Asymmetric Cost Behavior

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ABSTRACT: We synthesize the rapidly growing literature on asymmetric cost behavior—a new way of thinking about costs (and, by extension, earnings). While the traditional cost model describes a mechanistic relation between costs and concurrent activity, this alternative view emphasizes the role of deliberate managerial decisions in cost behavior. We integrate recent theoretical developments into an integrated framework of asymmetric cost behavior, formulate the empirical hypotheses of cost asymmetry and review the empirical evidence from extant research, which lends strong support to this framework and has important implications for both cost and financial accounting research. We clarify empirical implementation issues and address contrary claims about the validity of findings in the literature, showing that these claims are unwarranted because of econometric errors. We present new comprehensive evidence from Global Compustat, which demonstrates that asymmetric cost behavior is a pervasive global phenomenon. We also discuss promising new research directions.

Keywords: cost stickiness and anti-stickiness; resource adjustment costs; managerial decisions.
INTRODUCTION

Following the seminal paper on “sticky costs” by Anderson, Banker and Janakiraman (2003), henceforth ABJ, asymmetric cost behavior has emerged as a vibrant research area in accounting. Further, because costs are a fundamental determinant of earnings, insights into cost behavior can (and have been shown to) make an important contribution to financial accounting topics that rely on understanding or forecasting the earnings time series, including research on earnings quality, earnings prediction, detection of earnings manipulation, and analysts’ earnings forecasts. In this paper, we integrate recent research developments into a comprehensive theoretical framework of asymmetric cost behavior, review empirical evidence on the determinants and consequences of cost stickiness and anti-stickiness,¹ and discuss promising research directions.

Asymmetric cost behavior is far broader than a (naive) prediction that “costs are sticky.” It constitutes a new way of thinking about cost behavior (and, by extension, earnings behavior). While the traditional view of cost behavior envisions a mechanistic symmetric relation between costs and concurrent activity, modeled as fixed and variable costs, this new way of thinking is rooted in an explicit recognition of the role of deliberate managerial decisions in short-run cost behavior.

ABJ’s theory of asymmetric cost behavior builds on two observations about costs. First, many—but not all—costs arise because managers make a deliberate decision to commit resources. Second, although many resource commitments can be changed in the short run, doing so is costly—it entails incurring resource adjustment costs, such as severance payments to dismissed workers, training costs for new employees, installation and disposal costs for capital equipment. The interaction of deliberate managerial discretion and resource adjustment costs

¹ Costs are said to be “sticky” if they rise to a greater extent for sales increases than they fall for equivalent sales decreases (Anderson et al. 2003). Conversely, costs are “anti-sticky” if they rise less in response to sales increases than they fall when sales decrease equally (Weiss 2010).
introduces complex dynamics in the choice of resource levels. In particular, managers have to consider not only current activity, as in the traditional model, but also past resource levels, because they affect adjustment costs incurred in the current period, along with expected future sales, which affect future adjustment costs. Resource commitment decisions are further influenced by managers’ incentives and behavioral biases.

We combine these insights into an integrated theoretical framework of asymmetric cost behavior. We show that the theory predicts a complex pattern of cost asymmetry, which involves not only cost stickiness but also symmetric and anti-sticky cost behavior under certain conditions, and exhibits systematic variation in the degree of both cost stickiness and cost anti-stickiness. In other words, while many cost categories are expected to be sticky on average, not all costs should be sticky, and costs that are sticky on average are not always sticky. The main drivers of this systematic variation include the magnitude of resource adjustment costs, managerial expectations, prior activity changes, and managerial incentives. Further, this variation is a central part of the theory and, therefore, should be considered in any analysis that aims to validate or refute the theory.

We revisit the empirical models of asymmetric cost behavior and clarify several important empirical implementation issues. Additionally, we address claims in two recent working papers, Anderson and Lanen (2009) and Balakrishnan, Labro and Soderstrom (2013), that question the validity of findings of sticky costs. We show that these claims are unfounded because of econometric errors. Further, we demonstrate that a methodologically sound version of these authors’ own analysis lends additional support to the findings of asymmetric cost behavior.

Existing research, focusing primarily on U.S. data, has shown that the predictions of asymmetric cost behavior theory hold in the U.S., and a few studies have documented some of
these results for other countries. However, prior research does not show whether all of the main predictions hold in all countries, a broader implication that arises because the main drivers of the theory—managerial decisions and adjustment costs—are relevant world-wide. Therefore, we present new comprehensive global evidence, testing all of the main hypotheses for all countries with adequate sample size in Global Compustat data. Our results indicate that, as expected, asymmetric cost behavior is a pervasive global phenomenon, and all predictions hold in most countries.

In the next section, we present the theory of asymmetric cost behavior and review research findings. We then describe the empirical models of asymmetric cost behavior and empirical implementation issues, and address contrary claims about empirical validity of findings. We next present new global evidence. The final section concludes and suggests new research directions.

THEORY AND RESEARCH FINDINGS OF ASYMMETRIC COST BEHAVIOR

The Foundations of Cost Behavior: Adjustment Costs and Managerial Decisions

Costs are caused by resources. Therefore, to understand cost behavior one has to focus on how the underlying resource levels change in response to activity changes (Cooper and Kaplan 1992).

The traditional textbook model of cost behavior views all costs as fixed or variable with respect to concurrent sales (or another activity cost driver\(^2\)). The corresponding “fixed” and “variable” resources represent two opposite extremes in the ease of short-run resource adjustment (Cooper and Kaplan 1992). Fixed resources, such as buildings and major capital equipment, are prohibitively costly to adjust on short notice. Therefore, they have to be

\(^2\) For brevity, we use sales as our activity measure, recognizing that other cost drivers are more appropriate for some costs.
committed in advance, before actual demand is known, giving rise to costs that are “fixed” with respect to realized sales. Variable resources such as direct and indirect materials, on the other hand, can be adjusted flexibly in the short run. Therefore, they are consumed as needed based on actual demand, causing “variable” costs. The traditional model implies a mechanistic relation between sales and costs, in which fixed costs are predetermined, and variable costs reflect the consumption of variable resources conditional on concurrent sales.\(^3\)

ABJ show that empirical behavior of SG&A costs is inconsistent with the traditional model, and propose an alternative view of cost behavior that is based on resource adjustment costs and deliberate managerial decisions. They point out that many resources, such as skilled indirect labor, are neither fixed nor variable. Although such resources can be adjusted in the short run, doing so requires incurring substantial—but not prohibitive—resource adjustment costs, such as severance payments to dismissed workers or search and training costs for new hires.\(^4\) For brevity, we will refer to them as “sticky” resources, meaning that the frictions associated with resource adjustment are neither small enough to make these resources fully “variable” nor large enough to make them fully “fixed.”

Unlike (predetermined) fixed resources and (mechanically determined) variable resources, short-run adjustment of sticky resources involves a deliberate managerial choice.\(^5\) When current sales change, managers have to decide whether and how much to change the levels of sticky resources, taking into account adjustment costs associated with such changes. The interaction between deliberate managerial decisions and adjustment costs gives rise to rich dynamics in

\(^3\) Symmetric cost behavior does not require the cost function to be linear. For instance, if \(c=c(x), c'(\cdot) > 0\), represents activity costs and \(x\) measures the activity driver, the marginal cost remains the same regardless of whether \(x\) has increased or decreased relative to its level in the prior period.

\(^4\) Resource adjustment costs include not only out-of-pocket costs such as severance payments but also organizational costs such as loss of employee morale and erosion of human capital during layoffs (Anderson et al. 2003), or temporary productivity disruptions associated with the training of new workers.

\(^5\) In the long run, resource commitments that determine fixed costs and technological choices that affect variable costs are also subject to managerial discretion. However, this type of discretion does not extend into the short run.
resource adjustment. Managers’ resource commitments depend not only on concurrent sales, but also on (1) prior period resource levels, which affect adjustment costs that have to be incurred in the current period, (2) expected future sales, which affect future adjustment costs, and (3) agency and behavioral factors, which drive a wedge between optimal resources commitments for the firm and managers’ actual choices.

ABJ show that deliberate managerial decisions for sticky resources lead to asymmetries in cost behavior. Although subsequent studies have enriched, and in some cases revised, ABJ’s predictions of cost stickiness (e.g., Weiss 2010; Chen et al. 2012; Kama and Weiss 2013; Banker et al. 2013d), all of these extensions build on ABJ’s fundamental insight of asymmetric managerial discretion. In particular, when sales decrease, managers make a deliberate choice to retain some unused (slack) resources rather than incur adjustment costs to fully remove such resources. When sales increase, however, managers must add required resources, with less room for discretion.

Sticky costs research builds on this asymmetry to generate predictions for changes in sales and costs. However, because the traditional model of cost behavior focuses on the relation between the levels of sales and costs, we first examine the implications of asymmetric discretion in the context of levels. The asymmetric relation between the levels of sales and costs is illustrated in Figure 1. When current sales \( (Sales_t) \) exceed available resource capacity, determined by resources carried over from the prior period \( (Resources_{t-1}) \), managers will add the required resources. Therefore, costs will reflect current resource requirements (scenario A in Figure 1). When current sales are far below capacity, managers will cut resources to reduce slack capacity to an acceptable level. Therefore, costs will reflect resource requirements plus maximum acceptable slack (scenario B). Because managers weigh the costs of maintaining
unused resources against the adjustment costs that they would have to incur to dispose of these resources, they will tolerate only a limited amount of slack. The maximum acceptable slack will depend on expectations about whether sales will increase in future to absorb the slack, and also on the downward and upward adjustment costs.

At intermediate sales levels, available resources \( (\text{Resources}_t) \) are sufficient to accommodate current sales, and unused capacity is positive but acceptably low. Therefore, managers will maintain the original resource levels (scenario C). The shaded line in Figure 1 summarizes these resource choices for different levels of current sales, tracing out the short-run cost function. This cost function is defined conditional on the original resource level \( (\text{Resources}_{t-1} \text{ on the vertical axis}) \) and conditional on managers’ willingness to retain slack (the gap between the two upward-sloping lines).

[Insert Figure 1 here]

The cost function depicted in Figure 1 includes traditional fixed and variable costs as extreme cases. For resources that have low adjustment costs, managers will tolerate only a small amount of slack. Therefore, the cost function will converge to standard variable costs, as depicted in panel A of Figure 2. Conversely, for resources that have high—but not necessarily prohibitive—adjustment costs, managers will be willing to retain large amounts of slack, and the cost function will produce conventional fixed costs in the “relevant range” (panel B of Figure 2). Thus, standard fixed and variable costs should not be viewed as fundamental building blocks of cost behavior—instead, they are simply special cases within a far broader model that accommodates the full range of resource adjustment costs.

[Insert Figure 2 here]

The traditional model recognizes that many resources are neither entirely fixed nor entirely
variable, and interprets them as “mixed” costs (i.e., a linear combination of fixed and variable costs). However, as Figure 1 demonstrates, such resources give rise to asymmetric—rather than mixed—cost behavior.

**Main Hypotheses of Asymmetric Cost Behavior**

The main predictions of asymmetric cost behavior research are based on ABJ’s intuition of asymmetric managerial discretion in the presence of resource adjustment costs.

The first prediction is that many—but not all—costs are sticky on average, i.e., they typically fall less in response to concurrent sales decreases than they rise for equivalent sales increases. ABJ argue that because managers retain slack resources when sales decrease, costs are reduced less than proportionately. By contrast, because managers must add the required resources when sales increase, costs increase proportionately, i.e., cost response is on average stronger for sales increases than for sales decreases.

Banker et al. (2013d) point out that retained slack moderates not only the extent of resource reduction for current sales decreases but also the extent of resource expansion that will be needed when sales rebound in a subsequent period. Therefore, asymmetric slack retention does not automatically lead to cost stickiness. They argue that cost stickiness arises from an interaction with another important asymmetry—increasing long-term trends in sales. When the long-term trends are predominantly positive, as is the case in standard accounting datasets, slack resources that were retained during a sales decrease typically are fully utilized in subsequent periods (i.e., slack is close to zero). Given low initial slack, managers have to expand resources proportionately when sales increase, meaning that the moderating effect of (previously retained)

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6 For example, in U.S. Compustat data from 1978-2005, 63.0% of firm-year observations are sales increases and only 37.0% are sales decreases. The average (median) annual sales growth rate is 7.2% (5.2%). All numbers are deflated to control for inflation.
slack is unimportant for most of current sales increases. By contrast, the moderating effect of (newly retained) slack for current sales decreases is significant, given low initial slack. This implies that costs are likely to be sticky on average.\footnote{Conversely, firms that have negative long-term trends in sales are likely to exhibit cost anti-stickiness, because the moderating effect of retained slack disproportionately affects resource expansion for sales increases. Additionally, because of technological changes demand for resources such as unskilled direct labor may be decreasing even while sales are increasing. Therefore, some resources may exhibit average anti-stickiness even when the long-term trends in sales are positive.}

**Hypothesis 1 ("cost stickiness on average"):** Costs are sticky on average, i.e., they typically rise to a greater extent for concurrent sales increases than they fall for concurrent sales decreases.

Notably, Hypothesis 1 does not mean that all costs should be sticky, or that costs that are sticky on average should always be sticky. On the contrary, the theory implies that the magnitude and even the direction of asymmetry should vary systematically across different cost accounts, firms, industries, countries and time periods. For example, because managers retain slack to avoid incurring adjustment costs, one would not expect to observe either stickiness or anti-stickiness for resources that have minimal adjustment costs, such as direct materials. Further, many costs are likely to become anti-sticky under certain conditions. We describe the main sources of systematic variation in the degree of asymmetry in Hypotheses 2-5.

Contrary to some earlier claims, the prediction of cost stickiness on average does not require adjustment costs to be larger for resource reduction than for resource expansion. For example, in the context of skilled indirect labor, one is likely to observe cost stickiness regardless of whether the firing costs per employee are greater than, equal to, or less than the hiring costs. This is because managers retain slack resources not only to save on current period adjustment costs, such as severance payments to dismissed workers, but also to reduce future adjustment costs they would have to incur if sales rebound in subsequent periods, such as search and training costs for
new employees. Thus, even if the firing costs are zero, managers will choose to retain unused labor resources when sales decrease, leading to cost stickiness.

In addition to optimal resource planning with adjustment costs, cost stickiness may reflect agency factors such as empire-building (Anderson et al. 2003; Chen et al. 2012). Empire-building managers are motivated to maximize resources under their control. Therefore, they will cut resources too little when sales decrease and will expand resources excessively when sales increase. This can lead to cost stickiness even when the true economic adjustment costs to the firm are equal to zero.\(^8\)

Existing research documents that cost stickiness is prevalent across different cost categories and datasets. ABJ demonstrate that SG&A costs in U.S. Compustat firms exhibit statistically and economically significant stickiness, increasing by 0.55% on average for a 1% sales increase, but decreasing by just 0.35% on average for an equivalent sales decrease.\(^9\) Subsequent studies document the prevalence of cost stickiness for additional cost categories in U.S. Compustat data, including operating costs, COGS, labor costs, R&D costs and advertising costs (e.g., Weiss 2010; Kama and Weiss 2013; Anderson and Lanen 2009; Subramaniam and Weidenmeir 2003), for broad-based samples in other countries, and for detailed industry-specific samples. For example, Banker et al. (2013e) document that operating costs are sticky for 19 countries out of 20 in a sample of both developed and developing countries; Calleja et al. (2006) find similar results in a sample of four countries. Dierynck et al. (2012) document stickiness of labor costs, number of employees and hours worked for private firms in Belgium. Studies using proprietary

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\(^8\) Managerial preferences for empire-building can be thought of as an additional, personal adjustment cost, which is negative for resource expansion and positive for resource reduction (i.e., it motivates the former and discourages the latter). Because managers likely consider both true economic adjustment costs and their personal, agency-related adjustment costs, both types of adjustment costs have a similar effect on cost behavior.

\(^9\) Noreen and Soderstrom (1997) were the first to test for asymmetric cost behavior, using data for hospitals. However, their results were inconclusive. ABJ was the first study to document strong evidence of cost stickiness and to popularize sticky costs as a central concept in cost behavior research.
data for the health care sector find significant cost stickiness for multiple cost categories, including operating costs, salary costs and total hours, in samples such as physical therapy clinics (Balakrishnan et al. 2004) and hospitals in Canada (Balakrishnan and Gruca 2008), California (Balakrishnan and Soderstrom 2009) and Germany (Holzhacker et al. 2012). In summary, extant research provides strong and robust evidence of cost stickiness on average across multiple cost categories, including physical labor inputs,10 multiple datasets, including detailed industry-specific samples, and multiple countries. Notably, all of these studies also document substantial heterogeneity in cost stickiness across firms, time periods, cost categories or countries; we discuss this evidence after introducing the relevant hypotheses.

In the next four hypotheses, we focus on the main sources of variation in the degree of cost asymmetry. One of the key determinants is the magnitude of resource adjustment costs. When the adjustment costs (per unit of resource reduction or expansion) are higher, managers are more willing to retain unused resources to avoid these costs.11 Therefore, for a given sales decrease, they will reduce committed resources to a lesser extent. Adjustment costs also diminish managers’ willingness to expand resources when current sales increase. However, the latter effect is likely to be less important, because managers cannot accommodate increased activity levels unless they add the needed resources. Consequently, the degree of cost stickiness is likely to be increasing in the magnitude of resource adjustment costs.

**Hypothesis 2 (“adjustment costs and cost asymmetry”):** The degree of cost stickiness is increasing in the magnitude of resource adjustment costs.

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10 The evidence for physical input quantities (and physical activity measures in some of these papers) mitigates concerns that cost stickiness could be an artifact of price changes.

11 Because managers consider both current and future consequences, this mechanism is relevant not only for adjustment costs associated with (current) resource cuts but also for adjustment costs associated with (future) resource expansion. For example, when search and training costs per new hire are larger, managers are more willing to retain unutilized workers in the current period to avoid future hiring costs.
Because adjustment costs are not directly observable,\footnote{This is not only because publicly available financial data does not provide a sufficiently detailed cost breakdown but also because many adjustment costs are implicit costs of lost output, which are not explicitly recorded as costs in the internal accounting system.} empirical tests of Hypothesis 2 require empirical proxies for the magnitude of adjustment costs. ABJ argue that adjustment costs are higher for firms that rely more on internal resources—assets and employees—and less on purchases from outside suppliers. Therefore, the degree of cost stickiness should be higher in more asset- and employee-intensive firms. ABJ and many subsequent studies find results consistent with this prediction. Banker et al. (2013c) use the strength of employment protection legislation as a country-level proxy for labor adjustment costs. Using a sample of firms in 19 OECD countries, they find that cost stickiness is higher in countries with stricter employment protection, supporting Hypothesis 2. Balakrishnan and Gruca (2008) argue that in hospitals, adjustment costs (and, hence, the degree of cost stickiness) should be higher in core services (patient care) than in support services, and find results consistent with this argument. Banker et al. (2013e) argue that because jobs that exist in a more developed country are more human capital intensive, entailing greater labor adjustment costs, the degree of cost stickiness is increasing with a country’s development level. Using a broad sample of developed and developing countries, they find support for this prediction. In summary, empirical evidence using both firm- and country-level proxies confirms that resource adjustment costs play a central role in asymmetric cost behavior.

Another key factor is managerial expectations for future sales. When managers are optimistic about the future, they are anticipating a higher level of future resource requirements. Therefore, they are more willing to retain unused resources for current sales decreases—doing so allows them to reduce not only current adjustment costs but also future adjustment costs that will arise during the anticipated future resource expansion. Similarly, they are more willing to add
resources if sales increase in the current period, because they are unlikely to have to reverse these commitments in subsequent periods. Thus, managerial optimism weakens cost response to current sales decreases and amplifies cost response to current sales increases, both of which lead to increased cost stickiness.

Conversely, managerial pessimism implies larger cost cuts for sales decreases and smaller cost expansion for sales increases. This diminishes the degree of cost stickiness. Further, when pessimism is sufficiently strong, it is likely to lead to cost anti-stickiness. Highly pessimistic managers are anticipating significantly lower future resource requirements. When sales decrease in the current period, they will cut slack resources aggressively, because this reduces both current operating costs and future adjustment costs associated with subsequent resource cuts. Therefore, resource levels will likely decrease proportionately even if the initial slack is zero, and will decrease more than proportionately if the initial slack is positive. When sales increase in the current period, highly pessimistic managers will only add resources that are absolutely necessary to accommodate current requirements. Therefore, resources will likely expand less than proportionately. Consequently, costs are likely to become anti-sticky when managers are sufficiently pessimistic.

**Hypothesis 3 ("managerial expectations and cost asymmetry"):** Managerial optimism about future sales increases the degree of cost stickiness in the current period. Managerial pessimism about future sales reduces the degree of cost stickiness and, when pessimism is sufficiently strong, leads to cost anti-stickiness.14

13 If managers can temporarily increase resource utilization rate above the sustainable long-term level, they will be able to accommodate a temporary sales increase with less than normal capacity levels. Therefore, resource expansion is likely to be less than proportional even if the initial slack is zero.

14 Managerial optimism and pessimism may reflect either rational inferences about future sales based on available (favorable or unfavorable) information, or managers’ psychological biases, such as dispositional optimism (Weinstein 1980). Both interpretations lead to the same predictions.
ABJ argue that managers become more pessimistic if they observe two consecutive sales decreases; conversely, they are more optimistic during periods of strong macroeconomic expansion. Consistent with this argument, they find that cost stickiness is significantly lower during successive sales decreases and significantly higher during years of high GDP growth. Banker et al. (2013d) show that the degree of both cost stickiness and cost anti-stickiness varies with additional signals such as order backlog and analysts’ sales forecasts in ways consistent with Hypothesis 3.¹⁵ Banker et al. (2013f) show that although cost stickiness prevails in a typical year, costs became significantly anti-sticky in 2009, the lowest point of the severe recession of 2007-2009, reflecting the effects of unusually strong pessimism. Chen et al. (2013) argue that because managerial overconfidence leads to excessive optimism about future sales, it should increase cost stickiness; their empirical findings support this prediction. In summary, empirical evidence indicates that (both rational and irrational) managerial expectations play a key role in asymmetric cost behavior.

An important related determinant of cost asymmetry is the direction of prior period sales change. Banker et al. (2013d) argue that while cost stickiness prevails on average, this average asymmetry consists of two distinct processes: cost stickiness conditional on a prior sales increase, and cost anti-stickiness conditional on a prior sales decrease.

The direction of prior period sales change has two effects. First, following a prior sales increase, managerial expectations are optimistic, leading to increased stickiness; conversely, a prior sales decrease leads to significant pessimism, contributing to anti-stickiness (Hypothesis 3).

Second, prior sales change direction affects the amount of slack carried over into the current period. If sales increased in the prior period, then managers added only the required resources;
therefore, initial slack in the current period is close to zero. If sales increase further in the current period, managers will expand resources fully proportionately given negligible initial slack. If sales decrease in the current period, however, managers will cut resources only after they have reached the maximum acceptable level of slack capacity. Thus, cost response will be magnified for current sales increases and weakened for current sales decreases. This contributes to cost stickiness, reinforcing the effects of optimism.

Conversely, if sales decreased in the prior period, then managers retained significant unused capacity. Therefore, if sales increase in the current period, managers will add resources only after they have exhausted the initial slack. If sales decrease in the current period, however, managers will have to cut resources aggressively, because unused capacity was large even before the latest sales decrease. Thus, retained slack following a prior sales decrease leads to a weakened cost response for current sales increases and a magnified cost response for current sales decreases. This further increases anti-stickiness, complementing the effects of pessimism.

The combined effect of expectations and initial slack leads to the following prediction:

**Hypothesis 4 ("prior period sales change and cost asymmetry"):** Conditional on a prior period sales increase, costs in the current period are sticky. Conditional on a prior sales decrease, costs in the current period are anti-sticky.\(^{16}\)

Banker et al. (2013d) show that these predictions of conditional stickiness and anti-stickiness hold for all of the main cost categories in U.S. Compustat data, including SG&A costs, COGS, advertising costs, R&D costs, other SG&A costs and the number of employees. They also

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\(^{16}\) Balakrishnan et al. (2004) make a related prediction that costs are likely to be anti-sticky when capacity utilization is unusually low. However, Hypothesis 4 is broader in two important ways. First, because it does not require data on capacity utilization (which is rarely available even in proprietary industry- and firm-specific samples), it can be used in any of the standard accounting datasets. Second, it reflects not only the effect of capacity utilization (the sole focus of Balakrishnan et al.’s analysis) but also, and likely more important, the impact of prior sales changes on managers’ expectations.
demonstrate that recognizing the impact of prior period sales change can have a major impact on inferences. In particular, some cost categories appear to behave symmetrically on average, which would seem to be consistent with the traditional model of fixed and variable costs; however, conditional on prior sales change direction, they reveal significant asymmetries that conclusively reject the traditional model (we provide an example of this later on).

Because resource commitment decisions are made by self-interested managers, asymmetric cost behavior likely reflects not only optimal resource planning but also agency effects. For example, as discussed earlier, empire-building behavior by managers can lead to excessive cost stickiness that arises from wasteful overspending. The impact of empire-building is likely to be stronger when managers have a greater opportunity to overinvest, such as when they have large free cash flows. Conversely, good corporate governance is likely to constrain managers’ ability to overinvest, mitigating excessive cost stickiness (Chen et al. 2012).

Other agency factors can lead to inefficiently low cost stickiness. For example, when managers face strong incentives to meet an earnings target in the current period, they are likely to engage in (myopic) real earnings management: they will cut slack resources excessively when sales decrease and will delay acquisition of needed resources when sales increase (Dierynck et al. 2012; Kama and Weiss 2013). This will reduce cost stickiness below the efficient level.17

These examples illustrate a more general prediction: when managers face stronger incentives to report higher earnings or to contain costs, the degree of cost stickiness is likely to be lower.

**Hypothesis 5 (“managerial incentives and cost stickiness”):** Managers’ incentives to report higher earnings or to contain costs reduce the degree of cost stickiness.

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17 When managers retain an efficient amount of slack, they deliberately sacrifice part of current period earnings to avoid future adjustment costs, and they do so only as long as the expected future savings outweigh current losses. Therefore, although excessive resource cuts improve current financial performance, they are value-destroying in the long run, because they entail a disproportionately large increase in future adjustment costs.
Chen et al. (2012) show empirically that observed cost stickiness partly reflects wasteful empire-building behavior, and that strong corporate governance lessens the impact of empire-building. Dierynck et al. (2012) and Kama and Weiss (2013) find, using proxies such as small positive earnings and small earnings increases, that cost stickiness is diminished when managers face incentives to meet an earnings target. Banker and Fang (2013) show that for firms that obtain loan financing, cost stickiness is significantly reduced in the two years prior to the loan, suggesting that managers cut slack resources disproportionately to improve financial performance prior to loan approval; further, they find that greater intensity of financial covenants on earnings restrains cost stickiness in subsequent years. The evidence in these papers confirms that managerial incentives and agency factors play an important role in cost behavior.

**Implications for Financial Accounting Research**

Because earnings = sales – costs, better understanding of cost behavior contributes new insights for financial accounting research on the properties of both realized earnings and analysts’ earnings forecasts. Many of these implications have not yet been explored, suggesting a fruitful new research area that integrates findings from cost and financial accounting.

Banker and Chen (2006) examine the implications for earnings prediction. They develop the Cost Variability and Cost Stickiness (CVCS) model, which incorporates an explicit understanding of sticky costs as a component of earnings. They show that the CVCS model outperforms other earnings prediction models, including models that are based on decomposition of earnings into cash flows and accruals (Sloan 1996), and into operating and non-operating components (Fairfield et al. 1996). Banker et al. (2013d) refine the CVCS model by incorporating a two-period specification of asymmetric cost behavior, and show that this
refinement leads to further improvement in out-of-sample prediction accuracy.

Anderson et al. (2007) show that recognizing the influence of cost behavior affects the interpretation of SG&A cost ratio, one of the standard ratios in fundamental analysis of earnings components. Traditional fundamental analysis views increases in the ratio of SG&A costs to sales as evidence of poor cost control, a negative signal about future earnings (Lev and Thiagarajan 1993). However, Anderson et al. argue that this interpretation should be reversed during sales decreases: because managers retain more slack SG&A resources when they are optimistic about future sales, an increase in SG&A cost ratio in a revenue-decreasing period constitutes a *positive* signal about future performance. As expected, they find that the association between SG&A cost ratio increases and future earnings is negative in revenue-increasing periods but positive in revenue-decreasing periods, underscoring the value of incorporating an understanding of asymmetric cost behavior in fundamental analysis.

Weiss (2010) examines how firms’ asymmetric cost behavior influences analysts’ earnings forecasts. He argues that because cost stickiness magnifies the impact of sales decreases on earnings, firms that exhibit greater stickiness should have lower earnings predictability. Conversely, firms that have anti-sticky costs should have more predictable earnings. Consistent with this argument, he finds that analysts’ earnings forecasts are substantially less accurate for firms with sticky costs than for firms with anti-sticky costs. He also shows that the degree of cost asymmetry affects analysts’ and investors’ behavior, including analysts’ coverage and market responses to earnings surprises.

Dierynck et al. (2012) and Kama and Weiss (2013) document that the degree of cost stickiness is diminished when managers face incentives to meet an earnings target; Banker and Fang (2013) report a reduction in cost stickiness before new loan financing. These findings are
important not only in the context of cost behavior (Hypothesis 5) but also, more broadly, for understanding real earnings management in financial accounting research.

Banker et al. (2012b) examine whether investors fully understand the value implications of asymmetric cost behavior, and find that stock prices incorporate available information on cost variability to a greater extent than they incorporate information on cost asymmetry. They further show that slow incorporation of past cost asymmetry information is consistent with the post-earnings-announcement drift (PEAD) anomaly.

Banker and Chen (2012) analyze which cost behavior model analysts and investors use. They consider several potential models, including the proportional model implicit in fundamental analysis, the traditional model of fixed and variable costs, and the cost variability and cost stickiness (CVCS) model of Banker and Chen (2006). Because analysts’ and investors’ thought process is unobservable, the authors use the revealed preferences approach (MasCollel et al. 1995), and examine which model best approximates market participants’ observed behavior—analysts’ earnings forecasts and investors’ responses to earnings surprises. They find that analyst forecasts are most consistent with the standard model of fixed and variable costs, even though this model has inferior earnings forecast accuracy compared to the CVCS model. This indicates that analysts do not recognize asymmetric cost behavior, and that their forecasts can be improved by incorporating an understanding of sticky costs. \(^{18}\) They also find that investors’ expectations, revealed in market responses to earnings surprises, are closest to analysts’ forecasts, indicating that, similar to analysts, investors do not sufficiently understand asymmetric cost behavior.

Banker et al. (2012a, 2013a) examine the implications for research on conditional conservatism—asymmetric recognition of good versus bad news in reported earnings. They

\(^{18}\) In a related paper, Kim and Prather-Kinsey (2010) show that analysts do not fully understand the impact of fixed costs on cost and earnings behavior. However, these authors do not examine the role of asymmetric cost behavior.
argue that because sales decreases (the driver of retained slack) are positively correlated with bad news about future cash flows (the trigger of asymmetric loss recognition), cost stickiness is likely to be mistaken for conservatism, and more important, variation in cost stickiness is likely to be mistaken for variation in conservatism. Consistent with this argument, they find that cost stickiness leads to substantial bias in standard conservatism models, including Basu (1997) asymmetric timeliness and Khan and Watts (2009) conservatism score. In a related paper, Oded and Weiss (2013) show that economic factors that have an asymmetric effect on a firm’s operations, including stock option based compensation, sticky costs and monopolistic power, account for a large fraction of total variation in asymmetric timeliness.

EMPIRICAL ISSUES IN ASYMMETRIC COST BEHAVIOR RESEARCH

In this section, we briefly review the main empirical models of asymmetric cost behavior and clarify essential sample selection issues that researchers must be aware of to avoid potentially severe biases. We also examine claims made in recent working papers by Anderson and Lanen (2009) and Balakrishnan et al. (2013), who question the validity of research findings on sticky costs, and show that these claims are unfounded due to econometric errors.

Empirical Models of Asymmetric Cost Behavior

Most of the literature builds on ABJ’s cost stickiness model. The ABJ model is based on a piecewise-linear relation between log-changes in costs and concurrent log-changes in sales:

**ABJ model**

\[
\Delta \ln COST_{i,t} = \beta_0 + \beta_1 \Delta \ln SALES_{i,t} + \beta_2 DEC_{i,t} \Delta \ln SALES_{i,t} + \epsilon_{i,t}
\]

where \(\Delta \ln COST_{i,t} = \ln COST_{i,t} - \ln COST_{i,t-1}\) is the log-change in costs of firm \(i\) in year \(t\),
\[ \Delta \ln \text{SALES}_{i,t} = \ln \text{SALES}_{i,t} - \ln \text{SALES}_{i,t-1} \] is the log-change in sales revenue. 19 \( DEC_{i,t} \) is a sales decrease dummy, equal to 1 if \( \Delta \ln \text{SALES}_{i,t} < 0 \) and zero otherwise, and \( \varepsilon_{i,t} \) is an error term.

Because the theory pertains to resource adjustment in response to real activity changes, \( \Delta \ln \text{COST}_{i,t} \), \( \Delta \ln \text{SALES}_{i,t} \) and \( DEC_{i,t} \) should be based on deflated numbers to control for inflation. The slope coefficient \( \beta_1 \) approximates the percentage change in costs for a one percent sales increase, characterizing the relative importance of variable costs. The coefficient \( \beta_2 \) captures the degree of asymmetry in cost response to sales decreases versus increases. Cost stickiness (Hypothesis 1) implies that \( \beta_2 \) is negative, meaning that costs fall to a lesser extent for a one percent sales decrease than they rise for an equivalent sales increase (i.e., \( \beta_1 + \beta_2 < \beta_1 \)).

ABJ choose the log-log specification over a linear specification because (1) the Davidson and MacKinnon (1981) test of model specification rejects the linear form in favor of the log-log model, and (2) the log-change form improves the comparability of variables across firms and alleviates heteroskedasticity. However, a drawback of the log-log model is that it cannot be estimated for earnings, because logarithm is not defined for losses. Therefore, when the researcher’s objective is to capture the impact of cost stickiness on earnings behavior, a linear specification may be preferred. Because \( EARNING_{i,t} = \text{SALES}_{i,t} - \text{COSTS}_{i,t} \), the linear model can be estimated for either costs or earnings:

**Linear ABJ model for costs**

\[
\frac{\Delta \text{COST}_{i,t}}{\text{SCALE}_{i,t-1}} = \beta_0 + \beta_1 \frac{\Delta \text{SALES}_{i,t}}{\text{SCALE}_{i,t-1}} + \beta_2 DEC_{i,t} \frac{\Delta \text{SALES}_{i,t}}{\text{SCALE}_{i,t-1}} + \varepsilon_{i,t} \tag{2}
\]

19 ABJ and subsequent studies use sales revenue as an activity measure for two reasons. First, physical output data is not available in Compustat and other standard datasets. Second, even when such data is available, sales revenue typically is a more appropriate empirical activity measure than physical output. Physical units are not comparable across different outputs; further, even within the same product category, they are not comparable across firms due to product differentiation. Therefore, physical units have to be converted into a scale that is comparable across products and firms; appropriately deflated sales revenue provides such a common scale.
Linear ABJ model for earnings

\[
\frac{\Delta \text{EARNINGS}_{i,t}}{\text{SCALE}_{i,t-1}} = \alpha_0 + \alpha_1 \frac{\Delta \text{SALES}_{i,t}}{\text{SCALE}_{i,t-1}} + \alpha_2 \text{DEC}_{i,t} \frac{\Delta \text{SALES}_{i,t}}{\text{SCALE}_{i,t-1}} + \varepsilon_{i,t}
\]

(3)

where \( \Delta \text{COST}_{i,t} \equiv \text{COST}_{i,t} - \text{COST}_{i,t-1} \), \( \Delta \text{EARNING}_{i,t} \equiv \text{EARNINGS}_{i,t} - \text{EARNINGS}_{i,t-1} \) and \( \Delta \text{SALES}_{i,t} \equiv \text{SALES}_{i,t} - \text{SALES}_{i,t-1} \) denote annual changes in costs, earnings and sales, respectively, \( \text{SCALE}_{i,t-1} \) represents the scaling variable (such as lagged sales, lagged assets, lagged market or book value of equity), and the remainder of terms were defined previously. Because \( \Delta \text{EARNING}_{i,t} = \Delta \text{SALES}_{i,t} - \Delta \text{COST}_{i,t} \), the coefficients \( \alpha \) in (3) are algebraically linked to the coefficients \( \beta \) in (2): \( \alpha_0 = -\beta_0 \), \( \alpha_1 = (1-\beta_1) \), \( \alpha_2 = -\beta_2 \). Cost stickiness manifests as \( \beta_2 < 0 \) in model (2) and \( \alpha_2 > 0 \) in model (3).\(^\text{20}\)

The ABJ model (1) and its linear counterparts (2) and (3) are designed to capture the average degree of asymmetry in cost behavior. The theory predicts that both the magnitude and the direction of asymmetry vary systematically across firms and over time. Empirical research typically captures this variation by specifying the coefficients \( \beta \) in model (1) as a function of observable determinants of cost asymmetry; the same approach can be used in models (2) and (3).

In addition to model (1), ABJ tested several extended specifications, one of which has been widely used in subsequent studies:

**Extended ABJ model**

\[
\Delta \ln \text{COST}_{i,t} = \beta_0 + \beta_1 \Delta \ln \text{SALES}_{i,t} + (\beta_2 + \gamma_3 \text{SUCCDEC}_{i,t}) + \gamma_2 \Delta \text{GDP}_{t} + \gamma_3 \text{AINT}_{i,t} \\
+ \gamma_4 \text{EINT}_{i,t} \Delta \ln \text{SALES}_{i,t} + \varepsilon_{i,t}
\]

(4)

where \( \text{SUCCDEC}_{i,t} \) is a dummy variable for successive sales decreases, equal to 1 if sales decreased both in period \( t \) and in period \( t-1 \) (\( \text{DEC}_{i,t} = \text{DEC}_{i,t-1} = 1 \)) and zero otherwise, \( \Delta \text{GDP} \) is

\(^{20}\) The linear model is more sensitive to outliers than the log-log model. Therefore, it is essential to carefully screen the sample for extreme values and to ensure that the screening procedure does not introduce selection bias (later in this section, we provide examples of incorrect selection criteria found in a few recent working papers).
the GDP growth rate, $AINT_{i,t}$ is asset intensity, computed as the log-ratio of total assets to sales, $EINT_{i,t}$ is employee intensity, calculated as the log-ratio of the number of employees to sales, and the remainder of terms are defined previously. The degree of asymmetry in this extended model is equal to $(\beta_2 + \gamma_1 SUCCEED_{i,t} + \gamma_2 \Delta GDP + \gamma_3 AINT_{i,t} + \gamma_4 EINT_{i,t})$. As explained earlier, $SUCCEED_{i,t}$ and $\Delta GDP_t$ serve as signals of managers’ expectations. Hypothesis 3 implies that $\gamma_1$ is positive (successive sales decreases diminish stickiness) and $\gamma_2$ is negative (GDP growth increases stickiness). Asset intensity and employee intensity are used as proxies for the magnitude of resource adjustment costs; Hypothesis 2 implies that $\gamma_3$ and $\gamma_4$ are negative (cost stickiness is higher for asset- and employee-intensive firms).

Subsequent research on the determinants of sticky costs has employed further extensions of the ABJ model, using the following general type of models:

$$\Delta \ln COST_{i,t} = \beta_0 + \delta_0^X X_{i,t} + (\beta_1 + \delta_1^X X_{i,t}) \Delta \ln SALES_{i,t} +$$
$$+ (\beta_2 + \delta_2^X X_{i,t}) DEC_{i,t} \Delta \ln SALES_{i,t} + \varepsilon_{i,t}$$

where $X_{i,t}$ represents the vector of variables expected to affect the degree of cost asymmetry, and all other variables were defined earlier. Notably, ABJ’s extended model (4) assumes that resource expansion for sales increases is mechanistic, meaning that the slope for sales increases does not vary with $X_{i,t}$ (i.e., $\delta_1^X = 0$). However, some of the more recent studies (Banker et al. 2013c, 2013d) argue that the extent of resource expansion for sales increases is also subject to managerial discretion, which implies that the slope for sales increases may vary with $X_{i,t}$ (i.e., in general $\delta_1^X$ may differ from zero). The specific set of variables included in $X_{i,t}$ varies from study

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21 Because cost stickiness corresponds to a negative incremental slope for sales decreases, a positive $\gamma$ indicates a reduction in stickiness.

22 This prediction pertains to broad cost categories such as SG&A and operating costs. However, it does not necessarily extend to labor costs. For example, if labor-intensive firms primarily use unskilled workers, who have lower adjustment costs than skilled employees, then labor intensity may reduce stickiness of labor costs.
to study. For example, along with the standard determinants of cost stickiness from model (4), Chen et al. (2012) include firm-level proxies for empire-building incentives and corporate governance, while Banker et al. (2013c) include country-level labor market characteristics. For completeness, a few studies also include the stand-alone effects of $X_{i,t}$ (i.e., $\delta_0^X X_{i,t}$).

Banker et al. (2013d) propose the following two-period model:

**Banker et al. (2013d) two-period model:**

$$
\Delta \ln \text{COST}_{i,t} = \beta_0 + \beta_1^{\text{Pincr}} \text{INC}_{i,t-1} \Delta \ln \text{SALES}_{i,t} + \beta_2^{\text{Pincr}} \text{INC}_{i,t-1} \Delta \ln \text{SALES}_{i,t} + \beta_1^{\text{PDecr}} \text{DEC}_{i,t-1} \Delta \ln \text{SALES}_{i,t} + \beta_2^{\text{PDecr}} \text{DEC}_{i,t-1} \Delta \ln \text{SALES}_{i,t} + \epsilon_{i,t} \tag{6}
$$

where $\text{INC}_{i,t-1}$ ($\text{DEC}_{i,t-1}$) is a dummy variable equal to 1 if sales increased (decreased) in the prior period $t-1$ and zero otherwise, and the remaining terms were defined previously. The coefficients $\beta_2^{\text{Pincr}}$ and $\beta_2^{\text{PDecr}}$ capture current period cost asymmetry conditional on the direction of prior period sales change. Hypothesis 4 predicts that $\beta_2^{\text{Pincr}} < 0$ and $\beta_2^{\text{PDecr}} > 0$, corresponding to cost stickiness following a prior sales increase and cost anti-stickiness following a prior sales decrease, respectively. Recognizing that the extent of resource expansion for sales increases partly reflects managerial discretion, Banker et al. also predict that $\beta_1^{\text{Pincr}} > \beta_1^{\text{PDecr}}$, meaning that for the same magnitude of a current period sales increase, costs will expand to a greater extent in the case of a prior sales increase than in the case of a prior sales decrease.

While most of extant research has relied on ABJ-type models (1)-(6), several studies have pursued other approaches. Weiss (2010) proposes a firm-level measure of cost asymmetry:

**Weiss firm-level cost asymmetry measure**

$$
\text{STICKY}_{i,\tau} = \log \left( \frac{\Delta \text{COST}}{\Delta \text{SALE}} \right)_{i,\bar{\tau}} - \log \left( \frac{\Delta \text{COST}}{\Delta \text{SALE}} \right)_{i,\tau} \tag{7}
$$

where $\bar{\tau}$ ($\tau$) is the most recent period with a sales increase (decrease) over the last 4 periods.
The main benefit of this approach is that \( STICKY_{i,t} \) can serve as an explanatory variable to examine the impact of cost asymmetry on other outcomes. However, \( STICKY_{i,t} \) would be less useful as a dependent variable, because it entails significant data loss, and because it is likely to be noisy for small sales changes due to the small denominator problem. ABJ-type models (1)-(6), by contrast, are not affected by these problems. Therefore, these models are more appropriate when the objective is to examine the determinants of cost stickiness, whereas Weiss’s measure is more useful in investigation of the effects of cost stickiness.

Banker et al. (2012a, 2013b) propose an alternative model of asymmetric cost behavior. Whereas models (1)-(6) describe the relation between changes in sales and costs, this specification focuses on the relation between the level of sales and the level of costs or earnings. We present the model for earnings, because most of the relevant empirical applications focus on earnings behavior.

**Levels model for earnings**

\[
\frac{EARNINGS_{i,t}}{SCALE_{i,t-1}} = \alpha_{0,i} + \alpha_{1} \frac{SALES_{i,t}}{SCALE_{i,t-1}} + \alpha_{2} DEC_{i,t} + \epsilon_{i,t} \tag{8}
\]

where \( \alpha_{0,i} \) is a firm fixed effect, and all variables are defined previously. The scaling variable \( SCALE_{i,t-1} \) can be defined as lagged sales, lagged assets, lagged book or market value of equity. Banker et al. argue that because managers retain slack only for sales decreases, for the same level of current sales \( SALES_{i,t} \), earnings are lower if sales decreased rather than increased to this level.

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23 \( STICKY_{i,t} \) can be computed only for firms that had both a sales increase and a sales decrease in the last four periods, and the sample has to be restricted to observations for which sales and costs change in the same direction. This leads to substantial data loss. Further, it is essential to examine whether this pattern of data loss is correlated with the dependent variable, because such correlation can lead to significant selection bias in some applications.

24 The inclusion of firm fixed effects is essential—it ensures that the (short-run) cost structure is identified from time-series covariation in sales and costs, as opposed to cross-sectional variation across firms of different size.
(\(\alpha_2 < 0\)). 25 This alternative specification is useful when the researcher’s objective is to incorporate an understanding of asymmetric cost behavior into models that are traditionally formulated in terms of the level of (rather than change in) earnings, such as the CVP model in cost accounting (Banker et al. 2013b) or the Basu (1997) model in financial accounting (Banker et al. 2012a).

**Essential Sample Selection Issues**

In estimation of asymmetric cost behavior models, two sample selection criteria are potentially dangerous—when handled incorrectly, they lead to substantial selection bias.

One is a misguided notion, originated by Anderson and Lanen (2009), that observations in which sales and costs move in inconsistent directions (i.e., one decreases while the other increases) are “unusual” and should therefore be excluded from the estimation sample. However, this prescription is fundamentally flawed—it constitutes asymmetric selection on the dependent variable, an econometric error that leads to severe bias in cost stickiness estimates. For sales increases, this approach discards “unusual” observations with declining costs but keeps in the sample equally “unusual” observations with rapidly rising costs. 26 Thus, rather than diminish the impact of such observations, Anderson and Lanen’s approach amplifies their effect by discarding only one tail of the distribution. This leads to a bias in the slope for sales increases, distorting the estimates of cost stickiness. Similarly, for sales decreases this approach deletes observations with

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25 This model can be extended to incorporate a different slope (in addition to a different intercept) for sales decreases. However, theory provides no clear predictions for differential slopes in this model. The model can also be extended by adding known determinants of cost stickiness.

26 We use the quotation marks around “unusual” because, contrary to Anderson and Lanen’s claims, such observations do not indicate abnormal cost behavior. For example, costs may decrease while sales increase for at least two reasons. First, the firm may have experienced a favorable shock in input prices. Second, if managers have become pessimistic about future sales, they are likely to start reducing committed resources even before sales begin to decline. Further, standard regression analysis is sufficient to address both factors: by design, regression residual captures all unobserved factors including input price shocks, while controls for managerial expectations in extended models capture the effects of pessimism.
rising costs but retains observations with rapidly declining costs. This biases the slope for sales decreases, further distorting the estimates of cost stickiness. In Appendix A, we show using simulations that this bias has a dramatic impact on the estimates. For example, when we generate artificial data setting the “true” cost stickiness coefficient to $\beta_2 = -0.19$, which is consistent with ABJ’s estimates, the bias is strong enough to yield spurious estimates of no stickiness. Thus, discarding “unusual” observations from the estimation sample is both wrong theoretically and misleading empirically.

The second potential source of bias is incorrect application of one of ABJ’s standard sample selection criteria. ABJ delete observations for which SG&A costs exceed sales revenue; subsequent studies follow the same approach. However, ABJ do not specify whether this criterion is applied only in the current year ($SGA_t > SALES_t$) or both in the current and in the prior year (i.e., observation $t$ is deleted if $SGA_t > SALES_t$ or $SGA_{t-1} > SALES_{t-1}$). Further, they do not indicate whether this condition is imposed before or after the computation of log-changes, a choice that further affects sample composition.\(^{27}\)

This ambiguity is potentially risky, because one of these alternatives—screening for $SGA > SALES$ in current year only, performed after the computation of log-changes—leads to severe selection bias. As we show in Appendix B, in Compustat data this procedure would disproportionately discard observations for which SG&A costs expanded much more rapidly than sales, which would lead to dramatic downward bias in cost stickiness estimates. Thus, it is essential to use a correct screening procedure for $COSTS > SALES$ (for cost categories for which

\(^{27}\) If observations with $SGA_t > SALES_t$ are discarded from the sample before this computation, then log-changes (from year $t-1$ to year $t$) will be computable only for firm-years that satisfy both $SGA_t \leq SALES_t$ and $SGA_{t-1} \leq SALES_{t-1}$. By contrast, if observations with $SGA_t > SALES_t$ are discarded after the log-changes have been computed, then the estimation sample will be larger because it will also include log-changes for which $SGA_{t-1} > SALES_{t-1}$ and $SGA_t \leq SALES_t$.\)
such screening is reasonable to begin with). If this criterion is imposed after the computation of log-changes, as in the discussion above, then the correct approach is to screen for both $COSTS_{t-1} > SALES_{t-1}$ and $COSTS_t > SALES_t$. If this criterion is used before the computation of log-changes, however, then the equivalent procedure is to screen only for $COSTS_t > SALES_t$ (in this case, discarding observations with $COSTS_{t-1} > SALES_{t-1}$ would lead to unnecessary data loss).

**Contrary Claims Against the Findings of Sticky Cost Research**

Two recent working papers, Anderson and Lanen (2009) and Balakrishnan et al. (2013), question the validity of empirical findings of sticky costs in the literature. In this subsection, we briefly address these claims.

Anderson and Lanen (2009) make two main claims. First, they claim that the empirical findings of cost stickiness are “fragile,” because the estimates for SG&A costs become significantly weaker when they discard “unusual” observations in which sales and costs move in inconsistent directions. However, as we explain in the previous subsection, Anderson and Lanen’s approach of excluding “unusual” observations leads to severe selection bias; further, the size of this bias is sufficiently large to fully explain the purported fragility of their estimates. With correct screening criteria, Anderson and Lanen’s own estimates ($\beta_2 = -0.2105$, $t = -39.51$) support ABJ’s findings, and indicate statistically and economically significant stickiness.

Second, Anderson and Lanen report that the number of employees does not exhibit significant stickiness (in the ABJ model), which leads them to question the empirical validity of sticky costs. We get similar estimates in our replication. However, when we use the refined two-period model of Banker et al. (2013d) for the same sample, the estimates reveal significant stickiness.

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28 For example, for operating or total costs it would be incorrect to screen for $COSTS > SALES$, as that would exclude loss observations that constitute an important part of normal cost behavior.
conditional on a prior sales increase \( (\beta_{2}^{Pincr} = -0.081, t=-6.43) \) and significant anti-stickiness conditional on a prior sales decrease \( (\beta_{2}^{Pdecr} = 0.192, t=13.94) \). These estimates reject the traditional model of fixed and variable costs; further, they are fully consistent with the theory of asymmetric cost behavior.\(^{29}\) In other words, Anderson and Lanen’s contrary claims about the number of employees arise only because they reduce the empirical analysis to a single test of whether costs are sticky on average, ignoring other standard tests in the literature.

Balakrishnan, Labro and Soderstrom (2013), henceforth BLS, argue that the log-log transformation in the ABJ model may lead to spurious findings of cost stickiness, and advocate the use of an alternative linear model with scaling by lagged sales (model (2) in the present paper with \( SCALE_{i,t-1} = SALES_{i,t-1} \)). They then claim to show that the estimates of cost stickiness in this alternative model are close to zero, contrary to the standard findings of significant stickiness in the literature.\(^{30}\)

However, BLS’s claims are unfounded both theoretically and empirically. First, similar to Anderson and Lanen (2009), BLS artificially reduce the empirical content of asymmetric cost behavior to a single test of whether costs are sticky on average. In other words, they ignore the predictions of systematic variation in the degree of asymmetry that are central both to ABJ (e.g., three out of four hypotheses in ABJ deal with systematic variation) and to subsequent research. However, recognizing this systematic variation would lead to dramatically different conclusions.

\(^{29}\) Notably, the theory does not imply that the number of employees must be sticky on average. As mentioned earlier, if technological improvements in labor productivity outpace average sales growth, then managers can have decreasing labor resource requirements even when sales are increasing. This would diminish or reverse stickiness. Additionally, the number of employees is a crude measure of labor input. For example, if in downturns managers retain more productive employees while letting go of less skilled staff, then the decrease in effective labor input will be less than proportional to the number of employees. This likely explains why Anderson and Lanen find that labor costs are sticky on average while the number of employees is not.

\(^{30}\) An older version of their working paper also included simulations that claimed to show that a standard linear cost function can reproduce that findings of cost stickiness. However, these simulations have been refuted by Banker et al. (2011), who show that the key assumptions in these simulations are inconsistent with empirical data, and that under more realistic assumptions the same simulation would lead to the opposite of BLS conclusions. The latest version of BLS no longer relies on simulations.
from BLS’s own analysis.

In particular, BLS show algebraically that under the strong assumption that costs follow the traditional linear model of fixed and variable costs, the log-log ABJ specification can produce spurious estimates of cost stickiness. They argue that because their algebraic derivation can reproduce cost stickiness (Hypothesis 1), the traditional cost model cannot be rejected based on the findings of cost stickiness in the literature. However, even if this were the case, the traditional model (the assumption at the core of BLS argument) is decisively rejected based on other findings in the literature. For example, Banker et al. (2013d) predict and find that costs are anti-sticky conditional on a prior sales decrease (Hypothesis 4), a prediction that cannot be reproduced by BLS’s algebraic argument.31 Thus, even if the traditional cost model is not rejected using Hypothesis 1, it is rejected based on Hypothesis 4. The traditional model is similarly rejected based on the findings in ABJ’s extended analysis, including reduced cost stickiness for successive sales decreases, increased cost stickiness in periods of high GDP growth and reduced cost stickiness over longer aggregation periods.32 Thus, while BLS’s algebraic argument for the traditional cost model could potentially reproduce average cost stickiness, this argument is inconsistent with other standard findings in the literature that have been well known since Anderson et al. (2003).

Second, BLS claim to show that the estimates of cost stickiness in the sales-deflated linear

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31 For a linear cost function $C = F + vS$, where $F$ is fixed costs, $v$ is variable cost ratio and $S$ is sales revenue, the slope of the relation between log-sales and log-costs is $\beta = \frac{\partial \ln C}{\partial \ln S} = \frac{vS}{F+vS}$, which is increasing in sales $S$. Because current sales level $S$ is higher when sales increased rather than decreased from the prior period, the slope $\beta$ is higher for sales increases than for sales decreases. This can lead to spurious stickiness but cannot generate spurious anti-stickiness.

32 BLS’s analysis would predict the opposite of these findings. In particular, because the slope $\beta$ from the previous footnote increases in $S$ at a diminishing rate, the degree of asymmetry between sales increases and decreases (i.e., the extent of spurious stickiness) is higher for low sales levels. Therefore, spurious stickiness would be higher following a prior sales decrease. GDP growth would have no effect. Because aggregation over longer time periods increases the magnitude of sales changes, raising the asymmetry in slopes, spurious stickiness would be increasing with aggregation length. Given that all three implications of BLS argument contradict the empirical findings, any one of them is sufficient to reject this argument, ruling out the traditional model of fixed and variable costs.
model, which they view as more robust, are close to zero—contrary to the standard findings of significant stickiness in the log-log model. However, these contrary estimates arise because BLS deviate from the standard sample selection criteria and replace them with econometrically flawed criteria that, by construction, lead to severe selection bias. When we reproduce BLS’s empirical analysis after correcting this econometric error, the estimates in all models—including their favored sales-deflated specification—indicate robust and significant cost stickiness (we provide the replication details and explain the source of selection bias in Appendix C). Thus, the contrary claims of BLS are unwarranted both theoretically and empirically.

COMPREHENSIVE GLOBAL EVIDENCE ON ASYMMETRIC COST BEHAVIOR

While most of extant research has focused on the U.S., the fundamental drivers of asymmetric cost behavior—managerial discretion and resource adjustment costs—are universal global phenomena. Consequently, the main theoretical predictions (Hypotheses 1-5) are likely to hold globally. To illustrate the global pervasiveness of asymmetric cost behavior, we test each of these hypotheses using country-specific regressions for firms in Global Compustat, a dataset that spans a broad range of both developed and developing countries.

We use annual firm-level data from 1988-2008 for all countries in Global Compustat that

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33 This model would be more robust than the log-log specification only under the strong assumption that the true cost function is linear. However, as we show above, this assumption is conclusively rejected based on the standard findings in the literature.

34 The standard sample selection criteria involve discarding the log-change observation for year t if (1) SG&A costs in current year t exceed current year sales, or (2) SG&A costs in prior year t-1 exceed prior year sales. Notably, because log-changes in year t are based on both current and prior year values of sales and SG&A costs, it is crucial to use identical criteria in both years to avoid selection bias. BLS modify the second condition, discarding observations for which current SG&A costs exceed prior period sales. By using inconsistent screening criteria for current and prior year, BLS introduce a severe—and a priori predictable—selection bias in their estimation sample, which we analyze in Appendix C.

35 A few prior papers have used international data (e.g., Calleja et al. 2006, Dierynck et al. 2012, Banker et al. 2013c, 2013e). However, these papers focus on a single country or examine the drivers of cross-country variation, providing no direct evidence on whether the main predictions of asymmetric cost behavior prevail across all countries.
have at least 2,000 valid observations.\textsuperscript{36} We focus on operating costs, a broader measure of cost behavior than SG&A costs; untabulated results for SG&A costs are similar. We discard invalid observations that have missing or non-positive values for sales and operating costs, and extreme observations for which the ratio of operating costs to sales is less than 0.1 or greater than 10. All financial variables are deflated to control for inflation, using a country-specific GDP deflator. In computing annual log-changes, we require the reporting currency to be the same in both current and prior year. After discarding 0.5% extreme values on each tail for log-changes in sales and operating costs, the sample size ranges from 2,412 firm-year observations for Indonesia to 133,590 observations for the U.S., for a total of 315,967 firm-years across 20 countries (in regressions involving additional independent variables, the sample size is smaller due to missing data). The countries in the data exhibit substantial heterogeneity. For example, average annual GDP growth ranges from 1.5% in Japan to 9.8% for China, and the percentage of sales increases varies from 56% in Indonesia to 72% in India (untabulated).

We test Hypothesis 1 for each country using the ABJ model (1). The estimates are presented in column (1) of Table 1. Consistent with the theory, the cost stickiness coefficient $\beta_2$ is negative and significant at the 10% level for 16 countries out of 20; in the remaining 4 countries, $\beta_2$ has the expected sign but is insignificant. The degree of cost stickiness is economically significant, ranging (among statistically significant estimates) from -0.237 for China to -0.049 for Taiwan. Thus, as expected, cost stickiness is pervasive globally.\textsuperscript{37}

\[\text{[Insert Table 1 here]}\]

\textsuperscript{36} For most countries, data is not available prior to 1988. We supplement the sample with U.S. and Canadian data from Compustat North America. We require at least 2,000 observations per country to be able to draw meaningful country-by-country inferences.

\textsuperscript{37} In untabulated sensitivity checks, we use the linear model (2) with scaling by lagged sales, which Balakrishan et al. (2013) claim is more robust, in place of the log-log ABJ model. The results are similar: the cost stickiness coefficient is negative and significant at the 10% level for 14 countries out of 20; among the remaining 6 estimates, only two are positive and none of these is significant.
We test the next two hypotheses using the extended ABJ model (4). The estimates are presented in columns (2)-(5) of Table 1. The sample size in this analysis is substantially smaller because of missing data for the number of employees. Asset and employee intensity serve as proxies for resource adjustment costs. For both variables, almost all of the country-specific estimates have the expected negative sign ($\gamma_3<0$, $\gamma_4<0$), and most of these are significant at the 10% level; among the 3 contrary estimates, only one is significant (columns 2 and 3). Thus, as expected, the degree of cost stickiness in each country is heterogeneous across firms, and it varies systematically with the correlates of resource adjustment costs, supporting Hypothesis 2.

Successive sales decreases and GDP growth in this model are used as signals of managerial expectations for future sales (Hypothesis 3). As expected, cost stickiness is diminished in the case of successive sales decreases ($\gamma_1>0$): all but one of the coefficients have the expected sign, and a majority of them are significant (column 4 in Table 1). The evidence for GDP growth is consistent with the predictions but less strong: five countries have significant estimates of the expected sign ($\gamma_2<0$), two have significant estimates of the opposite sign, and the remainder are insignificant (column 5).38

We test Hypothesis 4 using the two-period model (6) of Banker et al. (2013d). All countries exhibit cost stickiness conditional on a prior sales increase ($\beta_{2Incr} < 0$), and all but one of these estimates are significant at the 5% level (column 6 in Table 1). As expected, this pattern is reversed in the case of a prior sales decrease (column 7): 18 countries out of 20 exhibit either significant anti-stickiness ($\beta_{2Decr} > 0$) or an insignificant degree of asymmetry, while only two

38 The two countries with significant contrary estimates, Switzerland and Malaysia, are small countries with extensive foreign trade. Therefore, local GDP growth is unlikely to be an accurate signal of future sales for firms from these countries. This can also explain insignificant estimates for GDP growth in several other countries.
countries, China and Malaysia, have significant (but diminished) stickiness.\footnote{Because China and Malaysia have experienced rapid economic growth during the sample period, managers’ expectations are likely to be moderately optimistic even in the case of a prior sales decrease, leading to significant cost stickiness. Further, cost stickiness in these countries is diminished relative to the case of a prior sales increase, which is consistent with the theory.}

We test Hypothesis 5 for two types of agency factors: incentives to avoid losses and earnings decreases (Kama and Weiss 2013), and empire-building incentives (Chen et al. 2012). We use the extended model specification (5), substituting the respective incentive variable in place of $X_{i,t}$.

Following Kama and Weiss (2013), in regressions for incentives to avoid losses (earnings decreases) we set the indicator variable $AVOID_{i,t}$ to one if net income (change in net income) in year $t$ is within $0\ldots0.01$ of beginning-of-year market value, and zero otherwise. The estimates are presented in columns (1) and (2) in Table 2. Consistent with Hypothesis 5, incentives to meet an earnings target diminish cost stickiness: in both analyses, the coefficient $\delta_2$ has the expected positive sign and is significant at the 10% level for 8 countries, and only two estimates (Brazil and South Africa in the analysis for losses) are significant in the contrary direction.

[Insert Table 2 here]

Following Chen et al. (2012), we use prior period free cash flows scaled by assets ($FCF_{i,t-1}$) as a proxy for managers’ empire-building incentives. The estimates are presented in column (3) of Table 2. Consistent with Hypothesis 5, empire-building incentives increase cost stickiness: the coefficient $\delta_2$ has the expected negative sign and is significant at the 10% level for 8 countries; the remaining estimates are insignificant and most of them have the expected sign.

In summary, our country-by-country analysis, which tested all of the standard hypotheses and was conducted for all countries in Global Compustat that had adequate sample size, indicates that asymmetric cost behavior is a pervasive global phenomenon. The estimates lend strong support to Hypotheses 1-5 for a majority of countries, and only a few contrary estimates are
significant even at the 10% level.\textsuperscript{40}

CONCLUSION

In this paper, we integrated recent research insights into a comprehensive framework of asymmetric cost behavior, reviewed the empirical evidence on sticky and anti-sticky cost behavior, showing that it lends strong and robust support to this new way of thinking about cost behavior, and clarified empirical implementation issues. We also provided new empirical evidence documenting that asymmetric cost behavior is pervasive globally, and refuted recent claims that questioned the validity of findings in the literature.

There are several important unresolved issues in existing research. For example, documented cost stickiness is consistent with both rational resource planning and wasteful empire-building (Anderson et al. 2003; Chen et al. 2012). Although both mechanisms involve asymmetric retention of slack, some of the implications are starkly different: the former represents desirable managerial behavior that contributes to firm value in the long run by avoiding excessive adjustment costs, whereas the latter reflects value-destroying overspending. Therefore, it is important to develop empirical tests that can reliably discriminate between efficient and excessive cost stickiness, and to identify performance evaluation methods and incentive mechanisms that discourage “bad” stickiness but do not deter “good” stickiness. Additionally, determination of optimal resource levels involves solving a prohibitively complex dynamic optimization problem and requires accurate estimates of adjustment costs (not all of which are recorded as costs in the accounting system). Therefore, an important practical challenge is to

\textsuperscript{40} Given the large number of countries in the analysis, many of which have small sample size, one should expect some significant contrary estimates. For example, if the true effect is small relative to the standard error of the estimate (which is likely in countries with small sample size), then one would expect almost 5% of country-specific estimates to be significant at the 10% level in the contrary direction, reflecting type I error.
develop heuristics that provide a simple but dependable approximation of optimal decision rules, and estimation methods to measure adjustment costs.

An important area for new research is to examine the implications of asymmetric cost behavior for other topics in both cost and financial accounting. For example, incorporating cost asymmetry requires significant modifications in many of the standard cost accounting tools, including budgeting and analysis of variances (Banker et al. 2013b), activity-based costing, performance scorecard and incentive compensation. Another important issue is how asymmetric cost behavior should affect pricing decisions. More broadly, because asymmetric cost behavior constitutes a new way of thinking about costs, which is far more general and nuanced than the traditional model of fixed and variable costs, it may require a fundamental rethinking of cost accounting.

Some of the most interesting new research is likely to be at the intersection of cost and financial accounting. Because earnings are determined by sales and costs, insights into cost behavior contribute to better understanding of earnings behavior, an important issue in many areas of financial accounting. Conversely, because reported costs data reflects not only real activity but also accounting recognition, findings from financial accounting areas such as conditional conservatism or accruals-based earnings management can lead to new insights for cost behavior, affecting many topics in cost accounting. Recent research has examined some of these implications; further integration of insights from cost and financial accounting is likely to generate new high-impact findings in both areas.

REFERENCES


Figure 1. Managers’ resource commitments as a function of concurrent sales

In scenario A, current sales exceed available resource capacity (determined by resources carried over from the prior period, $Resources_{t-1}$). Managers add the required resources. Therefore, costs reflect resource requirements conditional on current sales.

In scenario B, current sales are far below available resource capacity, and the level of unused resources is unacceptably high. Managers retain the maximum acceptable amount of slack resources, which allows them to avoid excessive adjustment costs, and cut resources to this maximum acceptable level. Therefore, costs reflect resource requirement conditional on current sales plus maximum acceptable slack.

In scenario C, slack capacity is positive but acceptable, such that it is more efficient to fully retain unused resources than to incur adjustment costs to dispose of them. Managers do not change resource levels. Therefore, cost reflect original resource levels ($Resources_{t-1}$).
Panel A: Negligible adjustment costs give rise to variable costs

Panel B: Large adjustment costs give rise to fixed costs in the relevant range

Figure 2. Variable and fixed costs are special cases within a general framework of asymmetric cost behavior
Table 1. Empirical tests of Hypotheses 1-4 in Global Compsustat data

\[
\Delta \ln COST_{it} = \beta_0 + \beta_1 \Delta \ln SALES_{it} + \beta_2 DEC_{it} \Delta \ln SALES_{it} + \epsilon_{it} \quad (1)
\]

\[
\Delta \ln COST_{it} = \beta_0 + \beta_1 \Delta \ln SALES_{it} + (\beta_2 + \gamma_1) SUCCDEC_{it} + \gamma_2 \Delta GDP_{it} + \gamma_3 \Delta INT_{it} + \gamma_4 \Delta EINT_{it} \Delta \ln SALES_{it} + \epsilon_{it} \quad (4)
\]

\[
\Delta \ln COST_{it} = \beta_0 + \beta_1^{\text{PInc}} \text{INC}_{it} \Delta \ln SALES_{it} + \beta_2^{\text{PDecr}} \text{DEC}_{it} \Delta \ln SALES_{it} + \epsilon_{it} \quad (6)
\]

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For brevity, we only report coefficients that are relevant in hypothesis tests. The numbers in parentheses are the t-statistics, based on standard errors clustered by firm. * *, *** indicate significance at 10, 5 and 1% levels, respectively, in two-tailed tests. The sample is Global Compustat from 1988-2008 after discarding invalid observations and 0.5% outliers on each tail. The estimates in boldface indicate strong support for the respective hypothesis.

a Model (4) is not estimated for Korea and Taiwan because of missing data for employee intensity.

Variable definitions:
\( \Delta \ln COST_{it} = \) log-change in operating costs in year t;
$\Delta \ln SALES_{i,t} = \log\text{-change in sales in year } t$;
$DEC_{i,t} = 1$ if sales decreased in year $t$, and 0 otherwise;
$SUCCDEC_{i,t} = 1$ if sales decreased both in year $t$ and in year $t-1$, and 0 otherwise;
$\Delta GDP_t = \text{GDP growth rate in year } t$;
$AINT_{i,t} = \text{asset intensity (log-ratio of total assets to sales)}$;
$EINT_{i,t} = \text{employee intensity (log-ratio of total employees to sales)}$;
$INC_{i,t-1} = 1$ if sales increased in prior year $t-1$, and 0 otherwise;
$DEC_{i,t-1} = 1$ if sales decreased in prior year $t-1$, and 0 otherwise.
Table 2. Empirical tests of Hypothesis 5 in Global Compustat data

\[ \Delta \ln \text{COST}_{i,t} = \beta_i + \delta_i X_{i,t} + (\beta_i + \delta_i X_{i,t}) \Delta \ln \text{SALES}_{i,t} + (\beta_i + \delta_i X_{i,t}) \text{DEC}_{i,t} \Delta \ln \text{SALES}_{i,t} + \epsilon_{i,t} \]

where \( X_{i,t} \) stands for \( \text{AVOIDLOSS}_{i,t} \), \( \text{AVOIDDEC}_{i,t} \), or \( \text{FCF}_{i,t-1} \).

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For brevity, we only report coefficients that are relevant in hypothesis tests. The numbers in parentheses are the \( t \)-statistics, based on standard errors clustered by firm. *, **, *** indicate significance at 10, 5 and 1% levels, respectively, in two-tailed tests. The sample is Global Compustat from 1988-2008 after discarding invalid observations and 0.5% outliers on each tail. The estimates in boldface indicate strong support for the respective hypothesis.

a We do not estimate the model with empire-building incentives for Taiwan because of missing data.

Variable definitions:
\( \Delta \ln \text{COST}_{i,t} = \log \text{-change in operating costs in year } t \);
\( \Delta \ln \text{SALES}_{i,t} = \log \text{-change in sales in year } t \);
\( \text{DEC}_{i,t} = 1 \text{ if sales decreased in year } t \text{, and } 0 \text{ otherwise}; \)
\( \text{AVOIDLOSS}_{i,t} = 1 \text{ if net income scaled by lagged market value is between } 0 \text{ and } 0.01, \text{ and } 0 \text{ otherwise}; \)
\( \text{AVOIDDEC}_{i,t} = 1 \text{ if the change in net income scaled by lagged market value is between } 0 \text{ and } 0.01, \text{ and } 0 \text{ otherwise}; \)
\( \text{FCF}_{i,t-1} = \text{ free cash flows in year } t-1 \text{ scaled by assets}. \)
Appendix A. Selection bias associated with “unusual” observations in Anderson and Lanen

We use simulations to illustrate the empirical magnitude of bias that arises when one follows Anderson and Lanen’s (2009) suggestion that “unusual” observations should be discarded from the sample. To ensure a realistic simulation, we choose “true” parameter values based on empirical estimates from a replication of Anderson and Lanen’s full sample, without discarding “unusual” observations. The “true” cost stickiness coefficient is $\beta_2 = -0.1926$. We then use these parameter values to simulate artificial costs data using the ABJ model.

Because the magnitude of bias may depend on the distribution of sales changes, for each observation in our Compustat sample we simulate log-change in costs conditional on the actual value of the corresponding log-change in sales, yielding 149,062 firm-year observations per simulation. After generating each simulated sample, we estimate the ABJ model for two sample definitions: the full sample, and the sample that remains after discarding Anderson and Lanen’s “unusual” observations (i.e., observations for which sales and costs move in opposite directions).

We repeat the simulation 200 times. The contrast between the two sets of estimates is striking. Estimation for the full sample successfully recovers the true degree of cost stickiness: all 200 estimates of $\beta_2$ fall within a narrow range [-0.2075, -0.1787] around the true value $\beta_2 = -0.1926$, all of them are significant at the 0.1% level, and the average of these estimates is virtually identical to the true value (-0.1921 versus -0.1926). By contrast, estimates obtained after imposing Anderson and Lanen’s criteria reveal a dramatic bias: the average estimate of $\beta_2$ is just -0.0064, understating the true degree of stickiness by a factor of 30 (-0.0064 versus -0.1926). Thus, discarding “unusual” observations from the estimation sample is both wrong theoretically and dangerous empirically.

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41 Compustat data from 1978-2005, after discarding missing and non-positive values of sales and costs, and after deleting 0.5% extreme values on each tail for log-changes.

42 ABJ report similar estimates ($\beta_2=0.1914$) for a sample ending in 1998.
Appendix B. Selection bias associated with incorrect screening for $SGA > SALES$

In this appendix, we illustrate the bias that arises when ABJ’s screening criteria for $SGA > SALES$ are specified incorrectly due to a misinterpretation of their verbal description. Assuming that the screening is performed after the computation of log-changes, the correct approach is to screen for $SGA > SALES$ in both current and prior year. The incorrect approach that we focus on in this analysis is to screen for $SGA > SALES$ in current year only (i.e., the log-change observation for year $t$ is deleted from the sample if $SGA_t > SALEs_t$ but not if $SGA_{t-1} > SALEs_{t-1}$ and $SGA_t \leq SALEs_t$).

Observations that are deleted under this incorrect procedure are predominantly firm-years for which SG&A costs expanded much more rapidly than sales. For example, in Compustat data from 1978-2005, the average growth rates of SG&A costs and sales for the discarded observations are 15.1% and 4.1%, respectively, i.e., the expansion in SG&A costs outpaced sales by 10 percentage points on average. Further, this procedure does not discard observations for which SG&A costs exceed sales in the prior but not in the current year ($SGA_{t-1} > SALEs_{t-1}$ but $SGA_t \leq SALEs_t$), which tend to be large sales increases accompanied by small SG&A increases. On average, sales for such observations expand by 43.4% while SG&A costs increase by just 5.9%. By deleting disproportionately large—but not disproportionately small—SG&A increases, this screening procedure leads to downward bias in the regression slope for sales increases, distorting the estimates of cost stickiness.

The magnitude of this bias in Compustat data is extremely large. When we use the correct procedure that was actually used by ABJ (i.e., screening for both $SGA_{t-1} > SALEs_{t-1}$ and $SGA_t > SALEs_t$), the cost stickiness estimate $\beta_2$ is -0.193 ($t=-23.70$), highly significant both

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43 Because this sample selection issue had been the source of some of the contrary claims made in older versions of working papers by Anderson and Lanen and by Balakrishnan, Labro and Soderstrom, we use sample definitions from Anderson and Lanen: Compustat data from 1978-2005 after discarding 0.5% extreme values on each tail.
statistically and economically. When we screen for $SGA > SALES$ in current year only, by contrast, the estimate of $\beta_2$ is just $-0.027 \ (t=-3.10)$, understating cost stickiness by 86\%.
Appendix C. Selection bias in BLS

BLS (Balakrishnan, Labro and Soderstrom 2013) argue that the sales-deflated linear model is more appropriate empirically than the log-log specification of ABJ, and claim to show that the evidence for cost stickiness in this linear model is far weaker and less robust than the standard findings (for the log-log model) in the literature. In this appendix, we demonstrate that these claimed results arise because of econometric errors that lead to severe selection bias. Further, we show that after correcting these errors, the empirical evidence in the linear model lends strong support to the standard findings of cost stickiness, contrary to these authors’ claims.

In our replication, we use Compustat data for sales and SG&A costs for 1980-2004, deflating all variables to control for inflation. We screen for non-positive and missing values for sales and costs, and discard 0.5% extreme values on each tail for log-changes. All of these sample definitions follow BLS exactly. BLS impose additional, non-standard screening criteria; these criteria are the main focus of our analysis.

Although BLS claim to follow the standard sample selection criteria, they deviate from the standard definitions in a way that leads to severe bias. In particular, the standard ABJ criteria involve discarding log-change observations for which current SG&A costs exceed current sales or lagged SG&A costs exceed lagged sales (\(SGA_t > SALES_t \) OR \(SGA_{t-1} > SALES_{t-1}\)). BLS use the same condition for the current year but modify the second condition, discarding observations for which current SG&A costs exceed lagged sales (i.e., \(SGA_t > SALES_t \) OR \(SGA_t > SALES_{t-1}\)).

This subtle change has a dramatic impact on sample composition. Among observations that

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44 This claim is accurate only under the strong assumption that the underlying true cost function in the data is linear and symmetric. As we show in the main text, this assumption is decisively rejected in Compustat data, meaning that this claim is not warranted either.
45 BLS maintain that they chose to use the “updated criteria” from Banker et al. (2011) rather than the original criteria of ABJ. However, this is misleading because Banker et al.’s criteria are identical to those in ABJ (the only difference is that Banker et al. extend the sample to a more recent period).
46 We use uppercase AND and OR to indicate Boolean operators, which convey a more precise meaning than the everyday use of “and” and “or.”
are discarded from the standard sample (those with $SGA_t > SALES_t$ OR $SGA_{t-1} > SALES_{t-1}$), BLS retain those that satisfy $SGA_t \leq SALES_t$ AND $SGA_{t-1} \leq SALES_{t-1}$ AND $SGA_{t-1} > SALES_{t-1}$. The last two inequalities imply $SGA_t < SGA_{t-1}$, meaning that by construction all of these “improperly retained” observations have decreasing SG&A costs. In the data, these observations represent unusually large SG&A decreases. For example, for “improperly retained” observations with increasing sales, the average change in SG&A costs is -34.4% and the average change in sales is +38.5% (the medians are -30.0% and +22.9%, respectively). Among the “improperly retained” sales decreases, the average change in SG&A costs is -45.4% and the average change in sales is -19.8% (the medians are -44.4% and -16.4%, respectively). Because these observations represent disproportionately large SG&A decreases both when sales are increasing and when sales are decreasing, their inclusion in the BLS sample leads to two biases: a downward bias in the slope for sales increases, and an upward bias in the slope for sales decreases. Both biases act against findings of cost stickiness.

Among observations that are included in the standard sample (those with $SGA_t \leq SALES_t$ AND $SGA_{t-1} \leq SALES_{t-1}$), BLS criteria discard those that satisfy $SGA_t \leq SALES_t$ AND $SGA_{t-1} \leq SALES_{t-1}$ AND $SGA_t > SALES_{t-1}$. The first and the third inequalities imply $SALES_{t-1} < SGA_t$, while the second and the third inequalities imply $SGA_{t-1} < SGA_t$. In other words, by construction all of these “improperly discarded” observations have increasing sales and increasing SG&A costs. By discarding these observations from their sample, BLS cause additional downward bias in the slope for sales increases, which further distorts the estimates against findings of cost stickiness.

Thus, by deviating from the standard sample selection criteria used in ABJ and in subsequent literature, BLS introduce selection bias that, by construction, acts against findings of cost stickiness. To illustrate the empirical magnitude of this bias, we estimate cost stickiness models
for two sample definitions: the “standard sample,” which discards log-change observations for year $t$ if $SGA_t > SALES_t$ OR $SGA_{t-1} > SALES_{t-1}$ following ABJ, and the “contaminated sample,” which screens for $SGA_t > SALES_t$ OR $SGA_{t} > SALES_{t-1}$ as in BLS. The remainder of sample selection criteria, described earlier, are identical to those in BLS.  

Replication results using the ABJ log-log model are presented in Table A1. Replication using BLS sample definitions (the “contaminated sample” in column 2) successfully reproduces their estimates ($\beta_2 = -0.1421, t = -15.84$ in replication versus $-0.1476, t = -16.34$ reported in BLS). When we use the standard sample definitions (column 3), however, the cost stickiness coefficient increases by 37% to $\beta_2 = -0.1952$ ($t = -22.99$). Thus, BLS’s deviation from the standard sample selection criteria leads to substantial downward bias in the estimates of cost stickiness. Notably, even BLS’s biased estimates in the log-log model indicate significant stickiness. However, they choose to dismiss these estimates and instead emphasize the estimates from their favored sales-deflated linear model, which they claim is more robust (a claim that is based on an algebraic argument that, as we show in the main text, is decisively rejected by the data).

[Insert Table A1 here]

Replication results for sales-deflated linear model are presented in Panel A of Table A2. Similar to BLS’s reported estimates (column 1), replication for BLS sample definitions indicates significant anti-stickiness ($\beta_2 = 0.0459, t = 13.61$ in column 2), which would seem to contradict the findings in the literature. However, when we use the standard sample definitions, the estimates reveal significant cost stickiness ($\beta_2 = -0.0264, t = -6.67$ in column 3). Thus, in the linear model, BLS’s deviation from the standard sample selection criteria leads to mistaken inferences not only about the magnitude but even about the sign of cost asymmetry, leading to qualitatively distorted

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47 The sample size and point estimates in our replication for the contaminated sample are slightly different from those reported in BLS because of retroactive inclusion of additional firms in Compustat.
conclusions.

BLS acknowledge that the linear model is more sensitive to outliers than the standard log-log model. Therefore, they also present estimates after further screening for outliers, using several combinations of two additional restrictions. First, they discard observations for which the variable cost ratio (VC ratio = ΔSGA/ΔSALES) exceeds ±1 or ±5. Second, they delete observations for which the percentage change in sales or costs exceeds ±100% or ±75%. Both of these restrictions are problematic and lead to further selection bias. First, the restriction on VC ratio is both completely unnecessary—regression coefficients are sensitive to extreme absolute deviations rather than extreme ratios—and dangerous, because it represents asymmetric selection on the dependent variable, an econometric error that can bias the estimates. Second, because costs are non-negative, percentage change cannot be below -100% (but can be above +100%). Therefore, restricting SG&A changes to be within ±100% constitutes asymmetric selection on the dependent variable. This leads to downward bias in the slope for sales increases, acting against findings of cost stickiness.48

Although these additional restrictions on outliers are a priori unreasonable and should never be used, we re-estimate the model to demonstrate that the findings of cost stickiness continue to hold even when we use these flawed restrictions. When we impose any combination of these restrictions on the standard sample (i.e., the sample with correct treatment of $SGA > SALES$), all of the estimates indicate statistically and economically significant stickiness (columns 1-6 in panel B of Table A2): $β_2$ ranges from -0.0283 to -0.0545, and is significant even at the 0.1%

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48 Screening for percentage changes in excess of ±75% is similarly flawed due to its asymmetric nature: a 75% decrease represents a decrease by a factor of 4, whereas a 75% increase is disproportionately smaller.
When we screen only for sales changes within ±100% or ±75% (which is the only one of BLS criteria that is econometrically acceptable, as it pertains to the independent variable), without imposing the econometrically flawed restrictions on SG&A change and VC ratio, the estimates of cost stickiness are even larger (columns 7-8).

Because the linear model is more sensitive to outliers than the log-log model, in panel C of Table A2 we present estimates for several additional—and econometrically appropriate—ways of dealing with extreme values. First, instead of discarding 0.5% extreme values as in the main sample, we screen for 1%, 2.5% or 5% extreme values on each tail. Because this approach affects both tails of the distribution equally, it does not introduce systematic bias in the estimates of cost asymmetry. All of these estimates (columns 1-3) continue to indicate significant stickiness: $\beta_2$ ranges from -0.0351 to -0.0458, and is significant at the 0.1% level. As an additional robustness check, in column 4 we use median regression, which is less sensitive to extreme values than OLS because it minimizes the sum of absolute (rather than squared) deviations (Wooldridge 2002, 348). Similar to OLS, median regression reveals significant cost stickiness ($\beta_2 = -0.0620, t = -19.67$).

Notably, when we use econometrically sound treatment of outliers (and standard treatment of $SGA > SALES$), the degree of cost stickiness in the linear model is comparable to that in the log-log model. For example, in the log-log model (column 3 in Table A1), the cost stickiness coefficient $\beta_2 = -0.1952$ is equivalent to 28.5% ($=0.1952/0.6856$) of the slope for sales increases. In the linear model with screening for 2.5% outliers (column 2 in panel C of Table A2), $\beta_2 = -0.0438$ is equal to 27.3% ($=0.0438/0.1602$) of the slope for sales increases, indicating an

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49Replication for the contaminated sample (i.e., the sample with non-standard treatment of $SGA > SALES$) with the same restrictions on outliers reproduces BLS estimates of insignificant stickiness or anti-stickiness (untabulated). This further confirms that BLS “findings” arise because, by using non-standard criteria for $SGA > SALES$, they create severe selection bias.
almost identical level of cost stickiness. Thus further underscores that BLS’s claims of bias in the log-log model are unwarranted empirically.

BLS conduct additional analyses, estimating the sales-deflated model by size decile, by year, and by revenue growth decile, and claim that they do not find reliable evidence of stickiness in these subsamples. In all of these analyses, they use econometrically flawed restrictions on outliers, in addition to non-standard treatment of $SGA > SALES$. To further illustrate the main source of bias in BLS analysis (i.e., incorrect treatment of $SGA > SALES$), we show that the estimates in all of these analyses are consistent with prior literature even when we use BLS restrictions for outliers. We also report estimates obtained after discarding 2.5% outliers on each tail. In all cases, we use the standard treatment of $SGA > SALES$.

The estimates for size deciles are presented in panel A of Table A3. Even when we use BLS restrictions for outliers, the estimates indicate statistically significant stickiness for 8 deciles out of 10 (columns 1 and 2); when we screen for outliers using an econometrically sound approach (column 3), the estimates indicate significant stickiness for all 10 deciles. Thus, contrary to BLS claims, this subsample analysis yields strong and robust evidence of cost stickiness.

[Insert Table A3 here]

The year-by-year estimates are presented in panel B of Table A3. Whereas BLS claim to find significant stickiness for only one year out of 25 (in estimates with $|VC\,\text{ratio}| \leq 5$), we obtain significant stickiness for 16 years out of 25 (column 1); when we use correct screening for outliers, the number of significant stickiness estimates increases to 20 out of 25 (column 3). Further, the timing of insignificant and anti-sticky estimates is consistent with the theory (the

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50 Because the two models are scaled differently, the relevant metric of economic significance is the ratio $\beta_2/\beta_1$ rather than the absolute magnitude of $\beta_2$.

51 In untabulated replication of these analyses for BLS’s contaminated sample, we successfully reproduce their estimates of insignificant stickiness or anti-stickiness.
effects of pessimism in Hypothesis 3). For example, the insignificant and anti-sticky estimates in column 3 are in years 1980, 2000 and 2002-2004, which correspond to a severe recession in 1980, the bursting of the tech bubble in 2000, and the economic turmoil following 9/11.

The estimates by sales growth decile are presented in panel C of Table A3. Consistent with the theory (Hypothesis 3), costs are sticky in the high growth deciles and anti-sticky or insignificantly sticky in the low growth deciles.52

BLS also claim that they do not find significant cost stickiness when they estimate the model industry-by-industry and then combine these estimates using the Fama-Macbeth approach. We report the Fama-Macbeth estimates in this analysis (using the standard treatment of $SGA > SALES$) in Table A4. Contrary to BLS claims, these estimates indicate significant cost stickiness. Further, while BLS report that only 3 out of 48 industry-specific coefficients indicate significant stickiness (in estimates for $|VC\ ratio|\leq5$), we find significant stickiness for 11 industries out of 48 (column 1); this number increases to 25 out of 48 when we use econometrically sound criteria for outliers (column 3).53

[Insert Table A4 here]

In summary, we show that the “findings” of insignificant stickiness in BLS are driven by severe econometric errors. First, and most important, they deviate from the standard (and well-known) screening criteria for $SGA > SALES$. Although this deviation affects relatively few observations, it leads to severe selection bias that acts against findings of cost stickiness.54 We

52 An exception is the highest growth decile in column 3, which exhibits insignificant anti-stickiness. However, this estimate is driven by a small number of firms that grew extremely rapidly during the sample period. When we restrict sales growth in this decile to be less than +100%, we obtain significant stickiness.
53 The large number of insignificant industry-level estimates reflects small sample size for many industries. Among industries that have at least 2,500 valid observations, 13 out of 17 exhibit significant stickiness.
54 Notably, this does not mean that “findings of sticky costs are sensitive to sample selection issues,” as BLS imply in their footnote 18. When sample selection criteria are manipulated in a way that, by construction, leads to severe selection bias, even a small number of observations can have a large impact on the estimates. This does not indicate
illustrate the nature of this bias theoretically, and show that it has a large impact empirically. When we undo this bias in estimation, using the standard treatment of $SGA > SALES$ from the extant literature, the estimates indicate strong and robust cost stickiness, supporting the standard findings in the literature.

Second, BLS use two additional questionable restrictions in screening for outliers: restrictions on the VC ratio, which are both unnecessary and dangerous, and screening for percentage changes in SG&A costs that exceed ±100%, which leads to additional selection bias that acts against findings of cost stickiness. We show that the standard findings of cost stickiness continue to hold even when we use these unreasonable restrictions; further, the evidence for cost stickiness is even stronger when we use econometrically valid treatment of outliers in place of these questionable restrictions.

that the estimates lack robustness—instead, it simply means that researchers should be careful in choosing sample selection criteria.
Table A1. Replication for the pooled sample using the log-log model

\[ \Delta \ln \text{COST}_{i,t} = \beta_0 + \beta_1 \Delta \ln \text{SALES}_{i,t} + \beta_2 \Delta \ln \text{SALES}_{i,t} + \epsilon_{i,t} \]  \hspace{1cm} (1)

<table>
<thead>
<tr>
<th></th>
<th>replication results</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>as reported by BLS in panel A of Table 2</td>
</tr>
<tr>
<td></td>
<td>(1)</td>
</tr>
<tr>
<td>( \beta_1 )</td>
<td>0.6608***</td>
</tr>
<tr>
<td></td>
<td>(121.15)</td>
</tr>
<tr>
<td>( \beta_2 )</td>
<td>-0.1476***</td>
</tr>
<tr>
<td></td>
<td>(-16.34)</td>
</tr>
<tr>
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<td>130,537</td>
</tr>
<tr>
<td>Adj. R(^2)</td>
<td>39.59%</td>
</tr>
</tbody>
</table>

For brevity, we do not report the intercepts. The numbers in parentheses are the \( t \)-statistics, based on standard errors clustered by firm. *, **, *** indicate significance at 10, 5 and 1% levels, respectively, in two-tailed tests. The data is Compustat from 1980-2004 after discarding invalid observations and 0.5% outliers on each tail. The standard sample uses standard ABJ criteria for \( SGA > \text{SALES} \). The contaminated sample is based on BLS deviation from these standard criteria.

Variable definitions:
\( \Delta \ln \text{COST}_{i,t} \) = log-change in SG&A costs in year \( t \);  
\( \Delta \ln \text{SALES}_{i,t} \) = log-change in sales in year \( t \);  
\( \Delta \ln \text{DEC}_{i,t} \) = 1 if sales decreased in year \( t \) and 0 otherwise.
Table A2. Replication for the pooled sample using the sales-deflated linear model

\[
\frac{\Delta \text{COST}_{i,t}}{\text{SALES}_{i,t-1}} = \beta_0 + \beta_1 \frac{\Delta \text{SALES}_{i,t}}{\text{SALES}_{i,t-1}} + \beta_2 \Delta \text{DEC}_{i,t} + \frac{\Delta \text{SALES}_{i,t}}{\text{SALES}_{i,t-1}} + \epsilon_{i,t} 
\]  

(2)

Panel A. Estimates without additional restrictions on outliers

<table>
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<th>replication results</th>
<th>contamination sample</th>
<th>standard sample</th>
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<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
<td></td>
</tr>
<tr>
<td>( \beta_1 )</td>
<td>0.1405***</td>
<td>0.1336***</td>
<td>0.1812***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(75.85)</td>
<td>(75.10)</td>
<td>(73.97)</td>
<td></td>
</tr>
<tr>
<td>( \beta_2 )</td>
<td>0.0382***</td>
<td>0.0459***</td>
<td>-0.0264***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(11.22)</td>
<td>(13.61)</td>
<td>(-6.67)</td>
<td></td>
</tr>
<tr>
<td>N</td>
<td>130,305</td>
<td>132,078</td>
<td>134,106</td>
<td></td>
</tr>
<tr>
<td>Adj. R(^2)</td>
<td>30.41%</td>
<td>29.52%</td>
<td>38.75%</td>
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Panel B. Estimates using BLS’s additional restrictions for outliers (standard sample only)

<table>
<thead>
<tr>
<th></th>
<th>Sales and SGA change</th>
<th>Sales and SGA change</th>
<th>Sales and SGA change</th>
<th>Sales change</th>
<th>Sales change</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>[VC ratio</td>
<td>≤5]</td>
<td>[VC ratio</td>
<td>≤1]</td>
<td>[VC ratio</td>
</tr>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
<td>(4)</td>
<td>(5)</td>
</tr>
<tr>
<td>( \beta_1 )</td>
<td>0.1817***</td>
<td>0.1796***</td>
<td>0.1903***</td>
<td>0.1873***</td>
<td>0.1802***</td>
</tr>
<tr>
<td></td>
<td>(73.83)</td>
<td>(72.76)</td>
<td>(75.51)</td>
<td>(74.01)</td>
<td>(75.08)</td>
</tr>
<tr>
<td>( \beta_2 )</td>
<td>-0.0283***</td>
<td>-0.0390***</td>
<td>-0.0472***</td>
<td>-0.0545***</td>
<td>-0.0349***</td>
</tr>
<tr>
<td></td>
<td>(-7.07)</td>
<td>(-9.57)</td>
<td>(-12.77)</td>
<td>(-14.37)</td>
<td>(-9.87)</td>
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<tr>
<td>N</td>
<td>131,454</td>
<td>120,267</td>
<td>125,446</td>
<td>125,417</td>
<td>121,713</td>
</tr>
<tr>
<td>Adj. R(^2)</td>
<td>39.86%</td>
<td>31.65%</td>
<td>32.76%</td>
<td>38.26%</td>
<td>30.33%</td>
</tr>
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</table>

Panel C. Estimates using alternative restrictions for outliers (standard sample only)

<table>
<thead>
<tr>
<th></th>
<th>1% outliers</th>
<th>2.5% outliers</th>
<th>5% outliers</th>
<th>0.5% outliers</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>on each tail</td>
<td>on each tail</td>
<td>on each tail</td>
<td>median regression</td>
</tr>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
<td>(4)</td>
</tr>
<tr>
<td>( \beta_1 )</td>
<td>0.1751***</td>
<td>0.1602***</td>
<td>0.1428***</td>
<td>0.1602***</td>
</tr>
<tr>
<td></td>
<td>(83.92)</td>
<td>(94.34)</td>
<td>(96.27)</td>
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</tr>
<tr>
<td>( \beta_2 )</td>
<td>-0.0351***</td>
<td>-0.0438***</td>
<td>-0.0458***</td>
<td>-0.0620***</td>
</tr>
<tr>
<td></td>
<td>(-10.31)</td>
<td>(-14.79)</td>
<td>(-16.27)</td>
<td>(-19.67)</td>
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<tr>
<td>N</td>
<td>131,885</td>
<td>125,405</td>
<td>115,327</td>
<td>134,106</td>
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<td>Adj. R(^2)</td>
<td>36.47%</td>
<td>33.19%</td>
<td>30.29%</td>
<td>19.92%</td>
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</table>

For brevity, we do not report the intercepts. *, **, *** indicate significance at 10, 5 and 1% levels, respectively, in two-tailed tests. The numbers in parentheses are the t-statistics, which are based on standard errors clustered by firm in all OLS regressions, and are based on bootstrapped standard errors in median regression in panel C. The data is Compustat from 1980-2004 after discarding invalid observations and 0.5% outliers on each tail, along with additional restrictions on outliers in panels B and C. The standard sample uses standard ABJ criteria for $\text{SGA} > \text{SALES}$, whereas the contaminated sample in panel A is based on BLS deviation from these standard criteria.

Variable definitions:
\[
\Delta \text{COST}_{i,t} = \text{change in SG&A costs in year } t; \\
\Delta \text{SALES}_{i,t} = \text{change in sales in year } t; \\
\text{DEC}_{i,t} = 1 \text{ if sales decreased in year } t, \text{ and 0 otherwise}; \\
\text{SALES}_{i,t-1} = \text{sales in year } t-1.
\]
Table A3. Replication for additional subsamples from BLS

$$\frac{\Delta\text{COST}_{i,t}}{\text{SALES}_{i,t-1}} = \beta_0 + \beta_1 \frac{\Delta\text{SALES}_{i,t}}{\text{SALES}_{i,t-1}} + \beta_2 \text{DEC}_{i,t} \frac{\Delta\text{SALES}_{i,t}}{\text{SALES}_{i,t-1}} + \epsilon_{i,t}$$

(2)

Panel A. Estimates of $\beta_2$ by size decile (standard sample only)

<table>
<thead>
<tr>
<th>Size decile</th>
<th>Sales and SGA change $\leq 100%$</th>
<th>VC ratio $\leq 5$</th>
<th>VC ratio $\leq 1$</th>
<th>2.5% outliers on each tail</th>
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<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>-0.0543***</td>
<td>-0.0550***</td>
<td>-0.0169**</td>
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</tr>
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</tr>
<tr>
<td>3</td>
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<td>-0.0769***</td>
<td>-0.0238***</td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>-0.0639***</td>
<td>-0.0772***</td>
<td>-0.0288***</td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>-0.0653***</td>
<td>-0.0716***</td>
<td>-0.0402***</td>
<td></td>
</tr>
<tr>
<td>6</td>
<td>-0.0536***</td>
<td>-0.0624***</td>
<td>-0.0452***</td>
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</tr>
<tr>
<td>7</td>
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<td>-0.0301***</td>
<td>-0.0198***</td>
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</tr>
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<td>-0.0258***</td>
<td>-0.0225***</td>
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<td>9</td>
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</tr>
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<td>-0.0017</td>
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<td>-0.0258***</td>
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Panel B. Estimates of $\beta_2$ by year (standard sample only)

<table>
<thead>
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<th>Year</th>
<th>Sales and SGA change $\leq 100%$</th>
<th>VC ratio $\leq 5$</th>
<th>VC ratio $\leq 1$</th>
<th>2.5% outliers on each tail</th>
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<td>(2)</td>
<td>(3)</td>
<td></td>
</tr>
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<td>-0.0156</td>
<td></td>
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<td>-0.0637***</td>
<td>-0.0708***</td>
<td>-0.0613***</td>
<td></td>
</tr>
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<td>-0.0410**</td>
<td>-0.0355**</td>
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<td>-0.0377**</td>
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### Panel C. Estimates of $\beta_2$ by sales growth decile (standard sample only)

<table>
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<tr>
<th>growth decile</th>
<th>[Sales and SGA change $\leq$100%]</th>
<th>2.5% outliers on each tail</th>
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</thead>
<tbody>
<tr>
<td></td>
<td>[VC ratio $\leq$ 5]</td>
<td>[VC ratio $\leq$ 1]</td>
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<tr>
<td>1</td>
<td>0.0452***</td>
<td>0.0663***</td>
</tr>
<tr>
<td>2</td>
<td>0.0218**</td>
<td>0.0334***</td>
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<tr>
<td>3</td>
<td>0.0077</td>
<td>0.0037</td>
</tr>
<tr>
<td>4</td>
<td>0.0192*</td>
<td>0.0335***</td>
</tr>
<tr>
<td>5</td>
<td>-0.0039</td>
<td>-0.0110</td>
</tr>
<tr>
<td>6</td>
<td>-0.0025</td>
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<td>-0.0335***</td>
<td>-0.0378***</td>
</tr>
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<td>10</td>
<td>-0.1006***</td>
<td>-0.1444***</td>
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</tbody>
</table>

*, **, *** indicate significance at 10, 5 and 1% levels, respectively, in two-tailed tests with clustering by firm. For brevity, we omit the $t$-values, and only report the cost stickiness coefficient and its significance level. The sample is Compustat from 1980-2004 after discarding invalid observations and 0.5% outliers on each tail, along with additional restrictions on outliers described in each column, using standard ABJ criteria for SGA > SALES.

Variable definitions:
- $\Delta COST_{t,i} = \text{change in SG&A costs in year } t$;
- $\Delta SALES_{t,i} = \text{change in sales in year } t$;
- $DEC_{t,i} = 1 \text{ if sales decreased in year } t, 0 \text{ otherwise}$;
- $SALES_{t-1,i} = \text{sales in year } t-1$. 

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Table A4. Replication of Fama-Macbeth estimates of cost stickiness (standard sample only)

\[
\frac{\Delta \text{COST}_{i,t}}{\text{SALES}_{i,t-1}} = \beta_0 + \beta_1 \frac{\Delta \text{SALES}_{i,t}}{\text{SALES}_{i,t-1}} + \beta_2 \text{DEC}_{i,t} \frac{\Delta \text{SALES}_{i,t}}{\text{SALES}_{i,t-1}} + \epsilon_{i,t}
\]

<table>
<thead>
<tr>
<th></th>
<th>[Sales and SGA change] (\leq 100%)</th>
<th>[VC ratio] (\leq 5)</th>
<th>[VC ratio] (\leq 1)</th>
<th>2.5% outliers on each tail</th>
</tr>
</thead>
<tbody>
<tr>
<td>(\beta_1)</td>
<td>0.1820***</td>
<td>0.1780***</td>
<td>0.1630***</td>
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</tr>
<tr>
<td></td>
<td>(11.29)</td>
<td>(11.14)</td>
<td>(15.28)</td>
<td></td>
</tr>
<tr>
<td>(\beta_2)</td>
<td>-0.0289***</td>
<td>-0.0369***</td>
<td>-0.0411***</td>
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<tr>
<td></td>
<td>(-2.68)</td>
<td>(-2.99)</td>
<td>(-5.83)</td>
<td></td>
</tr>
<tr>
<td># negative and significant estimates</td>
<td>11 out of 48</td>
<td>11 out of 48</td>
<td>25 out of 48</td>
<td></td>
</tr>
</tbody>
</table>

# negative and significant estimates, \(N>2,500\) | 10 out of 17 | 9 out of 14 | 13 out of 17 |

The table presents point estimates and \(t\)-values obtained from Fama-Macbeth aggregation of industry-specific estimates for 48 Fama-French industries. *, **, *** indicate significance at 10, 5 and 1% levels, respectively, in two-tailed tests. The sample is Compustat from 1980-2004 after discarding invalid observations and 0.5% outliers on each tail, along with additional restrictions on outliers described in each column, using standard ABJ criteria for \(\text{SGA} > \text{SALES}\).

Variable definitions:
\(\Delta \text{COST}_{i,t}\) = change in SG&A costs in year \(t\);  
\(\Delta \text{SALES}_{i,t}\) = change in sales in year \(t\);  
\(\text{DEC}_{i,t}\) = 1 if sales decreased in year \(t\), and 0 otherwise;  
\(\text{SALES}_{i,t-1}\) = sales in year \(t-1\).