average track closely in terms of level and trend. This alone marks a substantial win for the cost accounting approach, as it suggests that despite the simplicity of the approach, it is at least as good at measuring aggregate markups as the production function approach.

Figure 3: Markup Comparison: Annual Averages

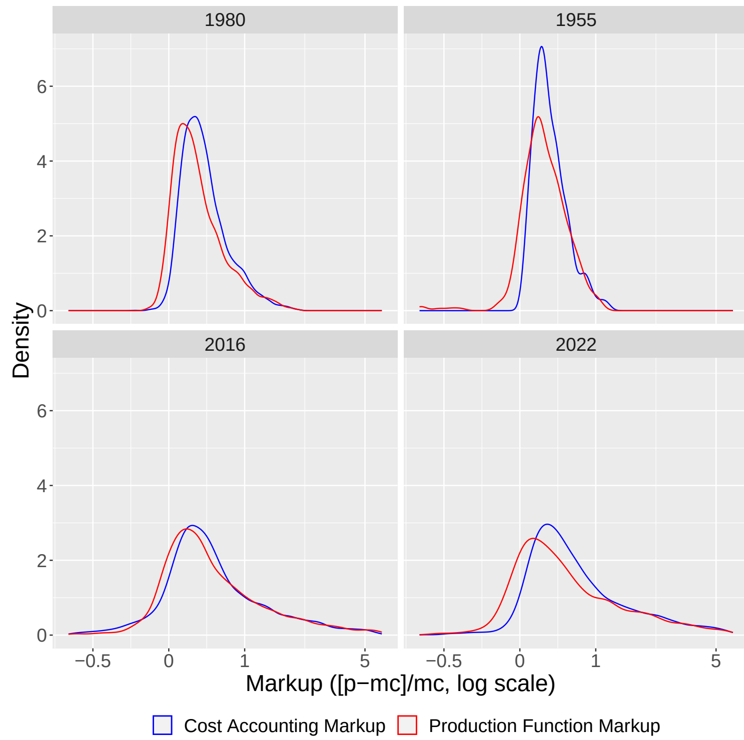
Notes: Average annual markups for CA and PF from 1955 to 2022. Correlation coefficient: 0.973.

The two average are highly correlated, with a correlation coefficient of 0.973. Sales weighted average, and averages by sector are presented in appendix A. The results for the sales weighted average are similar, and it admits a correlation coefficient of 0.880. The headline result of DEU, the markups rose between 1980 and 2016 (the last year included in their analysis) is robust both qualitatively, and quantitatively robust to the cost accounting approach of markup estimation. Given the theoretical differences between the two markup measures, this lends a lot of credence to the validity of this result. Furthermore, with the additional 6 years of data, the rise in markups seems to persist for both measures. It is worth noting, that given the unclear effects of the COVID-19 recession, one may be hesitant to forecast the future of this trend, but economists and policy makers should continue to follow this as time goes on.

The second major observation from DEU was that the aforementioned rise in markups was almost solely driven by a rise in "superstar firms", ie large, efficient firms that exhibit large markups. This can be seen by an increase in the right tail of of the markup distribution over time. For this reason, one may be concerned with the distribution of markups, in addition to their aggregate level.

Figure 4 compares the densities at 1980, and 2016 (the years that DEU marks as the primary period for the rise in markups) as well as those at 1955 and 2022, the first and last year in the data set used in this

Figure 4: Markup Comparison: Markup Densities



Notes: This density plot displays the distributions of CA and PF markups for the years 1980, 2016, the two years discussed in DEU as well as 1955, and 2022, the first and last years in the sample. Both methods show a notable elongation of the right tail over time, indicating an increase in the number of firms with high markups. The similarity in these distributions suggests that the rise of "superstar firms" with high markups is robust to the choice of markup estimation method.

paper. Overall, there is a stark similarity between the distributions of the two markup measures for all years.

As with the production function markups, we see the distribution elongate overtime. Particularly the right tail of the distribution is substantially fatter in the later years than in the earlier ones. As with the result on the rise in aggregate markups, the DEU result on the rise of superstar firms appears robust to the cost accounting approach of markup estimation. Comparison of densities across the entire sample are given in appendix A.

4 Biases and the Role of SALE/COGS

Considering the drastically different assumptions that underpinned the cost accounting and production function estimates respectively, the similarity between the two sets of estimates is jarring. This begs the questions of to what extent is this relation mechanical, and whether this result should inspire faith or skepticism of the two measures. I approach these questions first with a discussion of the issues and potential pitfalls of each estimation technique, and then through this lens hone in on the mechanical relation between the two. From (3) the production function markup estimates has two components, the production function estimation component in the form of the output elasticity θ, and the accounting component in the form of the ratio of revenue to expenditures on the variable input, which is $\frac{SALE}{COGS}$ in this context. The main contention with respect to cost accounting markups come down to its main assumption, constant marginal cost, where as the primary points of contention with respect to the production function technique relate to the production function estimation component. By inspection of (3) and (1) the similarities between the two measures come down to the use of the accounting variables of $SALE$, and $COGS$ which does not relate to the main criticisms of either method. This fact alone inspires some hope as to the validity of the two measures, but also begs the question how much of the variation in both measures are determined by this term alone.

4.1 Criticisms of Cost Accounting Markups

Bresnahan [1989] is the generally agreed upon citation for rejection of any accounting approach to markup estimation. Despite this, discussion of accounting approaches to markup measurement as such is quite minimal[32]. Chapter 17 of the Handbook of Industrial Organization, is largely dedicated to outlining the NEIO as a replacement to the "structure-conduct-performance paradigm (SCPP)", and discussion of accounting markups is limited to the following:

> *The NEIO is partly motivated by dissatisfactions over three maintained hypotheses in the SCPP: (i) economic price-cost margins (performance) could be directly observed in accounting data ... The NEIO is an attempt to continue the use of such evidence while returning to the study of single (or related) industries.*

The second portion of this quote is included to offer further context to the motivation of the NEIO. It is worth noting that the question of validity of accounting markups can in no way undermine the NEIO's toolkit of markup estimation, as the measurement of accounting markups does not admit a way to conduct counterfactual experiments without additional structure and data. Furthermore, invariably there are cases where marginal costs are not plausible observed in the data, trivially including cases like that of Rosse [1970] where markups are estimated from demand side data alone.

The assertion that marginal costs (and thus markups) cannot be observed in the data is not without merit. The primary hurdle to this comes to inferring marginal costs from variable costs. The crux of this issue is that if the constant marginal cost assumption does not hold true, making this assumption introduces a multiplicative error equal to the degree of returns to scale of the production function when ignoring fixed

[32] DEU's discussion of such an approach is limited to referencing this work.

costs, this can be seen directly:

$$\frac{AVC}{MC} = \frac{V}{Y \times MC} = \frac{V}{Y}\frac{\partial Y}{\partial V} = \frac{\partial log(Y)}{\partial log(V)} \equiv \gamma \tag{8}$$

Where γ can be thought of as the degree of returns to scale of the variable cost function. Trivially when the variable cost function is linear we have $\gamma = 1$ and observe marginal costs directly. Erring on the side of simplicity, this iteration of the cost accounting approach implemented here assumes constant marginal costs and $\gamma = 1$. It is important to note that this is not an assumption of constant returns to scale, as the inclusion of fixed costs implies increasing returns to scale. There is also the secondary consideration of properly observing variable cost, this is discussed in appendix B.1.

4.2 Criticisms of Production Function Markups

In recent years many critics have emerged with respect to the production function approach. Perhaps the two most concerning criticisms predate DEU however, emerging in response to Hall [1988]. There is the issue of unobserved prices, and that of unobserved variable utilization. From these two criticisms alone we are left with a collection of biases that could lead to an over or underestimation of the true markup. Ex-ante there is also no reason to believe that the sum of these biases' is constant over time, calling into the question the validity of any markup trend recovered from the production function approach.

The markup estimation literature is well aware of the first issue, first noted by Klette and Griliches [1996], with the relevance to the production function approach noted by Bond et al. [2021]. The issue is quite simple; output estimation in principle requires units measured in quantity, but in practice we have to units measured in monetary units. When ignoring this nuance, what is estimated is in principle closer to a revenue elasticity rather than an output elasticity, for the simple fact that the left hand side variable is revenue rather than output. Even in the most simple case where the only unobserved variable is output prices, Ridder et al. [2022] shows that the production function approach yields a markup that could be biased in either direction, though in practice it seems to induce a downward bias.

The markup literature has taken little note of the latter criticism, where Basu [1996][33] noted that unobserved variable utilization causes an upward bias in Hall's estimate of output elasticity. This issue arises as any correlation between inputs and input utilization will cause an overestimation of the output elasticity, as increased output due to utilization is incorrectly credited to input variation.

The criticism brought forth in Foster et al. [2022] is also of particular note. They find that production function markup estimates are sensitive to the definition of sectors, ie the level at which output elasticities

[33] See also Basu and Kimball [1997], and Basu et al. [2006]

are estimated. This suggests that output elasticties vary within the 2 digit NAICS sectors. These three issues will be explored in more depth in the following subsection, though additional concerns are discussed in appendix B.2.

4.2.1 Biases in The Production Estimation Component

There are three especially salient threats to identification of the output elasticity, that of unobserved prices, that of unobserved variable input utilization, and that of intrasectoral production technology variation. The issue with unobserved prices is twofold, rather than observing output Y, the econometrician observes revenue $R \equiv PY$, and rather than observing the variable input V, variable input expenditures are observed $\tilde{V} \equiv P^V V$. Next, issues of unobserved utilization arise when firms have an additional lever on production where they can increase production without increasing the inputs observed by the econometrician, then the production function takes the form $Y = F(U^v V; X^{-V})$ where U^v denotes the effective rate of utilization [34] Lastly, technological heterogeneity is perhaps most salient in the Cobb-Douglas case, where it can be modeled by allowing θ_v to vary within sector, denoting firm level measures by $\theta_{v,i}$

For illustration I will abstract away from the first stage by assuming away measurement error, along side IID productivity[35]. Furthermore to emphasis the role of the variable input consider a production function with only one input. Then denoting log revenue, log input prices, log variable expenditures, log input prices, and log utilization by $r, p, \tilde{v}, p^v$, and u^v respectively we have:

$$r_i \equiv y_i + p_i = \theta_{V,i} \left(\tilde{v}_i + u_i^v - p_i^v\right) + \omega_i + p_i \tag{9}$$

With these simplifications the moment condition analogous to (6) is:

$$\mathbb{E}\left(\left[r_i - \hat{\theta}_v \tilde{v}_i\right] \tilde{v}_i'\right) = 0 \tag{10}$$

Then from (9) we have $r_i - \hat{\theta}_v \tilde{v}_i = \left(\theta_{v,i} - \hat{\theta}_v\right) \tilde{v}_i + \theta_{v,i}\left(u_i^v - p_i^v\right) + p_i$. Then estimating (10) when the true DGP is given by (9) is asymptotically biased. This can be seen directly by combining (9) and (10) to see:

$$\hat{\theta}_v = \frac{\mathbb{E}\{\theta_{v,i}\tilde{v}_i\tilde{v}_i'\}}{\mathbb{E}\{\tilde{v}_i\tilde{v}_i'\}} + \frac{\mathbb{E}\{u_i^v\tilde{v}_i\tilde{v}_i'\}}{\mathbb{E}\{\tilde{v}_i\tilde{v}_i'\}} + \frac{\mathbb{E}\{[p_i - p_i^v]\,\tilde{v}_i\tilde{v}_i'\}}{\mathbb{E}\{\tilde{v}_i\tilde{v}_i'\}} \tag{11}$$

$$\frac{\hat{\theta}_v}{\mathbb{E}\{\theta_{v,i}\}} = 1 + \frac{\mathbb{E}\{[\theta_{v,i} - \mathbb{E}\{\theta_{v,i}\}]\,\tilde{v}_i\tilde{v}_i'\}}{\mathbb{E}\{\theta_{v,i}\}\mathbb{E}\{\tilde{v}_i\tilde{v}_i'\}} + \frac{\mathbb{E}\{u_i^v\tilde{v}_i\tilde{v}_i'\}}{\mathbb{E}\{\theta_{v,i}\}\mathbb{E}\{\tilde{v}_i\tilde{v}_i'\}} + \frac{\mathbb{E}\{[p_i - p_i^v]\,\tilde{v}_i\tilde{v}_i'\}}{\mathbb{E}\{\theta_{v,i}\}\mathbb{E}\{\tilde{v}_i\tilde{v}_i'\}} \tag{12}$$

[34] Allowing for unobserved input utilization also has implications on the Hall markup rule (3) and on the cost accounting markups. This is discussed in appendix.B.3 and B.4 respectively.

[35] Alternatively we can assume that the first stage perfectly purges all measurement error, and that TFP follows and AR(1) process with known parameters.

From (11) $\hat{\theta}_v$ converges to a weighted average level $\theta_{v,i}$ plus two bias terms, arising from unobserved variable utilization (and input prices) and from unobserved output prices respectively. Dividing by $\mathbb{E}\{\theta_{v,i}\}$ illuminates the bias relative to the the the average level of $\theta_{v,i}$, thus the right hand side of (12) gives the multiplicative bias on $\hat{\theta}_v$. From (12) any correlation between the output elasticity and the product of current and lagged variable input expenditures creates an additional bias. Under Cobb-Douglass production function, the expenditure share is proportional to the output elasticity, implying a positive correlation between $\theta_{v,i}$ and both $\tilde{v}$ and its lag; under this regime the first term on the RHS of (12) is positive. Next, positive correlation between utilization and variable input expenditure, along side persistent demand would imply the second term is also positive. Lastly, as noted in Ridder et al. [2022] the final term cannot be unambiguously signed, but given a downward slopping demand function and persistent demand shocks the most reasonable signing for the final term is negative, as their simulation and empirical exercises suggest.

4.3 The Role Of SALE Over COGS

By construction, any mechanical link between the production function and cost accounting markups must come from the accounting component of the production function markups, that is $\frac{SALE}{COGS}$. Note that from 1 and 3 the (log) production function and cost accounting markup can be decompose respectively as:

$$\begin{aligned}
Ln\left(\tilde{\mu}_{PF,i,t}\right) =& Ln\left(\frac{SALE_{it}}{COGS_{it}}\right) + Ln\left(\hat{\theta}_{v,s,t}\right) \\
Ln\left(\tilde{\mu}_{CA,it}\right) =& Ln\left(\frac{SALE_{it}}{COGS_{it}}\right) + Ln\left(\frac{COGS_{it}}{COGS_i + PPEGT_{it} \times r_t}\right)
\end{aligned}$$

This decomposition is valuable for two reasons. Firstly it separates each measure into a component that is above the main criticisms of each respective method, and a component that is sensitive to said criticisms. In the case of the production function markups this is obvious, given that the main criticisms of the method revolve around the production function estimation, which amounts to criticism of the production estimation component $\hat{\theta}_{v,s,t}$. In the case of the cost accounting markup this relation is a bit more nuanced. To illustrate consider a firm whose output (conditional on fixed costs) is dependent on two flexible inputs:

$$Y = F(V, K)$$

Then if we take the first order condition of each input, and multiply them by the ratio of said input to the level of output we have:

$$\theta_v = \frac{\partial F}{\partial V}\frac{V}{Y} = \lambda\frac{VP^V}{Y} = \lambda\frac{COGS}{Y} \tag{13}$$

$$\theta_k = \lambda\frac{\partial F}{\partial K}\frac{K}{Y} = \lambda\frac{KP^K}{Y} = \lambda\frac{PPEGT \times r}{Y} \tag{14}$$

Combining (13) and (14), and noting that $\theta_v + \theta_k = \gamma$ denotes the degree of returns to scale after fixed costs we then have:

$$\frac{COGS}{COGS + PPEGT \times r} = \frac{\theta_v}{\gamma} \tag{15}$$

The second, more apparent reason for this decomposition is that it highlights the common term of the two terms measures, $\left(\frac{SALE}{COGS}\right)$. This raises the question of how much of the variation in each measure is driven by variation in $\left(\frac{SALE}{COGS}\right)$. Ex-ante, it is possible that behind the complexity, each markup measure is largely just a linear transformation of $\left(\frac{SALE}{COGS}\right)$, which would go a long way to explain the similarity between the two measures. A straightforward way to facilitate this investigation is to regress each component on each markup measure, then the R^2 of each regression then tells us how much of the variation in a given measure can be attributed to a given component.

Table 1: Markup Decomposition

	$ln\left(\mu_{PF}\right)$	...	...	$ln\left(\mu_{CA}\right)$	...	...
(Intercept)	−0.152***	0.438***	0.262***	−0.043***	0.399***	0.408***
	(0.000)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
$ln\left(\frac{SALE}{COGS}\right)$	0.973***			0.798***		
	(0.000)			(0.001)		
$ln\left(\theta\right)$		0.561***			0.205***	
		(0.008)			(0.008)	
$ln\left(\frac{COGS}{COGS+r\times PPEGT}\right)$			−0.570***			0.294***
			(0.004)			(0.003)
N	254 662	254 662	254 662	254 662	254 662	254 662
R2	0.940	0.019	0.092	0.722	0.003	0.028

+ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

Notes: This table presents regressions of key accounting components on production function (PF) and cost accounting (CA) markups. The R^2 in columns 1 and 2 present the explanatory power of the accounting and production function components on the the PF. Note that the accounting component alone explains 94% of the variation in PF. The R^2 of columns 4 and 6 give the explanatory power of the PF accounting component and residual component on CA. Columns 3 and 5 present the explanatory power of components not used in the construction of each measure for comparison.

Table 1 regresses $\frac{SALE}{COGS}$, $\frac{COGS}{COGS+PPEGT\times r}$, and $\hat{\theta}_{v,s,t}$ on the two markups. Columns 1-3 and 4-6 regress one of the three components on the production function, and cost accounting markups respectively. The R^2's are the most interesting part of this table, as they tell us how much of the variation of a given markup measure can be attributed to a given component.[36] From the R^2 on column 1, 94% of the variation in the production function markups comes from variation in the accounting component of the measure, thus essentially none of the variation is owed to variation in the production function component. This would suggest that despite all the effort and criticisms related to the estimation of the the production function parameters, in practice it is essentially for nought, and nearly indistinguishable results could be attained by skipping the production function estimation step using $\frac{SALE}{COGS}$.[37] Next, column 4 tells us that the lion's share of variation of the cost accounting markup is also driven by $\frac{SALE}{COGS}$, though to a lesser degree than in the case of the production function approach. A scatter plot of markup estimates against $\frac{SALE}{COGS}$ is given in appendix A.

It is then clear that agreement between the two markup measures is owed to their respective correlation with $\frac{SALE}{COGS}$. This also sheds light on the relative performance of the cross sector, and cross time comparisons. Recall that taking annual averages yields the highest correlation between markup measures, while taking sector level averages yields the lowest. As noted in De Loecker et al. [2020], elasticity estimates do not vary much across time, with most of the variance coming in the sector cross section. Thus it is the sector cross section where the elasticity component plays the largest role leading to the largest discrepancy.

5 Advertising and Markups

It is clear that the aggregate predictions of estimates from the cost accounting and production function approach are qualitatively indistinguishable. While this suggests that the cost accounting approach is similar in its predictive power of underlying markups, it does not fully assuage the broader concern that variation in either measure is the product of measurement error, rather than variation in underlying markups. Nor does it tell us which method should be preferred when both are feasible. To address these two concerns, I will leverage the the Dorfman-Steiner (1954) advertising equation to test the relative performance of the two measures.

Dorfman-Steiner (1954) formalizes the relationship between advertising and markups, and tells us that advertising expenditures carry with them a signal of markups. It is this signal that forms the back bone of this section, and allows for a test with the ability to *i*) falsify the null that a given markup estimate carries a signal of underlying markups, and *ii*) compare the relative signal-to-noise ratios of the two measures.

[36] Technically speaking this interpretation is not valid for columns 3 and 5 as they correspond to a regression of one component onto a markup measure that does not utilize said component.

[37] Or, as implied by the regression coefficients $e^{-0.152}\left(\frac{SALE}{COGS}\right)^{.973}$

There are three competing theories of advertising. Advertising as "informative"[38] suggests that advertising arises as a solution to an information problem, where firms advertise to inform consumers of the quality and features of the goods the sell; firms are then incentives to increased sales by advertising to the consumers whose preferences align with the goods they sell. Advertising as "complimentary" suggests that consumption of advertising is complimentary to consumption of the good being advertised, so advertisement serves to shift incentives to increase demand for the good being advertised. Finally, advertisement as "persuasive" [39] suggests that advertising has no direct welfare enhancing effects, and increases demand for the underlying good by convincing consumers to buy goods or services that do not necessarily align with their underlying preferences.[40] What is common to all theories, and necessary for the link between advertising and markups is that advertising increases demand *holding prices constant*. That is, the demand for a given product can be written as a function of not only the price P, but also the level of advertisement A, ie: $Y = Y(P, A)$[41]. Normalizing to measure A in units of dollars spent, we can quite generally cast the flow profit for a single product firm with access to advertising as:

$$\pi = PY(A, P) - C(Y(A, P)) - A \tag{16}$$

Where $C(Y)$ denotes the total cost of producing Y units of good in the period of question, and within period demand Y is dependent on price P and advertisement spending A. Then, a well known result is as follows:

Theorem 1 (Dorfman-Steiner (1954)) *Single product firms facing demand $Y(A, P)$ have the optimal advertising rule:*

$$\frac{A}{Y \times P} = \frac{\partial log(Y)}{\partial log(A)} \times \frac{P - MC}{P}$$

Where A denotes advertising expenditure, MC denote marginal cost, and P denotes the price.

Theorem (1) can be seen directly by rearranging the first order condition from maximizing (16) with respect to A. Further intuition can be gained by noting when generating an additional sale through advertising, the firm still needs to produce the additional good, thus the return to advertising is dependent on on the wedge between the sale price and the marginal cost, ie the markup. This clarifies another well known result,

[38] See Grossman and Shapiro [1984]

[39] Dixit and Norman [1978], and Dixit and Norman [1979]

[40] Even in the persuasive model, advertisement is not without its economic benefits, as advertisements help fund the media which they appear in, acting as a subsidy in the case of print and Television programs and the main source of revenue for many online goods and social media.

[41] Taking all other relevant determinants of demand as given.

that under perfect competition where the markup is equal to 0, there is no incentive to advertise, and the only solution to the advertising problem is A = 0. To see Theorem (1) directly, first note that with advertising in units of expenditure, a \$1 increase in advertising expenditure yields $\frac{\partial Y}{\partial A} = \frac{Y}{A}\frac{\partial \log(Y)}{\partial \log(A)}$ additional sales, and an additional sale yields a return equal to the price cost margin: $P - MC$ since the firm now needs to produce the additional good. Thus equating the marginal cost of an additional sale generated from advertising to the marginal marginal benefit yeilds $\frac{A}{Y}\frac{\partial \log(A)}{\partial \log(Y)}$, which can be arranged as above.

The motivation for expressing theorem (1) with this rewrite comes down to the convenience of thinking of the advertising share of revenue, defined as $xad = \frac{A}{Y \times P}$[42], the advertising response elasticity $\varepsilon_{xad} = \frac{\partial log(Y)}{\partial log(A)}$[43], and the lerner index $1 - \frac{1}{\mu} = \frac{P-MC}{P}$[44]. Then the advertising rule can be represented more compactly as:

$$xad = \varepsilon_{xad} \times \left(1 - \frac{1}{\mu}\right) \tag{17}$$

As a result, the advertising share of revenue provides a signal about the markup, and thus about the level of market power, though this signal is muddied by the advertising response elasticity ε_{xad}. The generality of this relationship cannot be over stated, the general form in theorem (1) is reliant only on the assumption that firms internalize that advertising affects demand– an assumption without which we cannot rationalize advertising to begin with– and that firms behave rationally, which can be easily weakened by allowing for optimization and/or measurment error. Beyond that, yielding *some* relationship between advertising and the markup is only reliant on the aforementioned idea that the benefit of advertising necessarily depends on the markup. As long as firms internalize the fact that the return to additional sales is increasing in the markup there must be an equilibrium relationship between advertising and the markup, thus the idea that the advertising share of revenue provides some signal of markups requires very little structure.

5.1 Advertising Data

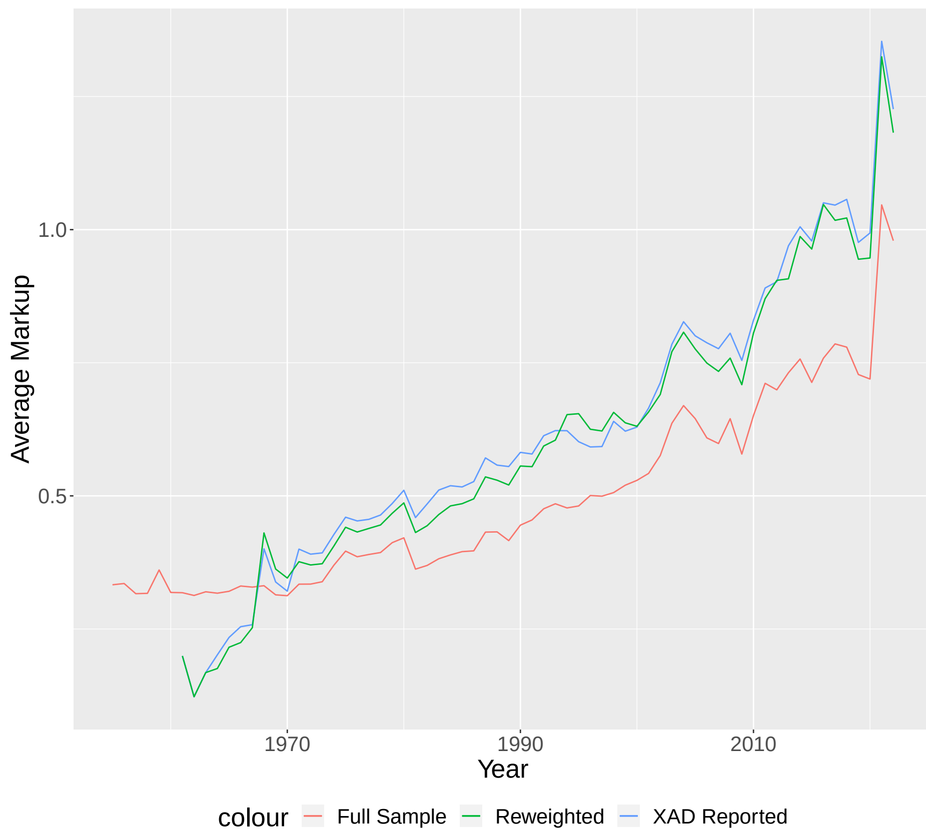
Data on advertising expenditures comes from COMPUSTAT in the form of "Advertising expenses" (XAD). XAD is defined as "the cost of advertising media (i.e., radio, television, and periodicals) and promotional expenses", and is taken in this analysis as representing the total level of advertising for the firms. Under GAAP, XAD is included as a portion of XSGA, and thus there is no overlap in expenses included in COGS. While firms are not legally required to report XAD as a separate line item, around 30% do opt to report.

[42]Which allows us to think of advertising relative to scale.

[43]A central question both for the marketing literature, and for managers of firms pertains to the shape of demand while varying quantity. This is known as the 'Advertising response function' to the marketing literature. The advertising response elasticity is then the elasticity of the Advertising response function.

[44]It is worth noting that Dorfman-Steiner take this approach one step further, noting that under monopolistic competition the Lerner index is at optimum equal to the inverse of the price elasticity of demand. It is worth noting that the underlying logic holds when prices are taken as given, thus the above expression is more general in that sense.

Figure 5: Average Markups by Advertising Reporting



Notes: This figure plots the average cost accounting markups for firms that report advertising expenditures compared to the full sample. The re-weighted series is constructed by taking sector population weights (at the 6 digit NAICS level) from the full sample and applying them to the advertising sample.

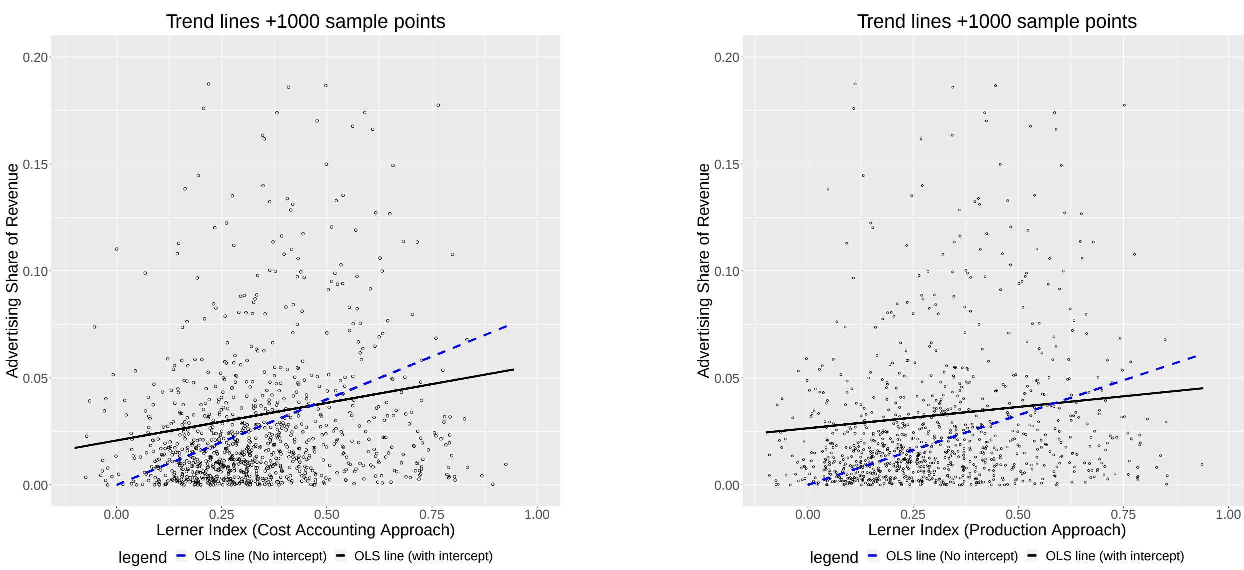
Figure 5 presents the annual average markups (as measured by the cost accounting approach) over time given the cost accounting markup estimate. It contains the values for the full sample, the sub sample of firms in the advertising balanced sample, and the advertising balanced sample reweighed to match the sector composition of the full sample. The reweighing is done by taking a weighted average of sector level (defined at the 6 digit NAICS level) average markups, with weights set by the the number of firms in a given sector in the full sample. The XAD reported average is nearly identical to the reweighed average, signaling that with respect to markups there is no selection by sector, thus the sample is effectively representative across sectors. With respect to selection, the most reasonable explanation is that firms that engage in higher levels of advertising are more likely to report their advertising, then (17) would imply that firms with larger markups are more likely to report advertising. This effect seems to occur within sectors given the similarity before and after reweighing. Additional summary statistics are given in appendix C.1.

Since advertising expenditures and total revenue are observed in the data we observe the advertising share directly. Deriving a specific test will require thinking critically about about error terms, but for the moment assume that the advertising share of revenue is observed with a mean 1 multiplicative error $e^{\epsilon_{xad}}$, then we have:

$$\tilde{xad} \equiv \frac{XAD}{SALE} = \frac{A}{Y \times P} \times e^{\epsilon_{xad}} = xad \times e^{\epsilon_{xad}} \tag{18}$$

There are various reasons we may expect a error term on $\tilde{xad}$, the most obvious cause would be measurement error, which could come by mistakes in reported numbers, issues with respect to the timing the advertising, or any distinction between the accounting definition of advertising expenditures and an economic definition of advertising expenses. The more nuanced cause is that of optimization error, as a literal interpretation of (17) would require perfect optimization by firms, thus exact equality may be unrealistic.

Figure 6: Advertising Vs Markup Measures



Notes: Scatter plot of markup measures (lerner index) on advertising share. Note the the Dorfman-Steiner equation predicts that if advertising response elasticity were constant the scatter plot would reduce to a ray from the origin.

Figure 7 presents a scatter plot the advertising share of revenue against the lerner index for the cost accounting and production function markup estimates, with 1000 randomly selected observations along side OLS trend lines with and without intercept estimated on the full sample. Both plots show fairly strong evidence of correlation, particularly the cost accounting markups. In order to more rigorously evaluate the relationship between each markup measure and the advertising share, and to develop the aforementioned tests on their performance requires more structure on the relationship between estimated and true markups.

5.2 Advertising Test

If the advertising response elasticity ε_{xad} was observed, equation (17) would lead to a direct test of a given markup measure[45]. While there are many studies that provide estimates of advertising response elasticises[46], none offer firm level estimates with enough granularity to allow such an analysis. The goal must then be much less heroic, and instead I will derive a test of the relative signal-to-noise ratios of the two measures. As a by product of this test is also the potential to out right reject the premise that a given markup measure contains *any* signal of underlying markups.

An additional challenge to utilization of (17) is that revenue in the form of the accounting variable $SALE$ appears in the numerator of both markup measures, and in the denominator of the observed advertising share, thus the presence of measurement error in $SALE$ leads to negative correlation between a given markup measure and the observed advertising share of revenue.

As will be shown more formally below, neither challenge prevents a test of relative signal-to-noise ratios, nor does it rule out our ability to falsify the null of uninformative markup estimates. Under the null that the a given markup measure holds no information about the true markup, ie that estimates $\tilde{\mu}_M$ is orthogonal to the true markup μ^*, it would also be orthogonal to the true advertising share of revenue via equation (17). Then the presence of measurement error in $SALE$ would lead to negative correlation with the observed advertising share. Thus, any statically significant positive correlation would allow us to reject the null that the cost accounting markup is uninformative about the true markup.

Furthermore, neither concern rules out the ability to benchmark cost accounting markups against the production function markup to learn about the relative in sample signal-to-noise ratios of the two measures. This follows from the fact that these two issue affect correlation between $\tilde{xad}$ and cost accounting markups the same way it effects the correlation between $\tilde{xad}$ and production function markups, thus we can still compare relative signal-noise ratios.

Consider the case where markup estimates from a given method are the product of underlying markups μ^*, and some source of noise. Given the structure of the two markup measures, multiplicative error seems to be the most reasonable type of noise to consider. Thus one can tractably represent error by assuming a mean 1 multiplicative noise term $e^{\epsilon_i^M}$, that is for $M \in \{CA, PF\}$

$$\log\left(\hat{\mu}_{M,i}\right) = \log\left(\mu_i^*\right) + \epsilon_i^M \tag{19}$$

[45] As well as offer an additional way to measure markups.

[46] See Henningsen et al. [2011] for a meta analysis including 659 estimates.

Then the signal to noise ratio for a given (log) measure is given by:

$$SR(\hat{\mu}_M) \equiv \frac{var(\log(\mu^*))}{var(\epsilon_i^M)} \tag{20}$$

Note that this definition of a signal-to-noise ratio, as well as the proceeding analysis is robust to allowing for a multiplicative and additive bias in log markups ie: $\log(\hat{\mu}_{M,i}) = \beta^M \left[\log(\mu_i^*) + \epsilon_i^M\right] + \alpha^M$ where β^M and α^M are constant within markup measures. For the sake of notations simplicity these terms will be suppressed. It is worth noting that the case of uninformative markups corresponds to $\beta^M = 0$, and $var\left(\epsilon^M\right) = \infty$, hence $SR(\hat{\mu}_M) = 0$ while $\beta^M \epsilon^M$ retains a finite variance.

Next lets turn to errors in the observed advertising share of revenue, $\tilde{xad}$. There are three clear sources of error in the context of the Dorfman-steiner equation, that of measurement errors in advertising expenditure and revenue, and optimization error. It is reasonable to consider all such errors as multiplicative, thus we can tractably model error in the observed advertising share of revenue with three mean 1 multiplicative errors[47] $e^{\epsilon^x}, e^{-\epsilon^s}, e^{\epsilon^a}$, where ϵ^s carries a negative sign since it appears in the denominator. Then we have:

$$log(\tilde{xad}_i) = xad_i + \epsilon_i^x - \epsilon_i^s + \epsilon_i^a \tag{21}$$

Where ϵ^a captures optimization error as well as any correlation between errors in advertising and revenue.

Recall now that both markup measures are constructed using revenue data in the numerator of their expressions, thus any measurement error in reported revenue appears in both markup measures. Then we can decompose both noise terms into the sum of ϵ^s and a measure specific noise term $\epsilon^{M'}$, that is for $M \in \{CA, PF\}$[48]:

$$\epsilon_i^M = \epsilon_i^s + \epsilon_i^{M'} \tag{22}$$

This is the first of the two aforementioned issue, that ϵ^s appears in both markup measures and in $\tilde{xad}$. This issue alone is enough to rule out the possibility of using the Dorfman-Steiner equation to estimate $SR(\hat{\mu}_{CA})$ and $SR(\hat{\mu}_{PF})$ without having to assume away measurement error. The second issue is that the advertising response elasticity, ε_{xad} is unobserved, and in general an endogenous object. For the purpose here, we need not impose any specific structure on the equilibrium relationship between ε_{xad} and underlying markups μ^*, and simply assume that they are in somewhat correlated. In order to form a valid test, all we need to assume is that each of the measure specific errors $\epsilon^{M'}$ are uncorrelated with ε_{xad}. Then the following

[47] Note that the subsequent analysis is unaffected by allowing for additive and multiplicative bias in $\log\left(\tilde{xad}\right)$

[48] Then $\epsilon^{PF'}$ corresponds to the error on $ln(\hat{\theta}) - ln(COGS)$, while $\epsilon^{CA'}$ corresponds to the error on $-ln(COGS + PPEGT \times r)$

result follows:

Theorem 2 *Denote the squared correlation coefficient between* $-log\left(1-\tilde{xad}\right)$ *and* $log\left(\hat{\mu}^M\right)$ *by* $R^2_{X,M}$ *for* $M \in \{CA, PF\}$*. Then:*

$$\frac{R^2_{X,CA}}{R^2_{X,PF}} = \frac{1+\frac{1}{SR(\hat{\mu}_{PF})}}{1+\frac{1}{SR(\hat{\mu}_{CA})}}$$

The immediate take away from theorem 2 is that if $log\left(\hat{\mu}_{CA}\right)$ is a better predictor of $-log\left(1-\tilde{xad}\right)$ than $log\left(\hat{\mu}_{PF}\right)$, it must have a higher in sample to signal-to-noise ratio, and vice versa. The intuition for this result is that the presence of ϵ^S and ε_{XAD} affect the correlation coefficients in the exact same manner, yielding a common term that is divided away by taking the ratio. Proof of theorem 2 is given in appendix C.2, and follows precisely from this intuition.

The decision to compare to $-log\left(1-\tilde{xad}\right)$ may appear non-obvious at first, and indeed the result would follow with any monotonic transformation of $\tilde{xad}$. This particular form is motivated by a desired to preserve as much signal of $\log\left(\mu^*\right)$ as possible, and is motivated by the fact that equation (17) can be rewritten as:

$$-log\left(1-\frac{\tilde{xad}}{\varepsilon_{xad}}\right) = \log\left(\mu^*\right)$$

Additional motivation can be seen from taking a Taylor expansion of $-log\left(1-\tilde{xad}\right)$, which is given in appendix C.2.

5.3 Advertising Test: Results

Table 2: Advertising Tests

Dependent Variable:	$-log(1-xad)$							
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables								
Constant	0.0221***	0.0241***						
	(0.0008)	(0.0007)						
$log\,(\hat{\mu}_{CA})$	0.0276***		0.0247***		0.0271***		0.0251***	
	(0.0020)		(0.0022)		(0.0019)		(0.0022)	
$log\,(\hat{\mu}_{PF})$		0.0258***		0.0235***		0.0245***		0.0230***
		(0.0018)		(0.0020)		(0.0017)		(0.0020)
Fixed-effects								
Industry			Yes	Yes			Yes	Yes
Year					Yes	Yes	Yes	Yes
Fit statistics								
Observations	89,635	89,635	88,867	88,867	89,635	89,635	88,867	88,867
R^2	0.02012***	0.01972***	0.03346***	0.03327***	0.04817***	0.04708***	0.05965***	0.05875***
	(0.00093)	(0.00092)	(0.00119)	(0.00118)	(0.0014)	(0.00138)	(0.00154)	(0.00153)
Within R^2			0.01482	0.01464	0.01878	0.01767	0.01495	0.01402

Clustered (Firm level) standard-errors in parentheses

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1. R^2 standard errors from Cohen et al. (2003).*

Notes: Regression of log markup measures on a function of the advertising share of revenue. Note that by theorem 2 the ratio of R^2 between measures gives the ratio of signal to noise ratios between two markup measures. The results then imply that signal to noise ratios are nearly identical, but CA is slightly higher in sample. Given the number of firms this can be interpreted as largely driven by within sector *times* time as is shown by the inclusion of industry and year fixed effects

Table 2 presents the results from an observation level regression of the cost accounting, and production function markups on the aforementioned function of advertising share of revenue. Across all specifications we have a statistically significant coefficient on both markup measure, thus we can conclude that each measure is providing some signal of underlying markups. Additionally, regressions with cost accounting markup yield slightly higher R^2, and by theorem (2) cost accounting markups have a slightly higher in sample signal to noise ratio.

The first two columns denote the baseline regression without any controls, whereas columns 3-8 include industry and year fixed effects, with industries defined at the 2 digit NAICS level. Including fixed effects implicitly allows multiplicative bias on $\hat{\mu}_M$[49] to vary at this level. Given that observations are at the firm, time level, prediction in this context is largely driven by within sector year variation. As such including sector, year fixed effects does not qualitatively change the story. It does however clarify interpretation, in that we can say that both measures have similar signal-to-noise ratios within sector-year.

This result is not entirely unsurprising, given the high correlation between the two measures. It does tell us however, that deviations between the two estimates are driven by errors in the two markups in approximately equal shares. One may questions how much can be gained by considering a convex combination of the two measures, to address this appendix C.3 includes a horse race regression with both measures. R^2 increases modestly from the cost accounting only specifications, and in all specifications the cost accounting receives a larger coefficient.

Recall now that the production function component of the production function markup was estimated at the industry by year level [50], and the lowest correlation between the measures was attained when considering sector averages. Given that the sector×time cross section contains the most disagreement between the two measures, this cross section is especially interesting, and serves as a more direct test of which measure is more credible in so far as they disagree.

Table 3: Advertising Test: Sector × Time Averages

Dependent Variable:	$-log(1-xad)$							
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables								
Constant	-0.0098***	0.0240***						
	(0.0037)	(0.0014)						
$log(\hat{\mu}_{CA})$	0.0279***		0.0282***		0.0283***		0.0285**	
	(0.0024)		(0.0085)		(0.0034)		(0.0100)	
$log(\hat{\mu}_{deu})$		0.0278***		0.0324***		0.0238***		0.0239**
		(0.0037)		(0.0107)		(0.0078)		(0.0105)
Fixed-effects								
Industry			Yes	Yes			Yes	Yes
time					Yes	Yes	Yes	Yes
Fit statistics								
Observations	1,030	1,030	983	983	1,030	1,030	983	983
R^2	0.12008	0.05255	0.32044	0.27843	0.25649	0.19283	0.43454	0.40117
Within R^2			0.09883	0.04313	0.11867	0.04321	0.08050	0.02623

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Notes: Regression of sector averages of log markup measures on a function of the advertising share of revenue. Note that by theorem 2 the ratio of R^2 between measures gives the ratio of signal-to-noise ratios between two markup measures. The results then imply that CA has a substantially higher signal-to-noise ratio in the sector × time cross section.

Table 3 presents the results from a regression of the cost accounting, and production function markups on

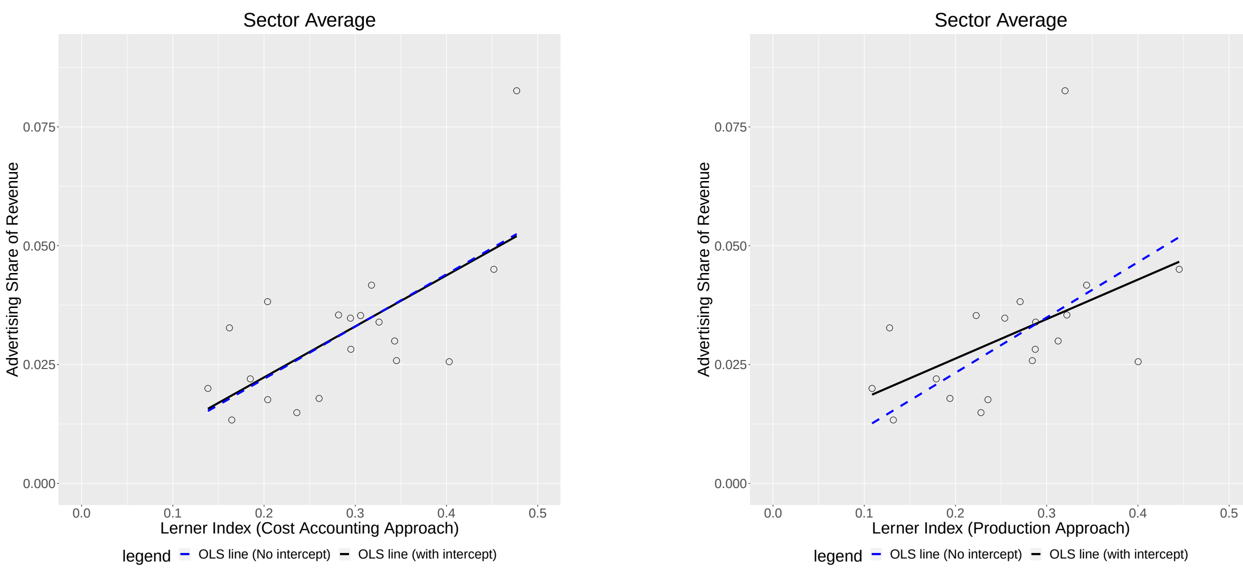
[49] Ie additive bias on $\log(\hat{\mu}_M)$

[50] With rolling windows.

the aforementioned function advertising share of revenue, with observations taken as sector $\times$ time averages. Across all specifications we see significantly higher R^2 compared to that of table 2, this is consistent with the idea that taking sector averages limits the attenuation bias from measurement error in revenue, and with advertising elasticity varying more within sectors than it does across sectors. Additionally, the R^2 for the cost accounting markup is consistently and substantially higher than that of the production function markup.

Again by theorem (2) this tells one that the cost accounting markup has a substantially larger signal to noise ratio in the sector $\times$ time cross section. Given that this is the cross section upon which we see the lowest degree of agreement between the two measures, this lends further credence to the accuracy of the cost accounting approach.

Figure 7: Advertising Vs Markup Measures



Notes: This figure illustrates the cross-sectional variation in markups across different sectors using both the cost accounting and production function approaches. Note this is the dimension in which we see the highest disagreement between measures.

Further intuition can be gained by looking at a simple scatter plot of sector level averages of xad and log markup measures from the two methods. This is given in figure 7. While it is difficult to draw any strong conclusions with so few observations, the overlap between the with and without intercept lines in the cost accounting approach is unmistakable. The cost accounting plot is much closer to what one would expect from a strong linear relationship as suggested by (17) with ε_{xad} constant. Coefficients from a regression at the sector level as well as alternative specifications are included in appendix C.3, alternative specifications can be thought of as representing different assumptions on the error terms.

6 Applications

Evidence suggests that both firm level approaches produce useful markup estimates, but there still remains the question of what measure is the most useful for a given application. Clearly, the distinction between IO style demand estimation approaches and the firm level approaches is a question of whether one is interested in product or firm level estimates, and one of data availability. Less clear is the distinction between the cost accounting and production function approach.

Relative to the production function approach, there are several advantages that make the cost accounting approach the clear choice in certain settings. The cost accounting method is the only of the three methods that can be implemented using only observation specific information[51], and in principle can be implemented with just 1 observation. In extremely data scarce environments it is thus the only feasible option.

Estimation of the production function parameter requires a large panel of firms who are assumed to have identical production technology. Even with COMPUSTAT, the largest data set of US firms firms parameters need to be estimated at the two digit level in 5 year rolling windows. This presents two weaknesses, the first is the restrictive assumption that firms within sectors have identical technology parameters. It is not clear why we should ex ante believe that the the tech giants of the information sector like *Microsoft*, *Alphabet* (formerly Google), and *Meta* (formerly Facebook) share production technology with smaller companies of the sector such as *RightNow Technologies Inc*, a customer relationship management software founded in Bozeman Montana in 2001 and acquired by Oracle in 2013. Nor is it clear that we should assume that the tech giants share production technologies with each other. Additionally, implicit in this assumption is one that technology does not vary over the firm life cycle, ruling out any possibility of learning by doing. Lastly the need to group into rolling windows threatens to dampen or remove any cyclical effects, making the production function approach suspicious in any high frequency analysis.

These observations motivate several small applications to highlight the strength of of the cost accounting approach. The first is a simple investigation of markups among tech giants, the strength here is the ability to track markups free of an imposition of identical production function parameters. The second application is an investigation of markups over the firm life cycle, leaning on the flexibility that production technology varies over the firm life cycle. The final application is an investigation of the response of markups to TFP shocks, emphasising the cost accounting approaches strength in high frequency analysis. These applications are not designed to reveal any ground breaking results, nor are they meant to be the final word on their respective environments. The goal is simply to demonstrate the types of questions where cost accounting markups are uniquely well suited to answering.

[51] Conditional on the user cost of capital

6.1 Seven Magnificent Markups

In the wake of Dotcom crash, slowly but surely several large technology companies rose to prominence, garnering large market shares in the information sector and market caps comprising a large portion of the $S\&P500$. By 2013 the acronym *FANG* rose to prominence first in the financial punditry spheres with the likes of TV's Jim Crammer, but quickly finding its way as a household term to describe the collective of (at the time trading under the name) *Facebook*, *Amazon*, *Netflix*, and (at the time trading under the name) *Google*. In the years following *FAANG* became the acronym of choice adding *Apple* to the ranks, then *MAMAA* with *Microsoft* replacing *Netflix* from the bunch.[52], and at the time of this paper *Magnificent Seven* is the term of choice to describe wall street's favorite bunch of tech companies, adding *Nvidia* and *Tesla* to the club[53]

Whether under the label of some acronyms, the more informal *Tech Giants* or the more insidious *Big Tech*, large tech companies have a long history of drawing the ire of regulators and economic pundits alike.[54] On the regulatory front, the first notable example came in 1990 when the Federal Trade Commission (FTC) launched an anti-trust investigation against Microsoft, and in 2000 Microsoft was found guilty of engaging in an illegal monopoly in the personal computer market. [55] Recently, a district court found that Google was acting as an illegal monopoly in the search engine market, with court documents revealing that it "enjoys an 89.2% share of the market for general search services, which increases to 94.9% on mobile devices".[56]

The cost accounting method offers a straightforward way to investigate the markups of these tech giants, using only accounting data from COMPUSTAT. Given that these companies are all publicly traded and founded after 1950, it is straight forward to calculate year level markups for each firm from the year of their initial public offering (IPO) to the last year in our data set.

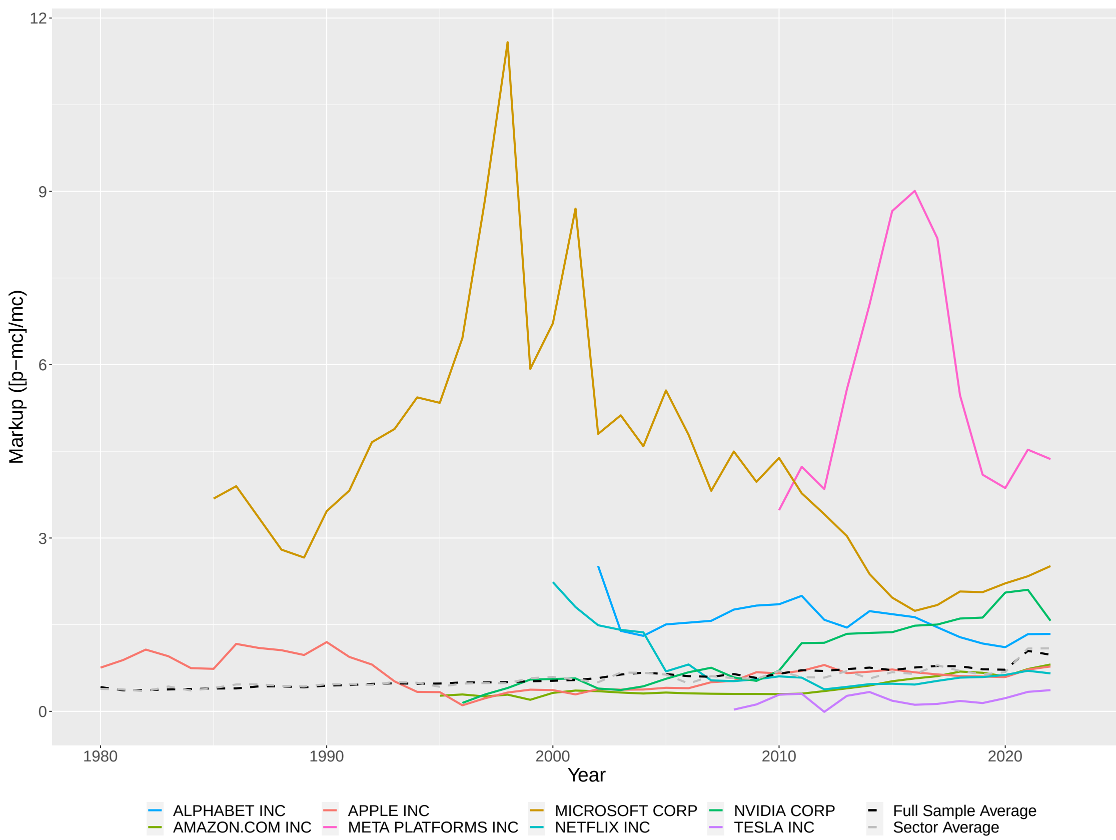
Meanwhile, the production function method is not feasible at the firm level without grouping firms and assuming equal production function parameters between them. Given that all but one of the aforementioned companies are in the information sector[57] the typical approach of the production function method would mean assuming that all firms share production parameters. It is the view of this author that given the uniqueness of these firms, an assumption of equal production technology between a given tech giant and any collection of other firms would be questionable.

It is also unclear how fitting the demand estimation approach is to this context, as it would require not only demand side data for each firm, but also for these firms competitors. This becomes even more daunting when we consider that the demand method must be implemented at the product level. To get firm level

[52] And reflecting the construction of parent companies Alphabet and Meta absorbing Google and Facebook respectively
[53] Hobbs
[54] Payne
[55] v. Microsoft Corp [a]v. Microsoft Corp [b]
[56] Press
[57] with the exception of *Tesla* in the manufacturing sector, despite many annalists viewing it as more of tech company.

markups for a given year one would need to estimate markups for each product sold by a given firm and aggregate up based on sales. Compare this to the cost accounting approach – which needs only one line of accounting data to produce a markup estimate – and the advantage is clear.

Figure 8: Tech Giant Markups



*Notes:*This figure presents the annual markups for leading tech firms from their IPO to 2022, alongside the full sample and sector averages. Note the scale of the Y axis puts Microsoft in the 99.9 percentile at their peak.

Figure 8 presents the annual markups for the eight companies mentioned thus far in this subsection[58] from their IPO to 2022. There is not one clear story that defines the life cycle dynamics of markups for these tech giants.Microsoft and Meta seem to follow an inverted U path, entering with quite large markups relative to the full sample average, eventually rising to astronomical peaks before returning to levels similar to their first 3 years. Then there is the Netflix and Alphabet, with slight downward trends following their IPOS, and NVIDIA unique as the one firm that sees gradual but persistent markup growth, with Apple and Amazon seeing modest and flat markups throughout their life time.

Microsoft sees a terrifying peak of its markups to $1,150\%$ of marginal cost in 1998, placing it well into the 99.9 percentile of markups in that year. In the years between the start of the FTC's investigation of

[58]The seven members of the Magnificent Seven and Netflix.

the company in 1990, and its eventual conclusion Microsoft goes from a firm with a notably large markup relative to the rest of the sample to an outlier even compared to its closest contemporaries. Following (or slightly before) the eventual ruling the company sees a crash that would be nearly as spectacular as its rise if not for the fact that it settles to a markup that that is more than respectable so long as it's not compared to the company's previous height.

6.2 Markups Over the Firm Life Cycle

How do markups vary over the firm life cycle? There are several candidate mechanisms that can lead to variation in markups throughout the firm life cycle. The literature on "customer markets" argues that firms initially charge low markups to increase sales, and raise markups once they have built marker share and consumer awareness[59], this would imply that markups rise over the firm life cycle. Additionally, price taking firms that increase their efficiency via learning by doing would see increasing markups as their marginal costs fall. Alternatively, if competition increases the longer a firm is in the market, this is most apparent in the canonical Schumpeterian creative destructive framework, where firms enter able to price out their competition and are later themselves.

As with the last application, the production function approach is not well suited for this context. As it is reliant on exploiting the changes in inputs for a given firm across years, it necessarily assumes that production technology is constant throughout the firm life cycle, even before we consider the need to group firms across sectors and time. Any changes in technology over the firm life cycle would bias any trend in markups with respect to firm age. The cost accounting approach is not reliant on a assumption that firm technology is unchanged through the firm life cycle, and thus better fit for investigating this question.

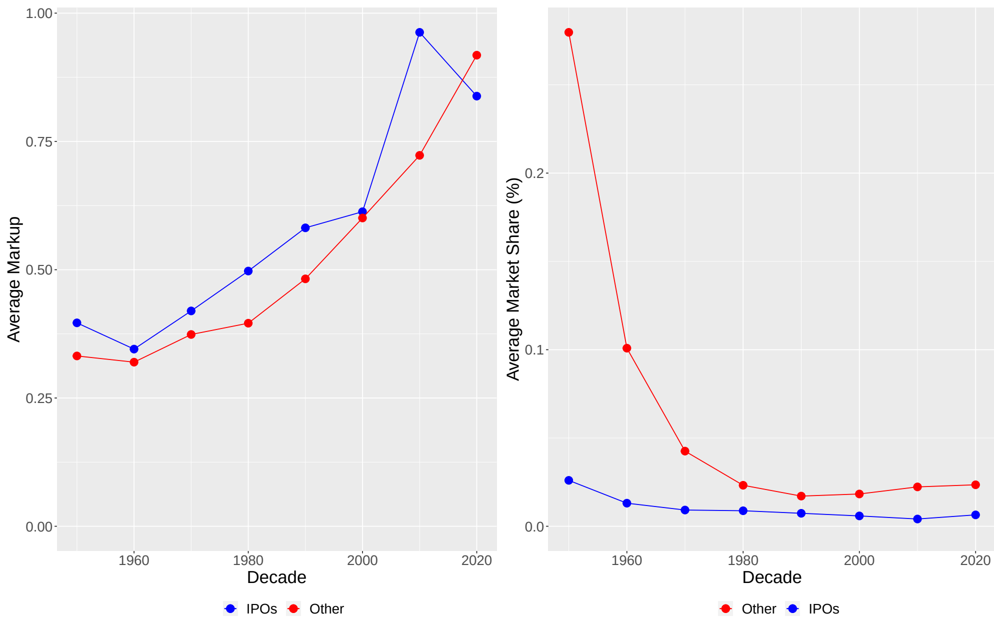
Fitzgerald and Priolo [2018] utilizes a demand estimation approach to answer a similar question within the consumer food industry. They find no evidence of a trend in markups over the firm life cycle in this market. This is suggestive of a larger patter, but there is no ex ante reason to believe that firms in different sectors have qualitatively similar life cycles, as different sectors may be more or less sensitive to any of the aforementioned mechanisms. The advantage of the cost accounting approach is then in its coverage, given the availability of accounting data relative to demand data the analysis that follows is not limited to a given sector.

Firms enter COMPUSTAT data following their IPO, and it is from that point forward that we are able to observe a firm. This may dampen the effects argued for in the "customer markets" literature, as some firms may develop notable market shares prior to their IPO. On the other hand, following an IPO firms receive an influx of capital, and thus are primed for expansion, if firms truly do increase market shares by setting

[59] See Fitzgerald and Priolo [2018] for a more in depth literature review.

temporarily low markups one would still expect to see a notable rise in markups in the years following an IPO. Additionally, limiting observation to a firm's IPO does not rule out the ability to observe the effects of a creative destruction, as the mechanism is more relevant to the latter end of the firm life cycle.

Figure 9: IPOs Over Time



Notes: This figure shows decadal average markups and market shares for IPO and non-IPO firms.

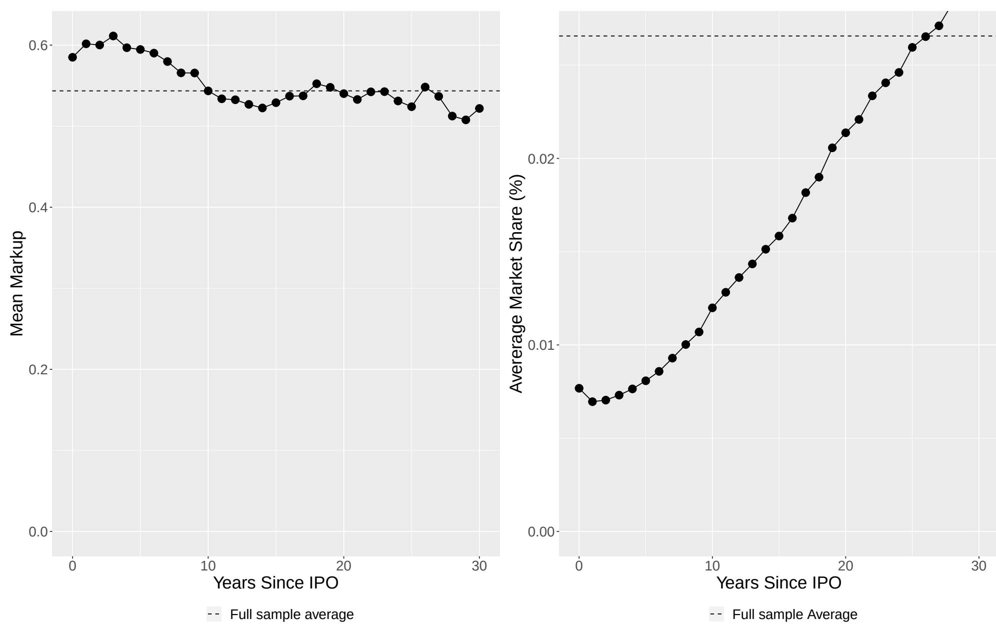
Figure 9 presents decadal averages of markups and market share[60] for IPOs and non-IPOs in the data set. IPOs see slightly higher markups than the non-IPOs with both following a similar upward trend over time. IPOs have market shares that are on average just a fraction of their incumbent counterparts. While an IPO does not represent a 'new firm' under the strictest definition, this does imply that on average firms are quite small at the time of IPO, and suggests that firms grow substantially later in their lives, which is something that can be checked directly.

Figure 10 present average level of markups, and market share in the years following an IPO. Firms indeed build substantial market share in the year following their IPO, with average market shares more than doubling within 15 years of IPO, additionally it takes the average firm more than 25 years to reach the full sample average market share. Despite this substantial rise in market shares, average market shares are nearly flat with a slight downward trend.

Unconditional averages do not necessarily paint an accurate picture of life cycle dynamics however, as they are influenced by the trend in average markups, changes in the age distribution across time, and survivor-ship bias. A simple linear regressions is more than capable of controlling for these issues, and estimating the

[60] Here market share is computer as the ratio of sales for a given firm in a given year, to the total sales of all firms in that year.

Figure 10: Life Cylcle Dynamics: Unconditional Averages



Notes: The figure tracks the average markup and market share for firms at different stages after their IPO. Older firms on average have on average larger markup shares but lower markups.

life cycle component of markups directly. Including time fixed effects directly addresses any concerns about underlying trend, as well as any issue with changes in the age distribution. Concerns about survivor-ship are addressed in two ways, first the inclusion of firm fixed effects absorbs an issues related to correlation between markups and time of exit, and an indicator for exit[61] absorbs any issues that can arise from patters of markups near failure and the timing of exit. Then we are left with a regression of the form:

$$\mu_{it} - 1 = \vec{\beta} \cdot \mathbf{1}\left\{age\right\}_{it} + \alpha_i + \gamma_t + \alpha_{it}^{Exit} + \epsilon_{it} \tag{23}$$

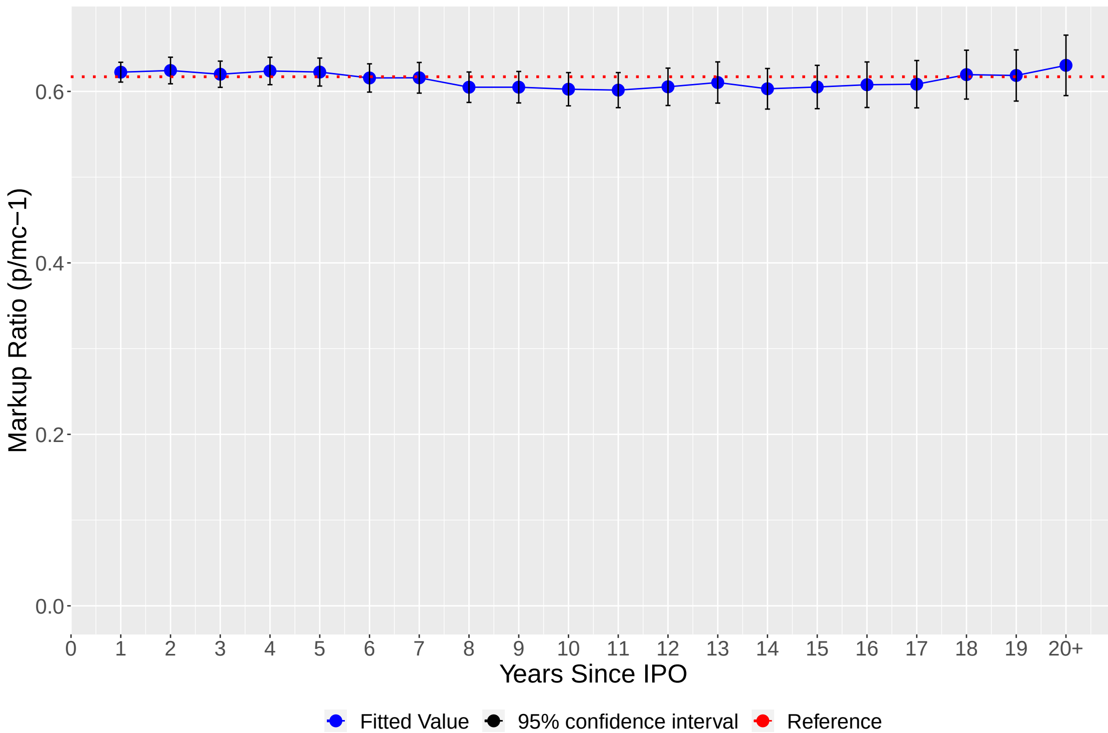
Where α_i, γ_t , and α_{it}^{Exit}, are firm, age and exit fixed effects respectively, and $\mathbf{1}\left\{age\right\}_{it}$ is an age indicator for $age \in \{1, ..., 19, 20+\}$. Then $\hat{\vec{\beta}}_j$ gives an estimate of the conditional average life cycle component at age j.

Figure 11 presents the fitted value from (23) for an average[62] firm of each age in the year 2018, while the reference line represents the markup for an average firm in the year 2018. There is no clear trend in markups over the firm life cycle, with the gap between the lowest and highest fitted value being absolutely negligent with respect to the overall distribution of markups. Standard errors bars are also extremely tight, though none of the estimates are statistically different from 0 or each other. We can confidently reject the existence of any trend in markups over the firm life cycle.

[61] Constructed as an indicator of a firms last year in the sample

[62] Constructed by taking the average of the firm fixed effects

Figure 11: Markups over the firm life cycle: Conditional Averages



Notes: Fitted values pertain to an average firm in the year 2018, with 95% confidence intervals attained from standard errors clustered at the firm level. The reference line is constructed by taking the sum of the fixed effect for the year 2018, the average of all firm fixed effects, and the average of the age coefficients, and can thus be interpreted as the expected markup for an average firm in 2018.

This result is surprising given the variety of mechanisms that would lead to various life cycle trends in markups. It is clear however, that for all of these mechanisms, in-so-far as they exist, must be relatively small on average. With respect to the consumer market framework, there is simply no evidence of firms setting low markups early into their life cycle to build market share. While there are certainly anecdotal examples of firm managers engaging in such a strategy (or any number of alternative strategies that would lead to life cycle trends) but this simply does not bear out in the aggregate. We cannot fully rule out some variation of creative destruction leading to exit, but even removing the indicator for firm exit does not lead to any trend in markups either.

Alternative specifications and unconditional averages by sector and decade of entry are given in appendix D. As with the main results there is no evidence of a in markups over the firm life cycle in the alternative specifications once firm and time fixed effects are included, and there is no clear life cycle trend in within decade for any of the two digit NAICS industries. Appendix D also contains an estimate of the life cycle component of market shares estimated in the same manner as (23). Unsurprisingly, there is a clear trend in market shares over the firm life cycle, so firms are indeed gaining market share as they age, it it just that they are not doing so by charging lower markups.

6.3 Markup Cyclicality

A key prediction of New Keynesian (NK) business cycle models is that of counter-cyclical markups. Models in the NK tradition predict a short run decrease in markups in response to positive demand shocks. This forms the backbone of the transmission mechanism of monetary and fiscal policy in these models, where markups above their long run level mechanically leads to a negative output gap (ie real GDP below its long run level) since aggregate quantity demanded is decreasing in price. The 'stickiness' of business cycles in these models comes from a combination of 'nominal' (ie sticky prices and stick wages) and 'real' rigidities, the latter of which emerges from strategic interactions between firms; a firm adjusting their prices will not return to the long run level when its competitors are charging markups above the long run level, instead adjusting to a price that remains above the long run level.[63] This leads to an insistent output gap, and motivates the role of monetary and fiscal policy. This role arises through the idea that with prices held fixed, a positive demand shock leads to inflationary pressure which raises marginal costs and lowering markups for all firms, addressing the nominal and real rigidities in one clean motion. Such mechanisms outline the transmission mechanism in canonical stick price/sticky wage models such, as well as heterogeneous agent new Keynesian (HANK) models.[64]

This mechanism underpins the modern understanding of business cycle dynamics, however there is no consensus as to the cyclical behavior of markups in the data, with examples of evidence supporting counter cyclical markups [65] as well evidence to the contrary[66]. As noted by Nekarada and Ramey [2020] the source of disagreement ultimately comes down to the manner by which markups are measured. To my knowledge this is the first attempt to estimate the cyclicality of markups aggregated from firm level estimates, rather than relying on an aggregate measure or proxy.

As mentioned prior, PF is not well suited for such a task, as the need to estimate parameters in rolling windows threatens to obscure or otherwise dampen high frequency movements, and a demand based approach is simply infeasible at such an aggregate level. Limiting to aggregate measures opens up alternative measures of markup estimation, and there are two additional approaches to consider. The first is the case of an aggregate production function approach, implicitly modeling a representative firm and considering the implied markup of said firm, in practice this can then be calibrated via the Hall et al. [1986] generalized sollow residual

[63]See Ball and Romer [1990].
[64]See Smets and Wouters [2007] and Debortoli [2018]
[65]Ex: Galeotti and Schiantarelli [1998], Rotemberg and Woodford [1999], and Bils and Kahn [2000].
[66]Ex: Domowitz et al. [1986], Hall [2012] and Nekarada and Ramey [2020].

[67], or via the aggregate labor share of income.[68] The second approach inferred the cyclicality of markups via proxy, such as Hall [2012] and Bils and Kahn [2000][69]. Limiting to aggregate measures is appealing for several reasons: it dramatically reduces data needs, it is plausibly representative of the entire economy, and it generally allows for the use of quarterly data. There are however downsides to this approach: it is not clear what a representative firm is actually measuring[70], and relying on aggregates ties ones hands on how to aggregate up. Focusing on firm level markups allows one to experiment with different methods of aggregation as well look at individual sectors separately.

To facilitate comparison to the existing literature, I will estimate structural vector auto regressions matching the specifications in Nekarada and Ramey [2020], using aggregated cost accounting markups in place of their markup measure.[71] In particular, I follow their specification to identify supply shocks using a SVAR including the Fernald utilization adjusted TFP growth, log real GDP per capita, three-month treasury bill rates and log markups, with shocks identified via a choleski decomposition.[72] For demand shocks I follow Nekarada and Ramey [2020] monetary policy shock identifed from a SVAR including log real GDP per capita, log GDP deflator, log commodity prices, the federal funds rate, and log markups, identified via a choleski decomposition [73].

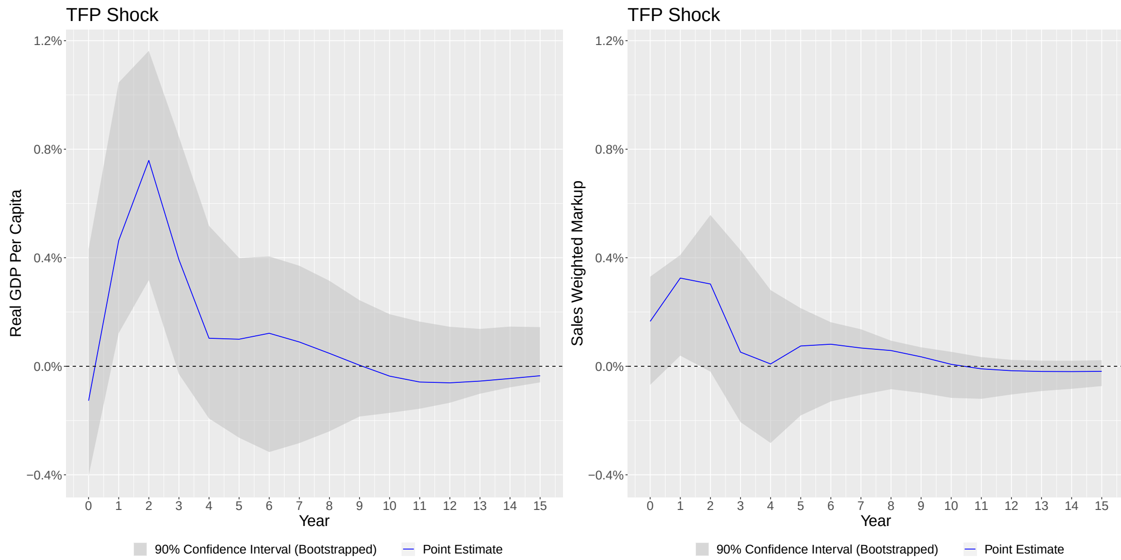
6.3.1 Markup Cyclicality: Results

Turning first to supply shocks, figure 12 gives the impulse response on real GDP per capita and sales weighted aggregate markups with respect to a one standard deviation shock in utilization adjusted TFP, estimated as outline above. Recall that NK models predict that markups should be *pro-cyclical* with respect to supply shocks, as TFP shocks lower marginal costs, thus price stickiness leads to an increase in markups [74]. In line with this figure 12 admits pro-cyclical markups of moderate size.

Turning next to demand shocks, figure 13 gives the impulse response on real GDP per capita and sales weighted aggregate markups with respect to a one standard deviation shock in the federal funds rate, estimated as outlined above. The sign of the federal funds rate is swapped so that a positive shock coincides with a decrease in the federal funds rate, thus figure 13 can be interpreted as the response to a positive monetary policy shock. Here is where NK models predict *counter-cyclical* markups, however figure 13 admits large and persistent pro-cyclical markups. This is entirely inconsistent with the transmission mechanism of NK

[67]See Haskel et al. [1995] and Marchetti [1999]
[68]See Rotemberg and Woodford [1999], Galeotti and Schiantarelli [1998], and Nekarada and Ramey [2020]
[69]There is also Domowitz et al. [1986]. which uses a sector level cost accounting approach.
[70]Recall that NK models are reliant on heterogeneous firms.
[71]Note they utilize quarterly data, while this paper is limited to annual data
[72]Ordered as above. I include the years 1955-2018, removing the COVID period, given markups behave very erratically during this period
[73]Ordered as above. I include the years 1955-2007, given the federal funds rate is uninformative in the following period.
[74]A similar mechanism holds with sticky wages

Figure 12: Impulse Response: Supply Shock



Notes: This figure shows the impulse response of real GDP per capita and sales-weighted aggregate markups to a one standard deviation TFP shock. 90% confidence intervals are constructed via bootstrapping with a block recursive structure. In line with New Keynesian models, markups are moderately pro-cyclical, rising in response to positive supply shocks.

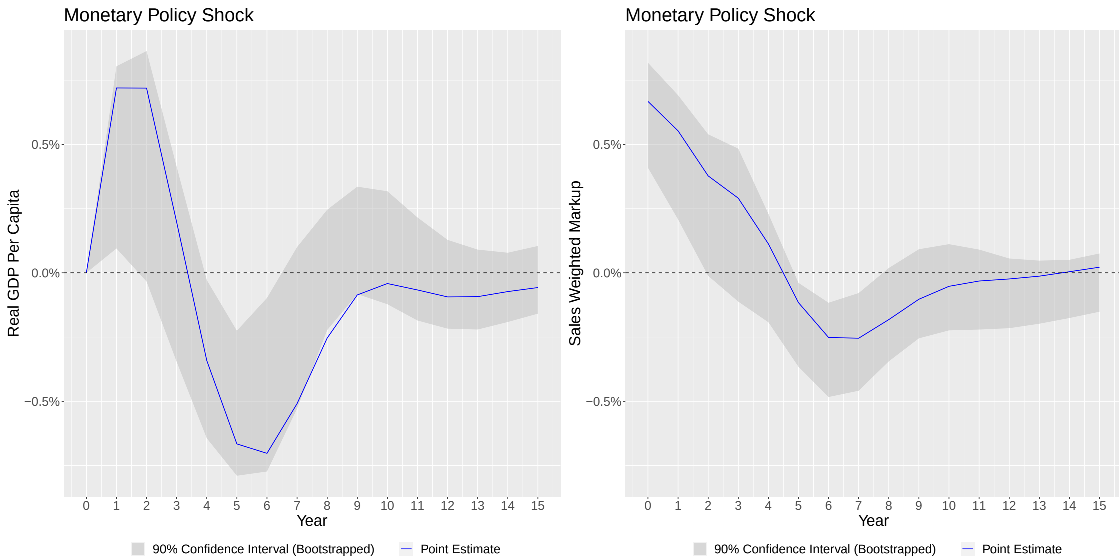
models, and further questions the accuracy of these models. It is worth noting that the sample is limited to publicly traded firms, however there is no clear reason to believe such firms should admit qualitatively different cyclically than that of the economy overall.

All above results are based on on sales weighted aggregate markups across the entire economy. One strength of this approach is it allows for alternative aggregation, appendix E includes the markup response to each shock broken down by sector. Wholesale firms see the highest degree of cyclically, while retail firms see the lowest, this is consistent with the idea that nominal rigities are highest for wholesale firms[75]. Additionally we can compare how different different forms of aggregation affect estimates, potentially shedding light on the aggregate approaches. To summarize measures of cyclically in a concise manner that allows for comparison across methods, I follow the norm in the literature and report the ratio of the areas below the impulse response functions in the first 5 years. The result can then be interpreted as the elasticity of markups with repespect to real GDP, through each of the two channels.

Table 4 reports the elasticises through each channel for several forms of aggregation, include the sector level specifications. For comparison the main specifications of Nekarada and Ramey [2020] and predictions of Smets and Wouters [2007]. Alternative forms of weighting do not qualitatively change the behavior of cyclically, and does not bring the results any closer to the aggregate approach or NK bench marks. Relative

[75] In the case of price rigidity this could be driven by contracts with customers, and in the case of wage rigidity it could be the product of unionization.

Figure 13: Impulse Response: Demand Shock



Notes: This figure shows the impulse response of real GDP per capita and sales-weighted aggregate markups to a positive monetary policy shock. 90% confidence intervals are constructed via bootstrapping with a block recursive structure. Contrary to New Keynesian predictions, markups are highly pro-cyclical, suggesting a need to rethink the role of demand-side factors in driving markup fluctuations.

Table 4: Impulse Response Elasticises

	Monetary policy	TFP
Cost Accounting Markups		
Sales Weighted μ	3.56	0.57
Mean μ	3.31	0.52
Median μ	4.44	0.38
Cost Weighted μ	4.07	0.49
Sales Weighted μ Manufacturing	3.99	0.71
Sales Weighted μ Retail	1.33	0.33
Sales Weighted μ Wholesale	4.69	1.45
Nekarada and Ramey (2020)		
CD, 1947–2017	.92	1.05
CD, 1964–2017	1.12	.51
CES, 1947–2017	1.11	2.74
CES, 1964–2017	1.28	2.27
NK Benchmark		
Smets and Wouters (2007)	-.51	.18

Notes: This table reports the elasticities of various markup measures in response to monetary policy and total factor productivity (TFP) shocks. They are constructed by taking the ratio of the area under the IRF of markups to that of TFP, for the first 5 years after a shock. Markups derived from the cost accounting approach exhibit a stronger pro-cyclical response to demand shocks, compared to supply shocks. Different forms of averaging make minimal difference, but Whole sale sees significantly higher cyclicality. Neither the directions nor scale of monetary policy reactions are inline with the NK benchmark.

to Nekarada and Ramey [2020] all results align in terms of sign, with markups pro-cyclical through both channels, the difference however is while their results suggest a higher degree of cyclically though supply shocks, cost accounting suggests a higher degree of cyclically through demand shocks. Neither the signs nor magnitudes are in line with the NK benchmark[76], but there is agreement in the idea that markups response more to demand than to supply shocks.

Collectively it seems that the use of firm level markups does not help the case of data consistency of NK models. At best the data suggests that the transmission mechanism of such models is questionable, and requires further investigation.

7 Conclusion

This paper outlines the value of the cost accounting (CA) approach to markup estimation, a data-minimal, highly transparent method. Despite its simplicity, the CA approach produces estimates that closely mirror those of the more complex production function (PF) method, which has become the standard in macroeconomic research. However, CA avoids all of the main criticisms and biases of PF, and achieves a higher signal-to-noise ratio, particularly in the sector time cross section.

The rise in U.S. markups, as well as the rise of superstar firms, is shown to b robust when using CA, lending further credibility to this narrative, despite the criticisms of PF. The component of the PF sensitive to its main criticisms and known biases does not drive its aggregate trend, to the contrary 94% of the variation in its estimates are owed to its accounting component, which is in turn highly correlated with CA, but lacks coherent micro-foundation.

Additionally, a novel test based on the Dorfman and Steiner [1954] advertising equation shows that both measures contain a signal of underlying markups, but CA possesses a higher signal-to-noise ratio. The low-structure and data-thrifty nature of the CA method also allow it to thrive in contexts where alternative methods may fail due to data constraints or problematic assumptions.

Collectively, these results suggest that the CA method is not only a reliable and effective tool for measuring markups but also holds potential for broader applications. The consistency of results across different methodologies, particularly regarding the trends in market power, suggests that the field of economics can measure markups with confidence, even when using simpler methods. The higher signal-to-noise ratio of CA further enhances its value as an accessible yet robust alternative, especially in data-limited scenarios or when dealing with biased assumptions in other approaches.

[76]It is worth noting that HANK models often produce larger movements in markups relative to represenative NK models.

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A Additional Figures

Figure 14: Markup Comparison: Sales Weighted Markups

Figure 15: Markup Comparison: Sector level Annual Averages

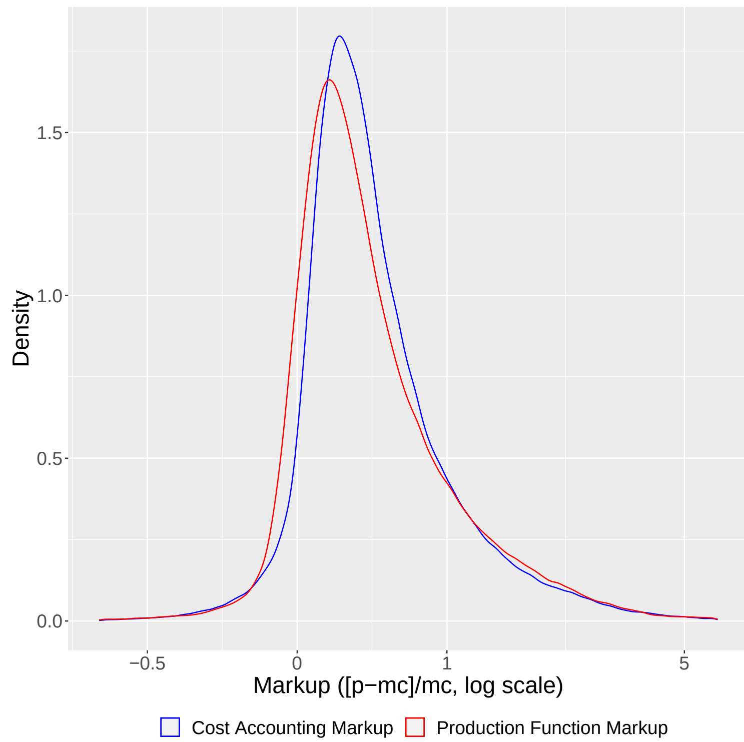

Figure 16: Markup Comparison: Full Density

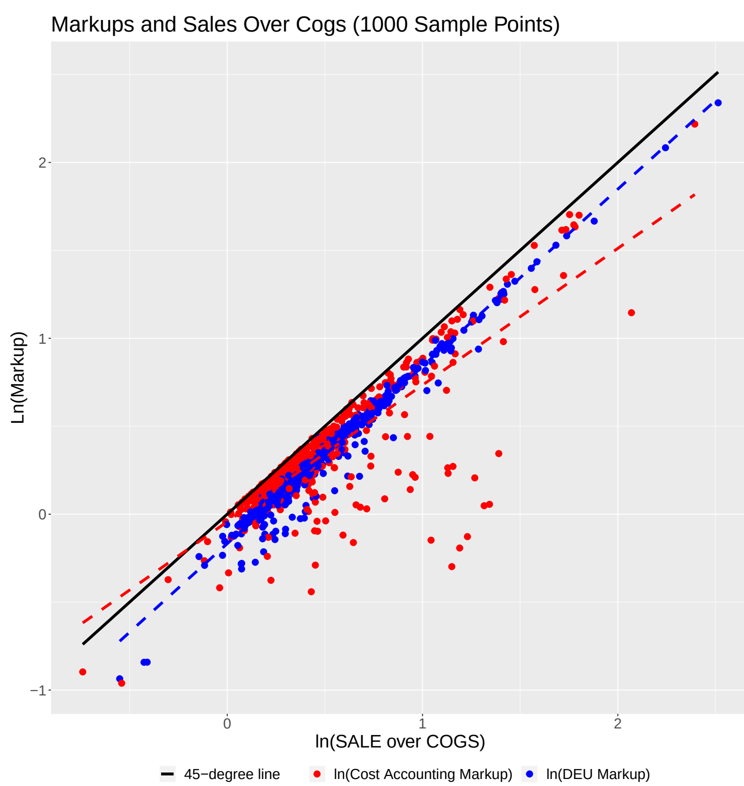

Figure 17: Markup Comparison: SALE over COGS

B Additional Markup Estimation Issues

B.1 Cost Accounting: Other Concerns

In light of observing variable cost, there are three main concerns, the validity of accounting marginal, measurement of user cost of capital, and the implications of variable utilization and adjustment costs.

The first issue comes down to a simple question of what is to be considered variable cost. On an accounting level, the division of accounting costs between COGS and XSGA is potentially motivated by industry norms, and not necessarily reflective of what costs are variable and which are fixed. Additionally, there is the question of fixed versus flexible capital. In the context of annual data, it would be unfair to assume capital stock fixed, though it is unclear that an assumption of full flexibility is much better[77].

The second issue arises from the fact that in the data, all costs are measured in units of dollars, however, accounting costs do not include the user cost of capital. That is, our measure of capital is more akin to a measure of the stock of capital than it is to its cost. As a result, we must infer capital costs by multiplying our measure of capital by a calibrated user cost of capital. Again siding on simplicity, I have chosen to adopt a simple approach to input the user cost of capital, though there is little evidence for the the value of deprecation and risk premium at an aggregate level. Advancement in measurement of this term is left as a future exercise, and will be taken as a potential driver of measurement error.

To understand the final issue, lets again turn to the model with adjustment costs given by (25). Then from (1) we see that we properly observe variable cost only if $COGS = V\left(P^v(U^v) + \Gamma(V)\right)$[78]. That is, if adjustment costs are reported as costs than the cost accounting approach properly measures variable costs, this could includes things like the cost of hiring, or on the job training. However, if the costs are not reported directly or indirectly, than the the cost accounting approach under states variable costs, such cases could include cognitive costs of hiring, or office culture implications[79]

B.2 Production Function Markups: Other Concerns

Many of the main concerns regarding the production function approach is noted in Bond et al. [2021]. In addition to the aforementioned observation of applicability of the Klette and Griliches [1996] critic, they also note that using a first stage to purge measurement error requires an AR(1) process on TFP, so while in principle one could follow the procedure allowing for a more complicated process on ω, assuming such a structure implies an additional structural error term. Furthermore Bond et al. [2021] demonstrates how any

[77] There is also the issue of rent, which is generally included in XSGA, though firm owned property appears in in PPEGT.
[78] which trivially includes the case $\Gamma = 0$
[79] Unless employees recieve additional compensation for these burdens.

effects of quality of inputs onto demand leads to further bias. Additionally, Raval [2023] demonstrates that estimating markups from different inputs yields different markup estimates, treating capital, materials, and labor as alternative variable inputs, with each admitting different markup trends.

B.3 Production Function Markup Rule With Variable input utilization

Allowing for variable utilization and adjustment costs not only affect estimates of output elasticity, but also affects marginal costs directly. To understand the implication on the production function markup rule, consider an alternative model with the following features: (i) firms face a adjustment costs with respect to the variable input V given by the function $\Gamma(V)$ which is dependent on some reference level V_r which is taken as given by the firms, (ii) firms have a choice over input utilization U^v, and (iii) variable input prices are a function of utilization, ie $P^V = P^v(U^v)$. In the simple case of labor as the variable input, we can imagine V denotes the number of employees and U^v is determined by either hourly adjustments, or an increase in the intensity of work effort. Then we are left with production technology and cost function given as:

$$Y = F(U^v V; X) \tag{24}$$

$$C(UV; X) = P^v(U^v)V + \Gamma(V) + \sum_i P_i X_i + F_C \tag{25}$$

Taking U^v and X as given at their optimal levels, the sub problem for the variable input V can be represented with:

$$\mathcal{L}(V, \lambda) = P^v(U^v)V + \Gamma(V) + \sum_i P_i X_i + \lambda(Y^* - F(U^v V; X))$$

From the first order condition with respect to V: $P(U) + \Gamma'(V) = \lambda \frac{\partial Y}{\partial V} = \lambda \frac{Y}{V} \theta_V$, ie:

$$\frac{P}{\lambda} = \theta_V \left(\frac{PY}{V\left[P^v(U^v) + \Gamma'(V)\right]} \right)$$

This then begs an important question: does $COGS$ include input adjustment costs? This is a difficult question to answer that remains out of the scope of this project, but the two most reasonable assumptions on the relation between $COGS$ and the true variable input are: (1) $COGS = VP^v(U^v)$ and (2) $COGS = V\left(P^v(U^v) + \Gamma(V)\right)$. In the first case we attain the true relation between output elasticity and the markup if and only if $\Gamma' = 0$, and in the second case we attain the true relation if and only if $\Gamma' = ae^V$ for some scalar a, and e denotes Euler's constant.

B.4 Cost Accounting Markups with Variable Input Utilization

The model with adjustment costs given by (25) also has implications on cost accounting markups through its effect on γ, though this will come down to the specific function form of F, P^v, and Γ. For example if we take F as Cobb-Douglas, $\Gamma(V) = \beta\left(V^\gamma - V_r^\gamma\right)$ and $P^v = P_r U^p$, then for a desired level of output Y^* marginal costs are given [80]:

$$\lambda = Y^{*\left(\frac{1-\rho\theta_v+\sum_i \theta_i}{\rho\theta_v+\sum_i \theta_i}\right)} \left(\frac{\alpha^{\rho\theta_v}\prod_i P_i^{\theta_i}}{\Omega}\right)^{\left(\frac{1}{\rho\theta_v+\sum_i \theta_i}\right)}$$

Where for simplicity of notation $\rho \equiv \frac{p(\gamma-1)}{p+\gamma-1} + 1$ and $\alpha \equiv pP_r^{\left(\frac{\gamma-1}{p+\gamma-1}\right)}\left(\frac{\gamma\beta}{p-1}\right)^{\frac{p}{p+\gamma-1}}$. Then the assumption of constant marginal cost requires $1 = \rho\theta_V + \sum_i \theta_i$ which is quite knife edge, and in general district from that of constant returns to scale, ie $1 = \theta_V + \sum_i \theta_i$.

B.4.1 Proof

Consider a firm with production technology and cost function given as:

$$Y = F(UV; X)$$
$$C(UV; X) = P(U)V + \Gamma(V) + \sum_i P_i X_i$$

Let $\bar{V} = UV$; $\bar{P} = P(U)V + \Gamma(V)$. Then the cost minimization problem can be decomposed into two sub problems. The first sub problem takes U, V given function of $\bar{V}$, and minimizing costs given $Y = F(\bar{V}; X)$. The second sub problem taking $\bar{V}$ as given and minimizing $\bar{P}$. The first sub problem can be represented as:

$$\mathcal{L}(\bar{V}, X, \lambda) = \bar{P}(\bar{V}) + \sum_i P_i X_i + \lambda(Y^* - F(\bar{V}; X))$$

FOC:

$$\bar{V}: \qquad \bar{P}'(\bar{V}) = \lambda F_{\bar{V}}(\bar{V}, X)$$
$$X_i: \qquad P_i = \lambda F_{\bar{X}_i}(\bar{V}, X)$$

[80] Derivation given below.

With a Cobb-Douglas structure: $Y = \Omega \bar{V}^{\theta_V} \prod_i X_i^{\theta_i}$:

$$\begin{aligned} \bar{V}: && \bar{P}'(\bar{V}) =& \lambda \theta_V \frac{Y^*}{\bar{V}} \\ X_i: && P_i =& \lambda \theta_i \frac{Y^*}{X_i} \end{aligned}$$

The second sub problem can be represented with:

$$\mathcal{L}(U, V, \lambda_2) = P(U)V + \Gamma(V) + \lambda_2 \left[\bar{V} - UV \right]$$

FOC:

$$\begin{aligned} U: && P'(U)V =& \lambda_2 V \\ V: && P(U) + \Gamma'(V) =& \lambda_2 U \end{aligned}$$

Then we have:

$$\bar{P}'(\bar{V}) = P(U) + \Gamma'(V) = UP'(U)$$

Next take $\Gamma(V) = \beta \left(V^\gamma - V_r^\gamma \right)$ and $P(U) = P_r U^p$. Then we can use the above expression along side $UV = \bar{V}$ to show:

$$\begin{aligned} \Gamma'(V) =& P'(U)U - P(U) \\ \gamma \beta V^{\gamma - 1} =& p P_r U^p - P_r U^p \\ =& (p-1) P_r U^p \implies \\ V^{\gamma-1} =& U^p \left(\frac{p-1}{\gamma} \right) \left(\frac{P_r}{\beta} \right) \implies \\ U =& V^{\left(\frac{\gamma-1}{p} \right)} \left[\left(\frac{\gamma}{p-1} \right) \left(\frac{\beta}{P_r} \right) \right]^{\frac{1}{p}} \\ \bar{V} =& VU = V^{\left(\frac{P+\gamma-1}{p} \right)} \left[\left(\frac{\gamma}{p-1} \right) \left(\frac{\beta}{P_r} \right) \right]^{\frac{1}{p}} \implies \\ V =& \bar{V}^{\left(\frac{p}{p+\gamma-1} \right)} \left[\left(\frac{\gamma}{p-1} \right) \left(\frac{\beta}{P_r} \right) \right]^{-\frac{1}{p+\gamma-1}} \\ U =& \frac{\bar{V}}{V} = \bar{V}^{\left(\frac{\gamma-1}{p+\gamma-1} \right)} \left[\left(\frac{\gamma}{p-1} \right) \left(\frac{\beta}{P_r} \right) \right]^{\frac{1}{p+\gamma-1}} \end{aligned}$$

Then:

$$
\begin{aligned}
\bar{P}'(\bar{V}) =& UP'(U) \\
=& pP_r\left(U\right)^p \\
=& pP_r\left(\bar{V}^{\left(\frac{\gamma-1}{p+\gamma-1}\right)}\left[\left(\frac{\gamma}{p-1}\right)\left(\frac{\beta}{P_r}\right)\right]^{\frac{1}{p+\gamma-1}}\right)^p \\
=& \bar{V}^{\left(\frac{p(\gamma-1)}{p+\gamma-1}\right)} pP_r^{\left(\frac{\gamma-1}{p+\gamma-1}\right)}\left(\frac{\gamma\beta}{p-1}\right)^{\frac{p}{p+\gamma-1}} \\
\equiv& \alpha\bar{V}^{\frac{1}{\rho}-1}
\end{aligned}
$$

Where for simplicity of notation $\rho \equiv \frac{p+\gamma-1}{p(\gamma-1)} + 1$ and $\alpha \equiv pP_r^{\left(\frac{\gamma-1}{p+\gamma-1}\right)}\left(\frac{\gamma\beta}{p-1}\right)^{\frac{p}{p+\gamma-1}}$. Then combining the above statement with the first order condition from the first sub problem:

$$
\begin{aligned}
\alpha\bar{V}^{\frac{1}{\rho}-1} =& \lambda\theta_V\frac{Y^*}{\bar{V}} \implies \\
\bar{V} =& \left(\frac{\theta_V}{\alpha}\lambda Y^*\right)^\rho
\end{aligned}
$$

Combing this and the other FOCs from the original sub-problem with the constrains:

$$
\begin{aligned}
Y^* =& \Omega\bar{V}^{\theta_V}\prod_i X_i^{\theta_i} \\
=& \Omega\left(\frac{\theta_V}{\alpha}\lambda Y^*\right)^{\rho\theta_V}\prod_i\left(\frac{\lambda\theta_i Y^*}{P_i}\right)^{\theta_i} \\
=& \frac{Y^{*\left(\rho\theta_V+\sum_i\theta_i\right)}\lambda^{\left(\rho\theta_V+\sum_i\theta_i\right)}\Omega}{\alpha^{\rho\theta_V}\prod_i P_i^{\theta_i}} \implies \\
\lambda =& Y^{*\left(\frac{1-\rho\theta_V+\sum_i\theta_i}{\rho\theta_V+\sum_i\theta_i}\right)}\left(\frac{\alpha^{\rho\theta_V}\prod_i P_i^{\theta_i}}{\Omega}\right)^{\left(\frac{1}{\rho\theta_V+\sum_i\theta_i}\right)}
\end{aligned}
$$

C Advertising

C.1 Additional Summary Statistics

	Accounting Variable	Full Sample		
		Mean	Median	No. of Obs
Years Since IPO		11.95	8	257,808
Years to Exit		11.98	8	262,546
Cost of Goods Sold	COGS	1,453,652	93,523	280,513
SG&A	XSGA	387,750	32,618	280,513
Capital	PPEGT	1,641,505	63,064	280,513
Revenue	SALE	2,174,914	159,549	280,513
Advertising	XAD	71,939	2,593	97,521
Advertising Share	xad	0.04	0.02	97,521
Cost Accounting Markup	$\tilde{\mu}-1$	0.66	0.34	278,704
		Advertising Balanced Sample		
	Accounting Variable	Mean	Median	No. of Obs
Years Since IPO		12.1	9	89,146
Years to Exit		10.94	8	89,654
Cost of Goods Sold	COGS	1,557,160	93,418	96,098
SG&A	XSGA	580,151	48,929	96,098
Capital	PPEGT	1,571,614	50,496	96,098
Revenue	SALE	2,526,687	173,340	96,098
Advertising	XAD	71,665	2,589	96,098
Advertising Share	xad	0.03	0.02	96,098
Cost Accounting Markup	$\tilde{\mu}-1$	0.89	0.48	96,098

Table 5: Summary Statistics

Table (3) provides summary statistics of COMPUSTAT data across the sample from 1955-2023, measured in thousands of USD and deflated to 2010 dollars using GDP deflator. The sample used in the previous section, labeled Sample A includes all observations with data on COGS, PPEGT, and SALE (as well as the aforementioned trimming).

Sample B further limits to firms that report non-negative values for XAD, so that (4) and (5) can be estimated, and is trimmed by 1% at the top and bottom of the ratio of XAD/SALES. The advertising balanced sample contains observations for 18 of the 19 2 digit NAICS industries, losing only "Public Administration" which consists of just 2 observations in the full sample.

Firms in the balanced sample have slightly higher revenue, approximately equal levels of variable costs, a higher level of fixed costs, and a slightly lower capital stock. Furthermore observations in both sample have similar measures of "Years since IPO" and "Years to exit" which denote how long the firm has been in the sample, and how much longer they remain in the sample respectively. Differences in Sales, fixed costs and level of capital can potentially driven in part by firms who engage more heavily in advertising being more inclined to report advertising expenditure, as firms with larger markups should optimally engage in a higher level of marketing[81]. For this reason, the measure of advertising response elasticity can be interpreted as the elasticity among firms who engage in a level of advertising that they deem notable.

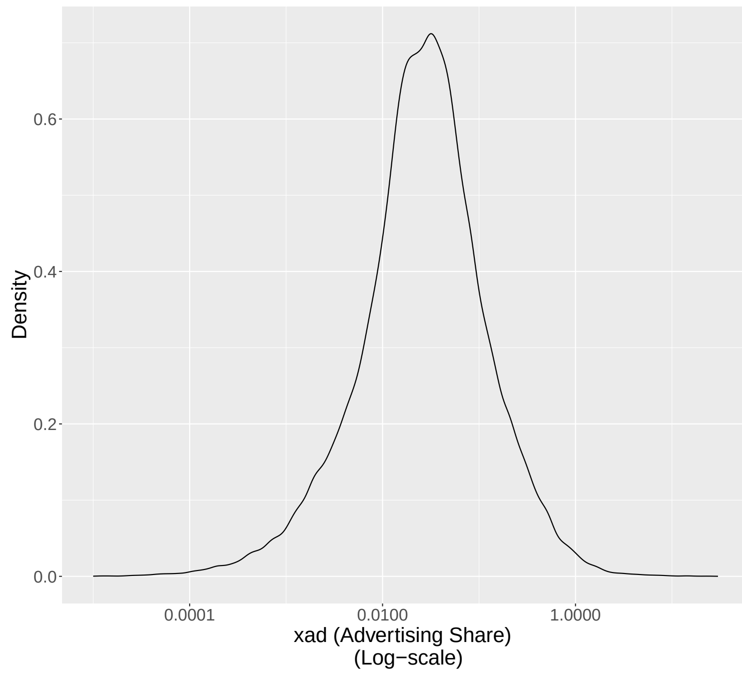

Figure 18: Advertising Share Density

Figure 18 presents the distribution of the advertising share among the firms that report advertising. It is worth noting that prior to trimming, just 1.3% of firms that report advertising report a level of precisely 0, which lends further credence to the interpretation that firms who report advertising are firms who engage in a higher level of advertising.

Figure 19 presents the distribution of markups as measured by the cost accounting approach, separate between firms who report advertising and the full sample. Conditioning on firms that report markups shifts the distribution to the right, but does not seem to have a large effect on the overall shape of the distribution. The rightward shift is consistent with the idea that firms reporting XAD engage in higher levels of advertising, since by Theorem 1 we expect these to be firms with higher markups.

[81] Note that for the relation with XSGA, advertising is mechanically a component of SGA, even if we assume firms who do not report XAD engage in 0 advertising, this discrepancy is not large enough to fully explain the difference.

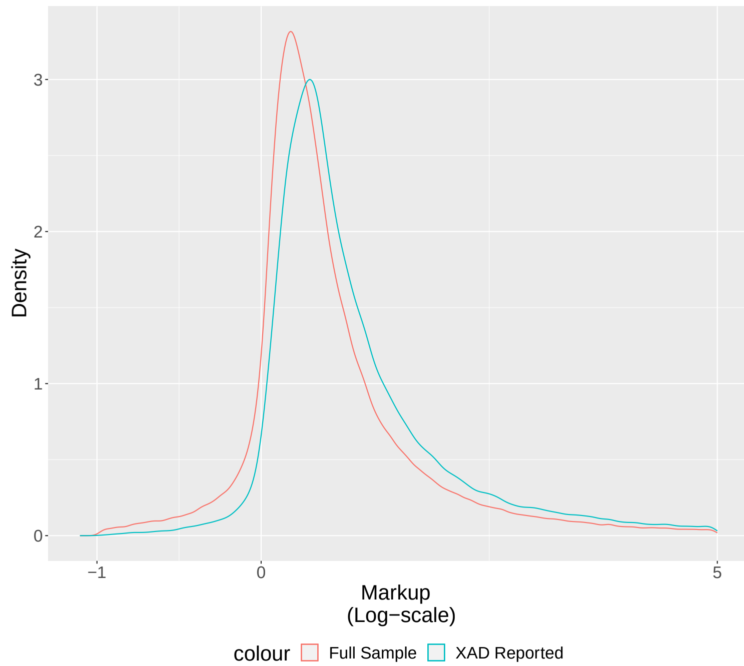

Figure 19: Markup Density

C.2 Proof of Theorem 2

Before showing the result lets first motivate the use of $-\log\left(1-\tilde{xad}\right)$. Combining (21) and (17):

$$\frac{1}{1-\tilde{xad}_i} = \frac{1}{1-\left(1-\frac{1}{\mu_i}\right)\eta_{xad,i}e^{\epsilon_i^a}e^{\epsilon_i^x}e^{-\epsilon_i^s}}$$

Then taking logs and taylor expanding around around $\eta_{xad,i}e^{\epsilon_i^a}e^{\epsilon_i^x}e^{-\epsilon_i^s}=1$:

$$\begin{aligned}
-log\left(1-\tilde{xad}_i\right) =& \log\left(\frac{1}{1-\left(1-\frac{1}{\mu_i}\right)\eta_{xad,i}e^{\epsilon_i^a}e^{\epsilon_i^x}e^{-\epsilon_i^s}}\right)\\
=& \log(\mu_i)+\left(\frac{\eta_{xad,i}e^{\epsilon_i^a}e^{\epsilon_i^x}e^{-\epsilon_i^s}-1}{\eta_{xad,i}e^{\epsilon_i^a}e^{\epsilon_i^x}e^{-\epsilon_i^s}\left(\mu_i-\eta_{xad,i}e^{\epsilon_i^a}e^{\epsilon_i^x}e^{-\epsilon_i^s}\right)}\right)+o\left(\left|\left|\eta_{xad,i}e^{\epsilon_i^a}e^{\epsilon_i^x}e^{-\epsilon_i^s}-1\right|\right|^2\right)\\
\equiv& log(\mu_i)+\epsilon_i^{xad}
\end{aligned} \tag{26}$$

Now note that ϵ_i^{xad} is unlikely to be mean 0, and is correlated with μ, η_{xad}, ϵ^a, ϵ^x and ϵ^s by construction, but uncorrelated with ϵ^{CA} and ϵ^{PF}. Then by (19), (22) and (26) note that the square correlation coefficient between $log\left(\hat{\mu}_i^m\right)$ and $-log\left(1 - \tilde{xad}\right)$ is given by:

$$
\begin{aligned}
R^2_{X,M} \equiv & \frac{cov\left(-log\left(1-\tilde{xad}\right), log\left(\hat{\mu}^m\right)\right)^2}{\left[var\left(-log\left(1-\tilde{xad}\right)\right)\right]\left[var\left(log\left(\hat{\mu}_i^m\right)\right)\right]} \\
= & \frac{\left[cov\left(\epsilon^{xad}, log(\mu)\right) + cov\left(\epsilon^{xad}, \epsilon^s\right)\right]^2}{\left[var\left(log(\mu) + \epsilon^{xad}\right)\right]\left[var\left(log(\mu)\right) + var(\epsilon^s + \epsilon^m)\right]} \\
= & \left(\frac{1}{1 + \frac{var(\epsilon^s+\epsilon^m)}{var(log(\mu))}}\right) \frac{\left[cov\left(log(\mu) + \epsilon^{xad}, log(\mu)\right) + cov\left(\epsilon^{xad}, \epsilon^s\right)\right]^2}{\left[var\left(log(\mu) + \epsilon^{xad}\right)\right]\left[var\left(log(\mu)\right)\right]} \\
= & \left(\frac{1}{1 + \frac{1}{SR(\hat{\mu}^m)}}\right) \frac{\left[cov\left(log(\mu) + \epsilon^{xad}, log(\mu)\right) + cov\left(log(\mu) + \epsilon^{xad}, \epsilon^s\right)\right]^2}{\left[var\left(log(\mu) + \epsilon^{xad}\right)\right]\left[var\left(log(\mu)\right)\right]}
\end{aligned} \tag{27}
$$

Thus:

$$
\frac{R^2_{X,CA}}{R^2_{X,PF}} = \frac{1 + \frac{1}{SR(\hat{\mu}^{PF})}}{1 + \frac{1}{SR(\hat{\mu}^{CA})}}
$$

Note that squared correlation coefficients are unaffected by linear transformation. Thus the result holds when adding constant within measure bias terms β^m and α^m:

$$
log\left(\hat{\mu}_i^m\right) = \beta^m\left(log\left(\mu_i\right) + \epsilon_i^s + \epsilon_i^m\right) + \alpha^m
$$

With the above $SR(\hat{\mu}^m) = \frac{var(log(\mu))}{var(\epsilon^s+\epsilon^m)}$ still denotes the signal to noise ratio, attain a value of 0 in the limit as $\beta^m \to 0$ while holding $\beta_m\left(var(\epsilon^s + \epsilon^m)\right)$ constant. Lastly from (27) note that as $var(\epsilon^s + \epsilon^m) \to \infty$, $R^2_{X,M} \to 0$, thus $R^2 \neq 0$ serves as a direct test of relevancy of markup measure m.

C.3 Advertising Test: Robustness

Dependent Variables:	$-log(1-xad)$				xad			
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables								
Constant	-0.0519**	0.0102			0.0026	0.0242***		
	(0.0206)	(0.0108)			(0.0090)	(0.0076)		
$log(\hat{\mu}_{CA})$	0.0563***		0.0231***					
	(0.0133)		(0.0024)					
$log(\hat{\mu}_{PF})$		0.0767**		0.1049***				
		(0.0323)		(0.0118)				
$1-\frac{1}{\hat{\mu}_{CA}}$					0.1031***		0.1113***	
					(0.0296)		(0.0089)	
$1-\frac{1}{\hat{\mu}_{PF}}$						0.0350		0.1180***
						(0.0294)		(0.0164)
Fit statistics								
Observations	16	16	16	16	19	19	19	19
R^2	0.56134	0.28644	0.31915	0.19091	0.41586	0.07683	0.38037	-0.55070
Adjusted R^2	0.53001	0.23547	0.31915	0.19091	0.38150	0.02252	0.38037	-0.55070

IID standard-errors in parentheses

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 6: Advertising Test: Horse Race

Dependent Variables:	xad				$log(xad)$			
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables								
Constant	0.0208***	0.0265***			-3.750***	-3.747***		
	(0.0008)	(0.0006)			(0.0299)	(0.0264)		
$1-\frac{1}{\mu_{CA}}$	0.0351***		0.0320***					
	(0.0027)		(0.0028)					
$1-\frac{1}{\mu_{PF}}$		0.0199***		0.0245***				
		(0.0017)		(0.0021)				
$log\left(1-\frac{1}{\mu_{CA}}\right)$					0.3658***		0.4421***	
					(0.0208)		(0.0201)	
$log\left(1-\frac{1}{\mu_{PF}}\right)$						0.3105***		0.3387***
						(0.0151)		(0.0146)
Fixed-effects								
Industry			Yes	Yes			Yes	Yes
time			Yes	Yes			Yes	Yes
Fit statistics								
Observations	89,837	89,837	88,968	88,968	85,977	82,753	85,187	82,136
R^2	0.02023	0.01289	0.06867	0.06670	0.03263	0.03743	0.14789	0.14067
Within R^2			0.01525	0.01316			0.04470	0.04317

Clustered (Firm level) standard-errors in parentheses

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 7: Advertising Test: Alternative Specifications

D Markups Over the Firm Life Cycle

Dependent Variable:	Markup						
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Variables							
Constant	0.6002***	0.1369***					
	(0.0057)	(0.0108)					
Firm Age	-0.0034***	-0.0077***	-0.0078***	-0.0061***	6.89×10^{-5}		
	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)		
Time		0.0121***					
		(0.0003)					
$Age \times I[Age < 6]$						0.0003	8.48×10^{-5}
						(0.0010)	(0.0010)
$Age \times I[5 < Age < 11]$						-0.0015**	-0.0018***
						(0.0007)	(0.0007)
$Age \times I[10 < Age < 20]$						-0.0008*	-0.0010**
						(0.0005)	(0.0005)
$Age \times i[Age > 20]$						-3.6×10^{-5}	-0.0002
						(0.0004)	(0.0004)
Fixed-effects							
Decade			Yes	Yes	Yes	Yes	Yes
Industry				Yes			
Firm					Yes	Yes	Yes
Exit indicator							Yes
Fit statistics							
Observations	234,968	234,968	234,968	232,161	234,968	234,968	234,968
R^2	0.00268	0.05231	0.05511	0.15457	0.78440	0.78445	0.78447
Within R^2			0.01357	0.00897	2.66×10^{-7}	0.00026	0.00036

Clustered (Firm) standard-errors in parentheses

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

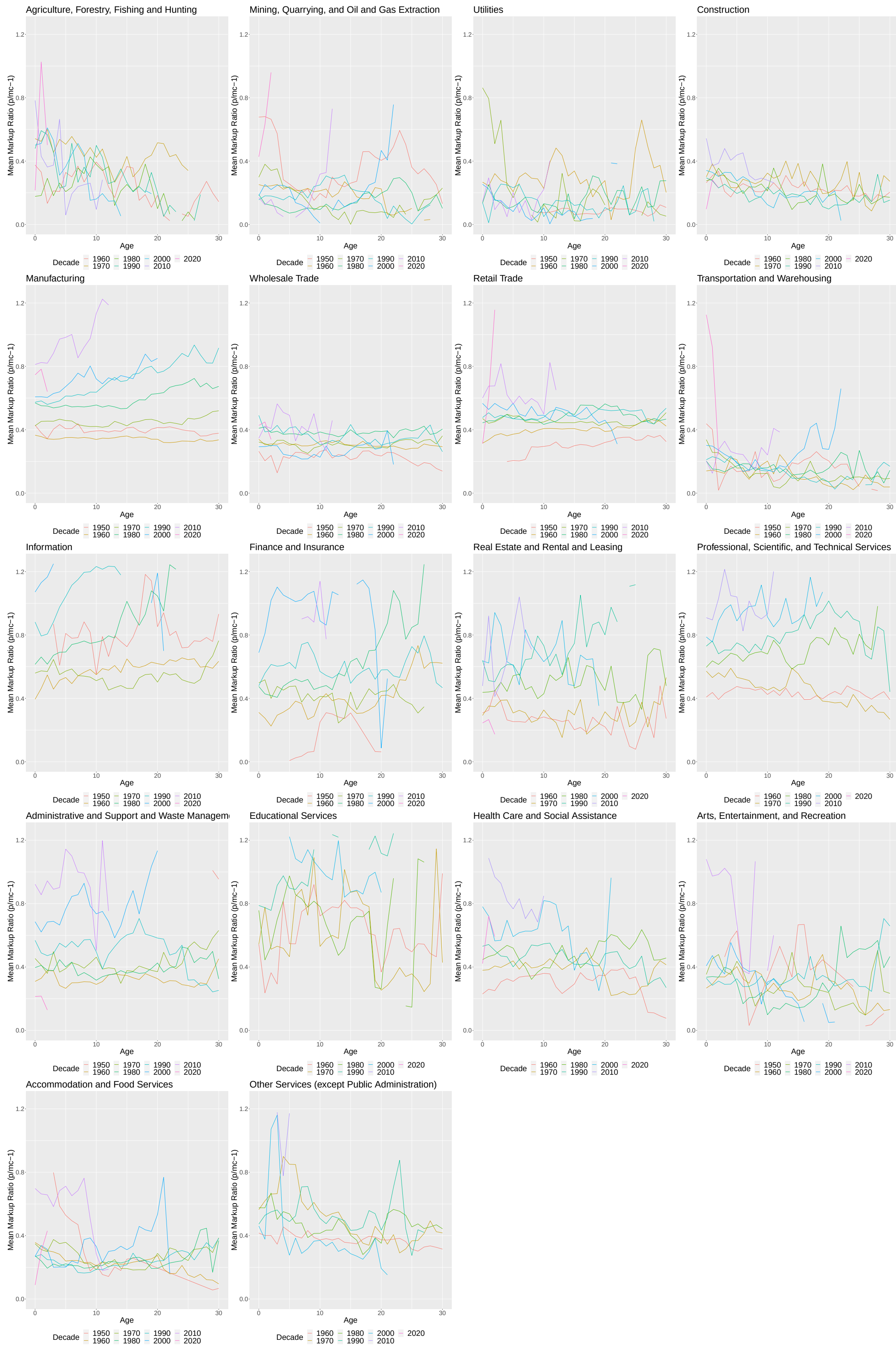

Figure 20: Firms After IPO By Sector and Decade

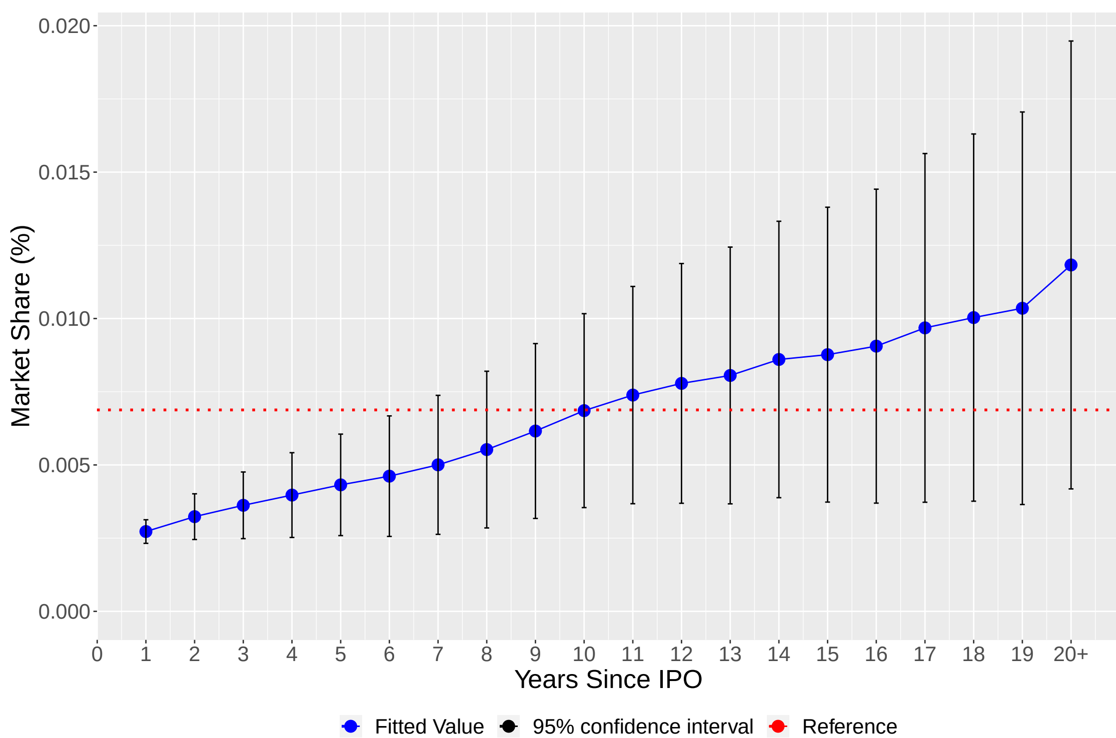

Figure 21: Conditional Average Market Share

E Markup Cyclically: Additional Figures

Figure 22: Markup Response to Supply Shocks by Sector

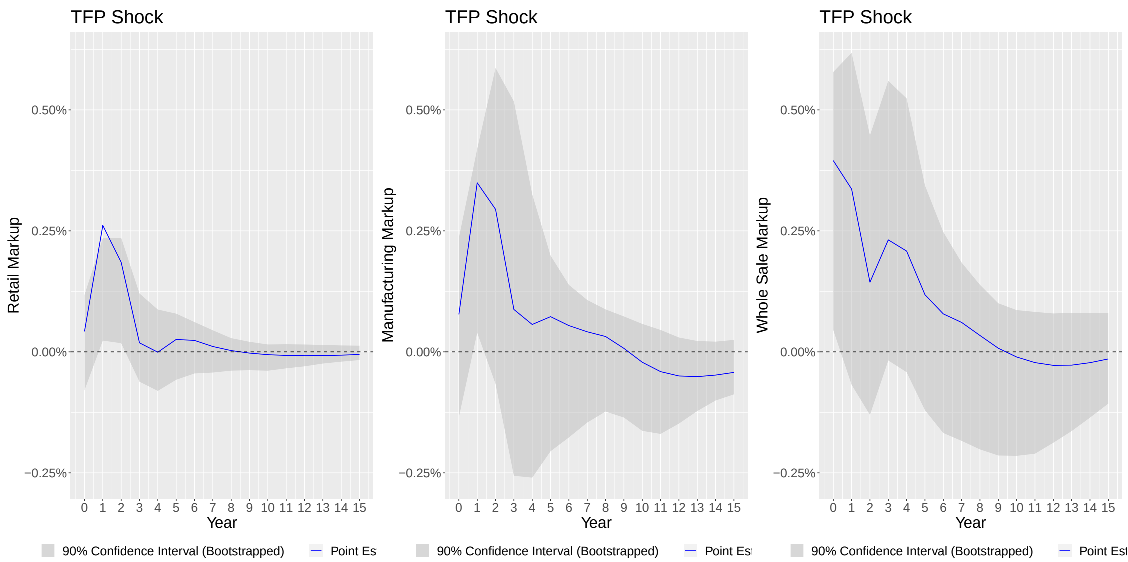

Figure 23: Markup Response to Demand Shocks by Sector