The Informativeness of Balance Sheet Disaggregations: Evidence from Forecasting Operating Assets

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ABSTRACT

We investigate the usefulness of balance sheet disaggregations in the context of forecasting operating asset growth and its implications for revenue growth. We find that models that use disaggregate relative to aggregate balance sheet information have greater accuracy, with the most accurate disaggregation scheme separately considering property, plant, and equipment, intangible assets, other non-current operating assets, and current operating assets. When investigating market participants' use of disaggregated balance sheet information, we find that growth predictions from a disaggregated model relative to those from an aggregate model are associated with year-ahead abnormal returns, suggesting that investors underutilize disaggregated balance sheet information. We corroborate this result by showing that returns are concentrated during the days around the earnings announcement, are more pronounced for stocks with low transient institutional ownership, and are predictive of subsequent improvements in actual financial performance. Finally, we find that the abnormal returns are driven mostly by the revenue consequences associated with the predicted growth in operating assets, rather than differences in predicted growth levels per se. Importantly, we find that our results are incremental to the information embedded in income statement disaggregations, even when forecasting income-statement items such as profitability. Overall, our study provides evidence on the informativeness of balance sheet disaggregations and specifically proposes the use of disaggregated models when forecasting growth in operating assets and its implications for future revenues.

Keywords: Balance sheet, Disaggregations, Forecasting, Operating Assets, Revenue Growth, Financial Statement Analysis, Valuation

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1. Introduction

Periodic balance sheet disclosures offer financial statement users important information on the scale and growth of a firm's productive capacity (Chen, Schipper, and Zhang 2022). In turn, the size of the productive capacity (i.e., the asset base) predicts future cash flows and is an important input in the valuation process (Bai, Philippon, and Savov 2016). While aggregate balance sheet information can provide relevant insights, it ignores the systematic differences in the individual assets and liabilities that together comprise the balance sheet total. In this paper, we focus on the usefulness of disaggregated balance sheet information for forecasting operating asset growth and its revenue consequences.

While disaggregations are potentially relevant for both the balance sheet and income statement, prior literature has mainly focused on the usefulness of income statement disaggregations. These studies conclude that disaggregations are informative when heterogeneous items are disaggregated into homogenous subcomponents, while further disaggregating already homogenous items yields no further benefits and can lead to adverse outcomes (e.g. Fairfield, Sweeney, and Yohn 1996; Esplin, Hewitt, Plumlee, and Yohn 2014; Holzman, Marshall, Schroeder, and Yohn 2021; Chen, Miao, and Shevlin 2015). Consistent with Chen et al. (2022), we focus on forecasting operating assets since they are directly related to a firm's operations, make up the vast majority of a firm's asset base, and, unlike financial assets, are a primary driver of firm value and revenues.[1] Hence, in this study, we evaluate the usefulness of balance sheet disaggregations for forecasting operating asset growth and its implication for future revenues.

[1] For example, in our holdout sample, we find that the mean (median) ratio of operating assets to total assets is 84% (90%), indicative of their greater importance. Moreover, firms have wide-ranging reasons for keeping financial assets on their balance sheets, making them inherently difficult to forecast.

To improve forecast accuracy, studies propose disaggregating items with differentially persistent components and/or predictive power in relation to the forecasted metric (Fairfield et al. 1996; Esplin et al. 2014; Holzman et al. 2021). A disaggregate model allows components to deviate in terms of base-level growth rates and growth persistence. In contrast, aggregate models assume that all components of operating assets grow at a similar rate. As such, aggregate models enjoy the benefit that any measurement error in the underlying components can be (partly) offsetting while using each component separately amplifies the measurement error in individual components (Bermingham and D'Agostino 2014). Within the context of the balance sheet, differences in line items' growth persistence arise because standard setters guide firms to group assets with homogenous attributes in terms of the expected time and form of realization, risk exposures, measurement base, and activity type (FASB 2016; IASB 2018).[2] Our disaggregation scheme starts with separating assets based on the expected timing of realization, effectively distinguishing current from non-current operating assets. Subsequently, we disaggregate each of these components into more fine-grained subcomponents.

To evaluate the informativeness of balance sheet disaggregations, we follow the literature on the informativeness of earnings disaggregations (e.g., Fairfield et al. 1996) and investigate the out-of-sample forecast accuracy of disaggregated forecasting models relative to an aggregate benchmark model that relies on total operating assets. Specifically, we follow a two-step forecasting procedure. First, for each operating asset component (e.g., *inventory*), we estimate economy-wide in-sample mean-reverting rolling regressions of asset growth (e.g., $inventory\Delta^{t}$) on lagged asset growth (e.g., $inventory\Delta^{t-1}$) using the previous 10 years of data. Next, we use the

[2] Regulators guide firms to group homogenous items and disaggregate heterogeneous items. See the FASB (2016) conceptual framework item PR37 for a non-exhaustive list of criteria that companies can use when making aggregation decisions. See the IASB's (2018) conceptual framework item 4.48 through 4.55 for a discussion on the presentation and (dis)aggregation of assets and liabilities.

component-specific in-sample coefficients and apply them to the realized growth levels in the last year of the in-sample estimation window to obtain a component-specific out-of-sample growth forecast for the following year. We then combine the component-specific growth forecasts into a forecast for overall operating asset growth. We obtain out-of-sample forecasts of the aggregate benchmark model in a similar fashion from a regression of operating asset growth on lagged operating asset growth.

We find that balance sheet disaggregations are informative in the context of forecasting operating assets. Our in-sample estimations reveal that there is substantial variation in baseline growth levels and growth persistence across the different components of operating assets. We find that forecasts of operating assets obtained from a disaggregated forecasting model are more accurate compared to forecasts obtained from an aggregate benchmark model that does not distinguish between operating asset components, suggesting that the benefits of incorporating differences in component-specific baseline growth and persistence levels more than offset any measurement error induced by using component-specific forecasts.

While there is theoretical guidance in determining when a disaggregated forecast model should lead to more accurate forecasts than those from an aggregate model, determining which set of disaggregations ultimately performs best, remains an empirical question. In this regard, we find that the most accurate disaggregation scheme separately considers *property, plant, and equipment (PPE), intangible assets, other non-current operating assets,* and *current operating assets* (the *non-current-dis* model). This disaggregation scheme highlights the use of disaggregating *non-current assets* in its underlying components and yields forecasting benefits that are pervasive across a wide range of industries and that are stable across years. On average, disaggregating beyond the *non-current-dis* model, specifically disaggregating *current assets* or *intangible assets* into their underlying subcomponents, yields no incremental forecast accuracy improvements, on average. However, motivated by the FASB's deliberations on goodwill measurement, we explore cross-sectional variation in the forecast improvements associated with intangible asset disaggregations and find that disaggregating *intangible assets* in *goodwill* and *other intangible assets* is informative for a subset of firms at risk of an impairment charge. This suggests that measuring goodwill via annual impairment tests, while being a costly measurement method, helps to distinguish it from other intangible assets when the downside risk for investors is greatest.

In theory, operating asset growth signifies an increase in productive capacity that is deployed to realize revenue growth (Bai et al. 2016; Chen et al. 2022). Consistent with such a mechanism, we forecast the revenue growth consequences associated with our operating asset growth forecasts, while allowing the growth in each component of the *non-current-dis* model to differ in terms of its revenue-generating ability. Specifically, to forecast the revenue growth consequences, we use a forecasting approach akin to the one outlined before, and estimate in-sample regressions of operating asset growth on revenue growth. The in-sample estimation reveals substantial variation in the revenue-generating ability of the components of the *non-current-dis* model. For example, a one percent growth in operating assets attributable to PPE corresponds to 0.62 percent growth in revenues, whereas a one percent growth in operating assets that is driven by current operating assets yields a 0.91 percent growth in revenues. To create our final out-of-sample revenue growth forecast, we multiply the predicted operating asset growth driven by each component with its respective predicted revenue growth effect. We derive out-of-sample revenue growth forecasts of the aggregate benchmark model similarly from a regression of the total growth in operating assets on revenue growth.

Next, we investigate investors' use of disaggregated balance sheet information. We find that revenue growth forecasts of the disaggregated *non-current-dis* model are associated with year-ahead abnormal stock returns. These results indicate that investors do not fully incorporate the information embedded in balance sheet disaggregations. Specifically, when we create annual decile ranks of the difference in predicted revenue growth from the disaggregated *non-current-dis* model and the aggregate benchmark model, we find that stocks in the highest decile earn abnormal returns that are 6.0 to 6.2 percent higher relative to stocks in the lowest decile. Moreover, a hedge portfolio that buys (shorts) stocks in the highest (lowest) decile of the annual difference in predicted revenue growth, earns an average annual abnormal hedge return of 9.4 to 7.4 percent. Importantly, we find that these returns are incremental to and distinct from the returns earned by trading on the information embedded in the income statement as the results hold after controlling for (i) income statement information, (ii) model forecasts that predict ΔROA, ΔPM, and ΔATO using both aggregate and disaggregate income statement information (e.g. Fairfield, Ramnath, and Yohn 2009; Fairfield et al. 1996), and (iii) related anomalies (e.g., accruals and ΔATO following Sloan 1996; Soliman 2008; Novy-Marx 2013).

Alongside these return tests, we provide corroborating evidence that is consistent with the abnormal returns likely being driven by investors underutilizing the information embedded in balance sheet disaggregations. First, consistent with prior literature that infers expectation errors from the market's response to (subsequent) earnings announcements, we show that a disproportionate amount of the returns is realized during the days surrounding the earnings announcement (So 2013; Bernard and Thomas 1990; Piotroski and So 2012). As such, these results are consistent with investors updating their estimates of firm value once fundamental information is revealed that contrasts their (erroneous) priors. In a similar vein, we find that the abnormal returns are concentrated among stocks with low institutional ownership, suggesting that sophisticated market participants more efficiently process the growth information embedded in balance sheet disaggregations. We find that these results are driven by transient institutional ownership, while we do not find that abnormal returns vary conditional on the level of dedicated ownership, consistent with prior literature that finds that mainly transient institutions engage in information-based trading and accelerate the pricing of information (Ke and Ramalingegowda 2005; Ke and Petroni 2004; Bushee 1998). Lastly, we provide evidence of a direct link between revenue growth forecasts of the model that uses disaggregated balance sheet information and improvements in reported financial performance. Specifically, when we decile-rank observations on the difference in predicted revenue growth between the disaggregated and the aggregate model, we find that firms in the highest versus the lowest decile experience significant improvements in revenue growth and return on assets (ΔROA). If we decompose the change in return on assets into its underlying components, we find that the improvements in ROA growth are driven by the model's ability to predict improvements in the efficiency with which firms utilize their asset base in generating revenues as reflected by the change in asset turnover (ΔATO), rather than predicting changes in operating costs (ΔPM).

Finally, we decompose the difference in the predicted growth in revenues from the disaggregated versus the aggregate model into two components, one that captures the difference in the operating asset growth forecast, and a second component that captures the difference in predicted revenue growth independent of the difference in operating asset growth predictions. The latter component thus exclusively captures differences in revenue growth predictions that arise from incorporating *which* individual asset components contribute most to overall operating asset growth and *how* the revenue-generating ability of those assets differs from the average revenue-generating ability of operating assets. We then investigate which of these components explains (most of) the abnormal returns that we documented earlier. We find that, on average, the abnormal returns are driven by the component that captures the revenue consequences associated with the predicted growth in operating assets. These results suggest that, on average, market participants mostly process disaggregated balance sheet information in forecasting operating asset growth, but fail to process such information when considering the revenue growth implications associated with the predicted growth in operating assets.

Overall, our results contribute to the financial statement analysis literature by documenting the extent to which balance sheet disaggregations are useful in predicting future growth in operating assets and its implications for future revenues. While prior literature has predominately focused on investigating the usefulness of income statement disaggregations (Fairfield et al. 1996) and the decomposition of earnings into its underlying components such as accruals and cash flows (Sloan 1996), or asset turnover and profit margin (Soliman 2008; Fairfield and Yohn 2001), limited research exists on the usefulness of balance sheet disaggregations for forecasting.[3] Yet, the balance sheet provides important information to investors about the productive capacity of a firm (Chen et al. 2022; Bai et al. 2016) and reflects the past investments made by the company, creating a direct link between the information on the balance sheet and the (future) revenues firms can generate.

In addition, our investigation of future stock returns contributes to the literature on market participants' efficient incorporation of accounting information. For example, prior literature has documented that investors fail to efficiently incorporate differences in the persistence of earnings

[3] Ohlson and Penman (1992) investigate the extent to which disaggregated accounting data, including disaggregated book values, explain stock returns, but they do not find evidence that book value disaggregations are incrementally informative in explaining stock returns. While we investigate a more recent sample that is characterized by new cohorts of firms with largely different asset compositions (Srivastava 2014), our study also differs in that we focus on the usefulness of disaggregations in forecasting *total* operating asset growth, which prior studies have found to be informative of stock returns (Chen et al. 2022), and our consideration of more disaggregated balance sheet information.

components (Soliman 2008; Sloan 1996), or the implications of past growth (Fairfield, Whisenant, and Yohn 2003; Cooper, Gulen, and Schill 2008). We contribute to this literature by documenting that market participants do not fully process the information embedded in balance sheet disaggregations when forecasting growth in operating assets and its implications for future revenues, profitability, and efficiency (e.g., ROA and ATO).

This study further provides important and timely insights to standard setters who, as illustrated by the various ongoing projects on the topic, are concerned about determining appropriate levels of financial statement disaggregation.[4] Our investigation of the extent to which disaggregated balance sheet information assists investors in making forecasts of future operating asset growth touches upon predictive ability and homogenous item creation, which are for standard setters important quality aspects of the financial statements. Despite the importance of balance information to financial statement users, little research exists on the importance of disaggregated balance sheet information. Hence, our results can be used as input into the process of designing financial reporting systems that provide sufficient information to investors, while not putting undue costs on firms and investors by requiring unnecessarily detailed balance sheet information. As a specific example, our study provides insights into the FASB's deliberations on goodwill measurement. Our evidence suggests that measuring goodwill via annual impairment tests, while being a costly measurement method to the reporting firm, does help to distinguish it from other intangible assets when the downside risk for investors is greatest.

While we believe that our investigation of the accuracy of disaggregated forecasting models captures an important mechanism by which disaggregations can be useful to investors, we

[4] Examples of disaggregation-related projects by standard setters are (project title in brackets) the aggregation of debt disclosures (FASB, Simplifying the balance sheet classification of debt), accounting for crypto assets (FASB, Accounting for and disclosure of crypto assets), and expense disaggregation (FASB & IASB, Disaggregation - Income statement expenses).

acknowledge that there are many other settings in which the provision of disaggregated information can be useful (e.g., risk estimation, stewardship). Moreover, while many studies estimate future growth using mean-reverting models, other models could exist in which further disaggregations (relative to the *non-current-dis* model) are informative. Similarly, other cross-sections could exist (other than firms at risk of a goodwill impairment) in which further disaggregations are useful. However, overall our results provide important insights into which disaggregations are informative when using widely employed mean-reverting models.

2. Informativeness of Balance Sheet Disaggregations

The balance sheet provides important information on the assets that firms have in place for running their operations and generating future income. Investors can use balance sheet information in making investment decisions as the balance sheet summarizes the consequences of past investments and, coupled with the other elements of the financial statements, provides information on how efficiently and profitably firms are using their productive capacity (see also Chen et al. 2022; Bai et al. 2016).

While aggregate balance sheet information can provide relevant insights, it ignores the systematic differences in the individual assets and liabilities that together comprise the balance sheet total. As processing information is costly and disaggregated disclosures are prone to measurement error, market participants face a cost-benefit tradeoff on what disaggregations to process, and what to ignore (Chan, Karceski, and Lakonishok 2003; Blankespoor, deHaan, and Marinovic 2020). Although the issue of determining the optimal level of disaggregation applies to all elements of the financial statements, much of the prior literature has focused on investigating the usefulness of income statement disaggregations. Within a forecasting context, Fairfield et al.

(1996) find that disaggregating earnings into operating earnings, non-operating earnings and taxes, special items, and non-recurring items, improves year-ahead forecasts of ROE over an aggregate model. Esplin et al. (2014) expand this literature and focus on the usefulness of disaggregating the operating and financing components of earnings and the infrequent/unusual item disaggregation. Francis, Schipper, and Vincent (2002) directly test the informativeness of earnings disaggregations to investors and find that a greater disaggregation of the income statement is associated with stronger market reactions to earnings announcements, while Berger, Choi, and Tomar (2023) find that income statement disaggregations of cost of sales provide information that is useful to competitors. Chen et al. (2015) develop a measure of disclosure quality that is based on the level of disaggregation of accounting data and find that disaggregation is associated with higher information quality.

Even though disaggregations can be useful in many settings, previous literature also shows that greater income statement disaggregation is not always better. Holzman et al. (2021) document that disaggregating homogenous earnings items (in terms of persistence) has adverse capital market effects because investors could incorrectly assume that such disaggregations have information content. In line with the differences of opinion literature, they find evidence consistent with investors disagreeing on the interpretation of these (redundant) disaggregated signals (Kandel and Pearson 1995; Bloomfield and Fischer 2011). Overall, the literature on income statement disaggregations confirms the view that determining the optimal level of disaggregation is a matter of balance. While the disaggregation of heterogeneous items is informative to investors, a further decomposition of homogenous components can lead to adverse capital market outcomes.

Next to the information in the income statement, periodic balance sheet disclosures also offer financial statement users information that is relevant for forecasting and valuation as the balance sheet enables investors to get insight into the scale and growth of a firm's productive capacity that is used to generate revenues. Bai et al. (2016) document that an increase in operating assets, driven by investments, is a strong predictor of future cash flows, and in turn, stock prices. Likewise, Chen et al. (2022) document that a change in operating assets prompts investors to update their priors on firm value depending on the extent to which balance sheet assets capture a firm's productive capacity and are informative about future operating income.

While, in line with Chen et al. (2022), aggregate balance sheet totals can provide relevant insights, such totals ignore the systematic differences in the individual assets and liabilities that together comprise the balance sheet. Individual assets can differ markedly in their ability to generate future earnings, while their valuation implications can also vary driven by, for example, differences in their inherent riskiness. In line with this argument, the conceptual framework of the FASB states that "*presenting only line items labeled total assets, total liabilities, and total equity would not be very helpful in differentiating the characteristics of an entity's assets and liabilities and the capacity of those assets to generate returns for resource providers* (FASB 2016)." In this regard, both the IASB and the FASB guide firms to separate (group) items with different (similar) characteristics in terms of the expected time and form of realization, risk exposures, measurement base, and activity type (FASB 2016; IASB 2018). Acknowledging these differences, they enact separate accounting treatments for balance sheet line items to enhance each component's informativeness to financial statement users, with for example PPE being measured at depreciable cost, while inventory is measured at the lower of cost or net realizable value.

The systematic differences in the characteristics of balance sheet items are the subject of investigation of various studies. Ohlson and Penman (1992) argue that balance sheet components are different in many aspects, including their perceived measurement error. While these differences should lead to different pricing in the market, they find only limited evidence of differential market reactions to these balance sheet components. Similarly, when digging deeper into the source of disaggregation as a driver of disclosure quality, Chen et al. (2015) find that greater disaggregation of the balance sheet is associated with a lower bid-ask spread and cost of equity. While mainly focusing on the implications of income statement disaggregations, Esplin et al. (2014) focus on differences in activity type and find that models that differentiate between earnings arising from operating assets and earnings arising from financial assets are more accurate relative to an aggregate model that ignores such a distinction. In addition, Christensen and Nikolaev (2013) expect and find that a firm's decision to adopt fair value accounting (versus historical cost) for non-financial assets is driven by market forces. Specifically, while used infrequently overall, firms that use fair value accounting for non-financial assets do so when the information provided in fair values is informative to investors in assessing performance. Finally, other studies investigate how the (opportunistic) use of accounting discretion can lead to substantial measurement error in the values of the affected asset components. For example, Barton and Simko (2002) show that the balance sheet reflects an accumulation of the effects of past accounting choices, including any prior earnings management, and they find that bloated balance sheets distort the relation between sales and assets. They further show that these results vary depending on the type of asset (working capital, fixed assets, and other long-term assets).

In the context of forecasting growth, it is important to understand that superior forecast accuracy is generally achieved by disaggregating asset components that exhibit differences in growth persistence (i.e., mean reversion) or the common growth benchmark they revert to (Vorst and Yohn 2018; Fairfield et al. 1996). Consistent with the literature on income statement disaggregations (Holzman et al. 2021; Fairfield et al. 1996), we evaluate the informativeness of balance sheet disaggregations by investigating whether the forecast accuracy of a model making use of disaggregated balance sheet data leads to more accurate forecasts relative to an aggregate benchmark model. This approach implies that the disaggregation of items with similar growth characteristics is undesirable because, relative to forecasts from an aggregate model, forecasts produced by a disaggregated model will be either equally accurate or inferior.[5] Equal forecast accuracy occurs when additional disaggregations add no differential growth information, but also no additional noise to the model. Inferior forecast accuracy occurs when aggregate models enjoy the benefit that measurement error in the underlying components is partly offset, while using each component separately amplifies the individual errors (Bermingham and D'Agostino 2014).[6]

This study deploys a disaggregation scheme that is designed to capture the informativeness of the most salient balance sheet items that are required to be disaggregated (FASB 2016; IASB 2018). Our first disaggregation separates current from non-current operating assets as standard setters guide firms to disaggregate assets realized or consumed within one year or operating cycle, from their long-lived counterparts (see ASC 210-10-05). This disaggregation is expected to result in greater forecast accuracy as growth persistence, a characteristic vital to our forecasting setting, likely differs substantially across these asset categories, with current assets exhibiting lower persistence levels driven by their greater variability and fast speed of reversal (Baber, Kang, and Li 2011; Dechow and Dichev 2002; Barton and Simko 2002). For example, Baber et al. (2011) find that income-increasing earnings management in one period constrains the ability of firms to beat earnings targets in subsequent periods driven by the fast reversal of current accruals.

[5] We acknowledge that a further disaggregation of balance sheet items beyond homogeneity in growth persistence and baseline growth may be useful for specific groups of financial statement users. We, however, take the perspective of an investor who is concerned with forecasting growth in operating assets.

[6] As explained in Bermingham and D'Agostino (2014), offsetting occurs only if the errors in the subcomponents are negatively correlated, with, for example, one component being overvalued and other components being undervalued. Similarly, we expect that if firms make investment decisions on individual asset components jointly (e.g., determining the total investment in net working capital), such information will be lost in a disaggregated forecast model.

Conversely, growth persistence is likely higher for non-current assets due to the gradual recognition and depreciation of multiyear investment projects (e.g., PP&E) with a longer horizon.

Both current and non-current operating assets can be further disaggregated into their underlying subcomponents. Regarding current assets, firms are required to provide extensive disaggregations (see e.g., ASC 210-10-45-1 for a list of items to be disclosed if applicable to the reporting entity). In this study, we separate the two primary constituents of current assets, accounts receivable and inventory, from the remainder of the current assets category.

Regarding non-current assets, standard setters (see e.g., FASB Statement 142) require firms to distinguish between assets with and without physical substance (e.g., PP&E vs. Intangible Assets). Exceptions aside, non-current operating assets with physical substance are typically measured at depreciated cost, while intangible assets are measured using a variety of techniques. These differences in measurement base also create differences in the growth persistence of non-current operating assets with systematic approaches like depreciation generally resulting in higher growth persistence for assets such as PP&E, relative to fair value techniques such as annual impairment testing, as commonly applied to intangible assets (Barton and Simko 2002; Richardson, Sloan, Soliman, and Tuna 2005; Christensen and Nikolaev 2013). The distinctions between PP&E and intangible assets extend beyond measurement base, as prior research also addresses differences such as the timing of recognition (Wyatt 2005) and the reliability of book values (Barth and Clinch 1998). Finally, informed by FASB's deliberations on simplifying goodwill measurement, we partition intangible assets into goodwill and other intangible assets. Proponents of the change argue that the mandated annual impairment test for goodwill is excessively costly compared to the information benefits if offers and instead, advocate simpler methods such as amortization, essentially bringing the measurement more in line with PP&E. Our approach allows us to test whether, under the current measurement model, the information in goodwill is significantly different from that in other intangible assets.

In summary, firms are required to disaggregate balance sheet items with dissimilar characteristics in terms of the expected time and form of realization, risk exposures, measurement base, and activity type (FASB 2016; IASB 2018). Because of these criteria, systematic differences in terms of growth persistence and baseline growth levels emerge, which we expect to result in disaggregated models being superior in terms of forecast accuracy, relative to an aggregate model. However, prior research has also shown that disaggregation is not always beneficial, such that there is an optimal level of disaggregation in which heterogeneous items are disaggregated and homogenous items are grouped. As it is ex-ante unclear what balance sheet disaggregation is most accurate in forecasting growth in operating assets, we do not make any prediction as to which level of disaggregation yields the highest forecast accuracy.

3. Forecasting Approach and Sample Selection

To investigate the usefulness of balance sheet disaggregations, we test the out-of-sample forecast accuracy of models using disaggregated balance sheet information over an aggregate benchmark model. Our approach follows Fairfield et al. (2009) in our focus on forecasting growth in operating assets. In addition, operating assets closely align with the concept of a firm's productive capacity as put forward by Chen et al. (2022), and are most directly related to the revenue-generating ability of the firm. To explicitly focus on the usefulness of decomposing the individual assets on the balance sheet, we focus on growth in 'unnetted' operating assets (rather than net operating assets, NOA) as reported on the balance sheet. Consistent with Nissim and Penman (2001), operating assets is defined as total assets (Compustat: AT) minus financial assets (Compustat: CHE +

IVAO). Growth is defined as the percentage growth rate from the previous to the current year. For detailed descriptions of the variables used in the in-sample estimation, see Table 1, Panel C.

Next, we systematically disaggregate operating assets into its underlying components. First, operating assets (*OA*) are disaggregated into a current and non-current component. Current operating assets (*OA_CUR*) are equal to current assets (Compustat: ACT) minus cash and cash equivalents (Compustat: CHE). Non-current operating assets (*OA_NCUR*) are equal to operating assets minus current operating assets. Hence, the aggregate benchmark model and our first disaggregated model are as follows:

$$\textit{aggregate benchmark: } OA = OA \tag{1}$$

$$\textit{cur-non-cur: } \quad OA = OA\_CUR + OA\_NCUR \tag{2}$$

We then further disaggregate the model that distinguishes between current and non-current operating assets (i.e., the *cur-non-cur* model). The *non-current-dis* model emphasizes the disaggregation of non-current operating assets and further decomposes non-current operating assets into property, plant, and equipment (*PPE*), intangible assets (*INTANG*), and other non-current operating assets (*OA_NCUR_OTHER*). The *current-dis* model instead disaggregates current operating assets and separately considers inventory (*INV*), accounts receivable (*ACCREC*), and other current operating assets (*OA_CUR_OTHER*), while keeping non-current operating assets at the aggregate level. Finally, the *full-dis* model combines both models and disaggregates both current and non-current operating assets. The models are as follows:

$$\textit{non-current-dis: } \quad OA = PPE + INTANG + OA\_NCUR\_OTHER + OA\_CUR \tag{3}$$

$$\textit{current-dis: } \quad OA = OA\_NCUR + INV + ACCREC + OA\_CUR\_OTHER \tag{4}$$

$$\textit{full-dis: } \quad OA = PPE + INTANG + OA\_NCUR\_OTHER + INV + ACCREC + OA\_CUR\_OTHER \tag{5}$$

To investigate the out-of-sample forecast accuracy of the different models, we follow a two-step forecasting procedure in which we first, for each operating asset component (e.g. *inventory*), estimate economy-wide in-sample mean-reverting (i.e., autoregressive) rolling regressions of asset growth on lagged asset growth using the previous 10 years of data to control for any inter-temporal instabilities (Esplin et al. (2014).[7] For each component, the resulting in-sample coefficient estimates and intercepts express the percentage of prior year growth that persists into the following year (i.e., the mean reversion rate) and baseline growth (i.e., mean growth), respectively. We then use these estimates and apply them to the realized growth levels in the last year of the in-sample estimation window to obtain a component-specific out-of-sample growth forecast. We then combine the component-specific growth forecasts to yield our final operating asset growth forecast. To illustrate, when forecasting (growth in) operating assets for 2017, the model uses data from 2007 to 2016 to derive the component-specific in-sample coefficients that are then applied to data from 2016 to produce an out-of-sample forecast for 2017.

For our in-sample estimation, we include all non-financial firms for the years 1990 until 2019 with available data in Compustat to calculate the growth variables. We require all contemporaneous components of the *full-dis* model to be at least $1 million.[8] Consistent with Fairfield et al. (2009), we exclude firms with absolute growth in operating assets over 100% to reduce the effect of large acquisitions. After applying the above-mentioned screens, the in-sample estimation data consists of 48,941 firm-year observations. Additionally, for each component's in-sample estimation procedure, we exclude observations with absolute growth or lagged growth greater than 100% to stabilize our component-specific growth persistence coefficients. Our

[7] Our results are robust to using alternative lengths for the in-sample estimation window, such as 6, 8 or 12 years.
[8] For "*other current operating assets*" and "*other non-current operating assets*", we require their combined value to be at least $1 million, to avoid unnecessary data loss.

holdout sample starts in 2000 and ends in 2019 and excludes observations with *lagged* absolute growth greater than 100% or observations with *lagged* values below $1 million for at least one of the components in the *full-dis* model.[9] Our final holdout sample contains 21,492 firm-year observations for which we have forecasts of growth in operating assets.

4. Results

4.1. Descriptive Statistics

Table 1 presents the descriptive statistics, a correlation matrix, and variable descriptions of the variables used in the in-sample estimation procedure. Panel A presents the descriptive statistics of the (lagged) growth in *operating assets* and its underlying components. Consistent with prior research, the mean (median) growth in *operating assets*, our metric of interest, is 8% (4.6%) (Vorst and Yohn 2018; Fairfield et al. 2009). Not surprisingly, the growth in *operating assets* and its components is right skewed, indicating that some firms experience extreme growth (Q3 = 15.5%), while growth for the majority of firms is modest. Panel B presents the Pearson (Spearman) correlations above (below) the diagonal. In addition, the utmost right column presents the Pearson correlation of each component with its lagged value. The contemporaneous correlation between growth in *operating assets* and growth in the underlying components ranges between .67 (.70) for *PPE* and .27 (.28) for *other non-current operating assets*, indicating that there is substantial variation in the growth rates of the *operating asset* components. More importantly, there is substantial variation in the correlation of each component's growth with its lagged growth, suggesting that a model that distinguishes between these components' persistence levels can lead to superior forecast accuracy (Esplin et al. 2014).

[9] To avoid a look-ahead bias, in our holdout sample, we only drop firms if their *lagged* values violate our sample screens.

[Table 1 about here]

4.2. Informativeness of Balance Sheet Disaggregations

Table 2, Panel A presents the mean in-sample coefficient estimates for the *aggregate benchmark* model that uses only the *operating asset* total, as well as the models that use disaggregated balance sheet information. Component-specific coefficients are constant across the different models as we apply the components forecasting approach (i.e., we estimate a separate regression for each component instead of a regression of all components on the forecasted metric). Therefore, only 'new' components are reported for the disaggregated models.[10] The reported estimates and adjusted R^2 are the means of the yearly regression models.

[Table 2 about here]

Concerning the growth estimates for the *aggregate benchmark* model, we find that the mean baseline growth (i.e., the intercept) in *operating assets* is equal to 6.2%. Moreover, we find that 20.8% of last year's growth persists into the following year. It should be noted that baseline growth captures a significant portion of the total growth in *operating assets* given that mean growth is equal to 8%. Baseline growth estimates for the components of *operating assets* range between 7.1% for *accounts receivable* and -3.8% for *other intangible assets*. Consistent with our expectations, growth persistence coefficients indicate that prior year growth is sticky for some components (e.g. *PPE;* 25.8%, *intangible assets;* 16.3%) while being of little to no importance in determining next year's growth for other components (e.g., *other current operating assets;* -4%,

[10] Esplin et al. (2014) suggest to use both an aggregate and components forecasting approach because it is ex-ante unclear which one is most accurate unless the data generating process is known. In our situation, in which we use percentage changes in assets components, the components forecasting approach is preferred since with the aggregate forecasting approach, asset-specific coefficient estimates jointly depend on asset persistence levels and the relative importance of the asset category. As such, this method implicitly assumes that each component's share of total assets is constant across all firms in the economy. For example, if growth persistence of PPE is 50% and PPE is 20% of total assets, the aggregate coefficient of lagged PPE growth on operating assets will be 0.1 (50% × 20%). Applying the 0.1 coefficient to a firm that has substantially greater amounts of PPE will yield a forecast that understates actual growth. As such, it is little surprising that the forecast accuracy of the disaggregated model in these cases is low (untabulated).

accounts receivable; 1.4%). Overall, the difference in growth persistence and baseline growth across the components of *operating assets* suggests that forecasting growth using a disaggregated model compared to the *aggregate benchmark* model can potentially improve forecast accuracy.

Table 2, Panel B reports descriptive statistics of the out-of-sample growth in *operating assets* forecast. Out-of-sample forecasts are derived from mathematically combining the coefficients presented in Panel A with the lagged values of the components, using the following formula:

$$\widehat{\Delta Op.Asset\ Forecast}_{i,t} = \frac{\left(\sum_{k=1}^{n}\left(1+\alpha_{k,t-1}+\ \beta_{k,t-1}\times\Delta k_{i,t-1}\right)\times k_{i,t-1}\right)-Op.Assets_{i,t-1}}{Op.Assets_{i,t-1}} \tag{6}$$

We also benchmark our forecasts against a random walk model that assumes that growth is equal to prior year growth. To alleviate concerns that the differences in forecast accuracy between the models are attributable to differences in the sample composition, we only select observations with forecasts available for all models, which yields 21,492 out-of-sample forecasts for the period 2000-2019.

The first three columns of Table 2, Panel B, present descriptive statistics of the model-based forecasts of growth in *operating assets*. The mean (median) forecasted growth in *operating assets* by the *aggregate benchmark* model is 6.63% (6.50%), while forecasted growth by the *non-current-dis* and *full-dis* models is lower at 4.61% (4.41%) and 4.53% (4.38%), respectively. Compared to the mean (median) *operating asset* growth of 8.0% (4.60%), these results suggest that growth forecasts by the *aggregate benchmark* model lean towards the mean, while the growth forecasts of the disaggregated models are closer to the median.

Next, we investigate signed forecast errors to investigate whether forecasts are systematically biased. The signed forecast error expresses the model bias as the percentage point deviation in estimated versus actual growth. For each forecast, we calculate the signed forecast errors as follows:

$$Signed\ Forecast\ Error_{i,t} = \Delta OpAsset\ Forecast_{i,t} - \Delta OpAsset\ Actual_{i,t} \tag{7}$$

We find that forecasting models that use disaggregations of *operating assets* are less biased when considering the median *(aggregate benchmark: 3.06%, current-dis: 2.62%, non-current-dis: 0.87%, full-dis: 0.82%*), but not the mean *(aggregate benchmark: -2.43%, current-dis: -2.79%, non-current-dis: -4.45%, full-dis: -4.53%)* signed forecast error. These results suggest that models using disaggregations of *operating assets* are considerably less biased for median firms, while disaggregated models are less accurate in predicting extreme levels of operating asset growth.

Finally, we consider the absolute forecast error (AFE) as a comprehensive measure of forecasting performance, which we calculate as follows:

$$Absolute\ Forecast\ Error_{i,t} = \left|Signed\ Forecast\ Error_{i,t}\right| \tag{8}$$

The mean (median) AFE of the *aggregate benchmark* model is 16.27% (8.37%). The mean (median) AFE of the disaggregated models is lower compared to the *aggregate benchmark* model, with the AFE of the *current-dis* model being equal to 16.27% (8.28%), the *non-current-dis* model reporting an AFE of 15.95% (7.70%), and the *full-dis* model's AFE being equal to 15.99% (7.73%). Overall, these results provide preliminary support for the proposition that disaggregating *operating assets* is informative in forecasting *operating asset* growth, with the disaggregation of *non-current operating assets* by the *non-current-dis* model yielding the greatest improvements.

Next, Table 3 presents our main results on the informativeness of balance sheet disaggregations for forecasting growth in *operating assets*. We evaluate the relative accuracy of disaggregated models by calculating, for each firm-year observation, a pairwise forecast improvement. For a hypothetical model 1 versus model 2 comparison, we calculate forecast improvements as follows (with positive values indicating that model 1 has greater accuracy):

$$Model1\ vs\ model2_{i,t} = \ AFE\ Model\ 2_{i,t} - \ AFE\ Model\ 1_{i,t} \tag{9}$$

We then calculate the annual mean (median) forecast improvement and test, based on a two-sided t-test (Wilcoxon signed-rank test), whether the grand mean (median) improvement across the 20 years in the sample period is significantly different from zero.

[Table 3 about here]

We first analyze each model's performance compared to the *aggregate benchmark model*. We start by documenting that a forecast model that distinguishes between *current* and *non-current operating assets* (*cur-non-cur*) is more accurate relative to the *aggregate benchmark* model. The median forecast improvement, relative to the AFE of the *aggregate benchmark* model, is 1.08%, while the mean forecast improvement is not significant.[11] Higher order balance sheet disaggregations yield greater forecast improvements. The mean (median) percentage forecast improvement for the model that disaggregates *non-current operating assets* (i.e., the *non-current-dis* model) is 2.03% (8.48%), while the model that disaggregates both current and non-current assets (i.e., the *full-dis* model) yields forecast improvements of 1.91% (8.60%). A model that disaggregates only *current assets* (*current-dis*) yields no significant forecast improvements relative to the *aggregate benchmark* model.

Next, we investigate what disaggregation is most accurate for forecasting *operating asset* growth. The model that disaggregates *non-current assets* (the *non-current-dis* model) significantly outperforms the other models, indicating the usefulness of disaggregating *operating assets* into *property, plant, and equipment (PPE), intangible assets, other non-current operating assets,* and *current operating assets*. Further disaggregating *current assets* into *accounts receivable*, *inventory,* and *other current operating assets,* as done in the *full-dis* model, does not improve

[11] We calculate the percentage forecast improvement as: $\frac{Forecast\ improvement}{AFE\ benchmark\ model}$. For example, in the case of the median improvement of the *cur-non-cur* model, the calculation is: 0.0009/0.0837, which yields a relative improvement of 1.08%, expressed in percentage terms of the absolute forecast error of the aggregate model.

forecast accuracy over the *non-current-dis* model. In contrast, forecasts by the *full-dis* model are significantly less accurate relative to forecasts of the *non-current-dis* model. To alleviate concerns that our results are driven by a small number of observations, Table 3 also reports the number of years and industries in which the forecast improvements are significantly positive or negative. In addition, Table 3, Panel B and C report the forecast improvements by Fama-French sector and year. Overall, these results highlight that the *non-current-dis* model is the most accurate model for forecasting growth in operating assets, with forecast improvements that are pervasive across industries and stable across years.

We continue by investigating if a further disaggregation of non-current operating assets, specifically, decomposing *intangible assets* into *goodwill* (*GOODWL*) and *other intangible assets* (*INTANG_OTHER*) yields forecast improvements over the *non-current-dis* model. Given the inherent differences in how these assets are generated and (subsequently) measured, the subcomponents of *intangible assets* can exhibit differences in growth persistence that can lead to greater forecast accuracy for a model that incorporates these differences. To test whether decomposing *intangible assets* increases forecast accuracy, the following disaggregation is used:

$$\textit{non-cur-intan: } OA = PPE + GOODWL + INTANG\_OTHER + OA\_NCUR\_OTHER + OA\_CUR \qquad (10)$$

The last rows of Table 3, Panel A, report the forecast improvements of the *non-cur-intan* model over the other models, including the thus far most accurate *non-current-dis* model. Due to the limited availability of data on goodwill, the sample decreases to 13,187 firm-year observations. On average, we find that decomposing *intangible assets* into *goodwill* and *other intangible assets* yields no significant forecast improvements over the *non-current-dis* model.

However, motivated by the FASB's deliberations on the optimal measurement model for goodwill and the merits of annual impairment testing, we investigate whether separating goodwill from other intangible assets is informative for a subset of firms at risk of an impairment charge. Specifically, we report the forecast improvement of the *non-cur-intan* model relative to the *non-current-dis* model for deciles of (lagged) idiosyncratic risk (Goyal and Santa-Clara 2003) and restructuring cost (Riedl 2004), as both are indicators of firms being at risk of an impairment charge. The results reported in Table 4, Panel A, indicate that separating goodwill from other intangible assets, while not improving forecast accuracy in our pooled tests, significantly improves forecast accuracy for firms most at risk of an impairment charge. Similarly, the results in Panel B in which we split forecast improvements by firm life cycle stage indicate that disaggregating intangible assets significantly improves forecast accuracy for firms in the introduction, shakeout, and decline stages (see Dickinson 2011). These firms are likely different from the average firm in our sample as they have higher betas and rely heavily on intangible investments, which likely explains the informativeness of the intangible asset disaggregation for these firms. Overall, our evidence suggests that measuring goodwill via annual impairment tests, while being a costly measurement method to the reporting firm, does help to distinguish it from other intangible assets when the downside risk for investors is greatest.

[Table 4 about here]

Collectively, our first set of analyses highlights the usefulness of balance sheet disaggregations when forecasting growth in *operating assets*. First, we show that there is substantial variation in growth persistence and baseline growth in the underlying components of *operating assets*. In line with the observed variation, our results indicate that models using disaggregations of *operating assets* are more accurate than the *aggregate benchmark* model when forecasting growth in *operating assets*, especially at the median. The most accurate disaggregation scheme for forecasting operating asset growth separately considers *PPE*, *intangible assets*, *other non-current operating assets*, and *current operating assets*, yielding forecast improvements that are pervasive across industries and stable over years.

4.3. Balance Sheet Disaggregations and Future Stock Returns

Thus far, our results indicate the informativeness of balance sheet disaggregations for forecasting operating asset growth. In this section, we investigate whether investor expectations fully reflect the information embedded in balance sheet disaggregations. In theory, growth in operating assets indicates an increase in the productive capacity that is deployed to realize revenue growth (Bai et al. 2016; Chen et al. 2022). Hence, we focus on the revenue growth consequences associated with our growth predictions to investigate the extent to which investors efficiently incorporate disaggregated balance sheet information.

To forecast the revenue growth consequences associated with our growth predictions, we use a forecasting approach akin to the two-step procedure outlined in section 3. First, we estimate in-sample regressions of revenue growth on operating asset growth, by running economy-wide mean-reverting rolling-regressions using the previous 10 years of data, using data on aggregate and disaggregated operating asset growth, respectively:

$$Revenue\Delta_{i,t}, = \alpha + \beta 1 \times OpAsset\Delta_{i,t} \quad (11)$$

$$Revenue\Delta_{i,t} = \alpha + \beta_1 \times PPE\Delta_{i,t} + \beta_2 \times Intang\Delta_{i,t} + \beta_3 \times OA\_Ncur\_Other\Delta_{i,t} + \beta_3 \times OA\_Cur\Delta_{i,t} \quad (12)$$

While in Section 3, we estimate a separate regression for each component of operating assets, such an approach is not preferred here because we cannot directly observe the revenues arising from individual asset components. In contrast, the pooled approach as described in equation (12) simultaneously regresses growth in each of the components of operating assets in the *non-current-dis* model on revenue growth, which allows us to estimate the revenue contributions of each asset component, incremental to the revenue contributions of other asset components.[12] To facilitate weighting in this regression specification, we redefine the growth in the components of operating assets as each component's contribution towards total operating asset growth: $\frac{k_{i,t} - k_{i,t-1}}{Op.Assets_{i,t-1}}$, where *i* indexes firms, *t* indicates years, and *k* refers to the components of operating assets. As a result, the sum of the contributions of all components to operating asset growth is equal to total operating asset growth, which we conjecture is associated with revenue growth. Second, we estimate the out-of-sample revenue growth that is associated with our asset growth predictions. Specifically, we multiply the in-sample coefficients from the aggregate and disaggregate model as estimated in equation (11) and (12), with the asset growth predicted by the a*ggregate benchmark model* and the component-specific asset growth predictions of the *non-current-dis* model, respectively.

[Table 5 about here]

Table 5 presents the mean in-sample coefficients. The in-sample estimation procedure reveals substantial variation in the revenue-generating ability of the components of the *non-current-dis* model, suggesting that considering differences in the revenue-generating abilities of components of operating assets is informative. For example, while one percent growth in operating assets attributable to PPE corresponds to 0.617 percent growth in revenues, one percent growth driven by current operating assets yields 0.905 percent growth in revenues.[13]

[12] Moreover, estimating a single regression facilitates the interpretation of the intercept, which in this specification captures the growth in revenues when growth in *each* operating asset component is zero. In contrast, if we were to estimate separate regressions for each asset component, the intercept of each of these regressions would capture the growth in revenues when the growth in the *individual* asset component is zero. The intercepts of these separate regressions, however, cannot easily be aggregated into a single revenue growth forecast.

[13] Similarly, we find that the R-squared of the disaggregated model as described in equation (12) is significantly higher than the R-squared of the aggregate model as described in equation (11).

We then investigate whether differences in the forecasted revenue growth between the *aggregate benchmark* model and the most accurate balance sheet disaggregation (i.e., the *non-current-dis* model) are predictive of year-ahead abnormal stock returns.[14] As such, our tests directly investigate whether the difference in (revenue) forecasts attributable to the use of disaggregated data, relative to aggregate data, is useful in generating returns. Moreover, consistent with prior studies providing evidence of investors' tendency to naively fixate on aggregate figures (Fairfield et al. 2003; Soliman 2008; Richardson, Sloan, Soliman, and Tuna 2005), our tests thus assume that investors employ a model that resembles the aggregate model. For example, Fairfield et al. (2003) document that investors fail to distinguish (i.e., thus equally overvalue) growth in operating assets driven by investments in long-term operating assets and accruals. Specifically, we estimate the following regression model:

$$Excess_{i,t} = \alpha_0 + \beta_1 Growth\ Difference_{i,t} + \beta_2 Market\ to\ Book_{i,t} + \beta_3 Size_{i,t} + \beta_4 Beta_{i,t} + \beta_5 Momentum_{i,t} + Income\ Statement\ Controls_{i,t} + \varepsilon_{i,t} \quad (13)$$

Growth Difference is the annual decile rank (ranging between 0 and 1) of the difference in the predicted year-ahead revenue growth of the *aggregate benchmark* model and the *non-current-dis* model, where positive values capture firm-years in which the disaggregate model predicts higher growth compared to the aggregate model. *Growth Difference* is calculated as:

$$\left(\alpha_{disagg,t-1} + \sum_{k=1}^{n}\left(\beta_{k,t-1} \times \widehat{\Delta k}_{i,t-1}\right)\right) - \left(\alpha_{agg,t-1} + \beta_{t-1} \times \Delta Op\widehat{Asset}_{\iota,t-1}\right) \quad (14)$$

where *i* indexes firms, *t* indicates years, and *k* refers to the components of operating assets. The hat ($\widehat{\ }$) indicates that we use *predicted* asset growth. Hence, $\widehat{\Delta \mathrm{k}}$ captures the predicted growth in

[14] While in the previous section we require data to be available on actual realized operating asset growth, in this section, to avoid a look-ahead bias, we do not impose such a sample requirement. Hence, even firms that delist prior to the end of the forecasted year can be included in the return test (i.e., we only require a valid forecast to be available).

operating asset category k using the *non-current-dis* model, while $\Delta \widehat{OpAsset}$ captures the predicted growth in operating assets using the *aggregate benchmark* model. *Excess* is the buy-and-hold return over the 12-month period starting in the fourth month of the year being forecasted, adjusted for movements in the CRSP value-weighted market portfolio (*Excess Return Value Weighted*) or the Fama-French five-factor adjusted return (*Excess Return Fama-French Five-Factor*). To mitigate concerns that our results are driven by differences in risk characteristics, we control for the beginning of the forecasted year market-to-book ratio (*Market to Book*), market capitalization (*Size*), stock beta (*Beta*), and momentum (*Momentum*). To ensure our results are incremental to the information embedded in income statement disaggregations, we control for the predicted change in return on operating assets estimated using the most accurate income statement disaggregation scheme (the OPINC model) from Fairfield et al. (1996), which we label *Predicted FSY ROAΔ*. We also ensure our results are incremental to other trading strategies based on well-known income statement signals as we control for prior to forecasted year accruals (*Accruals*) (Sloan 1996), changes in operating asset turnover (*ATOΔ*) (Soliman 2008), changes in operating profit margin (*PMΔ*), the level of gross-profitability (*Gross Profitability*) (Novy-Marx 2013), and predicted changes in operating asset turnover (*Predicted ATOΔ*), and operating profit margin (*Predicted PMΔ*). We estimate predicted changes using an economy-wide mean-reverting model following the method described in section 3. In line with our main variable of interest, all control variables are converted into annual decile ranks that range between zero and one.

[Table 6 about here]

The results reported in Table 6, Panel A, show that *Growth Difference* is positively and significantly associated with year-ahead abnormal returns, indicating that investors do not fully incorporate the growth information embedded in balance sheet disaggregations. In terms of economic significance, the results indicate that stocks in the highest decile of *Growth Difference* earn 6.0 to 6.2 percent higher returns relative to stocks in the lowest decile. Importantly, while we find that *Predicted FSY ROAΔ* is positively associated with future stock returns, illustrating the usefulness of income statement disaggregations, *Growth Difference* remains positive and significant, suggesting that the information embedded in balance sheet disaggregations is incremental to and distinct from the information in income statement disaggregations.[15]

Table 6, Panel B reports the results of hedge-return tests in which we construct portfolios that go long (short) in stocks for which the annually sorted difference in predicted revenue growth between the disaggregated and aggregated model is highest (lowest). Column (1) reports the results of tests in which we go long (short) in firms in the top (bottom) 10% of *Growth Difference* and shows that this strategy earns an average annual hedge return of 7.4 to 9.4 percent. Column (2) and (3) show that the trading strategy's returns persist, but become gradually smaller when the long and short portfolios include the top and bottom 20% or 30% of firms, respectively.

4.4. Investors' Underutilization of Disaggregated Balance Sheet Information

Thus far, we report evidence that (revenue) growth predictions based on disaggregated balance sheet data are predictive of future returns. In this section, we provide corroborating evidence that these returns are likely driven by investors underutilizing the information embedded in balance sheet disaggregations. Specifically, we provide evidence that these returns are (i) concentrated around earnings announcements, (ii) stronger for firms with lower levels of (transient) institutional ownership, and (iii) in line with actual improvements in revenue growth.

[15] To mitigate concerns that our results are driven by a few extreme return observations, in untabulated tests, we find that the results are robust to annually truncating returns at 0.5 percent and 99.5 percent (Kraft, Leone, and Wasley 2006).

Prior literature infers expectation errors by investigating the market's response to earnings announcements (So 2013; Bernard and Thomas 1990; Piotroski and So 2012). If investors' expectations do not fully reflect the implications of disaggregated balance sheet information for future (revenue) growth, we would expect prices to adjust once investors receive information that contradicts their biased expectations. Earnings announcements, which are typically accompanied by conference calls, 8-K filings, guidance, and updated analyst reports, reveal substantial amounts of new information on firm performance and (revenue) growth. Hence, we would expect a significant portion of the returns to be earned around earnings announcements. To investigate this, we repeat our stock return tests and replace the year-ahead buy-and-hold return with the compounded return that is earned during the three (or five) days surrounding the four quarterly earnings announcements during this period.

[Table 7 about here]

The results reported in Table 7 indicate that a disproportionate amount of the returns is realized around the four earnings announcements. We find that, relative to stocks in the lowest decile, stocks in the highest decile of *Growth Difference* earn 1.5 percent (1.9 percent) higher returns during the three-day (five-day) window around the earnings announcement. Using the 6.2 percent annual return from Table 6 as base, this indicates that 24 to 31 percent of the annual returns are earned during the four earnings announcements. As these windows constitute only 4.8 to 7.9 percent of the trading days in a given year (e.g., 4*3 = 12 or 4*5 = 20 trading days over 252 trading days in a year), this indicates that, relative to non-event days, earnings announcements are 5.1 to 3.9 times more important in explaining the annual return attributed to disaggregated growth predictions.

Next, we investigate whether the abnormal returns are concentrated among stocks owned by less-sophisticated investors. Prior research finds that institutional investors engage in informed trading (Bushee 1998; Collins, Gong, and Hribar 2003; Huang and Zhang 2012), while within the group of institutional investors, especially transient owners, those trading to maximize short-term gains, accelerate the speed with which information is impounded into stock prices (Ke and Ramalingegowda 2005). For example, Ke and Petroni (2004) report that within the group of institutional owners, only transient owners can predict a break in a firm's consecutive earnings increases, allowing them to evade the negative stock price response to such a break. If sophisticated investors are more likely to be aware of the usefulness of disaggregated balance sheet information, incorporate it into their decision-making, and facilitate its pricing, we expect that abnormal stock returns should be concentrated among stocks with low (transient) institutional ownership.

[Table 8 about here]

The results reported in Table 8 are in line with our expectations and show that for stocks with below-median levels of institutional ownership, abnormal returns range between 8.1 and 9.8 percent, while for stocks with above-median levels of institutional ownership, we do not find that growth forecasts based on disaggregated balance sheet information are associated with year-ahead returns. Column (2) and (3) show the results of tests in which we partition the sample based on transient and dedicated institutional ownership, respectively. We find that abnormal returns increase to 10.3-12.3 percent for stocks with low levels of transient institutional ownership, while we find no evidence of abnormal returns for stocks with high transient institutional ownership. In contrast, we find limited evidence that the level of dedicated institutional ownership affects the relation between disaggregated balance sheet information and future stock returns, in line with dedicated owners being less inclined to engage in information-based trading (Bushee 1998).

Overall, the results suggest that investor expectations do not fully reflect the (revenue) growth information embedded in balance sheet disaggregations, especially for stocks with low (transient) institutional ownership.

Finally, we provide evidence that the revenue growth predictions of a disaggregated balance sheet model are associated with actual improvements in reported financial performance. Specifically, we investigate how financial performance metrics change during the return accumulation period, i.e., the year being forecasted, for different deciles of *Growth Difference*.

[Table 9 about here]

The results are reported in Table 9. We find that observations in the top decile of *Growth Difference* show significantly greater improvements in return on operating assets (*ROAΔ*) and revenue growth (*RevenueΔ*), relative to observations in the bottom decile. We decompose *ROAΔ* into its underlying components, *ATOΔ* and *PMΔ*, to investigate whether growth forecasts are associated with changes in the revenue-generating ability of operating assets or changes in operating costs, respectively. Consistent with our return tests and with *Growth Difference* capturing changes in firms' productive capacity and revenue-generating ability, we find that the increase in *ROA* is driven by an increase in *ATO,* suggesting that firms for which the disaggregated model predicts higher revenue growth become more efficient in generating revenues with their operating assets. In contrast, we do not find evidence that these firms improve profit margins. Overall, the results reported in Table 9 show that firms for which a disaggregated forecast model predicts higher revenue growth, experience subsequent improvements in reported financial performance.

4.5. Decomposing the Returns to Disaggregated Balance Sheet Information

Differences in predicted revenue growth from an aggregate model and a disaggregated model can arise from two sources. First, as shown in Section 4.2, we find that operating asset growth predictions from a disaggregate model are different from and more accurate than forecasts from an aggregate model. Moreover, as done in Section 4.3, disaggregated predictions also allow us to predict changes in revenues using component-specific revenue growth implications. Hence, we decompose the difference in the predicted growth in revenues from the disaggregated versus the aggregate model into two components, one that captures the difference in the operating asset growth forecast, and a second component that captures the difference in predicted revenue growth independent of the difference in operating asset growth predictions. We then investigate which of these components is a more important driver of the abnormal returns to disaggregated balance sheet information that we have documented earlier.

To isolate the asset growth effect (*Difference Asset Growth),* we capture the difference between a revenue growth forecast from a model that uses aggregate balance sheet information for both the asset growth forecast and its associated revenue consequences, and a model that uses disaggregated data for the asset growth forecast, but uses the aggregate revenue-generating ability to measure the associated revenue consequences:

$$Difference\ Asset\ Growth_{i,t} = \left(\alpha_{agg,t-1} + \sum_{k=1}^{n}\left(\beta_{t-1} \times \widehat{\Delta k}_{i,t-1}\right)\right) - \left(\alpha_{agg,t-1} + \beta_{t-1} \times \Delta Op\widehat{Asset}_{i,t-1}\right) \quad (15)$$

To isolate the revenue growth effect (*Difference Revenue Consequence),* we calculate the difference between a revenue growth forecast of a model that uses disaggregated data for the asset growth forecast, but aggregate information for the revenue consequences, and a model that uses disaggregated balance sheet information for both components. *Difference Revenue Consequence* thus exclusively captures differences in revenue growth predictions that arise from incorporating *which* individual asset components contribute most to overall operating asset growth and *how* the revenue-generating ability of those assets differs from the average revenue-generating ability of operating assets.

$$Difference\ Revenue\ Growth_{i,t} = \left(\alpha_{disagg,t-1} + \sum_{k=1}^{n}(\beta_{k,t-1} \times \widehat{\Delta k}_{i,t-1})\right) - \left(\alpha_{agg,t-1} + \sum_{k=1}^{n}(\beta_{t-1} \times \widehat{\Delta k}_{i,t-1})\right) \tag{16}$$

where *i* indexes firms, *t* indicates years, and *k* captures the components of operating assets. The alphas and betas are derived from the in-sample estimation of the revenue-generating ability of the components of operating assets as estimated in equation (12). The hat ($\widehat{\ }$) indicates that we use asset growth *predictions*, such that $\widehat{\Delta k}$ captures the predicted growth in operating asset category *k* using the *non-current-dis* model and $\Delta\widehat{OpAsset}$ captures the predicted growth in operating assets from the aggregate benchmark model.

[Table 10 about here]

The results are reported in Table 10, in which we again use the decile-ranked variables (transformed such that they range between 0 and 1) to investigate the future return consequences. We find that, on average, the returns are driven by the component that specifically captures the difference in the revenue consequences of the operating asset components. Overall, these results thus suggest that, while market participants seem to mostly process disaggregated balance information in forecasting operating asset growth, they fail to incorporate such information when considering the revenue growth consequences associated with the predicted growth in operating assets.

4.6. Additional Analyses

4.6.1. Asymmetric Growth

Various studies show evidence of asymmetric behavior of accounting numbers based on whether growth is positive or negative (Hayn 1995; Banker and Chen 2006). Hence, we investigate forecast improvements of models in which we allow the mean-reversion coefficient to vary depending on whether each component's prior year growth was positive or negative. In untabulated tests, we do not find evidence that forecast improvements of disaggregated models, relative to an aggregate model, are different when we use these alternative estimations. Moreover, the accuracy of the aggregate model itself is not impacted by this research design choice, illustrative of the limited importance of incorporating asymmetric growth in the forecasting models.

4.6.2. Forecasting Net Operating Assets

The main forecasted metric, growth in *operating assets*, offers a good fit to our research setting since it closely aligns with the concept of a firm's productive capacity (Chen et al. 2022) and facilitates a systematic disaggregation into its underlying sub-components. Nevertheless, we test the robustness of our findings to using *net operating assets* (NOA), as previous financial statement analysis literature often relies on NOA. We calculate NOA as *operating assets* minus *operating liabilities* following Nissim and Penman (2001). To test whether our results are robust to forecasting growth in NOA, we extend the models as described in Section 3 with two additional components that we forecast, c*urrent operating liabilities* and *non-current operating liabilities*, which we subtract from our forecast of *operating assets* to yield our forecast of NOA (Soliman

2008; Nissim and Penman 2001).[16] Untabulated results indicate that, while mean forecast improvements of the *non-current-dis* model relative to the *aggregate benchmark* model are no longer statistically significant, median forecast improvements remain significantly positive.

5. Conclusion

Periodic balance sheet disclosures offer financial statement users important information on the scale and growth of a firm's productive capacity, i.e., a firm's operating asset base (Chen et al. 2022), thereby providing investors with information that is useful in the prediction of future cash flows and firm valuation. While overall operating asset levels can be informative to investors, knowing the composition of a firm's asset base can help investors make more accurate forecasts of future (asset) growth and cash flows. Hence, in this paper, we investigate the usefulness of balance sheet decompositions in the context of forecasting operating asset growth.

We find that models that use disaggregate relative to aggregate balance sheet information have greater accuracy, with the most accurate disaggregation scheme separately considering property, plant, and equipment, intangible assets, other non-current operating assets, and current operating assets. The forecasting benefits of this model are pervasive across a wide range of industries and stable over years. Overall, these results highlight the importance of balance sheet disaggregations in forecasting growth in operating assets.

In theory, growth in operating assets indicates an increase in productive capacity that is deployed to realize revenue growth (Bai et al. 2016; Chen et al. 2022). Consistent with such a mechanism, we forecast the revenue growth consequences of our operating asset growth forecasts,

[16] Non-current operating liabilities equal the sum of Liabilities Other (Compustat: LO) and Deferred Taxes and Investment Tax Credit (Compustat: TXDITC). Current operating liabilities is defined as Current Liabilities (Compustat: LCT) minus Debt in Current Liabilities (Compustat: DLC). This approach yields the same operating liability total as Soliman (2008), however, it uses the debit side instead of the credit side of balance sheet items.

while allowing the growth in each component of the *non-current-dis* model to differ in terms of its revenue-generating ability. We then use this to investigate market participants' use of disaggregated balance sheet information and find that (revenue) growth predictions from a disaggregated model are associated with year-ahead abnormal returns that are incremental to the returns earned by trading on disaggregated income statement information, especially for stocks with low transient institutional ownership. In line with these returns being driven by an underutilization of disaggregated balance sheet information on part of investors, we find that (i) a disproportionate amount of the returns are earned during the days surrounding the earnings announcement, (ii) returns are concentrated among stocks with low (transient) institutional ownership, and (iii) the difference in predicted growth of the *non-current-dis* model and the *aggregate benchmark* model is associated with subsequent improvements in reported financial performance as captured by changes in return on assets, asset turnover, and revenue growth.

Next, if we decompose the revenue growth prediction into two distinct components, we find that investors mostly incorporate disaggregated balance sheet information in the prediction of levels of operating asset growth, but fail to incorporate the distinct component-specific implications of growth for future revenues.

Overall, our study contributes to the financial statement analysis literature by documenting the relevance of disaggregated balance sheet information in forecasting operating asset growth. This is important as the assets reported on the balance sheet provide important information to investors about the productive capacity of a firm (Chen et al. 2022) and reflect the past investments made by the company, creating a direct link between the balance sheet and the (future) profits that firms can generate. As book values form the anchor of valuation in the residual income valuation model and, coupled with assumptions about efficiency (e.g., asset turnovers), also impact forecasts of future profitability and residual income, our results also have important implications for the literature on firm valuation (Feltham and Ohlson 1995). Indeed, we find that predictions of operating asset growth are predictive of improvements in financial performance, in particular changes in revenues and asset turnover. Relatedly, our results on stock returns provide insight into whether market participants incorporate the growth information embedded in predictions from a disaggregated balance sheet forecasting model.

Finally, our results could also be informative to standard setters. Although we exclusively focus on the usefulness of disaggregated balance sheet information in making forecasts of future operating asset growth, these results touch upon predictive ability and homogenous item creation, which are for standard setters important quality aspects of the financial statements. Hence, our results can be used as input into the process of designing financial reporting systems that provide sufficient information to investors, while not putting undue costs on firms and investors by requiring unnecessarily detailed balance sheet information.

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TABLE 1

Descriptive Statistics & Correlation Matrix

Panel A: Descriptive statistics of variables used in the in-sample coefficient estimation

Variables	**Mean**	**Std. Dev.**	**Min**	**Q1**	**Median**	**Q3**	**Max**	**N**
Operating AssetsΔ^{t}	0.080	0.218	-0.952	-0.032	0.046	0.155	1.000	44,065
Operating AssetsΔ^{t-1}	0.090	0.222	-0.944	-0.028	0.051	0.167	1.000	44,065
Non-Current Operating AssetsΔ^{t}	0.071	0.231	-0.977	-0.041	0.033	0.148	1.000	41,391
Non-Current Operating AssetsΔ^{t-1}	0.082	0.235	-0.963	-0.036	0.037	0.159	1.000	41,391
Current Operating AssetsΔ^{t}	0.073	0.225	-0.909	-0.053	0.055	0.178	1.000	43,719
Current Operating AssetsΔ^{t-1}	0.091	0.242	-0.968	-0.045	0.064	0.198	1.000	43,719
PPEΔ^{t}	0.063	0.216	-0.989	-0.046	0.035	0.143	1.000	44,215
PPEΔ^{t-1}	0.078	0.225	-0.986	-0.039	0.041	0.158	1.000	44,215
Intangible AssetsΔ^{t}	0.005	0.262	-0.999	-0.073	-0.012	0.064	1.000	35,199
Intangible AssetsΔ^{t-1}	0.020	0.263	-0.997	-0.067	-0.009	0.078	1.000	35,199
Other Non-Current Operating AssetsΔ^{t}	0.020	0.350	-1.000	-0.163	0.013	0.201	1.000	33,335
Other Non-Current Operating AssetsΔ^{t-1}	0.029	0.353	-1.000	-0.158	0.019	0.212	1.000	33,335
InventoryΔ^{t}	0.064	0.251	-0.993	-0.072	0.048	0.183	1.000	43,377
Inventory Δ^{t-1}	0.082	0.261	-0.993	-0.064	0.058	0.202	1.000	43,377
Accounts ReceivableΔ^{t}	0.070	0.255	-0.992	-0.071	0.055	0.195	1.000	43,503
Accounts Receivable Δ^{t-1}	0.087	0.267	-0.992	-0.064	0.065	0.215	1.000	43,503
Other Current Operating AssetsΔ^{t}	0.060	0.343	-1.000	-0.151	0.045	0.259	1.000	36,811
Other Current Operating Assets Δ^{t-1}	0.061	0.357	-1.000	-0.155	0.048	0.270	1.000	36,811
GoodwillΔ^{t}	-0.002	0.246	-1.000	-0.022	0.000	0.022	0.999	37,310
Goodwill Δ^{t-1}	0.007	0.251	-1.000	-0.024	0.000	0.031	1.000	37,310
Other IntangibleΔ^{t}	-0.045	0.271	-1.000	-0.126	0.000	0.000	1.000	30,410
Other Intangible Δ^{t-1}	-0.034	0.275	-1.000	-0.119	0.000	0.000	1.000	30,410

Panel B: Correlation matrix (variables used in the in-sample coefficient estimation)

		1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**Δt-1**
1	Operating AssetsΔ_t		.89	.74	.67	.60	.27	.56	.57	.28	.55	.38	.30
2	Non-Current Operating AssetsΔ_t	.85		.44	.72	.67	.34	.36	.34	.18	.61	.42	.30
3	Current Operating AssetsΔ_t	.75	.42		.39	.32	.11	.67	.77	.41	.30	.20	.11
4	PPEΔ_t	.70	.77	.41		.31	.13	.34	.30	.15	.28	.21	.29
5	Intangible AssetsΔ_t	.54	.60	.32	.35		.10	.25	.26	.13	.85	.58	.23
6	Other Non-Current Operating AssetsΔ_t	.28	.37	.11	.13	.09		.08	.09	.06	.10	.05	.03
7	InventoryΔ_t	.59	.37	.68	.37	.28	.09		.34	.14	.23	.17	.02
8	Accounts ReceivableΔ_t	.59	.35	.78	.32	.27	.10	.36		.12	.24	.15	-.02
9	Other Current Operating AssetsΔ_t	.28	.17	.40	.16	.13	.05	.15	.13		.13	.08	-.06
10	GoodwillΔ_t	.48	.52	.29	.30	.79	.09	.24	.26	.11		.32	.17
11	Other IntangibleΔ_t	.39	.44	.22	.25	.67	.06	.20	.18	.09	.33		.24

Panel C: Variable Definitions

Variable	Description	Computation
Operating Assets		AT - Financial Assets
Financial Assets		CHE + IVAO
Non-Current Operating Assets		Operating Assets - Current Operating Assets
Current Operating Assets		ACT - CHE
Intangible Assets		INTAN
Other Intangible Assets		INTAN - GDWL
Goodwill		GDWL
Other Non-Current Operating Assets		Non-Current Operating Assets - PPENT - INTAN
Other Current Assets		Current Operating Assets - RECT - INVT
Other Assets		Operating Assets - RECT - INVT - PPE - INTAN
PPE	Plant, property, and equipment (net of depreciation)	PPENT
Inventory		INVT
Accounts Receivable		RECT
Growth variables		$(Value^{t} - Value^{t-1})/Value^{t-1}$

This table provides descriptive statistics and variable definitions of the main variables used in the in-sample estimation procedure. Panel A reports the descriptive statistics of the various operating asset components used in the in-sample estimation procedure. The sample consists of firm-year observations from 1990-2019. The number of observations differs for every component of operating assets due to the component-specific filters imposed (i.e., absolute (lagged) growth of the respective component smaller than 100%). Panel B reports the Pearson (Spearman) correlations of the variables used in the in-sample estimation procedure above (below) the diagonal. The utmost right column of Panel B presents the Pearson correlation of each component with its lagged value. Panel C reports the variable definitions of the variables used in the in-sample estimation procedure, with Compustat codes provided in capital letters.

TABLE 2

Informativeness of Balance Sheet Disaggregations for Predicting Asset Growth

Panel A: In-sample coefficient estimates

		Intercept α	**Coefficient β**	**Adj. R^2**
aggregate benchmark:				
Operating Assets	Mean	0.062***	0.208***	4.6%
	t-statistic	[22.19]	[50.13]	
current vs non-current:				
Current Operating Assets	Mean	0.068***	0.082***	0.9%
	t-statistic	[26.87]	[8.87]	
Non-Current Operating Assets	Mean	0.055***	0.199***	4.2%
	t-statistic	[17.50]	[87.41]	
non-current-dis:				
PPE	Mean	0.039***	0.258***	7.5%
	t-statistic	[17.73]	[194.34]	
Intangible Assets	Mean	0.003**	0.163***	2.7%
	t-statistic	[2.32]	[98.19]	
Other Non-Current Operating Assets	Mean	0.018***	0.047***	0.3%
	t-statistic	[4.92]	[7.54]	
current-dis:				
Accounts Receivable	Mean	0.071***	0.014**	0.1%
	t-statistic	[25.41]	[1.98]	
Inventory	Mean	0.063***	0.050***	0.3%
	t-statistic	[28.54]	[7.94]	
Other Current Operating Assets	Mean	0.070***	-0.040***	0.2%
	t-statistic	[16.78]	[-8.07]	
non-cur-intan:				
Goodwill	Mean	-0.006***	0.116***	1.4%
	t-statistic	[-3.42]	[33.64]	
Other Intangible Assets	Mean	-0.038***	0.199***	4.2%
	t-statistic	[-72.37]	[30.26]	

Panel B: Out-of-sample descriptive statistics

	ΔOperating Asset Forecast			Signed Forecasts Error			Absolute Forecasts Error			
	Mean	Std. Dev	Median	Mean	Std. Dev	Median	Mean	Std. Dev	Median	N
random walk	0.0254	0.1489	0.0228	-0.0652	0.3929	-0.0158	0.1824	0.3541	0.0967	21,492
aggregate benchmark	0.0663	0.0339	0.0650	-0.0243	0.3794	0.0306	0.1627	0.3436	0.0837	21,492
cur-non-cur	0.0634	0.0274	0.0614	-0.0272	0.3797	0.0268	0.1625	0.3442	0.0828	21,492
current-dis	0.0627	0.0255	0.0610	-0.0279	0.3800	0.0262	0.1627	0.3445	0.0828	21,492
non-current-dis	0.0461	0.0284	0.0441	-0.0445	0.3795	0.0087	0.1595	0.3472	0.0770	21,492
full-dis	0.0453	0.0265	0.0438	-0.0453	0.3798	0.0082	0.1599	0.3474	0.0773	21,492
non-cur-intan	0.0353	0.0258	0.0346	-0.0585	0.3808	-0.0007	0.1571	0.3517	0.0713	13,187

This table reports the results of the in-sample estimation of the component-specific mean-reverting models of operating asset growth on lagged operating asset growth. Panel A presents the mean of the in-sample intercepts, coefficients, and adjusted R-squares of the auto-regressive mean-reversion models of growth in (the components of) operating assets estimated annually over the previous 10 years of data over the period 2000-2019 (i.e., the years used in our holdout sample). Panel B presents the pooled out-of-sample descriptive statistics for the predicted growth in operating assets in our holdout sample that runs from 2000 to 2019. 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. T-statistics are computed using the Fama-MacBeth procedure using the 20 annual estimates over the period 2000-2019. Signed forecast errors are equal to the operating asset growth forecast less the actual growth in operating assets. The absolute forecast error is the absolute value of the signed forecast error. *, **, *** indicate statistical significance at the 10 percent, 5 percent, and 1 percent levels, respectively (two-tailed).

TABLE 3

Out-of-Sample Forecast Improvements

Panel A: Forecast Improvements

		Mean Improvements					Median Improvements					
		Value	p-value		No. year pos|neg	No. Industry pos|neg	Value	p-value		No. year pos|neg	No. Industry pos|neg	N
aggregate	vs random walk	0.0191	0.00	***	17 | 0	30 | 0	0.0073	0.00	***	15 | 1	12 | 1	21,492
cur-non-cur	vs aggregate	0.0002	0.35		6 | 5	9 | 3	0.0009	0.02	**	9 | 3	12 | 1	21,492
current-dis	vs aggregate	-0.0001	0.88		6 | 7	7 | 3	0.0007	0.11		8 | 8	10 | 1	21,492
current-dis	vs cur-non-cur	-0.0003	0.03	**	2 | 9	2 | 2	-0.0001	0.12		3 | 10	1 | 3	21,492
non-current-dis	**vs aggregate**	**0.0033**	**0.00**	*******	**14 | 3**	**22 | 0**	**0.0071**	**0.01**	*******	**13 | 4**	**21 | 0**	**21,492**
non-current-dis	**vs cur-non-cur**	**0.0031**	**0.00**	*******	**14 | 3**	**22 | 0**	**0.0060**	**0.01**	******	**14 | 4**	**19 | 0**	**21,492**
non-current-dis	**vs current-dis**	**0.0034**	**0.00**	*******	**14 | 2**	**24 | 0**	**0.0064**	**0.00**	*******	**14 | 1**	**21 | 0**	**21,492**
full-dis	vs aggregate	0.0030	0.01	***	12 | 5	16 | 0	0.0072	0.02	**	12 | 5	16 | 0	21,492
full-dis	vs cur-non-cur	0.0028	0.00	***	12 | 4	19 | 0	0.0052	0.02	**	12 | 5	19 | 0	21,492
full-dis	vs current-dis	0.0030	0.00	***	13 | 3	21 | 0	0.0061	0.01	**	13 | 4	18 | 0	21,492
full-dis	vs non-current-dis	-0.0003	0.00	***	1 | 9	1 | 7	-0.0001	0.01	**	2 | 9	0 | 8	21,492
non-cur-intan	vs aggregate	0.0041	0.01	***	12 | 4	16 | 0	0.0088	0.02	**	12 | 4	14 | 0	13,187
non-cur-intan	vs cur-non-cur	0.0038	0.00	***	12 | 4	16 | 0	0.0077	0.03	**	12 | 4	13 | 0	13,187
non-cur-intan	vs current-dis	0.0041	0.00	***	12 | 3	18 | 0	0.0069	0.02	**	12 | 3	14 | 0	13,187
non-cur-intan	vs non-current-dis	0.0002	0.51		6 | 8	2 | 0	0.0002	0.57		8 | 8	4 | 1	13,187

Panel B: Forecast Improvements of the *non-current-dis* Model across Fama-French Sectors

	Mean Improvements			**Median Improvements**		
	Value	p-value		Value	p-value	
Business Equipment	0.0013	0.16		0.0039	0.15	
Chemicals and Allied Products	0.0056	0.00	***	0.0095	0.00	***
Consumer Durables	0.0043	0.00	***	0.0067	0.00	***
Consumer Non-Durables	0.0061	0.00	***	0.0089	0.00	***
Healthcare, Medical Equipment & Drugs	0.0013	0.38		0.0036	0.55	
Manufacturing	0.0043	0.00	***	0.0071	0.01	**
Oil, Gas, and Coal Extraction & Products	-0.0019	0.34		-0.0007	0.37	
Other	0.0036	0.01	***	0.0091	0.01	***
Telephone and Television Transmission	0.0073	0.00	***	0.0149	0.00	***
Utilities	0.0012	0.40		0.0038	0.47	
Wholesale, Retail, and Some Services	0.0023	0.03	**	0.0024	0.10	*

Panel C: Forecast Improvements of the *non-current-dis* Model across Years

	Mean Improvements			**Median Improvements**		
	Value	p-value		Value	p-value	
2000	0.0068	0.00	***	0.0121	0.00	***
2001	0.0118	0.00	***	0.0191	0.00	***
2002	0.0068	0.00	***	0.0137	0.00	***
2003	0.0018	0.03	**	0.0051	0.02	**
2004	0.0018	0.03	**	0.0052	0.05	*
2005	0.0052	0.00	***	0.0161	0.00	***
2006	-0.0024	0.00	***	-0.0072	0.01	***
2007	-0.0012	0.14		-0.0047	0.16	
2008	0.0102	0.00	***	0.0177	0.00	***
2009	0.0064	0.00	***	0.0095	0.00	***
2010	0.0001	0.81		-0.0008	0.94	
2011	-0.0017	0.03	**	-0.0049	0.04	**
2012	0.0042	0.00	***	0.0074	0.00	***
2013	0.0050	0.00	***	0.0085	0.00	***
2014	0.0043	0.00	***	0.0072	0.00	***
2015	0.0067	0.00	***	0.0102	0.00	***
2016	0.0019	0.00	***	0.0025	0.00	***
2017	-0.0013	0.06	*	-0.0051	0.01	**
2018	0.0031	0.00	***	0.0070	0.00	***
2019	-0.0029	0.00	***	-0.0066	0.00	***

This table presents the out-of-sample mean (median) improvements in the forecast accuracy of models predicting growth in operating assets for various model comparisons. Panel A compares the various models in terms of forecast accuracy and identifies the *non-current-dis* model as the most accurate. Panel B and C present the forecast improvements of the most accurate *non-current-dis* model over the *aggregate benchmark* model across Fama-French 12 sectors and years, respectively. We measure the improvement in forecast accuracy through a matched-pair comparison of the absolute forecast error (AFE) of the two competing models. Positive (negative) values indicate that the first model is more (less) accurate than the second. 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. No. years is the number of years (out of 20) in which the yearly improvement is significantly positive/negative at the 5% level. No. industries is the number of industries (out of the 48 Fama-French industries) for which the yearly improvement is significantly positive/negative at the 5% level. The reported mean (median) improvements in forecast accuracy are the grand means (medians) of the 20 yearly mean (median) forecast accuracy improvements. Test of means (medians) are calculated using a two-sided T-test (Wilcoxon signed rank test) on the 20 yearly mean (median) forecast improvements. *, **, *** indicate statistical significance at the 10 percent, 5 percent, and 1 percent levels, respectively (two-tailed).

TABLE 4

Forecast Improvements of Disaggregating Intangible Assets

Panel A: Forecast Improvements and Impairment Risk

Idiosyncratic Risk

	Median					Mean				
Decile	Value	non-current-dis versus aggregate		non-cur-intan versus non-current-dis		Value	non-current-dis versus aggregate		non-cur-intan versus non-current-dis	
1	0.009	0.0061		-0.0003		0.009	0.0030	*	-0.0001	
2	0.012	0.0088	*	-0.0003		0.012	0.0036	*	-0.0003	
3	0.015	0.0063	*	-0.0001		0.015	0.0031	***	-0.0002	
4	0.017	0.0052		-0.0001		0.017	0.0029	**	-0.0001	
5	0.019	0.0060	*	0.0000		0.019	0.0031	**	-0.0001	
6	0.022	0.0063	*	0.0003		0.022	0.0029	**	-0.0003	
7	0.025	0.0040	*	0.0000		0.025	0.0026	**	-0.0002	
8	0.029	0.0088	***	0.0010	**	0.029	0.0046	***	0.0011	***
9	0.036	0.0089	***	0.0010	***	0.036	0.0047	***	0.0012	***
10	0.049	0.0066	***	0.0013	***	0.054	0.0046	***	0.0019	***
D1 vs D10		0.0005		0.0016	***		0.0016		0.0021	***

Restructuring Expense

	Median					Mean				
Decile	Value	non-current-dis versus aggregate		non-cur-intan versus non-current-dis		Value	non-current-dis versus aggregate		non-cur-intan versus non-current-dis	
1	0.00	0.0079	**	-0.0001		0.00	0.0035	***	0.0000	
2	0.00	0.0085	***	-0.0001		0.00	0.0073	***	0.0002	
3	0.00	0.0079		0.0006		0.00	0.0034		0.0010	
4	0.00	0.0088	***	0.0006		0.00	0.0057	***	0.0010	
5	0.01	0.0148	***	0.0008	**	0.01	0.0068	***	0.0010	*
6	0.01	0.0105	***	0.0005		0.01	0.0042	**	0.0004	
7	0.01	0.0092	***	0.0003		0.01	0.0042	***	0.0003	
8	0.01	0.0088	***	0.0013		0.01	0.0069	***	0.0007	
9	0.02	0.0099	***	0.0010	**	0.02	0.0051	**	0.0014	***
10	0.04	0.0085	***	0.0012	**	0.05	0.0048	***	0.0011	***
D1 vs D10		0.0006		0.0013	**		0.0013		0.0011	*

Panel B: Forecast Improvements and Firm Life Cycle

	Firm Life Cycle Stage							
	Median				Mean			
	non-current-dis versus aggregate		non-cur-intan versus non-current-dis		non-current-dis versus nggregate		non-cur-intan versus non-current-dis	
Introduction	0.0087	***	0.0004	**	0.0049	***	0.0016	***
Growth	0.0040		-0.0001		0.0023	**	-0.0002	
Mature	0.0080	***	0.0002		0.0035	***	0.0001	
Decline	0.0053	***	0.0010	**	0.0042	***	0.0013	***
Shakeout	0.0068	***	0.0005	*	0.0042	***	0.0005	**

This table presents the results of tests in which we investigate the forecast improvements of disaggregating intangible assets into Goodwill and Other Intangible assets (the *non-current-intan* model) over the forecasts of the *non-current-dis* model. Panel A presents the forecast improvements by decile of proxies for impairment risk. Panel B presents the results by life cycle stage of the firm. The holdout sample consists of 13,187 firm-year observations for which we have available model forecasts for both the *non-current-dis* and *non-current-intan* model. The actual sample size varies conditional on the data availability of the partitioning variable(s). Idiosyncratic Risk is the standard deviation of the daily market model residual returns estimated over a one-year period starting from the fourth month after the start of the fiscal year. Restructuring Expense equals the absolute restructuring costs deflated by lagged operating assets. Life cycle is categorized following the cash flow classification in Dickinson (2011). To avoid a look-ahead bias, all partitioning variables are lagged. 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 5

Operating Asset Growth and Changes in Revenues

In-Sample Coefficient Estimates

	Mean
aggregate benchmark:	
Intercept	0.032***
	[13.52]
Operating AssetsΔ	0.606***
	[115.14]
Adj. R^2	32.8%
non-current-dis:	
Intercept	0.030***
	[12.86]
PPEΔ	0.617***
	[84.80]
Intangible AssetsΔ	0.360***
	[21.61]
Other Non-Cur Operating AssetsΔ	0.007**
	[2.17]
Current Operating AssetsΔ	0.905***
	[51.52]
Adj. R^2	37.6%

This table reports the results of the in-sample estimation of revenue growth on operating asset growth (Equation (11) and (12)). The reported numbers are the mean of the in-sample coefficients, intercepts, and adjusted R-squares of the mean-reversion models estimated annually over the previous 10 years of data for the period 2000-2019 (i.e., the years used in our holdout sample). T-statistics are computed using the Fama-MacBeth procedure using the 20 annual estimates over the period 2000-2019. *, **, *** indicate statistical significance at the 10 percent, 5 percent, and 1 percent levels, respectively (two-tailed).

TABLE 6

Disaggregated Balance Sheet Information and Stock Returns

Panel A: Differences in Revenue Growth Forecasts & Stock Returns – Regression Analysis

Variable	**Excess Return - Value Weighted**		**Excess Return - Fama-French Five-Factor**	
Growth Difference	0.090***	0.060***	0.065***	0.062***
	[6.462]	[3.619]	[4.455]	[3.569]
Size		-0.084***		
		[-4.476]		
Market to Book		-0.055***		
		[-2.675]		
Momentum		-0.126***		
		[-8.131]		
Beta		0.003		
		[0.197]		
Accruals		-0.005		-0.025
		[-0.383]		[-1.594]
Gross Profitability		0.026		0.076***
		[1.376]		[4.124]
$ATO\Delta^{t-1}$		0.028**		0.045***
		[2.019]		[2.850]
$PM\Delta^{t-1}$		0.014		0.011
		[0.869]		[0.667]
Predicted $ATO\Delta^{t}$		0.006		0.043*
		[0.281]		[1.798]
Predicted $PM\Delta^{t}$		-0.058**		0.014
		[-2.463]		[0.621]
Predicted FSY $ROA\Delta^{t}$		0.079***		0.049***
		[4.995]		[2.775]
Intercept	0.028***	0.129***	-0.007	-0.111***
	[4.180]	[3.768]	[-0.856]	[-3.596]
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

Panel B: Hedge Portfolio Returns

	Difference in Forecasted Growth								
	10% < Versus > 90%			20% < Versus > 80%			30% < Versus > 70%		
	Value	**VW**	**FF5**	**Value**	**VW**	**FF5**	**Value**	**VW**	**FF5**
Short	-0.031	0.035	-0.004	-0.026	0.044	0.010	-0.023	0.047	0.012
Long	0.017	0.129	0.070	0.010	0.122	0.065	0.006	0.112	0.058
Hedge return		0.094***	0.074***		0.078***	0.055***		0.065***	0.046***
		[4.432]	[3.365]		[5.387]	[3.539]		[5.797]	[3.871]
Num. Obs.		4,098			8,170			12,252	

This table presents the results of tests in which we investigate how revenue growth forecasts from disaggregated models predict future stock returns. The holdout sample consists of 21,492 firm-year observations for which we have available model forecasts. We drop firms that have missing data on the control variables, while, to avoid a look-ahead bias, for this test we do not require actual operating asset growth data to be available. Panel A presents the results of a regression of year-ahead returns on an annual decile rank (ranging between 0 and 1) of the difference in predicted growth in revenues between the non-current-dis model and the aggregate benchmark model (Growth Difference). Positive values indicate that the revenue growth prediction by the non-current-dis model is higher compared to the aggregate benchmark model. Panel B reports the results of a one-year hedge return test where we go long (short) in a portfolio of stocks for which the non-current-dis model predicts higher (lower) revenue growth compared to the aggregate benchmark model. Excess returns are calculated over a 12-month period that starts in the fourth month of year t (after the publication of the year t-1 financial statements) until three months after fiscal year-end. Excess returns are the firm buy-and-hold return over the period adjusted for movements in the CRSP's value-weighted market portfolio (Excess Return Value Weighted) or adjusted using the Fama-French Five Factor model (Excess Return Fama-French Five-Factor). Control variables are the decile ranks of the firm's beginning-of-year: market-to-book ratio (Market to Book), market capitalization (Size), stock beta (Beta), momentum (Momentum), accruals (Accruals), gross margins (*Gross Profitability*), change in asset turnover (ATOΔt-1), change in profit margin (PMΔt-1), predicted change in asset turnover (Predicted ATOΔt), predicted change in operating profit margin (Predicted PMΔt) and predicted change in return on operating assets (Predicted FSY ROAΔt) estimated using the OPINC income statement disaggregation scheme as in Fairfield et al. (1996). ATO is total revenue (REVT) divided by lagged operating assets. PM is operating income after depreciation divided by total revenues (OIADP/REVT). Gross Profitability is revenue (REVT) minus cost of goods sold (COGS) divided by lagged total assets. We calculate the predicted change in asset turnover and operating profit margin using an economy-wide mean-reverting model that is estimated analogously to the estimation of predicted operating asset growth using the previous 10 years of data. Beta is calculated as the sensitivity of a firm's return to market returns, estimated over the one-year period that ends three months after the end of the fiscal year prior to the year for which we predict growth and excess returns (year *t*). Momentum is the firm-specific excess return over the fiscal year prior to the year for which we predict growth (year *t*). Accruals is operating income after depreciation less operating cash flow, scaled by lagged total assets (OIADP – OANCF / lag AT). *, **, *** indicate statistical significance at the 10 percent, 5 percent, and 1 percent levels, respectively (two-tailed).

TABLE 7

Disaggregated Balance Sheet Information and Stock Returns - Earnings Announcements

	Raw Returns 5-Day Window -2|0|+2		Raw Returns 3-Day Window -1|0|+1	
Growth Difference	0.022***	0.019***	0.019***	0.015***
	[3.915]	[2.861]	[3.774]	[2.671]
Size		-0.004		-0.003
		[-0.634]		[-0.452]
Market to Book		-0.005		-0.006
		[-0.764]		[-0.914]
Momentum		-0.014**		-0.007
		[-2.337]		[-1.241]
Beta		0.002		0.000
		[0.382]		[-0.062]
Accruals		0.006		0.001
		[0.987]		[0.151]
Gross Profitability		0.018**		0.019***
		[2.408]		[2.841]
$ATO\Delta^{t-1}$		0.018***		0.013**
		[3.151]		[2.392]
$PM\Delta^{t-1}$		-0.014**		-0.013**
		[-2.265]		[-2.191]
Predicted $ATO\Delta^{t}$		0.007		0.006
		[0.875]		[0.756]
Predicted $PM\Delta^{t}$		-0.003		0.002
		[-0.312]		[0.211]
Predicted FSY $ROA\Delta^{t}$		0.017***		0.010*
		[2.865]		[1.882]
Intercept	0.009***	-0.004	0.006**	-0.002
	[3.170]	[-0.271]	[2.402]	[-0.200]
Num. Obs.	20,402	20,402	20,402	20,402
Adj. R^2	0.001	0.003	0.001	0.002
Clustering of S.E.	Firm	Firm	Firm	Firm

In this table, we investigate how revenue growth forecasts from disaggregated models predict future stock returns around the earnings announcement. The holdout sample consists of 21,492 firm-year observations for which we have available model forecasts. We drop firms that have missing data on the control variables and earnings announcement dates, while, to avoid a look-ahead bias, for this test we do not require actual operating asset growth data to be available. The dependent variable equals the cumulative raw return earned during the three (-1,0,+1) or five (-2,0,+2) days around each of the four quarterly earnings announcements for the forecasted fiscal year. Other variables are as defined before. *, **, *** indicate statistical significance at the 10 percent, 5 percent, and 1 percent levels, respectively (two-tailed).

TABLE 8

Disaggregated Balance Sheet Information and Stock Returns – Institutional Ownership

Panel A: Value-Weighted Returns

	Excess Return Value Weighted					
Variables	**Institutional**		**Transient**		**Dedicated**	
	Low	High	Low	High	Low	High
Growth Difference	0.081***	0.020	0.103***	0.010	0.073***	0.046**
	[3.030]	[1.036]	[4.096]	[0.465]	[3.045]	[2.072]
Size	-0.046*	-0.037	-0.075***	-0.053*	-0.080***	-0.096***
	[-1.933]	[-1.177]	[-3.164]	[-1.741]	[-3.347]	[-3.208]
Market to Book	-0.129***	0.024	-0.097***	-0.010	-0.051*	-0.057*
	[-4.563]	[0.817]	[-3.428]	[-0.346]	[-1.922]	[-1.808]
Momentum	-0.173***	-0.081***	-0.148***	-0.103***	-0.110***	-0.148***
	[-7.386]	[-3.989]	[-6.329]	[-4.819]	[-5.049]	[-6.399]
Beta	-0.002	0.084***	0.002	0.048**	-0.065***	0.078***
	[-0.103]	[4.499]	[0.073]	[2.316]	[-3.145]	[3.660]
Accruals	-0.028	0.023	-0.039*	0.020	0.003	-0.022
	[-1.213]	[1.389]	[-1.734]	[1.130]	[0.152]	[-1.174]
Gross Profitability	0.061**	-0.007	0.047	0.009	0.065**	-0.010
	[2.036]	[-0.324]	[1.571]	[0.389]	[2.400]	[-0.348]
$ATO\Delta^{t-1}$	0.032	0.023	0.054**	0.005	0.005	0.052**
	[1.547]	[1.210]	[2.568]	[0.261]	[0.284]	[2.474]
$PM\Delta^{t-1}$	0.061**	-0.055***	0.048*	-0.021	0.045*	-0.021
	[2.461]	[-2.893]	[1.939]	[-1.050]	[1.857]	[-0.992]
Predicted $ATO\Delta^{t}$	-0.026	0.012	-0.007	-0.001	0.023	-0.016
	[-0.739]	[0.504]	[-0.189]	[-0.054]	[0.742]	[-0.506]
Predicted $PM\Delta^{t}$	-0.054	-0.077***	-0.068*	-0.061**	-0.028	-0.090***
	[-1.519]	[-2.726]	[-1.905]	[-2.090]	[-0.821]	[-2.904]
Predicted FSY $ROA\Delta^{t}$	0.079***	0.090***	0.070***	0.089***	0.076***	0.079***
	[3.059]	[4.983]	[2.832]	[4.470]	[3.194]	[3.853]
Intercept	0.175***	0.023	0.148***	0.083*	0.083*	0.187***
	[3.391]	[0.528]	[2.943]	[1.762]	[1.762]	[3.626]
Low vs High return	0.061*		0.093***		0.027	
	[1.871]		[2.873]		[0.816]	
Num. Obs.	10,202	10,202	10,202	10,202	10,202	10,202
Adj. R^2	0.019	0.009	0.019	0.008	0.013	0.017
Clustering of S.E.	Firm	Firm	Firm	Firm	Firm	Firm

Panel B: Fama-French Five-Factor Model Adjusted Returns

	Excess Return Fama-French Five-Factor					
	Institutional		**Transient**		**Dedicated**	
	Low	High	Low	High	Low	High
Growth Difference	0.098***	0.009	0.123***	-0.003	0.073***	0.050**
	[3.497]	[0.446]	[4.579]	[-0.155]	[2.901]	[2.128]
Accruals	-0.061**	0.013	-0.058**	-0.001	0.003	-0.057***
	[-2.443]	[0.691]	[-2.378]	[-0.043]	[0.124]	[-2.680]
Gross Profitability	0.106***	0.027	0.100***	0.049**	0.094***	0.058**
	[3.590]	[1.221]	[3.299]	[2.071]	[3.431]	[2.136]
$ATO\Delta^{t-1}$	0.038	0.050**	0.064***	0.029	0.028	0.062***
	[1.616]	[2.401]	[2.741]	[1.403]	[1.300]	[2.693]
$PM\Delta^{t-1}$	0.036	-0.025	0.032	-0.007	0.038	-0.018
	[1.439]	[-1.285]	[1.270]	[-0.343]	[1.558]	[-0.824]
Predicted $ATO\Delta^{t}$	0.054	0.003	0.047	0.021	0.060*	0.022
	[1.410]	[0.126]	[1.246]	[0.728]	[1.746]	[0.647]
Predicted $PM\Delta^{t}$	0.041	-0.053*	0.015	-0.006	0.033	-0.006
	[1.264]	[-1.939]	[0.476]	[-0.218]	[1.059]	[-0.208]
Predicted FSY $ROA\Delta^{t}$	0.035	0.067***	0.036	0.060***	0.043	0.056**
	[1.209]	[3.338]	[1.352]	[2.676]	[1.638]	[2.402]
Intercept	-0.129***	-0.043	-0.138***	-0.058	-0.163***	-0.053
	[-2.705]	[-1.222]	[-2.881]	[-1.534]	[-3.716]	[-1.222]
Low vs High return	0.089***		0.126***		0.023	
	[2.613]		[3.679]		[0.689]	
Num. Obs.	10,202	10,202	10,202	10,202	10,202	10,202
Adj. R^2	0.005	0.001	0.006	0.001	0.003	0.003
Clustering of S.E.	Firm	Firm	Firm	Firm	Firm	Firm

This table presents the results of tests in which we investigate how revenue growth forecasts from disaggregated models predict future stock returns, conditional on the level of (transient and dedicated) institutional ownership. The holdout sample consists of 21,492 firm-year observations for which we have available model forecasts. We drop firms that have missing data on the control variables, while, to avoid a look-ahead bias, for this test we do not require actual operating asset growth data to be available. Institutional ownership data are extracted from 13-F filings and come from the Refinitiv Institutional Ownership database. We use the classification by Bushee (1998) to classify institutions as transient or dedicated. Other variables are as defined before. *, **, *** indicate statistical significance at the 10 percent, 5 percent, and 1 percent levels, respectively (two-tailed).

TABLE 9

Revenue Growth Forecasts and Financial Performance

Growth Difference Decile			Return on Assets		Asset Turnover		Profit Margin		Revenue Growth	
	Value	n	Level^{t-1}	Δ^{t}	Level^{t-1}	Δ^{t}	Level^{t-1}	Δ^{t}	Level^{t-1}	Δ^{t}
1	-0.031	2,040	0.105	-0.007	0.959	-0.070	0.108	0.009	0.146	-0.049
2	-0.021	2,040	0.103	0.000	1.001	-0.003	0.099	0.000	0.101	-0.030
3	-0.017	2,040	0.100	0.003	1.049	0.002	0.102	0.006	0.087	-0.019
4	-0.014	2,040	0.103	0.000	1.157	0.013	0.093	-0.001	0.095	-0.031
5	-0.011	2,040	0.114	0.002	1.295	0.010	0.090	0.002	0.086	-0.024
6	-0.008	2,040	0.117	0.001	1.455	0.016	0.080	-0.003	0.084	-0.021
7	-0.005	2,040	0.117	0.003	1.599	0.024	0.073	-0.001	0.071	-0.012
8	-0.001	2,040	0.117	-0.001	1.757	0.016	0.058	-0.008	0.059	-0.013
9	0.004	2,040	0.093	0.002	1.812	0.059	0.038	-0.006	0.039	0.003
10	0.016	2,039	0.042	0.011	1.759	0.229	0.000	0.006	-0.003	0.020
D1 vs D10				0.018***		0.300***		-0.003		0.069***
				[4.890]		[19.098]		[0.526]		[5.325]

This table reports the level and change of various financial performance metrics by decile of the difference in predicted revenue growth between the *non-current-dis* model and the *aggregate benchmark* model (*Growth Difference*). The holdout sample consists of 21,492 firm-year observations for which we have available model forecasts and data on actual operating asset growth. The actual sample size varies conditional on data availability of the financial performance variable(s). Column Level^{t-1} reports the mean value of the financial performance variable in the year prior to the forecasted year. The change in year t (Δt) is the change in financial performance during the year for which we predict operating asset growth (i.e., the forecasted year). Variables are defined as follows (Compustat codes in brackets):

Return on assets = Operating Income After Depreciation (OIADP) / Lagged Operating Assets,
Asset turnover = Revenue (REVT) / Lagged Operating Assets,
Profit Margin = Operating Income After Depreciation / Revenue (REVT),
Revenue Growth = (Value^{t} - Value^{t-1}) / Value^{t-1}

*, **, *** indicate statistical significance at the 10 percent, 5 percent, and 1 percent levels, respectively (two-tailed).

TABLE 10

Decomposing Revenue Growth Forecasts

	Excess Return – Value Weighted		**Excess Return – Fama-French Five-Factor**	
Difference Asset Growth	0.060***	0.031*	0.027	0.026
	[3.815]	[1.880]	[1.622]	[1.449]
Difference Revenue Growth	0.049***	0.043**	0.054***	0.053***
	[3.596]	[2.393]	[3.561]	[2.737]
Size		-0.083***		
		[-4.503]		
Market to Book		-0.055***		
		[-2.683]		
Momentum		-0.127***		
		[-8.146]		
Beta		0.002		
		[0.147]		
Accruals		-0.010		-0.033**
		[-0.693]		[-2.016]
Gross Profitability		0.023		0.071***
		[1.180]		[3.796]
$ATO\Delta^{t-1}$		0.027*		0.042***
		[1.894]		[2.674]
$PM\Delta^{t-1}$		0.014		0.010
		[0.844]		[0.614]
Predicted $ATO\Delta^{t}$		0.008		0.046*
		[0.367]		[1.910]
Predicted $PM\Delta^{t}$		-0.058**		0.011
		[-2.502]		[0.497]
Predicted FSY $ROA\Delta^{t}$		0.079***		0.049***
		[4.995]		[2.784]
Intercept	0.019**	0.126***	-0.015*	-0.112***
	[2.540]	[3.599]	[-1.677]	[-3.550]
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

This table presents the results of tests that decompose the difference in the predicted growth in revenues from the disaggregated versus the aggregate model into two components, one that captures the difference in the operating asset growth forecast (*Difference Asset Growth*), and a second component that captures the difference in predicted revenue growth independent of the difference in operating asset growth predictions (*Difference Revenue Growth*). The holdout sample consists of 21,492 firm-year observations for which we have available model forecasts. We drop firms that have missing data on the control variables, while, to avoid a look-ahead bias, for this test we do not require actual operating asset growth data to be available. To empirically isolate one component from the other, we forecast revenue growth forecasts using disaggregate information for the component of interest while the other is forecasted using only aggregate information, see equations (15) and (16). Consistent with the other tables, both differences are transformed into annual decile rank (ranging between 0 and 1). Other variables are as defined before. *, **, *** indicate statistical significance at the 10 percent, 5 percent, and 1 percent levels, respectively (two-tailed).