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Have Estimates of Cost Stickiness Changed Across Listing Cohorts?

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SUMMARY

While the discussion of changes in financial accounting properties over time is already well-established, there is a lack of evidence whether changing firm compositions in empirical samples might bias cost stickiness research. We document that with each additional listing cohort, the U.S. public firm universe becomes more knowledge-intensive and, at the same time, more cost sticky. Higher reliance on temporary labor by newer listing cohorts partly mitigates this development. Our results call for the use of listing cohort-specific slopes to allow for cohort-specific estimates of cost stickiness in future research.

JEL Classifications: D22; M41

Keywords: *Asymmetric Cost Behavior; Listing Cohorts; Adjustment Costs*

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1. Introduction

Cost stickiness, also referred to as asymmetric cost behavior, is a well-documented result of managerial discretion underlying the development of corporate cost compared to changes in firm activity. Cost stickiness builds on the notion that costs, on average, decrease less during downturns in firm activity than they increase for equivalent hikes (Anderson et al., 2003). Drivers of this behavior are manifold but can be summed up under three broad categories (Banker et al., 2017; Günther et al., 2014). First, managers trade-off adjustment cost of downsizing under-utilized capacity with its respective holding costs. Generally, the higher the adjustment costs, for instance in the form of severance pay for dismissed employees, the lower the willingness to reduce capacity. Second, if managers are optimistic about future business, they will most likely "sit out" the – presumably – short-term downturn to benefit disproportionally from future sales increases while the firms that downsized capacity incur additional cost to return to full capacity. Third, self-serving managers, with little oversight, might derive personal utility from empire-building. They will likely stall resource adjustments until the last possible moment to not admit value-destroying past investments in unnecessary capacity through, for instance, mergers and acquisitions. While the former are based on business judgement, the latter motive is rather problematic (e.g., Brüggen and Zehnder, 2014).

Cost stickiness research relies heavily on versions of a cross-sectional model established by Anderson et al. (2003), which are estimated over long time-series of 30 years and more (Banker et al., 2017). The method to estimate cost stickiness has not evolved much since, aside from the introduction of additional determinants for cost stickiness (for reviews of the literature, cf., Banker et al., 2017; Günther et al., 2014). Therefore, such as in the literature on value relevance of accounting information (Hail, 2013) and earnings management (Srivastava, 2014), changing underlying economic conditions and firm characteristics might influence or even bias proxies for cost stickiness. While aforementioned examples refer to financial accounting research, much of the same caveats might also apply to cost accounting and management. Conceptually, costs are a major component of accounting earnings (Banker and Byzalov, 2014). As such, the cost stickiness literature employs financial accounting data as a proxy for cost accounting data. Unsurprisingly, a line of literature exhibits the connection of financial accounting properties with cost stickiness, such as conservatism (Banker et al. 2016), zero earnings benchmark beating (Dierynck et al., 2012), meeting analyst earnings projections (Kama and Weiss, 2013) and income smoothing (Hartlieb and Loy, 2017).

We build on the notion by Srivastava (2014) that each new listing cohort (i.e., firms initially listed on the stock exchange during a decade) changes the fundamentals underlying cross-sectional samples. He conjectures his result, that earnings quality measures decline over successive listing cohorts, as, essentially, being a by-product of the U.S. economy's shift towards more knowledge-based firms (even if they belong to the same industry as firms listed in an earlier cohort). Conceptually, listing cohorts cover a range of intertwined factors associated with, but not limited to, (1) increasing average risk of newer firms, which exhibit low profitability but high growth prospects (Fama and French, 2004), (2) are involved in more competitive product markets (Srivastava and Tse, 2016), (3) have to hold more cash and lower inventories to create a buffer for increased R&D expenses, which are inherently riskier than capital expenditures (Bates et al., 2009), (4) different earnings and balance sheet properties between seasoned and newly listed firms (for instance, widening book-to-market ratios (e.g., Givoly and Hayn, 2000), as newly listed firms put more emphasis on intangible capital), (5) differences in executive compensation contracts which follow "fashions" across the decades (Murphy, 2013), and possibly also (6) effects of firms' life cycles as younger cohorts most likely consist of firms in earlier life cycle phases while firms in older listing cohorts mature. Related to cost accounting, prior evidence shows that increased investment in intangible capital in the form of, for instance, research & development (R&D), human capital (e.g., specialist employees, training) and advertising contributes to managers not cutting costs during downturns. This is attributable to the fear of deteriorating firm-specific intangible resources and capabilities if the level of investment is not kept at least constant (Venieris et al., 2015). If firms successively become more knowledge-intensive, this should increase average cost stickiness over the listing cohorts.

Replicating Anderson et al. (2003)'s basic cost stickiness model, which exhibits that selling, general, and administrative (SGA) costs increase (decrease) by 0.55% (0.35%) per 1% growth (decline) in sales, we find an interesting pattern. While the increase in SGA costs, following a 1% sales increase, fluctuates around a mean value of 0.68%[1] across listing cohorts, the corresponding cost decreases decline from 0.56% (for seasoned firms) to 0.30% (for the 2000s listing cohort).[2] As such, we find evidence that cost stickiness, in fact, does increase with each successive listing cohort.

One symptom of a possible and profound change in the properties of cost stickiness over time is the case of employee intensity. While much of the earlier research finds a positive association of employee intensity and the degree of cost stickiness (e.g., Anderson et al., 2003), the sign reverses in more contemporaneous papers (Chen et al., 2012; Dierynck et al., 2012; Hartlieb and Loy, 2017). A potential reason is the increased reliance on temporary labor in younger samples (Chen et al., 2012). Temporary labor is typically associated with relatively low adjustment cost. Over our sample period, the number of temporary workers in the United States increased more than tenfold, with the far overwhelming increase taking place from 1990 onwards (e.g., Segal and Sullivan, 1997; U.S. Department of Commerce, 2015).

In summary, we exhibit (1) that each new listing cohort, on average, invests more in intangible capital[3] through sales, general and administrative (SGA) and R&D expenses, (2) that each new listing cohort exhibits more cost stickiness, as proxied by a range of cost categories, and

[1] We attribute the higher value for cost increases to our longer sample period which ends in 2014, as compared to 1998 for Anderson et al. (2003)'s original contribution.
[2] Refer to Table 7 for additional results.
[3] We refer to the intangible asset definition by Lev et al. (2009) which builds on four concepts (p. 276): (1) *Discovery/learning intangibles*, largely attributable to R&D; (2) *Customer-related intangibles*, related to brands, trademarks, distribution channels and advertising expenses; (3) *Human-resource intangibles*, associated with specialist employees, training, and compensation systems; and (4) *Organization capital*, which refers to unique business processes and corporate cultures allowing the firm to create abnormal profits.

(3) that this development seems to be (partly) mitigated by increased reliance on temporary labor by younger listing cohort firms. Our additional results show that future cross-sectional cost stickiness research might benefit from the use of listing cohort-specific slope estimates for cost stickiness. Beyond these methodological adjustments, a new research agenda involving underlying changes of aforementioned motives for cost stickiness seems warranted. Besides well-documented industry-effects (e.g., Subramaniam and Weidenmier Watson, 2016), we show that the appropriate peer-group, researchers as well as practitioners (e.g., for executive compensation contracts) should use, seems to be a combination of industry and listing-cohort.

2. Data and Specifications

We use data from the Compustat NA universe from 1970 through 2014. After excluding Fama-French industries identified by numbers 44-47 (finance firms) and 48[4] (almost nothing), our initial sample comprises 267,827 observations. Then, we drop observations with missing values for the respective cost categories or sales revenues in the current and/or preceding year and observations for which costs exceed sales revenues. Finally, we trim the top and bottom 0.5 percent of changes in sales revenues and costs and exclude observations with missing values for our control variables. Following Srivastava (2014), we divide the remaining firms into five listing cohorts. The first year with available data in Compustat represents the firm's listing year. Firms with a listing year before 1970 are classified as seasoned firms, the others are classified as new firms. These firms are further divided into four listing waves for each decade (with the 2000s cohort ending in 2014).

Table 1 documents the economic magnitude of the (de-)listing phenomenon for our initial firm population. In 1970, our sample consists of 1,770 firms. This number increases to a peak of 9,494 firms in 1996 and, thereafter, decreases to 4,238 firms in 2014. By definition, there are

[4] The Fama-French industry 48 is a compound item for firms which are not included in one of the other 47 categories. More specifically, these include firms providing sanitary services, steam and air conditioning supplies, irrigation systems and cogeneration power producers.

only seasoned firms in 1970. However, at the end of our sample period, the proportion of seasoned firms only amounts to 11.6%. Thus, the dominant firm-population segment changed from the seasoned-firm segment to the new-firm segment over our sample period. The listing rate (i.e., compound annual growth rate of listings) ranges from 44% (1970s wave) to 10% (2000s wave). Delisting is also a very common phenomenon. Seasoned firms most likely prevail but still exhibit a delisting rate of 71.1%. For the other listing cohorts, the delisting rate even ranges from 79% to 87.4%. Hence, these descriptive results indicate that the (de-)listing phenomenon potentially plays an important role in the composition of samples employed in the cross-sectional cost stickiness literature.

[Insert Table 1 about here]

We present the industry distribution for each listing cohort of our initial sample in Table 2. We find that manufacturing is the most highly represented industry with respect to seasoned firms, whereas the new-firm segment rather contains firms from the healthcare and business equipment industries. This indicates that the listing cohorts partly capture effects of changes in the industry composition of samples underlying prior cost stickiness research. However, we find significant within-industry (de-)listing activities across all industries. This implies that listing cohort effects go beyond mere industry effects.[5]

[Insert Table 2 about here]

Depending on the respective cost category, the final sample ranges from 112,613 to 172,931 firm-year observations (Table 3). The sample is skewed towards the earlier listing cohorts. This is not surprising, as seasoned firms have a considerably longer time-series of yearly observations to contribute to the sample than, for instance, firms in the 2000s listing wave.

[Insert Table 3 about here]

[5] We test this by considering the descriptive results presented in Table 1 for each industry, separately. As an example, we exhibit the results for the manufacturing industry in Appendix B.

To test our research question whether new listing cohorts decisively change cross-sectional proxies for cost stickiness, we employ a standard cost stickiness model (Model (1)) in the spirit of Anderson et al. (2003) which includes economic controls for asset and employee intensity as well as successive sales decreases (Banker et al., 2014).[6]

$$\begin{aligned}
log\left(\frac{Cost_Category_{i,t}}{Cost_Category_{i,t-1}}\right) = \ & \beta_0 + \beta_1 log\left(\frac{Sales_{i,t}}{Sales_{i,t-1}}\right) \\
& + \beta_2 Decrease_Dummy \times log\left(\frac{Sales_{i,t}}{Sales_{i,t-1}}\right) \\
& + \beta_3 Decrease_Dummy \times log\left(\frac{Sales_{i,t}}{Sales_{i,t-1}}\right) \times Employee_Intensity_{i,t} \\
& + \beta_4 Decrease_Dummy \times log\left(\frac{Sales_{i,t}}{Sales_{i,t-1}}\right) \times Asset_Intensity_{i,t} \\
& + \beta_5 Decrease_Dummy \times log\left(\frac{Sales_{i,t}}{Sales_{i,t-1}}\right) \times Successive_Decrease_{i,t} \\
& + \beta_6 Employee_Intensity_{i,t} + \beta_7 Asset_Intensity_{i,t} \\
& + \beta_8 Successive_Decrease_{i,t} + industry_fe + year_fe + \varepsilon_{i,t} \qquad (1)
\end{aligned}$$

Subscripts i (t) reflect firm (time) indices, respectively. $Cost\_Category_{i,t}$ denotes the cost category employed in the respective regression: (1) SGA expenses, (2) costs of goods sold (COGS) as well as (3) core expenses (i.e., the sum of SGA costs and COGS), (4) noncore expenses, and (5) operating costs (OC). Prior literature finds cost stickiness for a range of cost categories, depending on the setting and the industry under consideration (for a review, cf., Günther et al. 2014). $Decrease\_Dummy_{i,t}$ proxies for periods of negative changes in firm activity.[7] In line with the literature on cross-sectional cost stickiness, we employ ratios and log-specifications. On the one hand, it enhances comparability and moderates heteroscedasticity. On the other hand, it enables easier interpretation of regression coefficients as percentages (Anderson et al., 2003). β_1 measures the increase in costs for each percent of sales increase. The sum of β_1 and β_2 jointly proxies for the average cost decrease for each percent of declining sales. As such, a significantly negative β_2 coefficient represents cost stickiness.

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6 Industry- and year-fixed effects control for unobserved factors. Robust standard errors, clustered at the firm-level, control for autocorrelation and heteroscedasticity.

7 All variables are defined in detail in Appendix A.

3. Results

Initial descriptive results

Table 4 presents first revealing insights. The listing cohorts differ considerably in terms of cost intensities computed on a wave-year basis. While the seasoned firms' COGS still outweigh SGA costs[8] by a large margin, the relationship gradually shifts towards intangible investments in various forms of intangible and organizational capital. Probably the most accurate indicator of more knowledge-based firms entering the sample might be R&D intensity which increases from each listing cohort to the other. While earlier sample years (i.e., prior to 1975) were not subject to SFAS 2, which requires immediate expensing of R&D outlays, the values for R&D intensity for the first two cohorts might be (slightly) understated.[9]

[Insert Table 4 about here]

With the average firm in a listing cohort becoming more knowledge-intensive compared to its prior cohort peers, we expect cost stickiness to increase from one listing wave to the next. Knowledge intensive firms perceive prior periods' investment in intangible and organizational capital as the basis of their capabilities and resources which might deteriorate when the level of investment is contemporaneously cut (Venieris et al., 2015).

Multivariate results

As previously predicted, we find that stickiness increases for a range of cost categories, most notably for SGA costs, core expenses and OC, in samples populated by gradually younger listing cohorts (Table 5).

[Insert Table 5 about here]

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8 SGA cost include all costs related to the running the operations, with the exception of production (e.g., spending on advertising, training, business travel and sales commissions).

9 Even for the seasoned and 1970s cohorts the effect should be minimal since at most, for a firm already listed in 1970, five firm-year observations are pre-SFAS 2. The only exception to the immediate expensing of R&D outlays are selective development costs for in-house software, following SOP98-1 (AICPA, 1998). This should – if at all – work against finding an increase in R&D intensity.

While the increase coefficient (β_1) remains largely stable across all cost categories, the decrease coefficient (β_2) becomes more negative until the 1990s listing cohort and subsequently increases back to the 1980s value for the 2000s listing cohort for SGA costs. While cost stickiness is less pronounced for COGS in the first place, which is in line with much of the literature, we observe a consistent increase in cost stickiness for core expenses (i.e., the sum of SGA costs and COGS) and operating costs (OC). The results for noncore expenses are less consistent with the previously observed pattern across listing cohorts. One reason for this might be that noncore expenses include other components besides knowledge-increasing R&D expenses (e.g., audit and legal fees, restructuring expenses etc.), which presumably are equally relevant for firms in older listing cohorts as they are, to some extent, mandatory as a result of (financial) regulation. Summing up, on average, we observe increasing cost stickiness from one listing cohort to the next across a range of cost categories, which the literature on cost stickiness discusses in different settings and industries (Günther et al., 2014).

In terms of economic controls, we observe that the three-way-interactions for asset intensity and successive decreases do not change significantly across listing cohorts (untabulated).

[Insert Table 6 about here]

Yet, we observe interesting patterns for employee intensity (Table 6). Whereas increased employee intensity contributes to significantly more cost stickiness in older listing cohorts for most of our cost categories (i.e., namely COGS and OC), the association reverses for younger cohorts (i.e., namely core expenses and OC). It has to be noted that also seasoned firms can benefit from more flexibility through temporary labor in later sample years, but the final two cohorts benefit from a fully developed and growing temporary labor force (Segal and Sullivan, 1997; U.S. Department of Commerce, 2015), which decreases adjustment costs, over their full time series. Nevertheless, it might also be the case that older listing cohorts have different underlying structures impairing adjustments (e.g., higher unionization rates in the manufacturing industry which dominates the seasoned firms and also presents a large fraction of the 1970s listing wave, cf. Table 2) or incentives not to adjust labor in periods of declining activity (e.g., attributable to differences in executive compensation contracts which also seem to follow “fashions” across the decades; Murphy, 2013). In combination, our results provide insights into the controversial results regarding the incremental effect of employee intensity, too. While earlier papers find a positive association of employee intensity with cost stickiness (e.g., Anderson et al., 2003), the association becomes negative in contemporaneous papers (Chen et al., 2012; Dierynck et al., 2012; Hartlieb and Loy, 2017). We will revisit this issue in the following section.

4. Additional Tests

Basic Cost Stickiness Model

In our empirical model, we include year- and industry-fixed effects and control for several important influencing factors of asymmetric cost behavior (i.e., employee intensity, asset intensity and a control for successive sales decreases). However, attributable to higher-order interaction effects, this makes it difficult to interpret the coefficients as percentage changes in relation to corresponding percentage changes in costs and sales. Therefore, we additionally repeat our analysis employing a basic (sparse) ABJ-model (i.e., without additional controls (Model (2)), which reads: $\Delta \ln C\_C_{i,t} = \beta_0 + \beta_1 \Delta \ln Sales_{i,t} + \beta_2 D\_D_{i,t} \times \Delta \ln Sales_{i,t} + \varepsilon_{i,t})$ for each listing cohort.

[Insert Table 7 about here]

The results, presented in Table 7, are generally in line with our main model. Almost all coefficients are significant, and we find that the degree of cost asymmetry increases for common cost categories such as SGA costs or OC over the successive listing cohorts. For instance, SGA costs (OC) increase by .707 (.957) percent per one percent increase in sales and decrease by .707 - .145 = .562 (.957 - .035 = .923) percent per one percent decrease in sales revenue for the seasoned firms. The coefficient β_2 increases for younger listing cohorts, implying greater cost stickiness, while the cost increase coefficient β_1 remains stable. As such, for the 2000s listing wave, a one percent increase in sales is associated with a .640 (.916) increase in SGA costs (OC) while the corresponding decrease is only associated with a SGA costs (OC) decrease of .640 - .343 = .297 (.916 - .168 = .748). Thus, this development is not only statistically but also economically meaningful.

Simultaneous control for industry- and time-variation in cost stickiness estimates across listing cohorts

Our results suggest that the degree of cost stickiness varies across listing cohorts. To address concerns that this effect is merely driven by time- and/or industry-variation underlying the listing cohorts (as presented in Table 1), we adjust our model. We again consider the basic ABJ-model and include a listing cohort trend-variable ($Cohort$), ranging from 1 (seasoned firms) through 5 (2000s wave), or an indicator variable that is coded as 1 for new firms and zero for seasoned ones (New), respectively. Additionally, we include year- and industry-fixed effects. Then, we interact all three (i.e., cohort-, time- and industry-) controls with $\Delta \ln Sales_{i,t}$ and $D\_D_{i,t} \times \Delta \ln Sales_{i,t}$, to allow for specific slope coefficients for cost stickiness. Consequently, the model (Model (3)) reads:

$$\Delta \ln C\_C_{i,t} = \beta_0 + \beta_1 \Delta \ln Sales_{i,t} + \beta_2 D\_D_{i,t} \times \Delta \ln Sales_{i,t} + \varepsilon_{i,t} \ ,$$

$$\text{with} \quad \beta_1 = \beta_{1,0} + \sum \beta_{1,1_j} \times Cohort(New)_j + \sum \beta_{1,2_i} \times Year_i + \sum \beta_{1,3_k} \times Industry_k \ ,$$
$$\text{and} \quad \beta_2 = \beta_{2,0} + \sum \beta_{2,1_j} \times Cohort(New)_j + \sum \beta_{2,2_i} \times Year_i + \sum \beta_{2,3_k} \times Industry_k . \quad (3)$$

This simultaneously controls for the time-, industry- and cohort-specific effects on cost-stickiness estimates (β_2) rather than just including year- and industry-specific intercepts, as presented in the main results (and in line with extant cost stickiness research).

[Insert Table 8 about here]

Table 8 shows the results. For parsimony, we only report the pertinent coefficients and only refer to the SGA cost category, since it is most commonly used in cost stickiness research (e.g., Anderson et al., 2003; Chen et al., 2002).[10] Integrating the indicator variable New (Column 1), we find that the coefficient on the interaction term is negative and significant at the 0.01 level (t=-4.29). Hence, even if we also control for industry- or time-variation in slopes, we find that new firms exhibit significantly more cost stickiness than seasoned firms. Using the $Cohort$ trend (Column 2) supports this result. For the 1980s, 1990s and 2000s wave, the coefficient is significantly negative and increasing, indicating that these firms are stickier than their counterparts from former cohorts. In summary, these additional results corroborate that listing cohorts have an effect on cost stickiness that goes beyond regular time- or industry-effects.

Mediation analysis

So far, our results indicate that listing cohorts have an effect on cost behavior but we can rather speculate about the channels through which listing cohorts impact cost stickiness, besides mentions of presumably higher reliance on temporary labor in younger samples (e.g., Chen et al., 2012). Therefore, we additionally conduct a mediation analysis to investigate potential channels. More precisely, we examine the effect of knowledge intensity, measured by R&D expenses, and temporary labor, proxied by employee intensity. We partition the sample using a median split for both variables and re-run the basic (sparse) ABJ-model (Model (3)) with an additional interaction term with the listing cohort dummy New and after controlling for industry- or time-variations in cost stickiness slope coefficients.

[Insert Table 9 about here]

In Table 9 (Column 1), we present our regression model for all firms with knowledge intensity below (or equal to) the sample median.[11] The coefficient of our three-way interaction term of interest is negative and significant (t=-2.20), which again supports our notion that new

[10] Employing OC, COGS and core expenses as our cost category does not alter the presented conclusions. Only for noncore expenses the results are generally insignificant and not in line with the expectations. We presume that this is in line with the multivariate results presented above (Table 5). Noncore expenses include many components unrelated to increasing intangible capital (e.g., audit and legal fees, restructuring expenses etc.).

[11] In line with extant literature in financial accounting (e.g., Roychowdhury, 2006), we set R&D expenses to zero if the value is missing. This presumes that firms which, in fact, undertake material R&D activities also disclose related expenditures in their financial reports. This procedure results in a median of zero R&D expenses and unequal subsamples.

firms tend to be cost stickier than seasoned ones. For the high knowledge intensity subsample (Column 2), the coefficient is even more negative and highly significant. Comparing the significant (t=2.32) difference between aforementioned coefficients implies that the effect of listing cohorts on cost stickiness is particularly strong when firms exhibit high knowledge intensity. Hence, knowledge intensity seems to mediate the effect of listing cohorts on cost behavior, potentially attributable to managers unwilling to run the risk of deteriorating past investment in intangible capital by reducing cost in periods of temporary downturns (Venieris et al., 2015).[12] For instance, attracting and developing key employees requires considerable investment. Thus, the reluctance to downsize the number of key employees, during – presumably – short-term downturns, is quite understandable. We find similar results for our temporary labor subsamples (Columns 3 and 4). The coefficient is larger for firms with above median employee intensity, as well. However, this difference is insignificant (t=1.14). Nevertheless, this result might be attributable to the fact that firms can exhibit high employee intensity from (non-)temporary labor, alike. Future research should develop better proxies for temporary labor and investigate the issue more closely.

5. Conclusion

The discussion whether fundamental changes in accounting standards or sample composition influence – or even bias – estimates in financial accounting research is already well established (e.g., Hail, 2013; Srivastava, 2014). Our results provide evidence that this is also an issue in cost stickiness research. Employing the traditional cross-sectional model of cost stickiness, which includes controls for asset and employee intensity as well as successive periods of decreasing revenues (Anderson et al., 2003; Banker et al., 2014), we show that proxies for cost stickiness vary decisively across listing cohorts. It has to be noted that even firms from different

[12] Alternatively, we also employ Tobin's Q/the market-to-book (MTB) ratio as a proxy for knowledge intensity in our mediation analysis. While the coefficient for cost stickiness is slightly more negative for the above median MTB-subsample, the difference between the coefficients for both subsamples is highly insignificant (t = 0.14). Nonetheless, the MTB ratio proxies for much more than just knowledge intensity, such as, but not limited to, growth propects, accounting conservatism and underinvestment (e.g., Dybvig and Warachka, 2015).

listing cohorts largely operate under much of the same economic and legal conditions, and even belong to the same industries. Therefore, it seems to be a fruitful area of further research to explore the commonalities of firms belonging to the same listing cohort with respect to their cost behavior. Our results also suggest that researchers should employ additional controls for these underlying factors (e.g., through listing cohort-specific slope coefficients for cost stickiness) to avoid spurious inferences of cost stickiness in cross-sectional samples. So far the literature did largely resort to include additional determinants of cost stickiness in the original cross-sectional model by Anderson et al. (2003) (for reviews of the literature on determinants of cost stickiness, cf., Banker et al., 2017; Günther et al., 2014).

As such, our results also call for a new, more fundamental research agenda with respect to cost stickiness. Researchers should take a look how the listing cohort-effect affects the three "classic" motives for cost stickiness. First, are there reasons to believe that managerial trade-off decisions, involving adjustment cost of downsizing under-utilized capacity against their holding costs, changed substantively over time? Second, are managers successively becoming more optimistic about future business prospects? And, if so, why? Or, finally, is it plausible that managers of firms in younger listing cohorts, on average, exhibit more self-serving behavior than their peers at the helm of "more seasoned" firms? Cumulatively, we renew the call for research "explaining more complex structures for cost stickiness" (Günther et al., 2014, p. 314). While our results exhibit that some of the (changing) results in the cost stickiness literature are attributable to changes in the underlying sample of firms with each new listing cohort, and delistings of firms in older cohorts, we can only provide first indications on the causal relations. Along the lines mentioned above, researchers should more closely examine the underlying changes in business activities, managerial behavior and investment patterns.

Our results are also meaningful to practitioners. While the regulatory playing field is largely level for all companies, with the potential exception of different unionization rates across industries or different labor laws across countries (e.g., Banker et al., 2013), it seems that the potential – or willingness – to cut costs during downturns depends not only on well-documented industry-effects (e.g., Subramaniam and Weidenmier Watson, 2016) but also significantly on the listing cohort peer-group. This is especially useful in composing executive compensation contracts, screening competitors and investment targets.

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Appendix A: Variable definitions

Variable	Definition
Panel A: Cost Stickiness Model	
$Sales_{it}$	Annual sales revenue (*sale*).
$Decrease\_Dummy_{it}$	Indicator variable that equals 1 if sales (*sale*) of firm i decrease between fiscal years $t-1$ and t ($Sales_{i,t} < Sales_{i,t-1}$), and 0 otherwise.
$Employee\_Intensity_{it}$	Employee intensity, calculated as the natural logarithm of the number of employees (*emp*) divided by sales (*sale*).
$Asset\_Intensity_{it}$	Asset intensity, calculated as the natural logarithm of total current assets (*act*) divided by sales (*sale*).
$Succsessive\_Decrease_{it}$	Indicator variable that equals 1 if sales (*sale*) decrease in two consecutive years ($Sales_t < Sales_{t-1} < Sales_{t-2}$), and 0 otherwise.
Panel B: Cost Categories	
SGA	Selling, general, and administrative expenses (*xsga).*
COGS	Cost of goods sold (*cogs*).
Core Expenses	The sum of SGA and COGS.
Noncore Expenses	Total expenses minus core expenses.
Operating Costs	Sales revenue (*sale*) less income from operations (*oiadp).*
Total Expenses	Sales revenue (*sale*) less income from before extraordinary items (*ib*).
R&D	Research and development expenditures (*xrd*).
Cost Intensity	The ratio of cost category to total expenses.
Panel C: Additional Tests	
$Cohort$	Listing cohort trend variable coded 1 for seasoned firms, 2 for firms of the 1970s wave, 3 for the 1980s wave, 4 for the 1990s wave and 5 for the 2000s wave, respectively.
New	Listing cohort indicator variable coded as 1 for firms of the new-firms (i.e., listed after 1970) segment, and 0 for the seasoned-firms segment.
KI	Knowledge intensity indicator variable coded as 1 if the value for R&D expenses is above the sample median, and 0 otherwise.
TL	Temporary labor indicator variable coded as 1 if the value for employee intensity is above the sample median, and 0 otherwise.

Compustat mnemonics in parentheses.

Appendix B: Magnitude of (de-)listing for each listing cohort for the manufacturing industry

Fiscal Year	*Total Number*	*Seasoned Firms*	*New Firms*			
			1970s Wave	*1980s Wave*	*1990s Wave*	*2000s Wave*
1970	393	**389**	4			
1971	405	389	16			
1972	419	389	30			
1973	443	389	54			
1974	551	389	162			
1975	560	389	171			
1976	568	389	179			
1977	577	389	188			
1978	592	389	203			
1979	612	389	**223**			
1980	638	389	223	26		
1981	660	389	223	48		
1982	708	389	223	96		
1983	761	389	223	149		
1984	814	389	223	202		
1985	873	389	223	261		
1986	929	389	223	317		
1987	983	389	223	371		
1988	946	368	196	382		
1989	915	339	170	**406**		
1990	899	319	156	374	50	
1991	925	311	143	358	113	
1992	974	310	134	334	196	
1993	1,005	294	125	315	271	
1994	1,027	285	116	293	333	
1995	1,062	272	108	269	413	
1996	1,081	264	101	248	468	
1997	1,055	251	95	224	485	
1998	1,023	233	86	196	508	
1999	980	217	79	164	**520**	
2000	931	196	73	154	470	38
2001	869	181	69	143	421	55
2002	810	171	62	130	371	76
2003	781	162	59	126	344	90
2004	738	153	55	117	315	98
2005	703	146	51	105	287	114
2006	677	143	45	93	264	132
2007	637	127	43	82	238	147
2008	609	123	39	77	217	153

2009	598	121	38	70	206	163
2010	572	115	37	64	189	167
2011	567	114	37	61	177	177
2012	542	111	37	52	167	175
2013	504	106	35	49	158	156
2014	377	95	21	39	121	**101**
Proportion in 2014 (pp)		25.2	5.6	10.3	32.1	26.8
Listing Rate (pp)			56.3	35.7	29.7	7.2
Delisting Rate (pp)		72.8	84.3	87.9	69.6	

The table presents the number of firm-year observations from the listing cohorts in each year for the Fama/French 12 industry 'Manufacturing'. The listing rate is calculated as the compound annual growth rate over the listing period (e.g., 1970–1979 for the 1970s wave). The delisting rate is calculated as 1 minus the percentage of firms that survived in 2014 from the last year of formation of that listing cohort (highlighted in bold font).

Table 1
Magnitude of (de-)listing for each listing cohort

Fiscal Year	*Total Number*	*Seasoned Firms*	*New Firms*			
			1970s Wave	*1980s Wave*	*1990s Wave*	*2000s Wave*
1970	1,770	**1,714**	56			
1971	1,860	1,714	146			
1972	1,941	1,714	227			
1973	2,161	1,714	447			
1974	2,711	1,714	997			
1975	2,793	1,714	1,079			
1976	2,857	1,714	1,143			
1977	2,939	1,714	1,225			
1978	3,043	1,714	1,329			
1979	3,207	1,714	**1,493**			
1980	3,462	1,714	1,493	255		
1981	3,769	1,714	1,493	562		
1982	4,345	1,714	1,493	1,138		
1983	4,805	1,714	1,493	1,598		
1984	5,284	1,714	1,493	2,077		
1985	5,939	1,714	1,493	2,732		
1986	6,531	1,714	1,492	3,325		
1987	6,988	1,712	1,492	3,784		
1988	6,924	1,627	1,334	3,963		
1989	6,841	1,545	1,191	**4,105**		
1990	6,960	1,482	1,110	3,841	527	
1991	7,256	1,445	1,039	3,589	1,183	
1992	7,695	1,425	979	3,363	1,928	
1993	8,140	1,386	924	3,178	2,652	
1994	8,543	1,343	881	2,913	3,406	
1995	9,143	1,278	845	2,633	4,387	
1996	9,494	1,240	790	2,412	5,052	
1997	9,478	1,181	751	2,181	5,365	
1998	9,467	1,103	695	1,911	5,758	
1999	9,325	1,033	637	1,645	**6,010**	
2000	8,941	951	579	1,500	5,420	491
2001	8,455	894	544	1,370	4,825	822
2002	8,097	865	503	1,253	4,326	1,150
2003	7,748	837	465	1,170	3,911	1,365
2004	7,472	808	421	1,101	3,616	1,526
2005	7,197	761	391	1,022	3,298	1,725
2006	6,926	736	361	939	2,999	1,891
2007	6,610	684	337	859	2,705	2,025

2008	6,339	657	322	798	2,457	2,105
2009	6,207	640	317	750	2,255	2,245
2010	6,079	623	301	700	2,071	2,384
2011	6,157	601	291	651	1,901	2,713
2012	6,014	581	274	596	1,754	2,809
2013	5,676	562	259	560	1,638	2,657
2014	4,238	495	187	431	1,265	**1,860**
Proportion in 2014 (pp)		11.6	4.4	10.2	29.8	43.9
Listing Rate (pp)			44.0	36.2	31.1	10.0
Delisting Rate (pp)		71.1	87.4	89.5	79.0	

Table 1 presents the number of firm-year observations from the listing cohorts in each year. The listing rate is calculated as the compound annual growth rate over the listing period (e.g., 1970–1979 for the 1970s wave). The delisting rate is calculated as 1 minus the percentage of firms that survived in 2014 from the last year of formation of that listing cohort (highlighted in bold font).

Table 2
Industry distribution by listing cohort

Fama/French 12 Industry Class. (in pp)	*Total Number*	*Seasoned Firms*	*New Firms*			
			1970s Wave	*1980s Wave*	*1990s Wave*	*2000s Wave*
Consumer Non-Durables	5.96	9.35	5.89	5.21	4.76	4.25
Consumer Durables	2.80	4.87	2.81	2.39	1.96	1.85
Manufacturing	12.43	21.74	14.19	9.58	9.05	6.63
Oil, Gas and Coal	5.72	4.50	5.35	7.04	4.44	9.33
Chemicals	2.36	4.11	1.52	2.18	1.57	2.54
Business Equipment	19.89	9.22	18.28	20.28	27.52	21.04
Telecommunication	3.98	2.02	5.53	3.30	5.23	3.97
Utilities	5.21	15.57	6.34	1.25	1.34	2.74
Shops	12.94	13.94	14.88	14.38	11.67	8.59
Healthcare	10.15	2.64	5,47	12.76	13.03	17.47
Other	18.57	12.03	19.73	21.35	19.43	21.59

Table 3
Final sample by cost category

	Seasoned Firms	*1970s Wave*	*1980s Wave*	*1990s Wave*	*2000s Wave*	Σ
SGA	39,474	23,860	33,480	36,633	8,455	141,902
COGS	51,616	28,358	38,980	43,813	10,164	172,931
Core Expenses	35,928	18,830	24,265	27,125	6,465	112,613
Noncore Expenses	38,595	22,915	32,866	36,367	8,384	139,127
Operating Costs	44,431	20,047	22,555	24,806	5,767	117,606

Cost categories are defined in Appendix A.

Table 4
Cost intensities across listing cohorts

	Seasoned Firms	*1970s Wave*	*1980s Wave*	*1990s Wave*	*2000s Wave*
SGA Intensity	19.94	27.10	35.32	36.90	39.26
COGS Intensity	68.09	63.79	56.38	54.03	33.50
Core Expenses Intensity	88.03	90.89	91.70	90.94	72.76
Noncore Expenses Intensity	11.97	9.11	8.30	9.06	27.24
OC Intensity	92.58	96.30	98.53	97.44	76.67
R&D Intensity	2.78	4.95	8.47	11.59	12.97

All cells reflect percentage points (pp) of cost intensities across listing cohorts. Following the procedure of Srivastava (2014), all intensities are first computed on a wave-year basis. This method results in 45 observations for the seasoned firms (1970-2014), 40 annual observations for the 1970s wave (1970-2014), 35 for the 1980s wave (1980-2014), 25 for the 1990s wave (1990-2014) and 15 for the 2000s wave (2000-2014). The overall average intensity of a listing cohort is computed by the mean of all annual intensities.

Table 5
Cost stickiness by cost category and listing cohort

Panel A: $\beta_1$coefficient

	Seasoned Firms	*1970s Wave*	*1980s Wave*	*1990s Wave*	*2000s Wave*
SGA	0.447 ***	0.502 ***	0.535 ***	0.590 ***	0.487 ***
	(11.20)	(12.74)	(24.29)	(34.64)	(16.77)
COGS	0.967 ***	0.899 ***	0.874 ***	0.875 ***	0.863 ***
	(42.00)	(26.48)	(43.27)	(55.92)	(32.83)
Core Expenses	0.853 ***	0.834 ***	0.812 ***	0.832 ***	0.817 ***
	(37.07)	(36.00)	(46.97)	(67.49)	(37.62)
Noncore Expenses	1.108 ***	0.680 ***	0.914 ***	0.866 ***	0.824 ***
	(10.65)	(4.52)	(16.81)	(20.20)	(11.44)
OC	0.911 ***	0.882 ***	0.839 ***	0.860 ***	0.874 ***
	(45.57)	(43.66)	(60.62)	(76.62)	(41.08)

Panel B: $\beta_2$coefficient

	Seasoned Firms	*1970s Wave*	*1980s Wave*	*1990s Wave*	*2000s Wave*
SGA	-0.054	-0.158 **	-0.283 ***	-0.382 ***	-0.255 ***
	(-0.91)	(-2.43)	(-6.62)	(-10.75)	(-3.88)
COGS	0.147 ***	0.042	0.015	0.044	-0.119 **
	(4.51)	(0.78)	(0.35)	(1.29)	(-1.97)
Core Expenses	-0.017	-0.118 **	-0.189 ***	-0.179 ***	-0.269 ***
	(-0.48)	(-2.25)	(-4.62)	(-4.36)	(-4.69)
Noncore Expenses	-0.646 ***	0.154	-0.270 *	-0.523 ***	-0.073
	(-3.75)	(0.47)	(-1.67)	(-4.50)	(-0.42)
OC	-0.002	-0.093	-0.197 ***	-0.155 ***	-0.407 ***
	(-0.06)	(-1.36)	(-5.75)	(-3.38)	(-6.05)

Table 5 reports the coefficients β_1 and β_2 for each cost category and listing cohort from our main regression model (Model (1)). For the sake of brevity, we do not report coefficients of control variables. $***$, $**$, $*$ indicate two-sided significance at the 0.01, 0.05 and 0.1 levels, respectively. Robust t-statistics, clustered at the firm-level, are presented in parentheses.

Table 6
Incremental effect of employee intensity on cost stickiness (β_3) by cost category and listing cohort

	Seasoned Firms	*1970s Wave*	*1980s Wave*	*1990s Wave*	*2000s Wave*
SGA	0.027	0.003	0.018	0.037 ***	-0.032
	(0.85)	(0.16)	(1.27)	(2.74)	(-1.24)
COGS	-0.028 ***	-0.023 *	-0.012	-0.027	0.023
	(-3.30)	(-1.86)	(-0.93)	(-1.27)	(1.08)
Core Expenses	-0.011	0.025	0.037 **	0.052 ***	0.066 ***
	(-1.34)	(1.57)	(2.04)	(2.97)	(2.83)
Noncore Expenses	0.062	-0.087	-0.099 *	-0.011	-0.165 ***
	(1.41)	(-0.94)	(-1.90)	(-0.30)	(-2.70)
OC	-0.012 **	-0.018	0.040 ***	0.035 *	0.086 ***
	(-1.95)	(-1.03)	(2.80)	(1.92)	(3.19)

Table 6 reports the coefficient β_3 on the interaction with employee intensity for each cost category and listing cohort from our main regression model (Model (1)). $***$, $**$, $*$ indicate two-sided significance at the 0.01, 0.05 and 0.1 levels, respectively. Robust t-statistics, clustered at the firm-level, are presented in parentheses.

Table 7
Basic ABJ cost stickiness model by cost category and listing cohort

Panel A: $\beta_1$coefficient

	Seasoned Firms	*1970s Wave*	*1980s Wave*	*1990s Wave*	*2000s Wave*
SGA	0.707 ***	0.634 ***	0.678 ***	0.726 ***	0.640 ***
	(65.00)	(48.55)	(83.09)	(109.83)	(49.09)
COGS	0.994 ***	0.950 ***	0.948 ***	0.937 ***	0.899 ***
	(195.35)	(93.08)	(152.12)	(169.48)	(80.75)
Core Expenses	0.950 ***	0.923 ***	0.927 ***	0.924 ***	0.888 ***
	(235.96)	(163.71)	(194.86)	(238.70)	(97.40)
Noncore Expenses	1.124 ***	0.975 ***	0.890 ***	0.907 ***	0.812 ***
	(53.88)	(30.35)	(45.15)	(57.90)	(25.21)
OC	0.957 ***	0.929 ***	0.937 ***	0.934 ***	0.916 ***
	(301.12)	(159.81)	(213.42)	(279.84)	(109.30)

Panel B: $\beta_2$coefficient

	Seasoned Firms	*1970s Wave*	*1980s Wave*	*1990s Wave*	*2000s Wave*
SGA	-0.145 ***	-0.139 ***	-0.224 ***	-0.266 ***	-0.343 ***
	(-8.67)	(-7.05)	(-14.54)	(-18.92)	(-11.38)
COGS	0.029 ***	0.005	-0.029 **	-0.012 *	-0.014
	(3.20)	(0.29)	(-2.06)	(-1.88)	(-1.55)
Core Expenses	-0.034 ***	-0.066 ***	-0.128 ***	-0.087 ***	-0.153 ***
	(-4.60)	(-4.59)	(-8.85)	(-7.41)	(-5.19)
Noncore Expenses	-0.381 ***	-0.231 ***	-0.361 ***	-0.368 ***	-0.434 ***
	(-8.09)	(-3.13)	(-7.62)	(-8.00)	(-5.09)
OC	-0.035 ***	-0.039 ***	-0.099 ***	-0.086 ***	-0.168 ***
	(-5.82)	(-2.57)	(-7.82)	(-7.42)	(-6.06)

Table 7 reports the coefficients β_1 and β_2 for each cost category and listing cohort from the basic (sparse) ABJ cost stickiness regression model (i.e., without control variables; Model (2)). Therefore, the coefficients presented here can be interpreted as percentage changes corresponding to changes in costs and sales. $***$, $**$, $*$ indicate two-sided significance at the 0.01, 0.05 and 0.1 levels, respectively. Robust t-statistics, clustered at the firm-level, are presented in parentheses.

Table 8

Extended model with simultaneous controls for year- and industry-variation

Dependent variable: *SGA*	***New* Indicator**	***Cohort* Trend Variable**
$\beta_{1,0}$: $\Delta \ln Sales$	0.881 ***	0.877 ***
	(12.38)	(12.35)
$\beta_{2,0}$: $D\_D \times \Delta \ln Sales$	-0.227 *	-0.219 *
	(-1.87)	(-1.81)
$\beta_{2,1}$: $D\_D \times \Delta \ln Sales \times New$	-0.097 ***	
	(-4.29)	
$\beta_{2,1}$: $Dec \times \Delta \ln Sales \times Cohort$		
1970		-0.032
		(-1.13)
1980		-0.099 ***
		(-3.67)
1990		-0.158 ***
		(-5.41)
2000		-0.312 ***
		(-6.90)
Adj. R^2	0.479	0.482

Table 8 presents results of the basic (sparse) cost stickiness model extended by interactions terms ($\beta_{2,1}$) with the listing cohort indicator (New) or the $Cohort$ trend variable (variable description in Appendix A) as well as industry- and year-indicators (Model (3)). $***$, $**$, $*$ indicate two-sided significance at the 0.01, 0.05 and 0.1 levels, respectively. Robust t-statistics, clustered at the firm-level, are presented in parentheses.

Table 9

Mediation analysis

Dependent variable: *SGA*	$KI \leq$ **Median**	$KI >$ **Median**	$TL \leq$ **Median**	$TL >$ **Median**
$\beta_{1,0}$: $\Delta \ln Sales$	0.854 ***	0.986 ***	1.605 *	0.845 ***
	(10.51)	(6.69)	(1.68)	(11.39)
$\beta_{2,0}$: $D\_D \times \Delta \ln Sales$	-0.182	-0.444 **	-1.709	-0.124
	(-1.22)	(-2.03)	(-1.42)	(-0.98)
$\beta_{2,1}$: $D\_D \times \Delta \ln Sales \times New$	-0.067 **	-0.125 ***	-0.069 **	-0.124 ***
	(-2.20)	(-3.91)	(-2.27)	(-3.48)
Difference in Three-Way Interaction Terms ($\beta_{2,1}$)	0.058 **		0.055	
	(2.32)		(1.14)	
Adj. R^2	0.463	0.509	0.471	0.494
N	75,263	66,639	70,963	70,939

Table 9 presents results of the mediation analysis. We conduct a subsample analysis employing Model (3) and compare the effect of our listing cohort dummy variable New on cost asymmetry by running the basic cost stickiness model for subsamples with a high knowledge intensity (*KI*) and temporary labor (*TL*) (variables are described in Appendix B) and low *KI* and *TL* (using a median split). $***$, $**$, $*$ indicate two-sided significance at the 0.01, 0.05 and 0.1 levels, respectively. Robust t-statistics, clustered at the firm-level, are presented in parentheses.