Cost Structure and Sticky Costs

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Abstract

Beginning with Anderson, Banker and Janakiraman (2003), the accounting literature attributes the asymmetric cost response to activity changes or sticky costs as resulting from managerial choices. Using a simulated dataset that excludes any role for managerial actions, we investigate whether cost structure alone could yield regression estimates similar to those the literature interprets as consistent with sticky costs. We show that either of two aspects of cost structure — fixed costs or scale diseconomies in variable costs — results in regression estimates consistent with sticky costs. We employ an algebraic model to offer intuition for these effects and to develop suggestions for how future research might control for the effects of cost structure. For a sample of COMPUSTAT firms, we show that the suggested controls provide an alternate explanation for results usually interpreted as reflecting current period managerial actions.

Key words: Sticky costs, cost structure, simulations

JEL Codes: M41, L2
I. Introduction

The accounting literature attributes findings of an asymmetric cost response to activity changes, or sticky costs (Anderson, Banker and Janakiraman 2003, hereafter ABJ) as resulting from short-term managerial choices. In this paper, we argue that mechanical effects stemming from cost structure (fixed costs and scale diseconomies in variable costs) provide an alternate explanation for such findings. We offer suggestions for how to control for these effects and show that the controls alter inferences.

Following Anderson, Banker and Janakiraman (ABJ 2003), many papers have examined the phenomenon of sticky costs. Using data from COMPUSTAT, ABJ regresses the change in Sales, General and Administrative (SGA) costs on changes in revenue. The innovation is to let the response coefficient differ based on the sign of the change in revenue. ABJ reports that the cost response to a decline in activity (measured as revenue) is reliably smaller than the cost response to an increase in activity (i.e., costs are sticky). ABJ interprets this difference as the outcome of deliberate short-run managerial actions, arguing that the difference in responses is consistent with managers considering the transaction costs of altering resource levels and the permanence of the demand decline in resource acquisition and deployment decisions.

ABJ spurred considerable follow up work because it offers a method of using a large sample data to gain insight into managerial decisions. A growing body of research documents that factors such as capacity utilization (Balakrishnan, Petersen and Soderstrom 2004), the criticality of the cost (Balakrishnan and Gruca 2008), incentives to manage earnings (Dierynck and Renders 2009), and the pattern of sales changes (Banker, Ciftci and Mashruwala 2008) moderate the asymmetric response. The sticky cost model has been questioned in recent years, however. Among others (e.g., Weiss 2009; Balakrishnan and Soderstrom 2009), Anderson and Lanen (AL 2009) does not find evidence of sticky costs consistently across cost categories and raises conceptual questions about whether ABJ’s approach allows us to draw any conclusion about managerial behavior. Our methodologically-oriented study demonstrates that firm-specific cost struc-

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1 There are two other broad groups of papers in this research area. Papers in the first group seek to generalize the finding. For example, Anderson, Banker, Chen and Janakiraman (2004), Banker and Chen (2006a) and Stelianos, Thomas and Calleja (2006) examine variations in adjustment costs across labor markets. While these papers focus on selling and administrative expenses, Subramaniam and Weidemier (2003) examines cost-of-goods-sold and find stickiness in that expense as well. Papers in the second group examine implications for firm value (Anderson, Banker, Huang and Janakiraman 2007; Banker and Chen 2006b) and analyst forecasts (Weiss 2009).
ture as well as the general economic climate could be important omitted variables in extant analyses of sticky costs.

Our research is motivated by the observation that most if not all of the work in this area rests on the unstated belief that examining differences in costs allows the researcher to focus on costs *controllable* by the manager over the relevant time period (usually a year). Moreover, prior works implicitly assume a linear cost structure and pay limited attention to issues of scale economies. We examine the validity of these implicit assumptions by simulating datasets for different cost structures, a feature that a manager *cannot control* in the short run. By design, short-run managerial influences are absent in our simulated data – the specified cost function yields the cost for any given level of activity. Further, because of its stark nature, the dataset avoids econometric issues identified by AL (2009). We then estimate the standard models to examine whether cost structure alone can result in asymmetric cost responses to changes in activity.

The first part of our three-pronged approach is to establish that cost structure influences the asymmetry in cost response. The intuition for why we expect such a relation is straightforward. The estimate of the cost response coefficient in the standard sticky cost regression is the percent change in costs over the percent change in revenues. With a linear cost function, this value is the same as the unit variable cost over total cost per unit, at the current level of sales. However, this ratio increases in sales because fixed cost per unit (which appears in the denominator) becomes smaller as sales activity increases. That is, observations with an activity increase bias the regression coefficient upwards, while observations with a decline in activity provide a downward bias. An analysis that estimates separate coefficients therefore is likely to find a smaller coefficient for observations that are sales declines than for observations that represent increases in sales activity. We note that managerial actions conforming to the sticky cost hypothesis also produce the same effect; a larger change in discretionary costs when activity increases.

Managers can acquire/dispose capacity resources, which actions change the level of fixed costs. They also could update product mix and prices, which change influences both activity volume and revenue. With real-world data, these actions make it difficult to isolate the effect of cost structure alone on the response to changes in activity even if we are willing to assume that managers’ decisions do not lead to sticky costs. In contrast, the deliberate absence of any kind of a short-run managerial decision in our simulated data permits a clean test of the relation between cost structure and sticky costs. We normalize prices to unity, thereby equating the quantity of activities and revenue. Our data also has the property that costs and revenues always move in the same direction. Finally, confounds such as the time available to adjust costs to changing activity levels or beliefs about the permanence of the demand shock, competitiveness of the output market, product portfolio and adjustment costs are not relevant.
versus when activity decreases induces a similar effect on the coefficient estimates. Thus, we view cost structure as an alternate explanation for observed results.

We verify our intuition by considering data generated using a linear cost model with fixed and variable costs that excludes any role for short-term managerial actions. Consistent with the above intuition, estimating the standard sticky cost regression with these data yields coefficients that indicate an asymmetric cost response to changes in activity – the response to a decline in sales activity is smaller than the response to an increase; i.e., costs are sticky. This result is robust to cost functions with step-costs, alternate regression specifications, and to variations in gross margin and dispersion of cost structure within the sample. In sum, our primary argument is that research designs need to rule out mechanical relations as a viable alternate explanation for findings of sticky costs.

In extensions, we document the following:

- Increasing the proportion of fixed costs increases the degree of asymmetry (defined as the ratio of the two responses) in the cost response. Indeed, the degree of asymmetry reliably differs across suitably chosen samples of firms indicating that the proportion of fixed costs could be an omitted variable in cross-sectional tests of cost stickiness.

- The proportion of observations with declines in activity affects the estimate of stickiness, meaning that industry classification and/or time could be omitted variables in studies that compare stickiness across firms or over time. Economic growth rates might differ along these dimensions, influencing the proportion of observations with declines in sales activity.

- Fixed costs induce scale economies by spreading the cost over larger volumes. Scale economies can also occur (e.g., due to learning or congestion costs) in variable costs. We algebraically show that diseconomies of scale would yield estimates that are consistent with sticky costs and that the estimates would indicate anti-sticky behavior when scale economies exist. Using simulations, we find that the effect of fixed costs dominates the effect of scale economies for the practically-relevant values we consider.

These results again emphasize the importance of controlling for cost structure (i.e., fixed costs and scale economies) and economic climate before drawing inferences about whether deliberate short-run managerial decisions contribute toward the asymmetry in cost response.4

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4 Admittedly, cost structure is an outcome of managerial decision in the previous period(s). However, the focus to the sticky cost literature is on ongoing managerial discretion in the current period. In the final
The second part of study offers suggestions for suitable controls for the influence of cost structure and economic climate. Current approaches include using similar firms in the analysis (Balakrishnan and Gruca 2008), using time-series data to develop a firm-specific measure (section 3.4 in ABJ 2003; Weiss 2009), or employing controls such as asset intensity and GDP growth (Dierynck and Renders 2009). These approaches almost exclusively assume that cost structure is constant across the sample firms or over time. In contrast, our analysis indicates that corrections for fixed costs should occur in the dependent variable and that corrections for industry- and time-specific effects must be specified as interaction terms.

The final part of our approach is to consider the effect of the suggested controls on inferences drawn from analysis of reported financial data. We begin by replicating the results in ABJ using data from COMPUSTAT. We then find that a correction for fixed costs (i.e., dividing cost changes by lagged sales or other measures of size rather than lagged costs) alone weakens the asymmetry in response but does not eliminate it. However, implementing the suggested control for scale economies (i.e., using Fama-Macbeth regressions, sorting observations by industry), either by itself or in conjunction with the control for fixed costs, eliminates the finding of an asymmetric response.

Our work has significant implications for the literature on sticky costs. First, it provides evidence that works that focus on short-run managerial incentives (e.g., Balakrishnan and Gruca 2008; Banker and Chen 2006b) might be omitting a plausible alternate explanation. Second, our analysis suggests deeper investigation of works (Banker and Chen 2006a; Weiss 2009) that link sticky costs to analyst forecasts and market returns. In this line of enquiry, the question becomes whether analysts employ good approximations of the underlying cost structure when predicting earnings. We can test this effect by, for example, forming portfolios that vary systematically on dimensions such as the magnitude of fixed costs and scale economies.

The remainder of this paper is organized as follows. Section 2 develops the intuition for how and why cost structure and industry characteristics might affect the response of costs to changes in sales. Section 3 describes the procedures we use to construct our simulated data. Section 4 reports tests and results and section 5 examines the suitability of our proposed controls. Section 6 concludes.
II. Cost Structure and Asymmetry in Cost Response

To investigate asymmetry in cost responses, ABJ regress the log of the change in costs on the log of change in revenues and allow the response coefficient to differ based on the sign of the change in revenue. The basic model ABJ estimate on panel data is:

\[
\log \left( \frac{TC_{i,t+1}}{TC_{i,t}} \right) = \alpha + \beta_1 \times \log \left( \frac{S_{i,t+1}}{S_{i,t}} \right) + \beta_2 \times \text{dec} \times \log \left( \frac{S_{i,t+1}}{S_{i,t}} \right) + \varepsilon. 
\]

(1)

where \( TC_{i,t} \) is total SGA cost and \( S_{i,t} \) is the sales of firm \( i \) in period \( t \), and \( \text{dec} \) is an indicator that assumes value = 1 if sales decline from period \( t \) to period \( t+1 \), and 0 otherwise. In this equation, the coefficient \( \beta_1 \) measures the percentage change in costs associated with a 1% increase in sales activity (ABJ, 52). The sum of the coefficients, \( \beta_1 + \beta_2 \), measures the percentage change in costs associated with a 1% decrease in sales activity. The sticky cost hypothesis is that the change in costs when sales increase differs from the change when sales decrease. That is, \( \beta_2 < 0 \) if the sticky cost model holds.

To develop intuition about how cost structure affects the estimates of \( \beta_1 \) and \( \beta_2 \), begin by considering a single firm with two periods of activity. (We later generalize to a setting with many firms and periods. Until then, we suppress the firm subscript.) Consider a firm with the cost structure, \( TC_t = FC + VC \times S_t \) where \( TC_t \) is total SGA cost and \( S_t \) is sales activity in period \( t \), \( FC \) is fixed cost and \( VC \) is the variable cost ratio. The lack of a time subscript on \( FC \) and \( VC \) emphasizes that cost structure is inter-temporally constant for any given firm. Normalize prices to unity so that there is no distinction between activity volume and revenue. With this setup, the percent change for costs and revenues period-over-period is:

\[
\Delta C_t = \frac{VC \times (S_{t+1} - S_t)}{FC + VC \times S_t} \text{ and } \Delta S_t = \frac{(S_{t+1} - S_t)}{S_t}. 
\]

Using the Taylor series approximation to the log function and considering only the first term in each of the expansions, dividing the log of the change in costs by the log of the change in revenue is equivalent to considering percentage changes. For analytic simplicity, we therefore develop a model in percentage changes. We replicate empirical results under both the log and percent change specifications.

Following ABJ and the literature, we consider year-over-year changes. As reported in table 2 of ABJ, using two, three or four-year periods for calculating changes reduces and eventually eliminates the findings of stickiness in costs. While increasing controllability of costs is one interpretation, ABJ interprets the finding as the outcome of deliberate short-term managerial actions.
Consider reverting to equation (1) and suppressing the potential for an asymmetric response (i.e., set $\beta_2 = 0$). Of course, this change does not alter the interpretation of the slope coefficient (i.e., $\beta_1$ in equation (1)) as the percent change in cost over the percent change in sales. For our linear cost equation, we calculate this ratio as:

$$\text{CstSales}(S_t, \text{Linear}) = \frac{\Delta C_t}{\Delta S_t} = \frac{VC \times S_t}{FC + VC \times S_t}.$$ 

This value is the proportion of variable costs at the current level of sales. Of particular interest, as noted by footnote 3 in ABJ, the value of $CstSales(S_t)$ is independent of the direction of change as $S_{t+1}$ is not a factor. Thus, when we allow for asymmetry, any observed difference in the cost response seems attributable to short-term managerial decisions. (Consistent with our analysis, ABJ also note that $\beta_1 < 1$ if fixed costs are positive.)

The central intuition for our analysis is that the proportion of variable costs is not constant in revenue (see Figure 1). To see this, rewrite

$$\text{CstSales}(S_t, \text{Linear}) = \frac{VC}{FC + VC}.$$ 

By inspection, the ratio of variable to total costs (now calculated per sales dollar) increases in revenue because we spread fixed costs over larger volumes. Formally, $\frac{\partial \text{CstSales}}{\partial S_t} > 0$ and

$$\frac{\partial^2 \text{CstSales}}{\partial S_t^2} < 0; \text{CstSales}(S_t) \text{ is monotonically increasing in } S_t \text{ at a decreasing rate.}$$

(Figure 1)

For intuition about how these properties of $CstSales(S_t)$ affect the estimated cost response to an increase versus a decline in activity, suppose that our sample comprises $F$ identical firms. That is, all $F$ firms have the same cost structure and sales volume, meaning that their responses lie on the same point on the line that plots the proportion of variable costs against sales. Further, assume that all of the firms experienced a 10% change in sales from period $t$ to period $t+1$, except some proportion $p$ has a decline in sales rather than an increase. The next year (i.e., from $t+1$ to $t+2$), all of the firms have a 10% increase in sales.
Suppose we estimate the following equation on the resulting panel dataset that has \( F \) firms and two changes for each firm:

\[
\Delta C_{it} = \alpha + \beta_1 \times \Delta S_{it} + \varepsilon.
\]

Consider the estimate for \( \beta_1 \).

- If \( p = 0 \), we have \( F \) responses estimated at \( S_t \) and \( F \) responses estimated at \( S_t \times 1.1 \). The estimate for \( \beta_1 \) (for the sample of \( 2F \) observations) will therefore be the average of these two values of the proportion of variable costs at the two levels of sales (\( S_t \) and \( S_{t+1} \)).
- If \( p = 1 \), we have \( F \) responses at \( S_t \) and \( F \) responses at \( S_t \times 0.9 \). The estimate for \( \beta_1 \) will again be the average of these two values.

Notice that the estimated value of \( \beta_1 \) with \( p = 1 \) will be smaller than the estimated value when \( p = 0 \) simply because \( CstSales'(S_t) > 0 \). From this observation, we conclude that the greater the proportion of observations with a decline in activity, the greater the downward bias introduced in the estimate of \( \beta_1 \). It follows that if \( 0 < p < 1 \) and if we separately estimate the bias by introducing a separate term for the decline firms, the incremental change would show up as a negative value. Relating this intuition back to the panel data set used in the literature, we argue that the presence of fixed costs negatively biases the estimated coefficient of \( \beta_2 \) (the measure for stickiness) away from zero, rejecting the null hypothesis of no asymmetry.

**Changes in Capacity Costs**

For additional insight, consider the case in which the firm can alter the levels of some capacity resources within a year. Let \( DCC_{t,t+1} \) represent the change in discretionary capacity costs from period \( t \) to period \( t+1 \). Then, we have:

\[
\Delta C_t = \frac{DCC_{t,t+1} + VC \times (S_{t+1} - S_t)}{FC + VC \times S_t} \quad \text{and} \quad \Delta S_t = \frac{(S_{t+1} - S_t)}{S_t}.
\]

With this change, the response coefficient becomes:

\[
\text{CstSales} = \frac{VC}{FC + VC} + \frac{\left( \frac{DCC_{t,t+1}}{S_{t+1} - S_t} \right)}{\frac{FC}{S_t} + VC}.
\]

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7 We use firm subscripts in the regression specification to emphasize the use of a panel data set. Also, the use of an intercept here is purely for econometric reasons; the estimate of \( \alpha \) does not have an economic interpretation.
The first term corresponds to the case with no change in fixed costs (see equation 2 which sets $DCC_{t,t+1} \equiv 0$). As argued earlier, this term is increasing in $S_t$, biasing estimates. Thus, for the ratio of (controllable cost / total cost) to flatten out and for regression estimates to be free of the bias due to fixed or non-controllable costs, the second term must be decreasing in $S_t$. That is, the change in “fixed” capacity costs must become proportionately smaller as sales activity increases. But, such a change is not consistent with posited behavior. If managers behave as posited by the sticky cost hypothesis, for a given change in sales, $DCC^+_{t,t+1} > DCC^-_{t,t+1}$, where the superscript indicates the sign of the change in sales. By inspection, such behavior accentuates the slope in $CstSales$. In sum, we argue that while the sticky cost hypothesis implicitly pertains to the second term (the change in capacity costs, a result of managerial actions, induces the differential response), the mechanical relation in the first-term could also induce the finding.

**Extensions**

In this section, we consider three extensions to the intuition presented earlier: (1) alternate levels of fixed costs, (2) the influence of economic conditions, and (3) cost structures that exhibit scale economies in variable costs. For these analyses, we fix capacity costs and do not permit them to change as sales activity changes (i.e., $DCC_{t,t+1} \equiv 0$).

**Proportion of Fixed Costs**

Consider how $CstSales(S_t)$ changes as $FC$ increases. First, for any positive value of $FC$, the lower and upper limits of $CstSales(S_t)$ are 0 and 1 (for zero and infinite sales, respectively). Second, for any positive value for $S_t$, $CstSales(S_t)$ is decreasing in $FC$, at a decreasing rate, *celer- ries paribus*. However, it is difficult to sign the cross-partial unambiguously. (To see why, note that, absent fixed costs, $CstSales(S_t) = VC$ and we do not expect an asymmetric response. Similarly, we expect no response asymmetry if all costs are fixed.) Thus, we use simulations to examine the relation between the proportion of fixed costs and the induced asymmetry in cost response to changes in activity.

**Growth Environment**

We noted above that the proportion of observations with declines in sales activity affect stickiness estimates. One factor that could influence this proportion is economic climate. In terms of our algebra, general growth conditions affect the value for $p$, which in turn affects the magnitude of the asymmetry in response. For example, a sample drawn during a shrinking economy would likely have a larger proportion of observations exhibiting a decline in activity than a
sample drawn during an expanding economy. These samples could have the same underlying levels of stickiness, but the empirical estimates would differ.

**Returns to Scale**

Fixed costs in a linear cost function induce scale economies as activity volume increases. Volume also might affect unit variable costs. For example, efficiencies due to learning reduce variable costs while congestion effects might increase them. To consider the effects of scale economies on variable (or controllable) costs, in line with the cost functions in the literature (Burnside et al 1995; Basu and Fernald 1997), we modify the cost function to be:

\[ TC_t = FC + VC \times S_t^{1/(1+RTS)} \]

In this cost equation, values of \( RTS < 0 \) imply that variable costs increase more than proportionately with volume while setting \( RTS > 0 \) models settings with scale economies. Obviously, setting \( RTS = 0 \) recovers the linear cost function.

With this change, dividing the change in costs by the change in sales yields:

\[ \frac{CstSales(S_t, S_{t+1}, RTS)}{S_{t+1} - S_t} = \frac{\frac{\text{VC} \times S_t^{1/(1+RTS)} - S_t^{1/(1+RTS)}}{\text{FC} + \text{VC} \times S_t^{1/(1+RTS)}}}{S_{t+1} - S_t} \]

Notice that, unlike the case with a linear cost function, the estimated coefficient (in a regression) will now depend on the level of current sales and the magnitude of the change; both \( S_t \) and \( S_{t+1} \) affect the response.

For intuition, set \( FC = 0 \) and simplify the expression to:

\[ CstSales(S_t, S_{t+1}, RTS) = \frac{S_t^{1/(1+RTS)}}{S_{t+1} - S_t} - \frac{S_t^{1/(1+RTS)}}{S_{t+1} - S_t} \]

Consider the case when \(-1 < RTS < 0\). It is easy to show that \( \frac{\delta CstSales}{\delta S_{t+1}} > 0 \) (see figure 2). Following the same logic we used for the linear cost function, it follows that diseconomies of scale induces estimated coefficients consistent with the interpretation of sticky costs. Further, \( \frac{\delta CstSales}{\delta RTS} < 0 \), meaning that larger diseconomies of scale (lower \( RTS \)) induce a steeper slope on \( CstSales \), at a
given change in sales. The opposite argument (leading to anti-sticky costs) holds for cost functions with scale economies \((RTS > 0)\).\(^8\)

(Figure 2)

Again, it is not possible to unambiguously sign the net effect when the cost function has both fixed costs and exhibits scale economies. We therefore employ simulations to investigate this issue further.

### III. Simulation Protocol

We use simulations to create samples in which there is no ongoing managerial discretion and that avoid econometric issues that pose problems with real data so that we can isolate the effect of cost structure. We follow a two-step procedure to simulate a sample of firm-year observations with a given cost structure, for which sales activity levels randomly decline or grow from year to year. For simplicity, we explain the protocol in the context of a linear cost structure. An appendix provides detail.

First, we specify the observation for the first firm and year by specifying values for sales, fixed costs and the variable cost ratio. We then perturb the parameters (sales, proportion of fixed costs, variable cost ratio) to generate the year 1 observations for each remaining firm \(i\) (indexed \(i = 2 \ldots F\)). We allow for up to a 20% variation in each of sales, fixed costs and the variable cost ratio. This step allows us to specify cost structure, while obtaining variation within the sample. At the end of this step, we have the first year of data for \(F\) firms.

Second, we simulate subsequent years \(t\) (indexed \(t = 2 \ldots Y\)) for each of these firms. We begin by modeling the economic climate via Uniform distributions with respective supports \((LB\text{Decline}, 100\%)\) and \((100\%, UB\text{Growth})\). Then, for each firm \(i\), we draw a lower bound \((\text{Decline}_i)\) and an upper bound \((\text{Growth}_i)\) from the two distributions. That is, we permit firm-level variations within an economy-wide growth rate. The sales activity for each firm then grows or declines depending on a random draw from its own Uniform distribution with supports \((\text{Decline}_i, \text{Growth}_i)\). We then calculate the relevant total costs as specified in the cost equation: \(TC_{it} = FC_i + VC_i \times S_t\). (From here on out, we introduce firm subscripts to \(TC\), \(FC\) and \(VC\) underscore that the cost structure for firm \(i\) is a random disturbance of the specified structure for the first firm.

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\(^8\) For additional intuition, consider equation (2). Scale diseconomies in variable costs automatically increase the fraction because it affects both the numerator and the denominator by the same amount. Thus, scale diseconomies in variable costs bias toward finding results consistent with sticky costs.
Notice that the parameters do not change over time for a given firm.) At the end of this step, we have total sales and costs for multiple years. That is, we have a panel data set that we could use to estimate the standard sticky cost regression.

To examine the effects of varying levels of fixed costs, we vary the mean proportion of fixed costs in the base year from 25% to 80%. We report results for four samples with mean values at 25%, 40%, 60% and 80%. (Loosely, we can think of each sample as an industry.) Within each sample, we induce variation around this proportion across firms, for the base year. Further, the proportion of fixed costs obviously also changes as sales volume changes.9

We examine the effect of increasing the percentage of observations in the sample that have declining unit sales by changing the lower bounds on the distribution of the change in sales (see Step 2 in simulation). Specifically, we set LBDecline and UBGrowth to (98,120), (94,120) and (90, 120), and respectively for the three samples employed in our fourth experiment. For each sample, we draw independent bounds for each firm from the relevant overall distribution.

To examine scale economies, we use the cost function: \[ TC_{it} = FC_i + VC_i \times S_{it}^{(1/(1+RTS))} \]. We initially consider the case with zero fixed costs (PropFC = 0%) and vary the levels of RTS to isolate the effect of scale economies.10 Subsequently, we vary both RTS and PropFC to consider interaction effects.

We simulate data for 1,000 firms (\( F = 1000 \)), each with 10 years (\( Y = 10 \)) of data. As we calculate changes in sales and costs, our regression employ 9,000 observations for each experiment.

**IV. Methods and Results**

Following the literature, we estimate the cost response to contemporaneous changes in activity levels and allow a different response for observations where activity levels increase versus when they decrease. Consistent with ABJ and our earlier discussion, we employ sales, \( S_{it} \), as

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9 Parameter choice is an important consideration in any simulation experiment. When the research focus is to model an observed phenomenon, it is critical that parameters conform to observed values so that we can generalize the results to a value that one might reasonably observe. To our knowledge, there is no survey evidence on typically observed proportions of fixed costs in various industries. However, it is conceivable that cost structures exist over the whole continuum, from mostly variable to mostly fixed, as parameterized here, while our analytical derivations cover the extremes. Our parameter choices for scale economies (RTS) are consistent with values documented in the macroeconomics literature.

10 Viewing each sample as an “industry” and scale as an industry-level construct, we do not change RTS across firms, unlike the values for FC and VC which do change across firms. We mix sub-samples with different RTS values when we consider cross-industry analyses.
the measure of activity volume by firm $i$ in period $t$. Our total cost measure $TC_{it}$ is the simulated total SGA cost. A decline indicator, $dec$, has value 1 when sales decline between period $t$ and period $t+1$, and has value 0 otherwise. Consistent with the algebra presented earlier, we specify changes as percentages and estimate:

$$\frac{TC_{i,t+1} - TC_{i,t}}{TC_{i,t}} = \alpha + \beta_1 \times \frac{S_{i,t+1} - S_{i,t}}{S_{i,t}} + \beta_2 \times dec \times \frac{S_{i,t+1} - S_{i,t}}{S_{i,t}} + \varepsilon.$$  

We replicate all results using ABJ’s specification in equation (1).

While our first enquiry is whether the data exhibit cost stickiness when there is no short-term managerial intention, we are also interested in the cross-sectional variation of this phenomenon. In our data, cross-sectional variation is equivalent to variations in parameter levels. Sample dimensions for such variations in the literature include industry, ownership and the nature of the cost. As noted in Balakrishnan and Soderstrom (2009), the appropriate test statistic for determining whether asymmetry varies across such subsamples is unclear because the responses to both increases and decreases in activity levels are likely related to differences between the subsamples. The choice is particularly important when cost structure differs across the subsamples—precisely the phenomenon that we study. We therefore report Wald tests of changes in the proportion of stickiness (i.e., $\beta_1 + \beta_2$) in our analyses that examine the differences in cost stickiness across subsamples. For this metric, values less than unity are indicative of sticky costs and that larger values indicate lower asymmetry in the response coefficients.

Results

Table 1 contains results of estimating equation (3) for different proportions of fixed to total costs. Panel A reports descriptive statistics for the sample. For the base year, the mean proportion of costs that are fixed varies from 25% to 80%. As we induce similar growth rates in sales, the percentage of observations that represent declines in activity and the growth rate in revenue do not differ across subsamples. As expected, given the difference in operating leverage across the subsamples, the gross margin (growth rate in total cost) differs significantly across subsamples, ranging from 7.89% (2.76%) for the subsample with 25% fixed costs to 13.92% (0.78%) for the subsample with 80% fixed costs.

(Table 1)

We report regression results in Panel B. As expected, we find high R-squared values because of the absence of any measurement error and because changes in sales activity mechanisti-
cally trigger a linear change in costs. All t-statistics in this and the remaining tables are based on firm-level cluster-adjusted standard errors (Petersen 2009).

All of the models in panel B yield coefficients consistent with an asymmetric response to activity (sticky costs). The estimates for $\beta_2$ are all significantly negative and significant at the 0.0001 level. However, we find these results in a dataset where, by design, there are no short-term managerial intentions related to cost adjustments. Thus, a plausible alternate explanation for the results in the literature is the effect of fixed costs on the estimated coefficients.

The results in panel B also indicate that the magnitude of fixed costs impacts the estimates of stickiness in costs. While the coefficients for $\beta_2$ differ across models, we do not find a monotonic relation. However, Wald tests reveal that the proportion of cost adjustment for activity decreases relative to the adjustment for activity increases differs significantly across models and decreases monotonically as the proportion of fixed costs increases. We test each model relative to the model with the next-highest level of fixed costs and find all differences to be statistically significant at $p < 0.01$. We also find that results for the model with the lowest level of fixed costs are significantly different from the model with the highest level of fixed costs ($p < .01$). We conclude that observations with the greatest proportion of fixed costs show the greatest degree of apparent stickiness.

Panel C presents results of estimating equation (1), the log form used by ABJ and the literature. Results are consistent with those of Panel B, although the differences in apparent stickiness are more pronounced. However, it is premature to conclude that the percentage specification is a better model than the log specification. As detailed later, real world data contain outliers which influence results to a greater degree in the percent model than in the log model.

In table 2, we examine whether the growth environment, which influences the percent of observations with declining sales, has an impact on the asymmetry of response to changes in activity levels. In this experiment, the underlying cost structure does not differ across subsamples.

Panel A of table 2 reports descriptive statistics. The percent of observations with a decline in sales ranges from 10.7% to 48.3%. Unsurprisingly, as the percent of observations with a decline in sales increases, gross margin, the growth rate in revenue, and the growth rate in total cost all decrease.

---

11 Consistent with the algebra, the coefficient estimates for $\beta_1$ are close to the proportion of variable costs to total costs. The values are upwardly biased because of the general growth in sales, which increases the proportion.
Panel B reports results for estimation of equation (3) for the different subsamples. All subsamples indicate an asymmetry in response to changes in activity levels. However, as the proportion of observations with declines in activity levels decreases, the degree of asymmetry declines. When 10.7% of the observations represent declines in activity levels, the ratio of response to decreases versus increases is 68%. When 48.3% of the observations represent declines in activity levels, the ratio of response to decreases versus increases is 93%. A Wald test of this difference (untabled) is significant at the .0001 level. Thus, the variation in growth rates alone is enough to induce variations in stickiness of costs, providing an alternate explanation for H3b in ABJ.

Our results indicate that existing results could be confounded by mingling observations across multiple years, with differing growth rates for the overall economy. Pooling of firms from different industries experiencing differing growth rates is also a concern. Empirically, we might correct for these effects by using standard errors clustered by both firm and by year. As we argue later (in the context of correcting for scale economies), it also might be preferable to estimate the equation separately by industry.

We next present analyses of the effects of scale economies in variable costs (Table 3). In this table, we focus on the interaction between scale economies and fixed costs.\(^\text{12}\) The primary conclusion from these results is that the effect of fixed costs overwhelms the anti-sticky results due to scale economies, even for fairly low values of PropFC, and for reasonable values of RTS as observed empirically (Burnside et al 1995; Basu and Fernald 1997). Consistent with the results for a linear model all the estimates exhibit a statistically significant asymmetry in the response to activity increases versus decreases. Although not completely monotonic, the Wald test (untabled) indicates a statistically significant difference in apparent stickiness for zero versus 20% returns to scale. We infer that the effect of curvature induced by fixed costs dominates the effects induced by scale economies, for the values we consider.

\(^{12}\) Consistent with the algebraic analysis, when we set FC = 0, simulated data show that diseconomies of scale induce a finding consistent with sticky costs. Conversely, scale economies (RTS values > 0) induce a finding of anti-stickiness. (These results are also seen in the first column in Table 3.) In table 3, we focus on the interaction between scale economies and fixed costs because both scale diseconomies and fixed costs push stickiness in the same direction. Our interaction analysis aims to provide a sense of the relative magnitudes of the effects.
V. Controlling for Cost Structure

In this section, we propose methods to alleviate the effect of fixed costs structure on the asymmetric response by suitable choices for scaling. Consider again the cost function, 
\[ TC_{i,t} = FC_i + VC \times S_{i,t} \]. Our algebra shows that fixed costs enter the picture because ABJ and others scale cost changes by lagged total costs to express the dependent variable as the percent change in costs. Rather than including controls of cost structure as independent variables, we expect the effect to be alleviated much more effectively if we scale the dependent variable by a measure of size that is unrelated to cost structure. In what follows, we scale by lagged sales activity.\(^{13}\)

We have:
\[ \Delta C_{i,t} = \frac{VC_i \times (S_{i,t+1} - S_{i,t})}{S_{i,t}} \] and \[ \Delta S_{i,t} = \frac{(S_{i,t+1} - S_{i,t})}{S_{i,t}} \].

The cost response to the scaled changes in sales is then,
\[ \text{CstSales}(S_{i,t}) = \frac{VC_i \times [S_{i,t+1} - S_{i,t}]}{(S_{i,t+1} - S_{i,t})} = VC_i. \]

That is, the proportion of fixed costs in total costs and the current level of sales cease to matter. Thus, we can reasonably interpret changes in the response coefficient as related to managerial actions. However, note that we can no longer interpret the regression coefficient as the percent change in costs for a one-percent change in sales; it is now more appropriately interpreted as the variable cost ratio if we specify a linear cost model, or as the controllable costs per sales dollar if we permit more general cost models. The sticky cost hypothesis would indicate that \( \beta_2 < 0 \), or that costs are less “controlled” when sales decrease.

Our algebraic investigations do not suggest a simple correction for the effect of scale economies in variable costs. However, because scale economies are likely to be similar across firms in the same industry, one (admittedly imperfect) correction might be to use the Fama-Macbeth approach to estimate separate equations for each industry cluster, and then aggregate across industries. This approach also might serve as a control for differential growth rates across industries. The core point is that differences in scale economies and/or growth rates manifest as

\(^{13}\) Mechanically, all that we need is to scale both the sales and the cost changes by the same metric. The choice of the appropriate scaling variable is of interest. The core point is that metric should be independent of cost structure or other factors that might induce spurious inferences. We scale by sales because it results in an economically interpretable independent variable (the % change in sales).
changes in the response coefficients to sales increase and to sales decreases, meaning that such controls must either appear as interaction terms or be estimated separately for each sub-sample.

We test these conjectures by replicating the results in ABJ.\textsuperscript{14} Table 4 reports this analysis. As noted earlier by AL (2009), inclusion of additional firms by COMPUSTAT makes it impossible to replicate ABJ’s sample exactly. Thus, AL draws a larger sample (138,700 firm-years versus 63,958 firm-years in ABJ) and show that sample characteristics are similar. We too draw a larger sample (139,614 firm-years). Untabulated data show key characteristics of our sample are comparable to the characteristics of the samples in AL and in ABJ. For example, the median sales revenues in millions (percent of sample with decreases in SG&A) for the ABJ, AL and our sample, respectively, are $87.53 (24.98%), $91.20 (27.03%), and $91.41 (26.64%).

\begin{table}[!ht]
\centering
\begin{tabular}{|c|c|c|c|}
\hline
\textbf{Variable} & \textbf{ABJ} & \textbf{AL} & \textbf{Our Sample} \\
\hline
\textbf{Median Sales} & $87.53$ (24.98%) & $91.20$ (27.03%) & $91.41$ (26.64%) \\
\textbf{Median SG&A} & $13.62$ (23.98%) & $16.20$ (27.03%) & $16.41$ (26.64%) \\
\hline
\end{tabular}
\caption{Summary statistics.}
\end{table}

(Table 4)

For ease of comparison, the first data column in panel A of table 4 reports the results in ABJ and second reports the replication in AL (2009). The next two columns replicate the results with our sample. For consistency with both ABJ and our analyses, we estimate the equation both in the log form (ABJ, equation 1) and in percent changes (our approach, equation 3). Consistent with earlier results and as expected, both approaches yield similar conclusions.\textsuperscript{15} Comparison with columns 2 and 3 indicates a successful replication of ABJ’s results.

Panel B reports the results from our adjustments for cost structure. The first column performs the analysis after scaling cost changes by lagged sales rather than lagged costs. Of course, such a change in the scaling is meaningful only in the context of a percent-change specification. We find the change in specification does not alter the core finding of sticky costs. The estimated value for $\beta_1$ is 0.19 ($p < 0.01$) as would be expected, as this estimate is now the variable (or controllable) SGA cost per sales dollar. More importantly, the estimated value for $\beta_2$ is -0.02 ($t=-4.27$, $p < 0.01$). However, note that the estimate for stickiness is smaller than in the original

\textsuperscript{14} Simulated data (untabled) confirm that the correction for fixed costs eliminates the finding of sticky costs when the cost function is linear. The correction reduces but does not eliminate findings consistent with sticky costs when scale diseconomies are significant. We also estimated Fama-Macbeth regressions on a sample with fixed costs ($\text{PropFc} = 40\%$) and with firms that exhibit varying returns to scale. In these regressions, we deflated cost changes by lagged costs so as to not remove the effects of fixed costs. We find results consistent with sticky costs suggesting that both corrections are needed.

\textsuperscript{15} We truncate cost and sales changes to ±100% when specifying the model as percentage changes. We find that a few outliers (e.g., cost changes over 600%) have a significant effect on reported results. This feature underscores the greater potential for erroneous inferences with the percent changes model, which does not “tuck in” observations as is automatic with the log specification. ABJ also report that the log model provides a better fit for the data relative to a linear (percent change) specification.
model ($\beta_2 = -0.05$, $t = -5.15$, $p < 0.01$) (see table 4, panel A). Thus, while a portion of the stickiness result in the literature stems from a lack of control for fixed costs, our proposed correction for fixed costs does not rule out an asymmetric response triggered by short-term managerial actions.

The next column in panel B reports Fama-Macbeth estimates (i.e., aggregation of industry specific estimates) for the sample. In this estimation, we scale cost changes by lagged costs so that we can identify the effects of correcting for scale economies alone. While 23 of 48 industry groups have estimates consistent with sticky costs, only 11 (of 23) are significant at $p < 0.05$ (3 of 25 industries are consistent with anti-sticky costs.) Further, the average estimate does not reliably differ from zero. The correction of scale economies thus alters inferences about the presence of sticky costs. The rightmost column reports results after correcting for fixed costs (i.e., scaling cost changes by lagged sales) and scale economies (i.e., Fama-Macbeth estimates). We continue to find that the overall estimate is not significant although 14 industries have estimates consistent with sticky costs.

VI. Discussion and Conclusion

In this paper, we offer a caveat for the rapidly growing literature on sticky costs -- the asymmetric cost response to changes in activity. This line of enquiry has gained popularity because the approach suggested by ABJ seems to provide a convenient way to employ large sample data to understand short-run managerial decisions. However, using algebraic analysis and simulated data that are devoid of any managerial actions, we show that the reported results could stem from cost structure alone. Both the presence of fixed (non-controllable) costs and scale diseconomies in variable costs could lead to the finding of an asymmetric response coefficient.

There are at least three ways in which we could reduce the influence of cost structure and economic climate in studies of sticky costs. The first is to focus on firms within a narrowly defined industry because such firms presumably have similar cost structures and scale economies. However, such an approach is likely to limit sample size (see, e.g., Balakrishnan and Gruca 2008; Balakrishnan et al. 2004). A second approach is to include independent variables such as asset intensity and GDP growth to control for fixed costs and the economic climate, respectively (Dierynck and Renders 2009). However, our analysis indicates that a proper correction for fixed costs must apply to the dependent variable. Moreover, a correction for economic climate and other industry-specific effects must appear as interaction terms. The latter implication is consistent with studies such as ABJ (2003) and Stelianos et al. (2006) that include an interaction term.
between industry dummies and the decrease term in equation (1). While providing partial control, this approach does not fully address differences across industries because the increase term is held constant. A final approach, which we advocate, is: (1) to scale the changes in costs by sales rather than total costs to control for the effects of fixed costs (meaning that we need to specify changes as percentages and pay particular attention to outliers) and, (2) to employ Fama-Macbeth type regressions to control for scale economies and other industry specific effects. Applying these controls to COMPUTSTAT data, we find that these controls alter findings reported in ABJ.

Our analysis can also be construed as examining the effect of long-term decisions about cost structure on our ability to detect short-term adjustments. In the long run, managers have considerable control over cost structure even within constraints imposed by technology. Our analysis indicates that these choices manifest as differences in the stickiness of costs in the short run. Then, because of managers’ long run choices are potentially made in response to environmental pressures (e.g., Kallapur and Eldenburg 2005), we might be able to use a series of short-run responses to examine changes in the long-run choice of cost structure. For example, Kama and Weiss (2010) pay particular attention to past technological choices as constraints when examining the managers’ use of current resource adjustments to meet earnings targets. An extension of this line of enquiry that takes our results into consideration could also investigate whether analysts are sensitive to cost structure.

Overall, our analysis indicates that, as both long- and short-term choices affect the asymmetry in response coefficient, researchers must account for the effect of both choices and their interactions when designing studies that link response coefficients to managerial choices. In particular, our results indicate that researchers must explicitly consider cost structure (fixed costs and scale economies in variable costs) as well as differential growth rates (for industries or for years) before attributing differences in estimated coefficients to deliberate short-run managerial actions.
REFERENCES


**Figure 1**
Plot of the ratio of Variable Costs to Total Costs

Notes:
Each line plots the proportion of variable costs, $(VC * S_t) / (FC + VC * S_t)$. The value of $VC$ is set at 0.1 for all the functions. The values for fixed costs ($FC$) are 30, 100, 300, 1,000, 4,500 and 9,000 from the lowest to the highest value. At a sales volume of $5,000$, the proportion of fixed costs are 6%, 17%, 37%, 67%, 90% and 95% respectively.
Figure 2
Plot of the Coefficient Estimate (CstSales) to the Ratio of Sales Changes

Notes:
Each line plots the coefficient for the ratio of change in variable costs to the ratio of the change in sales (i.e., plots the value for CstSales(S_t,S_{t+1},RTS)) in a cost function with zero fixed costs.
Table 1
Effect of Fixed Costs on Estimates of Cost Asymmetry

Panel A: Descriptive Statistics

<table>
<thead>
<tr>
<th>Item</th>
<th>Mean proportion of fixed costs to total costs as of Year 1</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>25%</td>
</tr>
<tr>
<td>Gross margin (mean)</td>
<td>7.89%</td>
</tr>
<tr>
<td>% of decline observations</td>
<td>28.53%</td>
</tr>
<tr>
<td>Growth rate in revenue</td>
<td>3.50%</td>
</tr>
<tr>
<td>Growth rate in total cost</td>
<td>2.76%</td>
</tr>
</tbody>
</table>

Panel B: OLS Estimation of Differences in Estimates of Cost Asymmetry for Increasing Levels of Fixed Costs Modeled with Changes in Percentages

\[
\frac{TC_{i,t+1} - TC_{i,t}}{TC_{i,t}} = \alpha + \beta_1 \times \frac{S_{i,t+1} - S_{i,t}}{S_{i,t}} + \beta_2 \times \text{dec} \times \frac{S_{i,t+1} - S_{i,t}}{S_{i,t}} + \epsilon.
\]

<table>
<thead>
<tr>
<th>Coefficient</th>
<th>Predicted sign</th>
<th>Mean proportion of fixed costs to total costs as of Year 1</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>25%</td>
</tr>
<tr>
<td>Intercept</td>
<td></td>
<td>-0.0004</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(-11.86)</td>
</tr>
<tr>
<td>(\beta_1)</td>
<td>+</td>
<td>0.7942</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(553.05)</td>
</tr>
<tr>
<td>(\beta_2)</td>
<td>-</td>
<td>-0.0556</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(-16.80)</td>
</tr>
</tbody>
</table>

\((\beta_1+\beta_2)/\beta_1\)  
9.30  0.90  0.84  0.78

N  
9,000  9,000  9,000  9,000

Adjusted R²  
99.69%  99.20%  97.89%  96.08%

Wald Test  
(Comparison)  
17.33  26.08  12.17  117.58  25% vs. 40%  40% vs. 60%  60% vs. 80%  25% vs. 80%
Panel C: OLS Estimation of Differences in Estimates of Cost Asymmetry for Increasing Levels of Fixed Costs Modeled with the Log Specification

\[
\log \left( \frac{TC_{i,t+1}}{TC_{i,t}} \right) = \alpha + \beta_1 \log \left( \frac{S_{i,t+1}}{S_{i,t}} \right) + \beta_2 \times \text{dec} \times \log \left( \frac{S_{i,t+1}}{S_{i,t}} \right) + \varepsilon.
\]

<table>
<thead>
<tr>
<th>Coefficient</th>
<th>Predicted sign</th>
<th>Mean proportion of fixed costs to total costs as of Year 1</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>25%</td>
</tr>
<tr>
<td>Intercept</td>
<td></td>
<td>-0.0006</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(-23.08)</td>
</tr>
<tr>
<td>( \beta_1 )</td>
<td>+</td>
<td>0.8043</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(569.81)</td>
</tr>
<tr>
<td>( \beta_2 )</td>
<td>-</td>
<td>-0.0736</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(-16.19)</td>
</tr>
<tr>
<td>( (\beta_1 + \beta_2)/\beta_1 )</td>
<td></td>
<td>0.91</td>
</tr>
<tr>
<td>N</td>
<td></td>
<td>9,000</td>
</tr>
<tr>
<td>Adjusted ( R^2 )</td>
<td></td>
<td>99.71%</td>
</tr>
<tr>
<td>Wald Test (Comparison)</td>
<td></td>
<td>38.22</td>
</tr>
<tr>
<td></td>
<td>25% vs. 40%</td>
<td>40% vs. 60%</td>
</tr>
</tbody>
</table>

Notes:
1. \( TC_i \) = Total Cost in period \( t \), \( S_i \) is revenue in period \( t \) and \( \text{Dec} \) is 1 only if sales have declined from period \( t \) to period \( t+1 \) and is zero otherwise.
2. For any given firm \( i \) and period \( t \), \( TC_{it} = FC_i + S_{it} \times VC_i \).
3. The first entry in each cell is the coefficient estimate and the second entry is the t-statistic based on cluster-adjusted standard errors. All tests are two-tailed.
Table 2
Effect of Differential Growth Rates (Percent of Observations with Declining Sales) on Estimates of Asymmetric Response

Panel A: Descriptive Statistics

<table>
<thead>
<tr>
<th>Item</th>
<th>Percent of Observations with Decline in Sales</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>10.7%</td>
</tr>
<tr>
<td>Gross margin (mean)</td>
<td>13.32%</td>
</tr>
<tr>
<td>Growth rate in revenue</td>
<td>7.03%</td>
</tr>
<tr>
<td>Growth rate in total cost</td>
<td>4.78%</td>
</tr>
</tbody>
</table>

Panel B: OLS Estimation of Differences in Estimates of Cost Asymmetry for an Increasing Proportion of Observations with Declines in Activity

\[
\frac{TC_{i,t+1} - TC_{i,t}}{TC_{i,t}} = \alpha + \beta_1 \times \frac{S_{i,t+1} - S_{i,t}}{S_{i,t}} + \beta_2 \times Dec \times \frac{S_{i,t+1} - S_{i,t}}{S_{i,t}} + \varepsilon.
\]

<table>
<thead>
<tr>
<th>Coefficient</th>
<th>Predicted sign</th>
<th>Percent of Observations with Decline in Sales</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>10.7%</td>
</tr>
<tr>
<td>Intercept</td>
<td>-0.0015</td>
<td>-0.0005</td>
</tr>
<tr>
<td></td>
<td>(-15.04)</td>
<td>(-11.41)</td>
</tr>
<tr>
<td>(\beta_1)</td>
<td>+</td>
<td>0.6986</td>
</tr>
<tr>
<td></td>
<td>(335.54)</td>
<td>(338.32)</td>
</tr>
<tr>
<td>(\beta_2)</td>
<td>-</td>
<td>-0.2265</td>
</tr>
<tr>
<td></td>
<td>(-17.07)</td>
<td>(-14.96)</td>
</tr>
<tr>
<td>((\beta_1+\beta_2)/\beta_1)</td>
<td>0.68</td>
<td>0.90</td>
</tr>
</tbody>
</table>

| N             | 9,000          | 9,000                          | 9,000                          |
| Adjusted R\(^2\) | 98.13%        | 99.20%                        | 99.61%                        |

Notes:
1. We could not directly manipulate the percent of decline observations. Rather we adjusted the ranges of possible demand shocks to induce different proportions.
2. \(TC_i\) = Total Cost for firm \(i\) in period \(t\), \(S_i\) is revenue for firm \(i\) in period \(t\) and Dec is 1 only if sales have declined from period \(t\) to period \(t+1\) and is zero otherwise.
3. For any given firm \(i\) and period \(t\), \(TC_i = FC_i + S_i \times VC_i\).
4. The first entry in each cell is the coefficient estimate and the second entry is the t-statistic based on cluster-adjusted standard errors. All tests are two-tailed.
Table 3
OLS Estimation of Differences in Estimates of Cost Asymmetry for Increasing Levels of Returns to Scale and with Positive Fixed Costs

\[
\frac{TC_{i,t+1} - TC_{i,t}}{TC_{i,t}} = \alpha + \beta_1 \frac{S_{i,t+1} - S_{i,t}}{S_{i,t}} + \beta_2 \frac{Dec_{i,t+1} - Dec_{i,t}}{S_{i,t}} + \varepsilon.
\]

<table>
<thead>
<tr>
<th>Returns to scale (RTS)</th>
<th>Mean Percent of fixed costs in Year 1 (PropFC)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0%</td>
</tr>
<tr>
<td></td>
<td>(\beta_1)</td>
</tr>
<tr>
<td>0%</td>
<td>0.8343 (2851.2)</td>
</tr>
<tr>
<td></td>
<td>(\beta_2)</td>
</tr>
<tr>
<td></td>
<td>-0.0296 (-4.04)</td>
</tr>
<tr>
<td>5%</td>
<td>0.9493 (∞)</td>
</tr>
<tr>
<td></td>
<td>(\beta_2)</td>
</tr>
<tr>
<td></td>
<td>0.0056 (74.29)</td>
</tr>
<tr>
<td>10%</td>
<td>0.9034 (∞)</td>
</tr>
<tr>
<td></td>
<td>(\beta_2)</td>
</tr>
<tr>
<td></td>
<td>0.0104 (72.63)</td>
</tr>
<tr>
<td>20%</td>
<td>0.8156 (∞)</td>
</tr>
<tr>
<td></td>
<td>(\beta_2)</td>
</tr>
<tr>
<td></td>
<td>0.0414 (73.45)</td>
</tr>
</tbody>
</table>

Notes:
1. \(TC_{it}\) = Total Cost for firm \(i\) in period \(t\), \(S_{it}\) is revenue for firm \(i\) in period \(t\) and \(Dec\) is 1 only if sales have declined from period \(t\) to period \(t+1\) and is zero otherwise.
2. For any given firm \(i\) and period \(t\), \(TC_{it} = FC_i + VC_i \times S_{it}^{1/(1+RTS)}\).
3. The first entry is the coefficient estimate and the second entry in each cell is the t-statistic based on cluster-adjusted standard errors. All tests are two-tailed.
Table 4  
Correcting for Cost Structure: COMPUSTAT Data


\[
\log \left( \frac{TC_{i,t+1}}{TC_{i,t}} \right) = \alpha + \beta_1 \times \log \left( \frac{S_{i,t+1}}{S_{i,t}} \right) + \beta_2 \times \text{dec} \times \log \left( \frac{S_{i,t+1}}{S_{i,t}} \right) + \varepsilon. \tag{1}
\]

\[
\frac{TC_{i,t+1} - TC_{i,t}}{TC_{i,t}} = \alpha + \beta_1 \times \frac{S_{i,t+1} - S_{i,t}}{S_{i,t}} + \beta_2 \times \text{dec} \times \frac{S_{i,t+1} - S_{i,t}}{S_{i,t}} + \varepsilon. \tag{2}
\]

<table>
<thead>
<tr>
<th>Coefficient</th>
<th>Predicted sign</th>
<th>Dependent variable scaled by current period costs</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>As reported by ABJ (Table 2)</td>
<td>As reported by AL (Table 3)</td>
</tr>
<tr>
<td>Intercept</td>
<td>0.0481 (39.88)</td>
<td>0.0419 (54.73)</td>
</tr>
<tr>
<td>(\beta_1)</td>
<td>+ 0.5459 (164.11)</td>
<td>0.5733 (239.73)</td>
</tr>
<tr>
<td>(\beta_2)</td>
<td>-0.1914 (-26.14)</td>
<td>-0.0395 (-7.10)</td>
</tr>
<tr>
<td>N</td>
<td>63,958</td>
<td>138,700</td>
</tr>
<tr>
<td>Adjusted R^2</td>
<td>36.63%</td>
<td>40.42%</td>
</tr>
</tbody>
</table>
Panel B: With Proposed Corrections for Cost Structure

\[
\frac{TC_{i,t+1} - TC_{i,t}}{S_{i,t}} = \alpha + \beta_1 \frac{S_{i,t+1} - S_{i,t}}{S_{i,t}} + \beta_2 \frac{S_{i,t+1} - S_{i,t}}{S_{i,t}} + \epsilon. \tag{C}
\]

<table>
<thead>
<tr>
<th>Coefficient</th>
<th>Predicted sign</th>
<th>Dependent variable scaled by current period costs</th>
<th>Corrected for effects of fixed costs</th>
<th>Corrected for scale economies (Fama-Macbeth regressions)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>0.0077</td>
<td>0.0400</td>
<td>0.0060</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(13.17)</td>
<td>(21.55)</td>
<td>(5.67)</td>
<td></td>
</tr>
<tr>
<td>(\beta_1)</td>
<td>+</td>
<td>0.19386</td>
<td>0.5980</td>
<td>0.1680</td>
</tr>
<tr>
<td></td>
<td>(67.74)</td>
<td>(28.93)</td>
<td>(19.18)</td>
<td></td>
</tr>
<tr>
<td>(\beta_2)</td>
<td>-</td>
<td>-0.0225</td>
<td>0.0070</td>
<td>0.0040</td>
</tr>
<tr>
<td></td>
<td>(-4.27)</td>
<td>(0.53)</td>
<td>(0.73)</td>
<td></td>
</tr>
<tr>
<td>N</td>
<td>139,598</td>
<td>n/a</td>
<td>n/a</td>
<td></td>
</tr>
<tr>
<td>Adjusted (R^2)</td>
<td>43.06%</td>
<td>38.70%</td>
<td>45.30%</td>
<td></td>
</tr>
</tbody>
</table>

Notes:
1. \(TC_{i,t}\) = Total Cost for firm \(i\) in period \(t\), \(S_{i,t}\) is revenue in period \(t\) and \(Dec\) is 1 only if sales have declined from period \(t\) to period \(t+1\) and is zero otherwise.
2. The data for these tables are drawn from COMPUSTAT as per the directions in ABJ (2003) and AL (2009).
3. The first entry in each cell is the coefficient estimate and the second entry is the t-statistic based on cluster-adjusted standard errors. Fama-Macbeth t-statistics reported in the two right most columns of panel B.
4. For the cost deflated model (equation B), we truncated the percentage changes for SGA and sales at ±100% to reduce the effect of outliers. Including these observations yields a \(\beta_2\) that is significantly positive. We also note that the correlation between the log and the percent specification for costs is 91%, which suggests that the truncated results are reasonable. We do not truncate observations for the final column, which presents the sales-deflated model. (Truncation does not alter inferences.)
5. Observations grouped into the Fama-French 48 industry clusters. Considering \(\beta_2\), 23 of 48 estimates are negative (11 significant) in the middle column; 25 of 48 estimates are negative (14 significant) in the last column.
Appendix
Details of the Simulation Protocol

**Step 1: Simulating the first observation for each firm in the sample with a given cost structure.**

We start with initializing the observation for firm 1 in year 1. Unit sales $S_{11}$ and total cost $TC_{11}$ are set at fixed levels of $2000$ and $1900$ respectively, as these are just seed values. (We initialize prices to unity, removing the distinction between activity and revenue.) Subsequently, we calculate the amount of fixed costs for firm 1 ($FC_1$) by calculating $FC_1 = PropFC \times TC_{11}$ where $PropFC$ models the proportion of fixed cost in total cost, and is the experimental variable of interest for our first set of results on the effect of fixed costs in the cost structure. We vary $PropFC$ along the range of potential cost structures, with values of 25%, 40%, 60% and 80%. To conclude the initialization of the observation for firm 1 in year 1, we calculate the variable cost rate that plugs this equation: $VC_1 = \frac{(TC_{11} - FC_1)}{S_{11}}$.

We next simulate the year 1 observation for all other firms $i$ in the sample. To create variance within the sample, we draw for each firm $i=2,..,F$ a sales factor $(SLFac_i)$, a fixed cost factor $(FCFac_i)$ and a variable cost rate factor $(VCFac_i)$ from a Uniform distribution with mean 100 and supports (90,110). We apply these to simulate unit sales, fixed cost and variable cost rates for all firms, from which we can subsequently calculate total cost figures, as follows:

- $S_{ii} = S_{11} \times SLFac_i/100$ ; $FC_i = FC_1 \times FCFac_i/100$
- $VC_i = VC_1 \times VCFac_i/100$ ; $TC_{ii} = FC_i + VC_i \times S_{ii}$

**Step 2: Simulating observations for subsequent years $t$ for each firm $i$.**

We model changes in sales and costs over time. For each sample, we draw the bounds of its growth parameters from a Uniform distributions with respective supports ($LBDecline,100$) and (100, $UBGrowth$). We set $LBDecline$ to 94% and $UBGrowth$ to 120%, ensuring an overall growth in the sample. We draw firm specific values as $Decline_i$ ($Growth_i$) from the two distributions. We draw the year over year change for firm $i$ (denoted $DeclGrowit$) as a random draw from a Uniform distribution with supports ($Decline_i$ and $Growth_i$). This procedure ensures that each firm grows or declines according to its specific simulated distribution. We then calculate the calculate the sales and total cost for firm $i$ in year $t$ as $S_{it} = S_{(i-1)} \times DeclGrowit$ and $TC_{it} = FC_i + VC_i \times S_{it}$.