**Online Appendix to "The Informativeness of Balance Sheet Disaggregations: Evidence from Forecasting Operating Assets"**

**Benjamin Noordermeer & Patrick Vorst**

**Overview**

This document contains the online appendices to "The Informativeness of Balance Sheet Disaggregations: Evidence from Forecasting Operating Assets." Section 1 presents the results of several cross-sectional analyses of forecast improvements of various model comparisons. Section 2 presents the results of tests that examine the relation between disaggregated model growth forecasts and analyst forecasts. Section 3 discusses how the returns associated with the difference in disaggregated versus aggregate growth predictions relate to the asset growth anomaly.

**Section 1: Cross-Sectional Analyses of Forecast Improvements**

Our results in Section 4.2 of the main manuscript demonstrate the pooled benefits of using balance sheet disaggregations when forecasting growth in *operating assets*. In this section, we report the results of cross-sectional tests investigating how forecast improvements vary across firms based on characteristics that we expect to be associated with the usefulness of balance sheet disaggregations. Specifically, for each cross-section, we create deciles based on the respective partitioning variable and calculate the within-decile mean and median forecast improvement. The "*Value*" column reports the mean or median value of the partitioning variable in each decile. To prevent a look-ahead bias, we use lagged values of the partitioning variable to create the deciles.

Table 1, Panel A, reports the forecast accuracy by decile of the concentration in prior years' *operating asset* components. For the *non-current-dis* model, we measure concentration with a Herfindahl index of each component's contribution to the *operating asset* total. High values of the concentration index indicate high asset concentration, while low values indicate a greater spread in prior years' *non-current operating asset* components. Grounded in the notion that disaggregated forecasting models leverage systematic differences between asset components, we expect and find a monotonic decrease in the mean (median) forecast improvement for firms with greater asset concentration, indicating that the disaggregation of *non-current operating assets* is most useful for firms with a high spread (low concentration) in the components of their non-current asset base.

Next, we conduct similar tests to investigate whether models that incorporate disaggregations beyond the *non-current-dis* model are more useful when there is a high spread (low concentration) in the newly decomposed asset components. Specifically, we adjust the Herfindahl index to measure the concentration in the additional disaggregates beyond the *non-current-dis* model. For example, when comparing the forecast improvements of the *full-dis* model to the *non-current-dis* model, we consider the concentration in *accounts receivable*, *inventory*, *other current operating assets*, and *non-current operating assets*. We do not find greater forecast improvements for the *full-dis* and *non-cur-intan* models compared to the *non-current-dis* model, even for firms with high spreads (low concentration) in the additional disaggregated asset components.

Next, in Table 1, Panel B, we investigate how the forecast improvements of the *non-current-dis* model over the *aggregate benchmark* model depend on the predictability of the asset categories that dominate the *operating asset* total. We expect that firms with a higher percentage of assets with predictable growth will experience greater forecast improvements. Asset intensity is measured as the component's percentage contribution toward the *operating asset* total. Asset growth predictability is based on the model fit (Adj. $R^2$) of the in-sample estimation procedure, as reported in Table 2, Panel A, of the main manuscript. We classify *inventory* and *accounts receivable* as unpredictable assets, while *PPE* and *intangible assets* are classified as predictable assets.[1] We find a monotonic decrease in forecast improvements for deciles based on unpredictable asset intensity. For firms with an asset base dominated by predictable assets, we observe greater forecast improvements for *intangible asset-intensive*, but not for *property, plant, and equipment-intensive* firms. Firms in the highest decile of *intangible asset* intensity experience percentage forecast improvements of 6.17% (median: 35.82%) for the *non-current-dis* model over the *aggregate benchmark* model.[2] Moreover, forecast improvements for the lowest intangible asset intensity deciles are insignificant, suggesting that the decomposition of *intangible assets* is an important factor driving the forecast improvements of the disaggregated model.

Finally, Panel C reports the results of cross-sectional tests in which we investigate how forecast improvements vary by decile of firm-specific growth stability. Specifically, we examine the absolute value of prior-year growth and acquisition intensity. We find that firms with moderate to low absolute growth experience greater benefits of asset disaggregation when forecasting *operating asset* growth. Moreover, firms in the highest deciles of growth experience no significant forecast improvements. These results suggest that the forecasting benefits of disaggregated models are smaller in the tails of the growth distribution. While a decline in forecast accuracy for firms with more extreme performance is normal for all mean-reverting models, the benefits of offsetting subcomponents' noise are likely greater for firms in the tail of the distribution. Hence, this can explain why disaggregated forecast models no longer outperform the aggregate model for firms

[1] For simplicity and because they represent a catchall of a variety of other types of assets, we do not use "*other current assets*" and "*other non-current assets.*"
[2] To account for possible differences in forecasting difficulty across the deciles of intangible asset intensity, the percentage forecast improvement is calculated as a percentage of the (untabulated) decile-specific *AFE* of the aggregate benchmark model. The reported numbers are calculated as follows: median: 0.0296/0.0824; mean: 0.0112/0.1816.

with extreme growth. For acquisition intensity, we find significant improvements for most deciles, even for firms in the highest acquisition intensity decile.[3]

Table 2 reports the results of more exploratory analyses of cross-sectional variation in forecast improvements of the *non-current-dis* model over the *aggregate benchmark* model. Specifically, we partition firm-year forecast improvements based on life cycle stage and deciles of firm size and performance.

Table 2, Panel A, reports cross-sectional variation in forecast improvements by life cycle stage, following Dickinson (2011). The *non-current-dis* model is more accurate than the *aggregate benchmark* model in all life cycle stages, except for median improvements for firms in the growth stage. Interestingly, while not improving forecast accuracy in our pooled tests, further disaggregating *intangible assets* into *goodwill* and *other intangible assets* (i.e., *non-cur-intan*) significantly improves forecast accuracy for firms in the introduction, shakeout, and decline stages. These firms are likely different from the average firm in the sample, and they rely heavily on R&D investments (see Dickinson 2011, p. 1976), which likely explains the informativeness of the intangible asset disaggregation for these firms. Next, we consider variation in forecast improvements across deciles based on firm size as measured by lagged *operating assets*. We find the greatest forecast improvements for large firms, while no significant improvements are found for firms in the smallest deciles.

Finally, in Table 2, Panel B, we examine how forecast improvements vary as a function of accounting performance and market pricing. We measure the former as return on assets, while the latter is measured by the market-to-book ratio. We find a monotonic decrease in forecast improvements of the *non-current-dis* model over the *aggregate benchmark* model as firm

[3] Note, however, that the sample is restricted to firms with lagged growth in operating assets less than 100 percent, which likely causes firms with the most extreme acquisition intensity to be excluded from our sample.

performance increases. As such, these findings are in line with our earlier result that for firms with extreme growth, which are likely more unstable in their growth parameters, asset decompositions are less useful for forecasting growth.

Thus far, we have examined univariate cross-sectional variation in forecast improvements. Since the characteristics we investigate are prone to be correlated, we expand the decile analysis with a multivariate regression of the forecast improvement of the *non-current-dis* model over the *aggregate benchmark* model as a function of the determinants included in the decile analysis. We winsorize the performance variables at the 1st and 99th percentile and include industry (Fama-French 48) and year-fixed effects. Standard errors are clustered by firm (Abadie, Athey, Imbens, and Wooldridge 2023). The results of the regression analysis are reported in Table 2, Panel C. The first column presents results with all variables from the cross-sectional analysis included. In contrast, columns two and three drop the asset intensity and concentration variables, respectively, as both aim to capture asset concentration and are consequently highly correlated. Overall, in the multivariate analyses, we find results largely consistent with those of the univariate analysis.[4]

**Spread and future stock returns**

The results of the cross-sectional analysis show that the *non-current-dis* model performs better when there is a high spread in the asset components. Additionally, in the main manuscript, we show that *Growth Difference*, which captures the difference in growth predictions of the *non-current-dis* model and the *aggregate benchmark* model, is positively related to future stock returns. Hence, spread could be an overlooked predictor of future performance, potentially driving the

[4] The positive association between intangible asset intensity and forecast improvements is subsumed in the multivariate analysis. This is due to its strong negative correlation with PPE intensity (-0.56). If we exclude PPE intensity, intangible asset intensity is significantly positive (coef. = 0.009; t.stat = 5.84).

stock return results as reported in Table 6 of the main manuscript. In untabulated tests, we indeed find that spread is positively associated with year-ahead improvements in asset turnover (although less so than *Growth Difference*). Nevertheless, to rule out that our stock return results are subsumed by spread, we add it as an additional control to the regression specification. The results reported in Table 3 show that spread is somewhat predictive of returns, but the returns generated by the growth information embedded in balance sheet disaggregations as captured by *Growth Difference* remain unchanged. These results suggest that spread might indeed be an overlooked predictor of financial performance, with some predictive ability for future returns; however, this effect is distinct from the effect of disaggregated balance sheet information that we document.

**TABLE 1 – Online Appendix**

*Cross-Sectional Analyses of Forecast Improvements – Asset Characteristics*

**Panel A:** Forecast improvements of the non-current-dis model over the aggregate benchmark model by lagged asset concentration decile

***Asset Concentration***

| | **Median** | | | | | | | **Mean** | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Decile | Value | Non-current-dis versus Aggregate | | Full-dis versus Non-current-dis | | Non-cur-intan versus Non-current-dis | | Value | Non-current-dis versus Aggregate | | Full-dis versus Non-current-dis | | Non-cur-intan versus Non-current-dis | |
| 1 | 0.29 | 0.0155 | *** | -0.0006 | * | 0.0038 | | 0.29 | 0.0071 | *** | -0.0005 | | 0.0011 | * |
| 2 | 0.33 | 0.0125 | *** | -0.0003 | * | -0.0001 | | 0.33 | 0.0049 | *** | -0.0007 | *** | 0.0002 | |
| 3 | 0.35 | 0.0087 | ** | -0.0005 | ** | 0.0006 | | 0.35 | 0.0033 | ** | -0.0005 | ** | -0.0001 | |
| 4 | 0.37 | 0.0074 | ** | -0.0004 | * | 0.0001 | | 0.37 | 0.0034 | ** | -0.0003 | | -0.0001 | |
| 5 | 0.40 | 0.0050 | ** | -0.0005 | ** | 0.0010 | | 0.40 | 0.0024 | ** | -0.0005 | *** | 0.0003 | |
| 6 | 0.42 | 0.0036 | ** | -0.0002 | | -0.0003 | | 0.42 | 0.0031 | *** | -0.0003 | *** | -0.0001 | |
| 7 | 0.45 | 0.0035 | | -0.0001 | | 0.0003 | | 0.45 | 0.0021 | * | -0.0001 | | 0.0001 | |
| 8 | 0.49 | 0.0036 | ** | -0.0001 | | -0.0001 | | 0.50 | 0.0022 | ** | -0.0002 | ** | 0.0000 | |
| 9 | 0.56 | 0.0037 | ** | -0.0001 | | 0.0001 | | 0.56 | 0.0028 | *** | -0.0001 | * | 0.0000 | |
| 10 | 0.69 | 0.0010 | | -0.0001 | *** | 0.0000 | | 0.71 | 0.0014 | | -0.0001 | ** | 0.0000 | |
| D1 vs D10 | | -0.0145 | *** | 0.0005 | | -0.0038 | | | -0.0057 | *** | 0.0004 | | -0.0011 | * |

**Panel B:** Forecast improvements of the non-current-dis model over the aggregate benchmark model by lagged asset intensity decile

| | ***PPE Intensity*** | | | | | | ***Intangible Asset Intensity*** | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Decile | Value | Median | | Value | Mean | | Value | Median | | Value | Mean | |
| 1 | 0.06 | 0.0083 | *** | 0.05 | 0.0053 | *** | 0.01 | 0.0014 | | 0.01 | 0.0007 | |
| 2 | 0.11 | 0.0096 | ** | 0.11 | 0.0038 | ** | 0.04 | 0.0015 | | 0.04 | 0.0005 | |
| 3 | 0.15 | 0.0065 | ** | 0.15 | 0.0032 | ** | 0.07 | 0.0032 | | 0.07 | 0.0012 | |
| 4 | 0.19 | 0.0058 | * | 0.19 | 0.0031 | ** | 0.11 | 0.0047 | * | 0.11 | 0.0017 | * |
| 5 | 0.24 | 0.0053 | *** | 0.24 | 0.0037 | *** | 0.16 | 0.0063 | * | 0.16 | 0.0025 | ** |
| 6 | 0.30 | 0.0056 | * | 0.30 | 0.0023 | ** | 0.21 | 0.0061 | * | 0.21 | 0.0025 | ** |
| 7 | 0.38 | 0.0088 | ** | 0.38 | 0.0040 | *** | 0.28 | 0.0084 | ** | 0.28 | 0.0031 | ** |
| 8 | 0.47 | 0.0054 | ** | 0.47 | 0.0037 | *** | 0.36 | 0.0113 | ** | 0.37 | 0.0039 | ** |
| 9 | 0.61 | 0.0069 | ** | 0.61 | 0.0024 | ** | 0.47 | 0.0206 | *** | 0.47 | 0.0076 | *** |
| 10 | 0.78 | 0.0021 | | 0.79 | 0.0018 | ** | 0.63 | 0.0296 | *** | 0.65 | 0.0112 | *** |
| D1 vs D10 | | -0.0062 | ** | | -0.0035 | *** | *** | 0.0282 | *** | | 0.0105 | *** |

| | ***Inventory Intensity*** | | | | | | ***Accounts Receivable Intensity*** | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Decile | Value | Median | | Value | Mean | | Value | Median | | Value | Mean | |
| 1 | 0.01 | 0.0163 | *** | 0.01 | 0.0062 | *** | 0.03 | 0.0100 | *** | 0.03 | 0.0046 | *** |
| 2 | 0.02 | 0.0102 | *** | 0.02 | 0.0037 | *** | 0.06 | 0.0144 | *** | 0.06 | 0.0069 | *** |
| 3 | 0.04 | 0.0095 | *** | 0.04 | 0.0047 | *** | 0.09 | 0.0126 | *** | 0.09 | 0.0055 | *** |
| 4 | 0.08 | 0.0108 | *** | 0.08 | 0.0055 | *** | 0.12 | 0.0138 | *** | 0.12 | 0.0051 | *** |
| 5 | 0.11 | 0.0104 | ** | 0.11 | 0.0033 | ** | 0.14 | 0.0083 | *** | 0.14 | 0.0048 | *** |
| 6 | 0.14 | 0.0096 | ** | 0.14 | 0.0038 | *** | 0.17 | 0.0052 | | 0.17 | 0.0029 | ** |
| 7 | 0.17 | 0.0060 | * | 0.17 | 0.0026 | ** | 0.20 | 0.0072 | ** | 0.20 | 0.0032 | ** |
| 8 | 0.21 | 0.0048 | | 0.21 | 0.0020 | * | 0.23 | 0.0023 | | 0.23 | 0.0018 | |
| 9 | 0.27 | 0.0009 | | 0.27 | 0.0014 | | 0.28 | 0.0013 | | 0.28 | 0.0006 | |
| 10 | 0.38 | -0.0001 | | 0.40 | 0.0005 | | 0.38 | -0.0008 | | 0.41 | -0.0015 | * |
| D1 vs D10 | | -0.0164 | *** | | -0.0057 | *** | | -0.0108 | *** | | -0.0061 | *** |

**Panel C:** Forecast improvements of the non-current-dis model over the aggregate benchmark model by growth stability decile

| | *\|Operating Asset Growth\|* | | | | | | *Acquisition Intensity* | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Decile | Value | Median | | Value | Mean | | Value | Median | | Value | Mean | |
| 1 | 0.01 | 0.0127 | *** | 0.01 | 0.0057 | *** | 0.00 | 0.0064 | *** | 0.00 | 0.0037 | *** |
| 2 | 0.02 | 0.0097 | *** | 0.02 | 0.0055 | *** | 0.00 | 0.0060 | *** | 0.00 | 0.0039 | *** |
| 3 | 0.03 | 0.0105 | *** | 0.03 | 0.0049 | *** | 0.00 | 0.0048 | ** | 0.00 | 0.0028 | *** |
| 4 | 0.05 | 0.0110 | *** | 0.05 | 0.0047 | *** | 0.00 | 0.0062 | *** | 0.00 | 0.0031 | *** |
| 5 | 0.06 | 0.0075 | *** | 0.06 | 0.0038 | *** | 0.00 | 0.0066 | ** | 0.00 | 0.0034 | ** |
| 6 | 0.08 | 0.0037 | ** | 0.08 | 0.0028 | *** | 0.00 | 0.0099 | *** | 0.00 | 0.0049 | *** |
| 7 | 0.11 | 0.0075 | * | 0.11 | 0.0029 | ** | 0.01 | 0.0088 | *** | 0.01 | 0.0040 | *** |
| 8 | 0.14 | 0.0020 | | 0.14 | 0.0010 | | 0.02 | 0.0024 | | 0.02 | 0.0010 | |
| 9 | 0.20 | 0.0032 | | 0.20 | 0.0012 | | 0.04 | 0.0013 | | 0.04 | -0.0001 | |
| 10 | 0.33 | 0.0019 | | 0.36 | 0.0019 | | 0.11 | 0.0133 | *** | 0.13 | 0.0062 | *** |
| D1 vs D10 | | -0.0108 | ** | | -0.0038 | * | | 0.0069 | ** | | 0.0025 | |

This table presents the results of tests in which we investigate cross-sectional variation in the forecast accuracy improvements of disaggregated forecasting models conditional on asset characteristics. The holdout sample consists of 21,492 firm-year observations for which we have available model forecasts and data on actual operating asset growth, except for the *non-cur-intan* model for which we have 13,187 firm-year forecasts. The actual sample size varies depending on the data availability of the partitioning variable(s). Panel A presents the improvements in the accuracy of operating asset growth forecasts of various model comparisons by decile of asset concentration. The measure of asset concentration differs for every column. In the first column, concentration is a Herfindahl index of the components of the *non-current-dis* model. In the second and third columns, asset concentration is a Herfindahl index of the additional components of the respective model beyond the *non-current-dis* model. For the second column, the index measures concentration in accounts receivable, inventory, other current assets, and non-current operating assets. In the third column, the index measures concentration in goodwill, other intangible assets, and the remaining operating assets (Operating assets - goodwill - intangible assets). Panel B presents the forecast improvements of the *non-current-dis* model over the *aggregate benchmark* model for deciles of various asset intensity measures (Property, Plant, & Equipment, Intangible Assets, Inventory, and Accounts Receivable). *Asset Intensity* is the lagged ratio of the asset component over total operating assets. Panel C presents the forecast improvements of the *non-current-dis* model over the *aggregate benchmark* model for deciles of lagged absolute operating asset growth and acquisition intensity. |*Operating Asset Growth*| is equal to the lagged absolute value of growth in operating assets. *Acquisition Intensity* is equal to the lagged value of acquisitions (Compustat: AQC) over lagged operating assets. The "Value" column reports the mean (median) value of the partitioning variable in each decile. *, **, *** indicate statistical significance at the 10 percent, 5 percent, and 1 percent levels, respectively (two-tailed).

**TABLE 2 – Online Appendix**

*Cross-Sectional Analyses of Forecast Improvements – Firm Characteristics and Firm Performance*

**Panel A:** Forecast improvements of the non-current-dis model over the aggregate benchmark model by size decile

***Firm Size***

| | **Median** | | | | | | **Mean** | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Decile | Value (bn.) | Non-current-dis versus Aggregate | | Full-dis versus Non-current-dis | | Non-cur-intan versus Non-current-dis | Value (bn.) | Non-current-dis versus Aggregate | | Full-dis versus Non-current-dis | | Non-cur-intan versus Non-current-dis |
| 1 | 0.08 | 0.0025 | | -0.0004 | ** | 0.0005 | 0.08 | 0.0006 | | -0.0006 | *** | 0.0006 |
| 2 | 0.21 | 0.0010 | | -0.0003 | ** | -0.0003 | 0.21 | 0.0006 | | -0.0005 | *** | -0.0002 |
| 3 | 0.39 | 0.0011 | | -0.0005 | *** | 0.0002 | 0.40 | 0.0019 | | -0.0004 | *** | 0.0003 |
| 4 | 0.65 | 0.0067 | ** | -0.0001 | | -0.0001 | 0.66 | 0.0038 | *** | -0.0002 | | 0.0002 |
| 5 | 1.04 | 0.0025 | | -0.0002 | ** | -0.0005 | 1.05 | 0.0027 | ** | -0.0004 | ** | -0.0003 |
| 6 | 1.68 | 0.0082 | ** | -0.0002 | ** | 0.0001 | 1.70 | 0.0034 | *** | -0.0004 | ** | 0.0002 |
| 7 | 2.78 | 0.0084 | ** | -0.0001 | ** | 0.0000 | 2.86 | 0.0041 | *** | -0.0003 | ** | 0.0000 |
| 8 | 5.23 | 0.0079 | *** | 0.0000 | * | -0.0001 | 5.35 | 0.0047 | *** | -0.0003 | * | 0.0003 |
| 9 | 11.48 | 0.0122 | *** | 0.0000 | | 0.0001 | 12.18 | 0.0056 | *** | -0.0001 | | 0.0001 |
| 10 | 36.76 | 0.0109 | ** | -0.0001 | | 0.0002 | 55.15 | 0.0054 | *** | 0.0000 | | 0.0002 |
| D1 vs D10 | | 0.0084 | | 0.0003 | ** | -0.0003 | | 0.0048 | *** | 0.0006 | ** | -0.0004 |

**Panel B:** Forecast improvements of the non-current-dis model over the aggregate benchmark model by lagged performance decile

| | *Return on Assets* | | | | | | *Market-to-Book* | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Decile | Value | Median | | Value | Mean | | Value | Median | | Value | Mean | |
| 1 | -0.06 | 0.0054 | *** | -0.13 | 0.0006 | | 0.29 | 0.0093 | *** | -15.52 | 0.0075 | *** |
| 2 | 0.02 | 0.0104 | *** | 0.02 | 0.0006 | | 0.92 | 0.0110 | *** | 0.92 | 0.0083 | *** |
| 3 | 0.05 | 0.0119 | *** | 0.05 | 0.0019 | | 1.23 | 0.0107 | *** | 1.23 | 0.0066 | *** |
| 4 | 0.07 | 0.0112 | *** | 0.07 | 0.0038 | *** | 1.51 | 0.0100 | *** | 1.51 | 0.0059 | *** |
| 5 | 0.09 | 0.0110 | *** | 0.09 | 0.0027 | ** | 1.81 | 0.0073 | ** | 1.81 | 0.0035 | *** |
| 6 | 0.10 | 0.0081 | ** | 0.10 | 0.0034 | ** | 2.18 | 0.0070 | | 2.17 | 0.0026 | ** |
| 7 | 0.13 | 0.0113 | ** | 0.13 | 0.0041 | *** | 2.64 | 0.0054 | | 2.65 | 0.0014 | |
| 8 | 0.16 | 0.0003 | | 0.16 | 0.0047 | *** | 3.30 | -0.0030 | | 3.31 | 0.0004 | |
| 9 | 0.20 | -0.0066 | * | 0.20 | 0.0056 | *** | 4.42 | -0.0023 | | 4.47 | -0.0002 | |
| 10 | 0.31 | -0.0108 | *** | 0.36 | 0.0054 | *** | 7.94 | -0.0079 | | 25.40 | -0.0013 | |
| D1 vs D10 | | -0.0162 | *** | | 0.0048 | *** | | -0.0172 | *** | | -0.0088 | *** |

**Panel C:** Multivariate test on the determinants of forecast improvements of the non-current-dis model over the aggregate benchmark model

| **Lagged Variable** | **Decile Analysis** | **Forecast Improvements** | | |
|---|---|---|---|---|
| *Size* | + | 0.001*** | 0.001*** | 0.001*** |
| | | [6.727] | [9.574] | [6.749] |
| *Market-to-Book* | - | 0.000*** | 0.000*** | 0.000*** |
| | | [-6.870] | [-6.830] | [-6.827] |
| *Return on Assets* | - | -0.020*** | -0.023*** | -0.020*** |
| | | [-11.451] | [-13.115] | [-11.417] |
| *Concentration* | - | -0.003 | -0.006*** | |
| | | [-1.266] | [-3.273] | |
| *PPE Intensity* | - | -0.006** | | -0.008*** |
| | | [-2.158] | | [-2.868] |
| *Intangible Asset Intensity* | + | 0.004 | | 0.003 |
| | | [1.399] | | [1.048] |
| *Accounts Receivable Intensity* | - | -0.015*** | | -0.017*** |
| | | [-4.365] | | [-5.048] |
| *Inventory Intensity* | - | -0.007* | | -0.008** |
| | | [-1.939] | | [-2.450] |
| *Abs Growth* | - | -0.015*** | -0.017*** | -0.015*** |
| | | [-5.729] | [-6.495] | [-5.813] |
| *Acquisition Intensity* | ? | 0.031*** | 0.044*** | 0.032*** |
| | | [5.202] | [7.420] | [5.275] |
| Num. Obs. | | 20,280 | 20,280 | 20,280 |
| Adj. $R^2$ | | 0.065 | 0.059 | 0.064 |
| Clustering of standard errors | | Firm | Firm | Firm |
| Year fixed effects | | X | X | X |
| Industry fixed effects | | X | X | X |

This table presents the results of tests in which we investigate cross-sectional variation in the accuracy improvements of disaggregated forecasting models conditional on firm characteristics and financial and market performance. The holdout sample consists of 21,492 firm-year observations for which we have available model forecasts and data on actual operating asset growth, except for the *non-cur-intan* model, for which we have 13,187 firm-year forecasts. The actual sample size varies depending on the data availability of the partitioning variable(s). Panel A presents the improvements in the accuracy of operating asset growth forecasts of various model comparisons by firm life cycle stage and size decile. Panel B presents the improvements in the accuracy of operating asset growth forecasts of various model comparisons by deciles of financial and market performance (Return on Assets & Market-to-Book). Panel C reports the results of a multivariate regression of the determinants of the forecast improvement of the *non-current-dis* model over the *aggregate benchmark* model. The partitioning variables are lagged by one year and are defined as follows (Compustat variables in brackets):

*Size* = log(Operating Assets)
*Return on Assets* = Operating Income After Depreciation (OIADP) / Lagged Operating Assets
*Market-to-Book* = (Stock price at the end of the fiscal year* Shares Outstanding at the end of the Fiscal Year)/Book Value of Equity ((PRCC_F*CSHO)/CEQ)

*Life Cycle* is categorized following the cash flow classification in Dickinson (2011). Industry fixed effects are based on the Fama-French 48 industry classification. Other variables are defined in Table 1 of the online appendix and Table 4 of the main manuscript. The column ''Value'' reports the mean (median) value of the partitioning variable in each decile. *, **, *** indicate statistical significance at the 10 percent, 5 percent, and 1 percent levels, respectively (two-tailed).

**TABLE 3 – Online Appendix**

*Revenue Growth Forecasts using Disaggregated Balance Sheet Information and Stock Returns*

| Variable | Excess Return - Value Weighted | | Excess Return – Fama-French Five-Factor | |
|---|---|---|---|---|
| *Growth Difference* | 0.090*** | 0.066*** | 0.065*** | 0.067*** |
| | [6.462] | [3.947] | [4.453] | [3.774] |
| *Spread* | | -0.039*** | | -0.031** |
| | | [-2.949] | | [-2.176] |
| *Size* | | -0.085*** | | |
| | | [-4.527] | | |
| *Market to Book* | | -0.054*** | | |
| | | [-2.622] | | |
| *Momentum* | | -0.128*** | | |
| | | [-8.203] | | |
| *Beta* | | 0.002 | | |
| | | [0.164] | | |
| *Accruals* | | -0.004 | | -0.018 |
| | | [-0.294] | | [-1.129] |
| *Gross Profitability* | | 0.026 | | 0.088*** |
| | | [1.289] | | [4.550] |
| *$ATO\Delta^{t-1}$* | | 0.006 | | 0.041* |
| | | [0.317] | | [1.915] |
| *$PM\Delta^{t-1}$* | | -0.026 | | 0.005 |
| | | [-0.987] | | [0.165] |
| *Predicted $ATO\Delta^{t}$* | | -0.016 | | -0.009 |
| | | [-0.516] | | [-0.269] |
| *Predicted $PM\Delta^{t}$* | | -0.101*** | | -0.081** |
| | | [-2.623] | | [-2.120] |
| *Predicted FSY $ROA\Delta^{t}$* | | 0.074*** | | 0.037** |
| | | [4.655] | | [2.062] |
| *$ROA^{t-1}$* | | -0.051 | | -0.122*** |
| | | [-1.370] | | [-3.179] |
| *$ROA\Delta^{t-1}$* | | 0.060* | | 0.009 |
| | | [1.918] | | [0.248] |
| Intercept | 0.028*** | 0.208*** | -0.007 | 0.033 |
| | [4.180] | [3.744] | [-0.859] | [0.608] |
| Num. Obs. | 20,404 | 20,404 | 20,404 | 20,404 |
| Adj. $R^2$ | 0.002 | 0.013 | 0.001 | 0.003 |
| Clustering of S.E. | Firm | Firm | Firm | Firm |

In this table, we investigate the robustness of the stock returns earned by trading on differences in predicted revenue growth of disaggregated versus aggregate models (*Growth Difference*) to the inclusion of the spread in the components of the disaggregated models. All variables are as defined in the main manuscript except *Spread*, which is an annual decile rank (ranging between 0 and 1) of a Herfindahl index of the components on the *non-current-dis* model's contribution to the operating asset total. *, **, *** indicate statistical significance at the 10 percent, 5 percent, and 1 percent levels, respectively (two-tailed).

## Section 2: Balance Sheet Disaggregations and Analyst Forecasts

The results in Section 4.3 of the main manuscript are consistent with an underutilization of balance sheet disaggregations by investors. In this section, we document related evidence that shows that disaggregated model growth predictions are informative about future operating performance, incremental to the information in analyst forecasts of future operating performance.[5] Inspired by our result that the difference in predicted growth between the disaggregated and the aggregate model is informative for improvements in operating performance (see Table 9 of the main text), we focus on analysts' ROA forecasts as an important performance measure that investors and analysts care about.[6] We then investigate whether analyst forecasts fully reflect the implications of disaggregated revenue growth predictions for changes in ROA. We do so by examining whether the difference in predicted growth rates between the models (*Growth Difference*) is associated with actual changes in ROA after controlling for analyst forecasts of changes in ROA (*Analyst ROAΔ*). We compute *Analyst ROAΔ* by subtracting last year's actual ROA from the I/B/E/S mean consensus forecast issued closest to the fiscal year-end of the forecasted year.[7] To correct for outliers, we winsorize *Analyst ROAΔ* and *ROAΔ* at the 1st and 99th percentile. Standard errors are clustered at the firm level (Abadie et al. 2023). The final sample includes 12,373 firm-year observations with available model and analyst forecasts.

The results, as reported in Table 4, show that *Growth Difference* is positive and significant even after including *ANALYST ROAΔ,* indicating that the information in *Growth Difference* is

[5] Previous literature documents that some equity analysts rely on residual income valuation methods (see e.g., Hand et al. 2017 and Gleason et al. 2013), illustrating how forecasts of operating asset growth matter to these analysts.

[6] While in the previous tests, in line with our focus on operating asset growth, we investigate the informativeness of growth predictions for operating asset turnover and return on operating assets, in this section we use return on assets (income before extraordinary items scaled by lagged total assets) to be consistent with the I/B/E/S ROA forecasts.

[7] This test provides a conservative estimate of the extent to which the information in the disaggregated model is incremental to the information in analyst forecasts as we use forecasts that are issued close to fiscal year-end. Hence, we allow analysts to incorporate information that becomes available only in the period after the construction of the (disaggregated) model forecast.

incremental to the information in analyst forecasts of *ROAΔ*. These results hold after controlling for the number of analysts issuing ROA forecasts (*Numest*) and varying combinations of year, industry, and firm fixed effects. Finally, to ensure that the information in disaggregated balance sheet information is incremental to the information embedded in income statement disaggregations, we control for *Predicted FSY ROA*$\Delta^t$, which, as before, is defined as the predicted change in return on operating assets estimated using the most accurate income statement disaggregation scheme in Fairfield, Sweeney, and Yohn (1996). In line with our results regarding future stock returns, we find that *Growth Difference* remains positive and significant even after including *Predicted FSY ROAΔ*, reconfirming that the information in balance sheet disaggregations is incremental to the information in income statement disaggregations even in analyses using income statement-type performance measures.

While the previous section shows that the information in disaggregated growth predictions is informative about future changes in ROA even after controlling for analyst ROA forecasts, we next provide evidence that is consistent with financial analysts failing to incorporate the growth information embedded in balance sheet disaggregations into their sales growth forecasts. Consistent with prior studies that document that even sophisticated financial analysts tend to fixate on aggregate bottom-line figures and fail to appreciate the differential persistence of underlying components (Picconi 2006; Soliman 2008), we assume that analysts use a model that resembles the aggregate model. For example, Soliman (2008) documents that analysts fail to fully incorporate the information in the disaggregation of (the change in) return on assets into (changes in) asset turnover and profit margin. Specifically, we compute analyst forecasted sales growth by taking the percentage growth from last year's actual sales to next year's mean consensus forecasted sales (Fairfield, Ramnath, and Yohn 2009). Analyst sales forecasts come from I/B/E/S and we select the last available consensus forecast issued prior to the end of the forecasted fiscal year. To correct for outliers, we truncate analyst forecasted sales growth at the 1st and 99th percentile. As we estimate a Vuong test, truncation is preferred over winsorization as the latter creates artificial variance for the extreme percentiles; however, the interpretation of our results remains the same if we winsorize at the 1st and 99th percentile. The final sample includes 20,673 firm-year observations with available model and analyst forecasts.

The results in Table 5 indicate that the explanatory power for analyst estimates of sales growth is significantly smaller for the model that uses disaggregated balance sheet information (i.e., the *non-current-dis* model) compared to the benchmark model that uses aggregate information. This finding is in stark contrast to the greater accuracy of this model in predicting operating asset growth. A Vuong (1989) test confirms that the $R^2$ of the *aggregate benchmark* model is significantly greater than that of the *non-current-dis* model. Hence, these results suggest that analyst forecasts are not consistent with the use of disaggregated balance sheet information when making sales growth forecasts. As such, these results also suggest that analysts' sales growth forecasts can be improved by incorporating the systematic differences in growth rates across asset components as captured by the *non-current-dis* model.

**TABLE 4 – Online Appendix**

*Analyst ROA Forecasts and Disaggregate Balance Sheet Information*

| | *ROAΔ* | |
|---|---|---|
| *Growth Difference* | 0.014*** | 0.027*** |
| | [7.107] | [7.874] |
| *Analyst ROAΔ$^t$* | 0.009*** | 0.010*** |
| | [2.664] | [2.603] |
| *Numest* | -0.010*** | -0.008** |
| | [-2.829] | [-2.392] |
| *Predicted FSY ROAΔ$^t$* | 0.705*** | 0.800*** |
| | [35.086] | [36.105] |
| *NOA Δ$^{t-1}$* | 0.001*** | 0.000 |
| | [3.829] | [-0.381] |
| *Agg. Pred. Revenue GrowthΔ$^t$* | 0.000 | 0.014*** |
| | [-0.158] | [4.515] |
| Num. Obs. | 12,373 | 12,373 |
| Adj. $R^2$ | 0.428 | 0.515 |
| Clustering of S.E. | Firm | Firm |
| Year fixed effects | X | X |
| Industry fixed effects | X | |
| Firm fixed effects | | X |

This table reports the results of tests in which we investigate whether disaggregated models predict future improvements in return on assets (*ROA*), incremental to the information in analyst forecasts of ROA. For this test, to align with analyst ROA forecasts, we define ROA as income before extraordinary items (IB) divided by lagged total assets (AT). The sample consists of 12,373 firm-year observations for which we have available model forecasts, analyst forecasts of ROA, and data on actual ROA growth. We compute the analyst forecasted change in ROA (*Analyst ROAΔ$^t$*) by subtracting last year's actual ROA$^{t-1}$ from the I/B/E/S mean consensus ROA forecast issued closest to the fiscal year-end of the forecasted year. *ROAΔ* is calculated by subtracting the previous year's actual ROAt-1 from the next year's actual *ROA$^t$*. *Growth Difference* and *Predicted FSY ROAΔ$^t$* are as defined before. *Numest* is equal to the number of analysts that have issued ROA forecasts. *Analyst ROAΔ$^t$* is winsorized at the 1st and 99th percentile. Industry fixed effects are based on the Fama-French 48 industry classification. *, **, *** indicate statistical significance at the 10 percent, 5 percent, and 1 percent levels, respectively (two-tailed).

**TABLE 5 – Online Appendix**

*Analyst Sales Forecasts and Aggregate versus Disaggregated Growth Forecasts*

| | ***Analyst Forecasted Sales $\Delta^t$*** | |
|---|---|---|
| *Agg. Pred. Revenue Growth$\Delta^t$* | 1.359*** | |
| | [31.784] | |
| *DisAgg. Pred. Revenue Growth$\Delta^t$* | | 1.077*** |
| | | [22.939] |
| Intercept | -0.039*** | -0.008** |
| | [-11.595] | [-2.457] |
| Num. Obs. | 20,673 | 20,673 |
| $R^2$ | 0.047 | 0.025 |
| Diff. in $R^2$ Vuong Test p.value | | 0.000*** |

This table reports the results of a test on analysts' use of disaggregated versus aggregate balance sheet information. Analysts' sales growth forecasts are calculated as the percentage growth from the prior year's actual sales to the current year's consensus sales forecast issued closest to the fiscal year-end of the forecasted year. Analysts' sales growth forecasts are truncated at the 1st and 99th percentile. The *aggregate benchmark* model and the *non-current-dis* revenue growth prediction are derived from the models explained in section 3 of the main manuscript. The difference in explanatory power is tested using a Vuong test (Vuong 1989). *, **, *** indicate statistical significance at the 10 percent, 5 percent, and 1 percent levels, respectively (two-tailed).

**Section 3: Disaggregate Balance Sheet Information and the Growth Anomaly**

The results reported in section 4.3 are consistent with an underutilization of balance sheet disaggregations on the part of investors. Given that we investigate how differences in predicted asset/revenue *growth* of disaggregated versus aggregate models relate to future stock returns, in this section, we examine how our results relate to the asset growth anomaly that has been documented in prior literature (e.g., Cooper, Gulen, and Schill 2008; Fairfield, Whisenant, and Yohn 2003). Studies have shown that investors extrapolate past growth too far into the future, leading to a negative relation between past growth and stock returns (Lakonishok, Shleifer, and Vishny 1994; Chan, Karceski, and Lakonishok 2003). As our investigation also deals with (differences in disaggregated versus aggregate) growth predictions, in this section, we report the results of several tests that investigate the relation between our measure (i.e., *Growth Difference*) and the asset growth anomaly, and we show that our results are partially correlated yet still distinct from the growth anomaly.

First, we augment the pooled stock return test, as presented in Table 6 of the main manuscript, by adding controls for the growth anomaly. Specifically, we include the aggregate model growth forecasts and lagged NOA growth (Fairfield et al. 2003). The aggregate model forecast is included as a proxy for the growth anomaly since it is a mean-reverting estimate of future growth based on past operating asset growth. We find that the coefficient on *Growth Difference* remains positive and significant in three out of four specifications (see Table 6 of this appendix). In contrast, the coefficients on lagged NOA growth and the aggregate model growth prediction are negative, which is in line with the asset growth anomaly. Importantly, in the samples that we assume capture investors' underutilization of disaggregated balance sheet information, we find that *Growth Difference* is positively and significantly related to future returns in all specifications. Specifically, when we partition the sample on the level of (transient) institutional ownership, we find that

*Growth Difference* is significantly positive in the subsamples of low institutional ownership, also after controlling for the aggregate growth forecast and lagged NOA growth. Furthermore, we find that *Growth Difference* exhibits a positive and significant relation with earnings announcement returns, also after controlling for predicted aggregate growth and lagged NOA growth (see Table 7 in this appendix). Overall, these results show that, while there is overlap in the factors that drive the returns to disaggregated growth predictions and the asset growth anomaly, our returns still capture an aspect distinct from the growth anomaly.

**TABLE 6 – Online Appendix**

*Growth Forecasts, the Growth Anomaly, and Stock Returns*

| | Excess Return - Value Weighted | | Excess Return – Fama-French Five-Factor | |
|---|---|---|---|---|
| *Growth Difference* | 0.058*** | 0.025 | 0.046*** | 0.037** |
| | [4.179] | [1.437] | [3.066] | [2.054] |
| *NOA*$\Delta^{t-1}$ | -0.032 | -0.051** | -0.045* | -0.029 |
| | [-1.345] | [-2.059] | [-1.764] | [-1.095] |
| *Agg. Pred. Revenue Growth*$\Delta^{t}$ | -0.073*** | -0.048** | -0.023 | -0.039 |
| | [-3.108] | [-2.005] | [-0.900] | [-1.477] |
| *Size* | | -0.084*** | | |
| | | [-4.451] | | |
| *Market to Book* | | -0.050** | | |
| | | [-2.397] | | |
| *Momentum* | | -0.130*** | | |
| | | [-8.219] | | |
| *Beta* | | 0.008 | | |
| | | [0.500] | | |
| *Accruals* | | 0.019 | | -0.003 |
| | | [1.278] | | [-0.187] |
| *Gross Profitability* | | 0.028 | | 0.090*** |
| | | [1.432] | | [4.693] |
| *ATO*$\Delta^{t-1}$ | | 0.013 | | 0.047** |
| | | [0.659] | | [2.145] |
| *PM*$\Delta^{t-1}$ | | -0.03 | | 0.003 |
| | | [-1.145] | | [0.107] |
| *Predicted ATO*$\Delta^{t}$ | | -0.038 | | -0.023 |
| | | [-1.205] | | [-0.727] |
| *Predicted PM*$\Delta^{t}$ | | -0.093** | | -0.075** |
| | | [-2.456] | | [-1.980] |
| *Predicted FSY ROA*$\Delta^{t}$ | | 0.055*** | | 0.024 |
| | | [3.522] | | [1.363] |
| *ROA*$^{t-1}$ | | -0.04 | | -0.110*** |
| | | [-1.079] | | [-2.932] |
| *ROA*$\Delta^{t-1}$ | | 0.059* | | 0.006 |
| | | [1.877] | | [0.183] |
| Intercept | 0.097*** | 0.252*** | 0.037*** | 0.061 |
| | [7.648] | [4.361] | [2.600] | [1.102] |
| Num. Obs. | 20,351 | 20,351 | 20,351 | 20,351 |
| Adj. $R^2$ | 0.005 | 0.014 | 0.002 | 0.004 |
| Clustering of S.E. | Firm | Firm | Firm | Firm |

In this table, we investigate how the stock returns earned by trading on differences in predicted revenue growth of disaggregated versus aggregate models (*Growth Difference*) relate to the asset growth anomaly. All variables are as defined in the main manuscript. We add the annual decile rank (ranging between 0 and 1) of the lagged growth in net operating assets (*NOA*$\Delta^{t-1}$) as well as the aggregate revenue growth forecast (*Agg. Pred. Revenue Growth*$\Delta^{t}$), both of which proxy for the growth anomaly. *, **, *** indicate statistical significance at the 10 percent, 5 percent, and 1 percent levels, respectively (two-tailed).

**TABLE 7 – Online Appendix**

*Growth Forecasts, the Growth Anomaly, and Stock Returns*

| | **Excess Return - Value Weighted** | | **Excess Return - Fama French Five-Factor** | | **Earnings Announcements** | |
|---|---|---|---|---|---|---|
| | Low Institutional | Low Transient | Low Institutional | Low Transient | 5-day -2 \| 0 \| +2 | 3-day -1 \| 0 \| +1 |
| *Growth Difference* | 0.038 | 0.065** | 0.072** | 0.100*** | 0.013** | 0.011** |
| | [1.387] | [2.556] | [2.494] | [3.651] | [1.974] | [1.962] |
| *NOA$\Delta^{t-1}$* | -0.037 | -0.029 | -0.020 | -0.004 | -0.011 | -0.005 |
| | [-1.088] | [-0.815] | [-0.558] | [-0.119] | [-0.965] | [-0.490] |
| *Agg. Pred. Revenue Growth$\Delta^{t}$* | -0.089** | -0.076** | -0.056 | -0.052 | -0.002 | -0.004 |
| | [-2.568] | [-2.097] | [-1.492] | [-1.349] | [-0.189] | [-0.354] |
| *Size* | -0.046* | -0.076*** | | | -0.007 | -0.003 |
| | [-1.884] | [-3.185] | | | [-1.050] | [-0.592] |
| *Market to Book* | -0.128*** | -0.093*** | | | -0.005 | -0.005 |
| | [-4.542] | [-3.182] | | | [-0.776] | [-0.927] |
| *Momentum* | -0.175*** | -0.149*** | | | -0.012** | -0.006 |
| | [-7.375] | [-6.294] | | | [-2.018] | [-1.091] |
| *Beta* | 0.001 | 0.005 | | | 0.004 | 0.001 |
| | [0.034] | [0.224] | | | [0.659] | [0.163] |
| *Accruals* | -0.003 | -0.017 | -0.038 | -0.038 | 0.011* | 0.005 |
| | [-0.117] | [-0.744] | [-1.442] | [-1.510] | [1.738] | [0.944] |
| *Gross Profitability* | 0.052* | 0.043 | 0.116*** | 0.116*** | 0.020*** | 0.021*** |
| | [1.705] | [1.403] | [3.786] | [3.607] | [2.693] | [3.174] |
| *ATO$\Delta^{t-1}$* | 0.024 | 0.041 | 0.047 | 0.075** | 0.020** | 0.010 |
| | [0.860] | [1.414] | [1.523] | [2.254] | [2.430] | [1.307] |
| *PM$\Delta^{t-1}$* | 0.019 | 0.003 | 0.046 | 0.046 | -0.015 | -0.018* |
| | [0.546] | [0.072] | [1.148] | [1.058] | [-1.416] | [-1.805] |
| *Predicted ATO$\Delta^{t}$* | -0.040 | -0.038 | 0.006 | -0.020 | -0.012 | -0.010 |
| | [-0.858] | [-0.829] | [0.124] | [-0.409] | [-1.086] | [-1.084] |
| *Predicted PM$\Delta^{t}$* | -0.028 | -0.075 | -0.016 | -0.078 | -0.031* | -0.023** |
| | [-0.523] | [-1.416] | [-0.286] | [-1.449] | [-1.903] | [-2.060] |
| *Predicted FSY ROA$\Delta^{t}$* | 0.056** | 0.047* | 0.008 | 0.010 | 0.011* | 0.007 |
| | [2.139] | [1.814] | [0.259] | [0.338] | [1.912] | [1.335] |
| *ROA$^{t-1}$* | 0.042 | -0.003 | -0.074 | -0.121** | -0.035** | -0.031*** |
| | [0.781] | [-0.047] | [-1.343] | [-2.157] | [-2.295] | [-2.655] |
| *ROA$\Delta^{t-1}$* | 0.055 | 0.059 | -0.016 | -0.023 | -0.002 | 0.005 |
| | [1.307] | [1.239] | [-0.322] | [-0.423] | [-0.182] | [0.440] |
| Intercept | 0.232*** | 0.239*** | 0.006 | 0.034 | 0.041* | 0.035** |
| | [2.800] | [2.963] | [0.071] | [0.414] | [1.863] | [2.033] |
| Num. Obs. | 10,175 | 10,175 | 10,175 | 10,175 | 20,349 | 20,349 |
| Adj. $R^2$ | 0.020 | 0.020 | 0.006 | 0.007 | 0.003 | 0.002 |
| Clustering of S.E. | Firm | Firm | Firm | Firm | Firm | Firm |

In this table, we investigate how the stock returns earned by trading on differences in predicted revenue growth of disaggregated versus aggregate models (*Growth Difference*) relate to the asset growth anomaly. Specifically, we analyze subsamples of firms with low (transient) institutional ownership as well as returns around the four quarterly earnings announcements in the forecasted year. All variables are as defined in the main manuscript. We add the annual decile rank (ranging between 0 and 1) of the lagged growth in net operating assets (*NOA$\Delta^{t-1}$*) as well as the aggregate revenue growth forecast (*Agg. Pred. Revenue Growth$\Delta^{t}$*), both of which proxy for the growth anomaly. *, **, *** indicate statistical significance at the 10 percent, 5 percent, and 1 percent levels, respectively (two-tailed).

## References


Abadie, A., S. Athey, G. W. Imbens, and J. M. Wooldridge. 2023. When Should You Adjust Standard Errors for Clustering? *The Quarterly Journal of Economics* 138 (1):1-35.

Chan, L. K., J. Karceski, and J. Lakonishok. 2003. The Level and Persistence of Growth Rates. *The Journal of Finance* 58 (2):643-684.

Cooper, M. J., H. Gulen, and M. J. Schill. 2008. Asset Growth and the Cross-Section of Stock Returns. *The Journal of Finance* 63 (4):1609-1651.

Dickinson, V. 2011. Cash Flow Patterns as a Proxy for Firm Life Cycle. *The Accounting Review* 86 (6):1969-1994.

Fairfield, P. M., S. Ramnath, and T. L. Yohn. 2009. Do Industry-Level Analyses Improve Forecasts of Financial Performance? *Journal of Accounting Research* 47 (1):147-178.

Fairfield, P. M., R. J. Sweeney, and T. L. Yohn. 1996. Accounting Classification and the Predictive Content of Earnings. *The Accounting Review* 71 (3):337-355.

Fairfield, P. M., J. S. Whisenant, and T. L. Yohn. 2003. Accrued Earnings and Growth: Implications for Future Profitability and Market Mispricing. *The Accounting Review* 78 (1):353-371.

Gleason, C. A., W. Bruce Johnson, and H. Li 2013. Valuation model use and the price target performance of sell-side equity analysts. *Contemporary Accounting Research* 30 (1):80-115.

Hand, J. R., J.G. Coyne, J.R. Green, and X.F. Zhang 2017. The use of residual income valuation methods by US sell-side equity analysts. *Journal of Financial Reporting* 2 (1): 1-29.

Lakonishok, J., A. Shleifer, and R. W. Vishny. 1994. Contrarian Investment, Extrapolation, and Risk. *The Journal of Finance* 49 (5):1541-1578.

Picconi, M. 2006. The Perils of Pensions: Does Pension Accounting Lead Investors and Analysts Astray? *The Accounting Review* 81 (4):925-955.

Soliman, M. T. 2008. The Use of Dupont Analysis by Market Participants. *The Accounting Review* 83 (3):823-853.

Vuong, Q. H. 1989. Likelihood Ratio Tests for Model Selection and Non-Nested Hypotheses. *Econometrica: Journal of the Econometric Society*:307-333.