Decomposing Firms' Revenue into Price and Quantity *

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Abstract

We examine a unique disclosure setting in India that required firms to disclose the quantity of products sold to learn about the incremental information provided by such disclosures and their impact on stock price efficiency. We find that revenue growth is more persistent when quantity growth drives them. Therefore, decomposing revenue growth into its quantity and price components helps predict future revenue growth better as it enables the identification of shifts in demand. Consequently, such disclosure also increases the informativeness of stock prices, as reflected by changes in dispersion in analysts' revenue forecasts and post-earnings stock price reactions.

Key Words: Disclosures; Sales Quantities; Revenue Persistence, Efficiency of Stock Prices

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I Introduction

Despite the trend of increased disclosures worldwide, no regulator, to our knowledge, requires firms to disclose the decomposition of their sales revenue into quantity sold and price.[1] We examine a short-lived disclosure regime in India which required firms to disclose the decomposition of sales into quantity and price. We find that the persistence of growth in sales is higher when it is due to quantity growth rather than price growth. Therefore, disclosures reveal information about the persistence of sales growth and enhance stock price efficiency. The evidence adds to the growing literature on the impact of public disclosures on stock price efficiency.[2]

Recent decisions by several large firms to discontinue voluntary disclosures relating to the quantity of goods sold, number of users, usage intensity, etc., have sparked a debate about the value relevance of information relating to product quantity. Anecdotal evidence suggests that stock markets react negatively to the discontinuation of quantity disclosures. For instance, the stock price of Netflix fell by 7.3% following its announcement to cease disclosure of subscriber numbers - a key metric for estimating revenue per subscriber.[3] Similarly, Apple recorded a stock price decline of 7% when the company announced that it would stop reporting unit sales of its products such as iPhones, iPads, and Macs from 2019 onwards.[4] The stock price of Meta Platforms also reacted similarly when it announced the discontinuation of reporting information relating to the number of daily active users.[5]

The above examples highlight that information about product-level revenues and quantities sold may be value-relevant for investors and warrant examination. However, examining

[1] A few companies such as Caterpillar Inc. voluntarily decompose the variance in revenues to changes in quantity sold, price changes and other items such as foreign currency effects (`https://s25.q4cdn.com/358376879/files/doc_financials/2023/q4/4Q-2023-Analyst-Slide-Deck-FINAL-2.pdf`)

[2] Morris and Shin (2002), Banerjee et al. (2018), Gao (2008), Goldstein and Yang (2019)

[3] See `https://www.reuters.com/technology/netflix-slips-after-stopping-subscriber-tally-report-downbeat-q2-revenue-2024-04-19/`

[4] See `https://www.bloomberg.com/news/articles/2018-11-01/apple-to-stop-reporting-unit-sales-of-iphones-ipads-and-macs`

[5] https://www.marketwatch.com/livecoverage/meta-earnings-facebook-q1-stock-results-expectations/card/why-meta-s-earnings-report-will-look-a-little-different-this-time-bgGB7YPnpkCmnWCDuUWL

the impact of product-level quantity disclosures is challenging because such disclosures are typically voluntary worldwide and can, therefore, be endogenous. Fortunately, in India, we found a small window of time when Indian manufacturing firms were required to disclose product-level quantity and price data. We exploit this setting to test whether the decomposition of revenue into quantity and price components provides better information about the future fundamentals and, consequently, enhances the efficiency of current stock prices.

We obtain product-by-product data for every firm-year for relatively larger Indian firms from the database maintained by the Center For Monitoring Indian Economy (CMIE). Apart from the usual financial variables reported in the annual reports, we obtain information about firm-wise product quantities and revenues. We follow De Loecker et al. (2016) and Bau and Matray (2023) to obtain the product-level prices using the above data. The quantity and price data are available for 2011 and before, as India discontinued the mandate to report such granular information to align its accounting standards with global accounting standards.

We start our empirical analysis by asking what additional information does the decomposition of revenue into quantity and price provides. A natural question to explore is whether the disclosure about quantities provides incremental information about future revenue over and above the information provided by current revenue numbers. We investigate this question because information on quantities allows us to distinguish between instances of 'shifts in demand' and 'movement along the demand curve' as we can identify changes in quantity after accounting for price change. Thus, the question is akin to asking whether revenue growth due to a shift in demand is more or less persistent.

Our first set of tests examines the association between revenue growth in a year and the same during the subsequent year at a firm-product-year level. Our results indicate that revenue growth, in general, exhibits mean reversion. The finding is in line with the extant research (Nissim and Penman (2001), Fairfield et al. (2009)). Note that when we look at aggregate revenue data, we cannot separate instances of shifts in demand and movement along the demand curve due to price changes. In the latter case, some customers having inelastic demand in the short run may eventually find substitutes, causing a decline in future growth. This could plausibly explain mean reversion in general.

What happens when there is a shift in demand? In this case, we hypothesize that the substitution is less likely and the growth is likely to be relatively more persistent. However, to identify exogenous demand shock, we need to identify changes in quantity, which is independent of price changes. The disclosure of quantity information allows us to study the impact of quantity after accounting for the impact of price changes. In line with our hypothesis, we find that revenue growth is relatively more persistent when it is caused by growth in the quantity of products rather than an increase in prices.

In terms of economic magnitude, our results indicate that for a firm with median sales growth (9.6%) in the current period, where growth is solely attributed to price changes, there is a 2.14 percentage point (pp) decline in sales growth in the next period (indicating mean reversion). However, when the entire revenue growth in the given scenario is attributed to quantity growth, the decline in sales growth in the next period is only 29 basis points (bps). This suggests that quantity-driven growth appears to mitigate the mean reversion of sales growth. Our tests include firm X product and product X year fixed effects. Thus, the results are not due any factor related to a firm specific product characteristic or time varying product specific characteristic.

To better understand what additional information disclosures about product price and quantity sold can convey, consider a hypothetical example with two Indian firms, A and B, and a non-Indian firm C. Assume that all three firms achieved revenue growth of 10% in a year. Based on this data alone, we can predict that next year's annual revenue growth will likely be lower than 10%, on average, due to mean reversion. Now, assume firms A and B tell us about their decomposition of revenue growth into quantity and price growth. Suppose 80% (10%) of firm A's (B's) growth is due to quantity growth and the remaining due to price growth. This additional information suggests that firm A's revenue growth is driven more by demand shocks than firm B's. Thus, we can now predict that the mean reversion in growth next year is likely to be lower for firm A than for firm B. We cannot make these predictions for firm C, which does not disclose price and breakdowns. Thus, disclosure about quantity and price potentially enriches the information set available to the investors.

So far, our analysis is focused on the relationship between quantity growth in a year and revenue growth in the immediately succeeding year. A reader may be curious to know how long does the impact of quantity growth persist? To address this question, we estimate an impulse response function and find that quantity growth influences the persistence of revenue growth for at least four years. Interestingly, we also find that the negative relationship between the current and future revenue growth also persists for four years.

We conclude the first part of the paper by noting that we cannot investigate whether profits caused by quantity growth are relatively more persistent due to data limitations. We do not have data on profits at the product level. Therefore, we cannot conduct the same firm-product-year level test that we do to test the persistence of product revenues.

In the second part of the paper, we investigate whether the public disclosure of quantity increases the informational efficiency of stock prices. If the provision of public information on quantity crowds out private information production (Morris and Shin (2002)), then quantity disclosures may reduce the informational efficiency of stock prices. If not, they are likely to enhance the informational efficiency of stock prices. We test this hypotheses by exploiting India's decision to discontinue mandatory quantity disclosures for exogenous reasons to align Indian accounting standards with global accounting standards.

As noted earlier, anecdotal evidence indicates that information on quantity improves stock price efficiency. We use two measures of stock price efficiency. Our first measure is based on the accuracy of analysts' forecasts of revenues (Ertimur et al. (2003), Jegadeesh and Livnat (2006), Keung (2010), Bochkay and Joos (2021)). Revenue forecast error is a direct measure that examines whether analysts incorporate the additional information contained in quantity disclosure. If quantity disclosures added to the informativeness of stock prices, then analysts' ability to forecast revenue should decline after the discontinuation of quantity disclosures, leading to higher divergences. The second measure is the stock market reaction to earnings announcements. If stock prices incorporate forward-looking information using the persistence property of quantity growth, abnormal stock price reactions to earnings announcements should be lower when quantities are disclosed and higher after the discontinuation of disclosures.

For identification, we exploit the quirk that product-level disclosure was mandatory only for manufacturing firms and not for firms operating in the services sector. Although manufacturing and service sector firms are different, we do not find any pre-existing trend of either convergence or divergence in analyst revenue forecast errors. Neither do we find any other event that coincided with the discontinuation of quantity disclosure and also impacted the two sectors differently. Nonetheless, as an additional robustness, we employ a second identification strategy. We designate the firms that mainly produce products from the producer price index (PPI) as treated firms and those that mainly produce products from the consumer price index (CPI) as control firms in a difference-in-differences setup. The underlying intuition is that the information about quantity and prices of CPI-based products are more easily verifiable than products in PPI, even in the absence of mandatory disclosures. Thus, the discontinuation of disclosure by firms should impact products that belong to the PPI more than those belonging to the CPI.

Our difference-in-differences (DID) test using service firms as the control group shows that the errors in analysts' revenue forecasts increase significantly after the discontinuation of the disclosure. The revenue forecast error increases by about 2.86 times after the discontinuation of the disclosure norms. Therefore, it is reasonable to consider these magnitudes economically meaningful. We find similar results using the alternative identification strategy that compares PPI and CPI products. Thus, the results suggest that the information provided in the product-level disclosures seems to improve the efficiency of stock prices.

In line with the above thesis, we also find an increase in the magnitude of stock market reaction to earnings announcements after the mandatory quantity disclosures were discontinued for manufacturing firms. Specifically, we conduct an event study of earnings announcements of manufacturing firms and document that the magnitude of the 3-day cumulative abnormal return (CAR) of stocks goes up by 42 bp after the discontinuation of product level disclosures. This is more than 10% of the average abnormal return in response to earnings announcements in the pre-event period. Note that 42 bps is the abnormal return per earnings announcement. Therefore, the overall impact on the firm value is likely to be an order magnitude higher.

Although we examine multiple events staggered over time, a remaining concern is that the results are attributable to some time-varying endogenous factor connected with the discontinuation of disclosures. To address this concern, we conduct a similar event study for service sector firms and assess their market reaction. We fail to find any significant change in the absolute value of CARs of service sector firms after the discontinuance of quantity disclosures. We find similar results using our second identification strategy where we compare firms belonging to PPI and CPI. Thus, our findings are in line with the thesis that product-level quantity disclosures increase the informational efficiency of stock prices and do not crowd out private information.

In general, the results provide tentative support for a regime where firms are asked to disclose quantity and price data. We fully understand the myriad trade-offs associated with mandatory disclosure. At the very least, we hope the evidence we provide stimulates debate about an alternate reporting model that helps an investor assess the quantity and price variance in revenue changes.

II Related Literature

Our study is directly related to the literature on the impact of public disclosures on the informativeness of stock prices. The conventional wisdom, often put forward by regulators, is that greater disclosures improve the functioning of financial markets (Goldstein and Yang (2017)). The claim is consistent with findings of several academic papers (Diamond and Verrecchia (1991), Easley and O'hara (2004), Gao (2008)) and has inspired several landmark legislations, such as the Sarbanes-Oxley Act of 2002 and the Dodd-Frank Act of 2010.

In contrast, a prominent strand of literature argues that public disclosures could crowd out private information production and hamper overall stock price and real efficiency. For instance, in their seminal contribution, Morris and Shin (2002) argue that public disclosure of information plays both informational and coordination roles and, therefore, gets disproportionately higher weight in investor decision-making when compared to private information. Thus, higher disclosures can potentially crowd out private information production and reduce the efficiency of stock prices. Allen et al. (2006) endogenize the coordination role of public information using short horizons of investors. Several other studies have a similar flavor. For instance, in Goldstein and Yang (2019), public disclosure about issues that a real decision maker wants to learn from the markets could hamper efficiency as disclosures can crowd out private information production pertaining to the issue under consideration. Similarly, in Banerjee et al. (2018), strategic complementarity between information about fundamentals and information on the likely trading pattern of other traders could trigger disproportionate focus on the latter at the expense of fundamental information when public disclosures cross a threshold level.

We contribute to this literature by examining whether information relating to the decomposition of revenue into quantity and price falls into the first or the second category described above. Our results suggest that the public disclosure of the above information increases stock price efficiency and does not crowd out private information production.

There is also a large empirical literature on the impact of public disclosures. Notable studies such as Healy and Palepu (2001) and Roychowdhury et al. (2019) have provided a detailed review of the impact of disclosures on various aspects of firms, including their cost of capital, investment decisions, and overall firm valuation. Moreover, Lambert et al. (2007) specifically suggests that higher quality disclosures lead to lower cost of capital. Expanding the focus to initial public offerings (IPOs), Hanley and Hoberg (2010) find that disclosures can reduce the likelihood of underpricing, while Hanley and Hoberg (2012) demonstrate that disclosures also serve to mitigate litigation risks for issuers and underwriters in IPOs. Improvement in the quality of accounting disclosures is also known to increase the likelihood of cross-border mergers (Erel et al. (2012)).

However, some empirical studies have also pointed out the crowding-out effect of public disclosures. For instance, Jayaraman and Wu (2019) show that the introduction of mandatory segment reporting in the US reduced real efficiency. Da and Huang (2020) find similar results in an experimental setting- higher exposure to public information reduces reliance on private information. Similarly, Pinto (2023) find that firms with reduced disclosure requirements attract more informed investors and are associated with higher learning from financial markets than those with stricter disclosure requirements.

Most extant studies limit themselves to examining the implications of disclosures on price or real efficiency without explicitly stating what value-relevant information is provided by a disclosure. We go a step further by showing that the decomposition of revenue into quantity and price provides information about the likely persistence of sales growth, thereby improve price efficiency.

III Institutional Detail

Schedule VI of The Companies Act outlines the presentation format and the structure in which public corporations must report their financial statements in India. In 2011, the Ministry of Corporate Affairs (MCA) overhauled Schedule VI of the Companies Act.[6] The objective was to synchronize the reporting format in line with international reporting standards. The amended format was mostly inspired by the International Financial Reporting Standards (IFRS).[7]

Most of the changes involved cosmetic variations in the presentation of the financial statements. For instance, asset and liability line items in the balance sheet are now categorized under subheads for current and non-current portions in line with IFRS reporting standards. In another change, the asset line item 'sundry creditors' is renamed 'trade creditors' for ease of interpretation. The list of key changes enacted by the amendment in Schedule VI is

[6] Refer to the circular from MCA stating that revised schedule VI is applicable from the financial year 2011-2012 onwards. (`https://www.mca.gov.in/Ministry/pdf/General_Circular_21_2012.pdf`)

[7] Refer to the practitioner guide on implementing schedule VI, prepared by the Institute of Chartered Accountants of India (ICAI) in 2012 (https://kb.icai.org/pdfs/PDFFile5b28b538b280c7.98705447.pdf)

presented in Table A1 of the online appendix.

While most of the reporting requirements under the revised format primarily involve changes in presentation without substantial impact on the conveyed information, there is one notable exception. The previous guidelines mandated manufacturing firms to disclose the amount of sales revenues and quantities related to each product. However, the updated reporting template now only requires reporting revenues under three broad categories: sales of products, sale of services, and other operating revenues, and it no longer necessitates the disclosure of quantity sold for each product. In this study, we exploit the discontinuation of the product quantity related disclosures to understand the information content of quantities.

Neither the US Generally Accepted Accounting Principles (GAAP) nor the International Financial Reporting Standards (IFRS) require the disclosure of sales quantity. Additionally, firms rarely choose to disclose quantity information voluntarily. To demonstrate the scarcity of this information, we provide an illustration of the quantity and sales-related details for a selection of well-known companies. We download and analyze sales related disclosures of Amazon Inc., Home Depot, and Tata Steel.

Amazon is one of the world's largest technology companies, with an array of products and services such as e-commerce, cloud computing (AWS), online advertising, and other services. However, the annual report of Amazon in 2022 does not disclose revenue for each product category. Instead, the revenues are classified under North America, International, and AWS. Similarly, Home Depot, largest home improvement retailer in the US, discloses revenues under three different product lines – Building materials, Décor, and Hardlines – and their merchandising departments. However, there is no information on the product wise quantities sold or their prices for its products. As a result, it is challenging to determine whether the revenue growth is driven by price growth, quantity growth, or a combination of both.

However, Tata Steel, which is a Fortune 500 company and is the largest steel manufacturer in India, provides the sales as well as the quantity sold for all seven product categories in its annual report in 2010: Bearings, Charge Chrome, Ferro Manganese, Metallurgical

Machinery, Saleable Steel, Steel and Scrap (semi-finished), and Welded Steel Tubes. For example, it disclosed sales of 5.5 million tons of finished steel and a revenue of INR 194.5 billion from steel in 2010.

IV Data

We obtain data related to the annual sales quantities and revenues of products of firms from the Prowess database maintained by the Centre for Monitoring of Indian Economy (CMIE). As discussed in section III, manufacturing firms were required to report quantities sold and revenues earned at the product level in their audited financial statements until 2011. We derive the average price of each product of a firm by dividing the revenue earned from the product by the quantity of the product sold in that year. We follow De Loecker et al. (2016) and Bau and Matray (2023) in this regard.

We examine the association between the growth rates in revenue, quantity, and price to overcome the mechanical persistence of levels of the variables (Pesando (1974)). Therefore, we transform the above variables into year-on-year growth variables. Specifically, we create the variable "sales growth," which is calculated as the percentage change in sales of a product of the firm in a year compared with an analogous metric from the previous year. Similarly, we create the variables "quantity growth" and "price growth," which denote the annual change in a firm's product quantity and price. We winsorize the data at 1% on both sides to mitigate the impact of outliers. We provide the definitions of key variables in Table 1.

IV.A Sample Construction

We conduct two types of tests. The initial set of tests examines the relation between variables in the pre-2011 period when disclosure of sales quantity was mandatory, and the second set of tests examines the change in relations between variables in response to the removal of the disclosure mandate in 2011. For the first category of tests, we use a fifteen-year panel of time spanning 1997 to 2011.[8] Panel A of Table 2 presents the process underlying the construction of the sample. As shown in the table, we find 270,614 firm-product-year level observations in the data. Of these, for 81,639 observations, we cannot calculate sales growth even for a year as we do not have sales data for consecutive years. Thus, we are left with 188,975 firm- product-year level observations. However, note that we cannot calculate growth for observations pertaining to the last year in the sample. Therefore, we can use only 136,053 observations in our regressions. These observations pertain to 11,807 unique manufacturing firms and 22,672 unique products. We have 33,272 unique firm-product pairs and 58,423 firm-year-level observations.

We create a separate sample using a 10-year observation window from 2007 to 2016 for the second set of tests that compare pre-2011 mandatory disclosure period with the post-2011 non-disclosure period. Panels B and C of Table 2 present the sample construction details for the market efficiency test. We extract the stock price data and earnings announcement dates from Prowess, and index level information from the website of the National Stock Exchange (NSE) of India. The stock-returns data are available for a total of 3,522 firms, of which 2,166 are manufacturing firms, resulting in 13,036 firm-year observations. To test the accuracy of analyst forecasts, we retrieve revenue forecast data from Refinitiv's IBES database and manually match the firm names with the firm names in Prowess. Analysts' revenue forecasts are available for 2,452 firm-year observations corresponding to 425 firms during the sample period.

IV.B Variable Creation and Summary Statistics

We present the summary statistics of the variables used in the paper in Table 3. We observe that the median annual growth in revenues in our sample is 9.57%. Similarly, the median growth rate in quantity and price of products sold is 5.02% and 3.23%, respectively. The average values of the variables are larger due to the presence of outliers. We, therefore, winsorize the growth variables by 1%. Across the quartiles of the distributions, we observe

[8] We utilize data starting from 1997 due to the limited coverage of firms by CMIE before 1997.

that quantity growth exceeds price growth.

Our initial objective is to examine whether growth in sales driven by quantity demand shocks is persistent. To determine the relative contribution of shifts in demand to sales growth, we calculate the "Quantity Growth Factor" (q^f), which represents the proportion of revenue growth explained by quantity growth. This is measured as the ratio of the change in quantity to the sum of the changes in quantity and price during the period.

The median (mean) value of q^f is 0.85 (0.72), indicating that for the median firm, 85% of sales growth is driven by growth in quantity. A q^f value of one indicates that sales growth is entirely attributed to shifts in demand for the product. Thus, a higher value of q^f suggests a greater contribution of demand-led sales growth to overall sales growth.

Finally, we create variables to test the informational efficiency of quantity disclosures. We focus on two different types of variables: analyst revenue forecast accuracy and abnormal returns around earnings announcement dates. As noted in Table 1, we calculate *Rev surprise* as the difference between the actual revenues of the firm in the year and the average consensus revenue estimate of the firm right before the earnings announcements, divided by the average consensus revenues estimate for the firm in that year. This measure provides the percentage deviation between the mean analyst expectations and realized revenues. Because we intend to measure the deviation of the forecast from the actuals irrespective of the direction of the deviation from actuals, we consider the absolute value of the revenue surprise for our analysis. In the sample of revenue forecast data, we find that the median value of divergence between analyst forecasted revenues and actual revenues is 4.7%.

For the second measure, we calculate the cumulative abnormal return (CAR) of the stock for a small window around earnings announcement dates. Specifically, we first calculate the buy-and-hold returns of stocks around earnings announcement dates. We then adjust the stock return by the expected return over the same window around the earnings announcement date to calculate abnormal returns. We use four different benchmarks to arrive at the CAR: (i) market return during the holding period; (ii) CAPM expected return; (iii) Fama French 3 factor expected return (Fama and French (1996)); and (iv) 4-factor expected return (Carhart

(1997)). The daily benchmark returns used in the factor models are available in Agarwalla et al. (2013).[9] We then take the absolute values of the CARs to arrive at the magnitude of the abnormal market reaction.

Further, we vary the size of the window for computing CAR. For example, CAR[-1,1] represents the abnormal return for 3 days around the earnings announcement date. Similarly, we also compute CAR[0,2], CAR[0,4] and CAR[-2,2] for the days 0 to 2, 0 to 4, and -2 to 2 with respect to the earnings announcement. The median (mean) of the absolute value of CAR[-1,1] using the market-adjusted returns is 3.3% (4.6%). As expected, the factor model-adjusted returns are lower than the market-adjusted returns, and the average CAR decreases with the increase in risk factors.

V What information does quantity sold reveal?

The paper aims to investigate the information provided by the disclosure of product-level quantities sold. The decomposition allows us to examine the impact of a change in quantity after accounting for the impact of a change in prices. The part of quantity growth that is orthogonalized from changes in price reflects "shifts in demand" rather than movement along the curve. This leads to a natural question—does a shift in demand have a different relationship with future fundamentals than a change in demand brought about by price changes? We answer the above question by examining how the relative contribution of quantity growth vs price growth in current-period sales growth impacts future sales growth.

V.A Absence of quantity and price information

Before examining the information content in the product-level disclosures, we conduct a first-stage test to analyze the role of current sales growth in predicting future sales growth. That is, we test the persistence of sales growth in general. Recall the examples related

[9] We are unable to use the 5-fact model (Fama and French (2015)) due to unavailability of the risk-factor premiums for the two additional risk factors.

to Amazon and Home Depot mentioned in Section 3. Such firms provide revenue data without disclosing quantity and price information. In this section, we examine the revenue predictability of such firms by employing a first-order autoregressive model. The regression specification is as follows.

$$\Delta\text{Sales}_{\,i,j,t+1} = \beta_0 + \beta_1 * \Delta\text{Sales}_{\,i,j,t} + \gamma_i + \delta_j + \theta_t + \varepsilon_{i,j,t} \tag{1}$$

Here, $\Delta\text{Sales}_{\,i,j,t}$ represents sales growth, which is calculated as the percentage change in sales of a product j of a firm i in year t, compared to year t-1. Similarly, $\Delta\text{Sales}_{\,i,j,t+1}$ denotes the sales growth in the next year. We include firm and product-level fixed effects to control for time-invariant firm and product-level heterogeneity. We also include year-level fixed effects to account for time trends. Finally, we use a set of four control variables that could plausibly impact the sales growth of a firm: (i) size – logarithm of total assets of the firm; (ii) profitability – operating margin of the firm; (iii) industry level competition – logarithm of the Herfindahl-Hirschman Index (HHI) of the industry; and (iv) market share of the firm in the year (Gale (1972)).

We present the results in Table 4. In columns 1 and 2, we find a negative coefficient on current-year sales growth, suggesting that sales growth exhibits mean reversion over the next period. Specifically, in column 1, the coefficient is approximately -0.16, indicating that the next year's growth rate reduces by -0.16 pp if the current year's growth rate is 1 pp.

In a more restrictive design, we use firm X product level fixed effects to absorb time-invariant firm-product level heterogeneity. The intuition is that a product sold by a particular firm may differ from the same product sold by a different firm on quality. We report the results using firm X product-level fixed effects in columns 3 and 4. We find a slightly higher mean reversion with this adjustment relative to the results reported in columns 1 and 2.

Finally, in columns 5 and 6, we include product X year fixed effects along with firm X product fixed effects. The purpose is to absorb any time varying product level shocks along with firm specific product level shocks. The results remain almost unchanged. Thus, sales growth exhibits mean reversion that is broadly in line with prior literature (Nissim and Penman (2001), Fairfield et al. (2009)).

V.B Persistence of Sales Growth Caused By Demand Shock

Next, we ask whether sales growth exhibits persistence when contribution of quantity growth in overall sales growth is high, i.e., when there is a demand shock. We use the following regression specification to test the stated conjecture.

$$\begin{aligned}\Delta\text{Sales}_{i,j,t+1} =& \beta_0 + \beta_1 * \Delta\text{Sales}_{i,j,t} + \beta_2 * q^f_{i,j,t} + \beta_3 * q^f_{i,j,t} * \Delta\text{Sales}_{i,j,t} \\ &+ \gamma_i + \delta_j + \theta_t + \varepsilon_{i,j,t}\end{aligned} \tag{2}$$

Here, $\Delta\text{Sales}_{i,j,t}$ refers to the percentage change in sales of product j, of firm i, in year t, compared to the year t-1. Quantity growth factor (q^f) is defined in Section IV.B. An increase in q^f denotes a higher likelihood of positive demand shock, whereas a value of zero indicates that the entire sales growth is driven by price growth. We use the same fixed effects structure as in equation 1.

We determine the effect of demand shocks on future sales growth using two terms: the coefficient of q^f and the coefficient of the interaction between q^f and the current year's sales growth. The specification is in the spirit of the earnings persistence auto-regressive models developed in Richardson et al. (2005), Skinner and Soltes (2011), and Dechow et al. (2010).

We present the results in Table 5. In column 1, we find that the coefficient on $\Delta\text{Sales}_{i,j,t}$ (β_1) is negative, as reported before. In terms of economic magnitude, a product of a firm with a median level of sales growth (9.6 pp) in the current year but without any growth in quantity sold in the current year ($q^f = 0$, i.e., without any demand shock-related growth), is likely to experience a change of -2.14 pp in sales growth in the next year. Thus, sales growth aided by price growth does not seem to persist.

However, the coefficients of the term q^f and the interaction term $q^f \times \Delta\text{Sales}_{i,j,t}$ (β_2 and β_3, respectively) are both positive and statistically significant, with values of 0.97 and 0.09, respectively. This suggests that the observed mean reversion in sales growth is moderated in the presence of a demand shock (i.e., when q^f increases). Specifically, a 100% increase in q^f from 0 to 1 (i.e., q^f is 1 when entire revenue growth is attributed to quantity growth) corresponds to a 0.97 pp increase in next year's sales growth on account of q^f alone. Further, the coefficient of the interaction term (β_3) is 0.09. Thus, the increase of q^f from 0 to 1 for a firm with a median level of revenue growth in the current year translates into a 0.87 pp (=0.09 $\times$ 9.6 pp $\times$ 1) increase in the next year's sales growth due to the interaction term.

Therefore, in terms of combined economic magnitude, a demand shock leading to a rise in q^f from 0 to 1 for a firm that experiences a median level of sales growth in the current year is associated with a -0.29 pp change in sales growth in the next year.[10] This decline in sales growth by 0.29 pp is significantly lower than the expected decline of 2.14 pp when the sales were entirely driven by price growth (i.e., when q^f was 0). In other words, future sales growth is 86% higher when current sales growth is entirely driven by increases in quantity rather than prices (changing from -2.14 pp to -0.29). Thus, revenue growth driven by shifts in demand seems to persist.

Therefore, the information available in product-level quantities and prices provides valuable insight into future sales growth. Next, we repeat the test using firm X product-level fixed effects in columns 3 and 4 and find that our results are similar. Finally, our results largely remained unchanged in columns 5 and 6 where we include product X year level fixed effects along with firm X product fixed effects. Overall, our results indicate that sales growth is persistent when driven by quantity rather than product price growth.

V.C How Long Does The Quantity Effect Persist?

Having established that the current year's quantity growth is positively associated with the next year's sales growth, we ask how long the impact persists. In other words, we seek

[10]Note that the median level of sales growth is 9.6 pp. Therefore, an 9.6 pp increase in sales growth with an increase in q^f by 1 leads to (i) a 2.14 pp decline in future sales growth due to mean reversion, (ii) a 0.97 pp increase due to an increase in q^f by 1; and (iii) a 0.87 pp increase due to the interaction term between q^f and ΔSales. Overall, it leads to a 0.29 pp decline in sales growth in the next year.

to understand whether a change in quantity in one year is associated with higher revenue growth beyond the immediate succeeding year. To this end, we create an impulse response function to analyze the effect of quantity growth on revenue growth over subsequent years. Specifically, we employ the following regression equation:

$$\begin{aligned}\Delta\mathrm{Sales}_{i,j,t+1} = &\beta_0 + \beta_1 * \Delta\mathrm{Q}_{i,j,t} + \beta_2 * \Delta\mathrm{Q}_{i,j,t-1} + \beta_3 * \Delta\mathrm{Q}_{i,j,t-2} + \beta_4 * \Delta\mathrm{Q}_{i,j,t-3} + \beta_5 * \Delta\mathrm{Q}_{i,j,t-4} + \\ &\eta_1 * \Delta\mathrm{Sales}_{i,j,t} + \eta_2 * \Delta\mathrm{Sales}_{i,j,t-1} + \eta_3 * \Delta\mathrm{Sales}_{i,j,t-2} + \eta_4 * \Delta\mathrm{Sales}_{i,j,t-3} + \\ &\eta_5 * \Delta\mathrm{Sales}_{i,j,t-4} + \gamma_i + \delta_j + \theta_t + \varepsilon_{i,j,t}\end{aligned} \tag{3}$$

Here, $\Delta\mathrm{Sales}_{i,j,t+1}$ is the dependent variable and denotes the revenue growth for the next year. The variable $\Delta\mathrm{Q}_{i,j,t}$ denotes the change in the quantity for the current year, i.e., the percentage change in the quantity of product j, of firm i, in year t, compared to the year t-1. Similarly, $\Delta\mathrm{Q}_{i,j,t-1}$, $\Delta\mathrm{Q}_{i,j,t-2}$, $\Delta\mathrm{Q}_{i,j,t-3}$, and $\Delta\mathrm{Q}_{i,j,t-4}$ denote the one, two, three and four year lagged values of change in quantities for the firm-product, respectively. Since sales growth exhibits mean reversion, we include the current year and up to four years of lagged sales growth of the firm product. Finally, we add firm, year, and product fixed effects.

To assess the impact of quantity growth on sales growth in subsequent years, we plot the coefficients of the lagged values of the quantity growth in Figure 1. The graph shows that quantity growth positively affects revenue growth, and the impact persists for up to five years. That is, quantity growth can help predict future revenue growth for up to five years. Similarly, we also plot the coefficients of the lagged sales growth coefficients in Figure 2. As expected, we find that the lagged revenue growth has a negative effect on future sales growth.

VI Informational Efficiency of Additional Disclosures

Having shown that product-level disclosures provide information about the persistence of sales growth, we next ask: Do such disclosures help improve stock price efficiency or reduce the same by crowding out private information production? We answer this question by examining two measures of stock price efficiency. The first measure is the accuracy of analysts' revenue forecast (Ertimur et al. (2003), Jegadeesh and Livnat (2006), Keung (2010), Bochkay and Joos (2021)), and the second measure is the stock price reaction to earnings announcement (Easton and Zmijewski (1989), Francis et al. (2002)).

VI.A Accuracy of Analysts' Revenue Forecasts

Our first measure directly examines whether quantity-related disclosures crowd out private information production by examining the accuracy of analysts' forecasts. Suppose the disclosure of product level quantity sold is informative about the future sales growth of firms and does not crowd out private information production by analysts. In that case, the absence of information should lead to higher uncertainty among analysts about firms' future revenue. This should increase their errors. If, on the other hand, the disclosure of quantity information crowds out private information production, then its discontinuance should improve the accuracy of analysts' forecasts.

To test the above hypotheses, we employ a DiD specification. Note that the treatment here is the discontinuation of the quantity disclosure. Therefore, an ideal control group should consist of firms subject to the regulation before and after 2011. Unfortunately, we do not have any such category of firms. Given the above limitation, we use firms in service industries as the control group because they were never subject to the disclosure requirement. In other words, due to data limitations, we consider firms that were always treated as the control group and the firms that were treated after 2011 as the treated group. Since service firms remain unaffected, they constitute a valid control group.

We acknowledge that our DiD design differs slightly from commonly employed DiD designs. Unlike usual research designs where the treated and control group of firms are similar ex-ante and dissimilar post-intervention, our treated and control firms are dissimilar (in terms of disclosure) before the intervention but converge to similar disclosure requirement ex-post. The regression specification takes the following form. The regression specification is as follows.

$$\begin{aligned} \text{abs(Rev\_surprise)}_{i,t} =& \beta_0 + \beta_1 * \text{post}_t + \beta_2 * \text{treated}_i + \beta_3 * \text{post}_t * \text{treated}_i \\ & + \beta_4 * X_{i,t} + \gamma_i + \theta_t + \varepsilon_{i,t} \end{aligned} \tag{4}$$

Here, the dependent variable *abs(Rev_surprise)* is the absolute value of the average analyst revenue surprise for a firm in a year. We calculate the mean revenue surprise as the ratio of the actual revenue of the firm in a year minus the mean value of the most recent analysts' revenue forecasts for that year, divided by the mean value of the most recent analysts' revenue forecasts for that year. Because our focus is on the magnitude of the surprise and not its direction, we calculate the absolute value of the surprise as shown below.

$$\text{abs(Rev\_surprise)}_{i,t} = abs(\frac{actual\_revenue - mean\_revenue\_forecast}{mean\_revenue\_forecast}) \tag{5}$$

We use the sample for the years 2007 to 2016. The variable *post* is a time indicator variable set to one for the years 2012 to 2016 when the product quantity disclosure did not apply and zero for the years 2007 to 2011 when disclosures were mandatory.[11] The variable 'treated' takes a value of one for firms that belong to the manufacturing sector and zero for firms in the services sector. We include a set of three control variables: operating profit margin, size of the firm, and market share of the firm in the industry. All these variables can potentially influence the abnormal returns of the firms (Abarbanell and Bushee (1998), Battalio and Mendenhall (2005)). We employ firm-fixed effects and year-fixed effects to control for firm-level heterogeneity and time trends. The coefficient of interest is β_3, which

[11] We limit our data to 2016 because India adopted the revised accounting standards from the financial year 2017 onwards. The new reporting mandates can potentially conflate the impact of the product-level disclosures we study.

provides the effect of the discontinuation of disclosure on the magnitude of analysts' revenue forecast errors in a DiD sense.

We present the results in Table 6. In columns 1 and 2, we find that the coefficient of the interaction term is positive and statistically significant. Thus, analysts' estimates of revenues seem to diverge more after the change in financial statement reporting requirements. Specifically, in column 2, which shows the estimates for the full-fledged specification, we find that the coefficient of the DiD term is 13.42. Since the unconditional median of revenue forecast errors is 4.7%, the coefficient represents a 2.86 times increase in the size of errors in analysts' revenue estimates. Thus, the increase in analysts' errors after the discontinuation of quantity disclosure suggests that the disclosure of product-level quantity information enhanced stock price efficiency.

Next, in columns 3 and 4, we test for the existence of any pre-trends in revenue surprise even before the disclosure regulation came into effect. None of the interaction terms with the pre-event years and the treatment variable is statistically distinguishable from zero. However, the positive difference shows up after the cessation of required disclosures. Thus, the results are unlikely due to a mechanical continuation of any pre-existing trends.

VI.B Market Reaction to Earnings Announcements

As an additional test of the impact of quantity disclosures on stock price efficiency, we compare the abnormal stock returns around earnings announcements before and after the discontinuation of mandatory quantity disclosures. A reduction in the informational efficiency of a stock is likely to increase the abnormal stock price reaction to the announcement of accounting results.

We conduct event studies to calculate the absolute value of the cumulative abnormal returns (CAR) for firms around their earnings announcement dates (Aharony and Swary (1980), Bernard and Thomas (1989)). We then examine whether the absolute CAR for firms is different during the post-period as compared to the pre-period.

To conduct the event study, we consider the earnings announcements during the ten years around the disclosure regulation in 2012. We consider the years 2012 to 2016, when the product quantity disclosure did not apply, as the post-period and the years 2007 to 2011, when disclosures were mandatory, as the pre-treatment period. Further, we drop firms that do not have at least one observation with CAR in the pre-period or the post-period. That leaves us with 2,166 distinct manufacturing firms with 9,247 earnings announcement dates where CARs are available.

We calculate the CARs by cumulating the daily holding period return of the stock over a short window around the earnings announcement dates and then deducting the expected return for that window. Because we are interested in the magnitude of the abnormal return and not the sign, we calculate the absolute values of the CARs for each event window. Finally, we calculate the average value of absolute CARs for the firms during the pre-period and the post-period. Our objective is to test whether the average magnitude of abnormal returns differs before and after the withdrawal of the product quantity disclosures.

We tabulate the results in Table 7. Here, the *Return window* denotes the short window around the earnings announcement date for which the CAR is calculated. We calculate the CARs using several short-term windows around the earnings announcement dates. For instance, CAR[-1,1] represents the cumulative abnormal return for the stock for the days from T-1 to T+1, where T is the earnings announcement date. Similarly, we also calculate the abnormal returns using windows of [0,2], [0,4], and [-2,2].

Further, our CAR calculations can be sensitive to the market return benchmark used to arrive at the abnormal portion of the daily returns. We, therefore, use several different benchmarks to calculate the CARs. In rows 1 to 4, we use the holding period return of the market index portfolio as the benchmark. In rows 5 to 8, we calculate the CARs for each holding period by adjusting the expected CAPM return for that window. We infer CAPM beta using the historical data of daily returns over the previous one-year period (250 trading days). In rows 9 to 12, we use the Fama-French 3-factor model (Fama and French (1996)) to arrive at the stock's expected return, which is then used to calculate the CAR of the stock. Finally, in rows 13 to 16, we use the 4-factor model developed by Carhart (1997), which includes the momentum factor in addition to the FF 3-factor model to arrive at the abnormal return of the stock.[12]

The columns *Mean abs(CAR)* present the average of the absolute values of the abnormal returns for the pre-period and the post-period. We then test whether the difference in absolute CARs between pre- and post-period is statistically different. We find that, across the specifications, the post-period absolute CAR is significantly higher than the pre-period value of the absolute CAR. For instance, the average magnitude of three-day market-adjusted CAR around the earnings announcement date (i.e., CAR[-1,1]) is 42 bps higher in the absence of product-level information. This increase in the absolute CAR is an economically sizeable 9% of the absolute average market-adjusted CARs observed during the pre-period.

Note that the 42 bps change in market value is the average of the market reactions per announcement. Therefore, the overall economic impact on the market value of firms is likely to be several times larger. Within our sample period, there are 5 earnings announcements after the discontinuation of quantity disclosures. Therefore, the overall economic impact within our sample period is likely to be 2.1 pps. This is likely to be the lower bound as effect is likely to persist beyond our sample period. Similarly, we observe a significant increase in the magnitude of the CARs across all return windows and market risk-factor benchmarks.

In summary, our findings are consistent with public disclosure of product-level information leading to improvement in stock market efficiency, as evident from the lower CARs surrounding the earnings announcement dates in the pre-period.

VI.B.1 Market Reaction for Control Firms

A reader may be concerned that the above findings are attributable to some time-varying endogenous factor that is correlated with the cessation of mandatory disclosure. Even after a

[12]We obtained the market risk factors for the Fama French 3-factor model and the Carhart 4-factor model from Agarwalla et al. (2013). The data are available on the website: `https://faculty.iima.ac.in/iffm/legacy/`.

careful analysis of Indian regulations relating to accounting disclosures, we could not identify any such endogenous factors. Nonetheless, we conduct a robustness test to examine whether a similar increase in the magnitude of abnormal returns is observed in firms that are not impacted by the disclosure regulation.

As noted in Section VI.A, the firms belonging to the service industry were not subjected to disclosure requirements during the pre-period. That is, nothing changed for the service firms from the treatment year. Therefore, we test whether the CARs for service industry firms also increased in the post-treatment period.

We present the results for the changes in absolute CARs for the service industry firms in Table 8. Here, we replicate the event study specifications that are shown in Table 7 for the service sector firms. As shown in the table, we find that the differences between the absolute value of CARs in the post-period and the pre-period are largely statistically insignificant. Even the magnitude of the differences in average CARs is negligible in most specifications.[13] The absence of any effect on the service firms suggests that the increase in the size of abnormal returns observed in manufacturing firms is likely due to the discontinuation of product-level disclosures.

VI.B.2 Market Reaction using Difference-in-Differences Approach

To further mitigate residual concerns regarding endogenous factors influencing the shift in market reactions to earnings announcements, we conduct a robustness test using a DiD specification similar to equation 4. The regression specification is as follows.

$$\text{abs(CAR)}_{i,t} = \beta_0 + \beta_1 * \text{post}_t + \beta_2 * \text{treated}_i + \beta_3 * \text{post}_t * \text{treated}_i + \beta_4 * X_{i,t} + \gamma_i + \theta_t + \varepsilon_{i,t} \tag{6}$$

Here, $abs(CAR)$ is the absolute value of the 3-day abnormal returns of the company's stock around the earnings announcement date. We calculate abnormal returns using the market index returns or CAPM-expected returns as the benchmark normal returns. All the above

[13]Note that we find a statistical difference for CAPM adjusted CAR[0,2] for the service sector firms. However, the CAR is negative in this case, whereas the same for manufacturing firms is positive.

variables in the specification are the same as mentioned in section VI.A. The coefficient of interest is β_3, which provides the effect of the regulatory change on the abnormal returns in a DiD sense.

We present the results in Table A2 of the online appendix. We use the CAR for the 3-day window around the earnings announcement date as the dependent variable (CAR[-1,1]). In columns 1 and 2, we use the market-adjusted CAR, whereas columns 3 and 4 use the CAPM-adjusted CAR.

In columns 1 and 2, we find that the coefficient of the DID interaction term is positive and statistically significant, suggesting that the abnormal returns around earnings announcements increase after the cessation of the disclosure requirement. The coefficient of 0.43 percentage points is economically meaningful because it represents 13% of the median value of the average absolute 3-day market-adjusted CAR. In columns 3 and 4, we use CAPM-adjusted CAR and find similar results.[14]

Overall, our inferences from the robustness tests using the DiD design are similar to the findings of the event study. That is, the removal of product quantity disclosure reduces the efficiency of stock prices and results in higher abnormal returns around earnings announcement dates.

VII Robustness Tests

Our results in sections VI.A and VI.B show the impact of non-disclosure of product-level information using the differential impact on manufacturing firms over service sector firms. We acknowledge that concerns may arise because manufacturing and service sector firms differ on several dimensions. To address theses concerns, we conduct additional robustness tests. In the first robustness test, we employ an alternate definition of treated and control firms; in the second, we create a balanced set of treated and control firms by matching the

[14]In untabulated results, we find that our inferences are qualitatively similar when we use the Fama French 3-factor model or Carhart 4-factor model for determining the CARs.

groups of firms based on observable characteristics.

VII.A Alternate identification

Here, we conjecture that quantities and prices of products sold to end customers (and usually a part of the consumer price index or the CPI) are likely to be observed more easily relative to quantities and prices of intermediate products (usually part of the producer price index-PPI). The intuition is that prices of finished products bought by end consumers are more readily verifiable in the market, making it less costly for analysts to collect such data. Consider a hypothetical analyst collecting data on two products: the price of a sports shoe, which is a finished good and part of the consumer price index (CPI), and the wholesale prices of rubber, a raw material that is used in the production of shoes and is part of the producer price index (PPI). In this scenario, it is more straightforward and less costly to observe the prices and infer the quantity sold from the revenues and prices of the manufactured shoe in the retail market than to observe the prices and quantities of rubber in the wholesale markets. This is because CPI products are often traded in open markets, and their prices are publicly available. Whereas, PPI items usually trade between fewer buyers and sellers, and their prices are opaque and are impacted by long-term contracts, costs of raw materials and services, etc.; thus, prices of PPI items are not observed directly and can be costly to ascertain.

We exploit the above differences to demarcate industries that primarily manufacture products categorized under the PPI as the treated sample. We identify industries that primarily produce products falling under the CPI as the control sample. To determine these treated and control groups, we rely on the list of industries mapped by Cotton and Garga (2022) as CPI or PPI product-based industries. We then replicate our DiD tests using this identification to estimate the effect of disclosures on informational efficiency.

We present the results in Table A3 of the Online Appendix. In columns 1 and 2, we replicate Equation 4 and report the impact on analysts' revenue forecast errors. In columns

3-6, we use Equation 6 to estimate the impact on CAR around earnings announcements. The even-numbered columns include the control variables. Throughout the specifications, we observe that our inferences remain unchanged. Thus, our findings are consistent with the conclusion that public disclosure of product-level data leads to higher informational efficiency of stock prices.[15]

VII.B Matching between treatment and control groups

In the final robustness test, we address concerns about differences between the treated and control groups by using matching techniques. Specifically, we employ entropy balancing to match treated firms with control firms based on key dimensions such as asset size, sales, and profitability.

We then rerun the DiD specification equation on the balanced sample of matched firms. The results are presented in Table A6 of the online appendix. Columns 1 and 2 display the estimates for equation 4, while columns 3 to 6 present the findings for the regression specification 6. Across all specifications, the results remain consistent with our earlier findings. Specifically, the disclosure of price and quantity of products sold by firms enhances the informativeness of stock prices and does not appear to crowd out the assimilation of private information.

VIII Conclusion

We examine the implications of public disclosures on market efficiency by using a unique regulatory regime in India where manufacturing firms were required to disclose product

[15] For completion, we conduct event studies similar to those described in Section VI.B separately for PPI and CPI firms. We report the results in Table A4 for PPI firms and Table A5 for CPI firms. These tables mimic Tables 7 and Table 8. As expected, we find an increase in abnormal returns for PPI firms after the discontinuation of quantity disclosures. For CPI firms, the market reaction is significant in most cases. In two specifications, we find a decline in abnormal returns for CPI firms. Given the above results, it is reasonable to conclude that the abnormal returns in response to earnings announcements increase more for PPI (treated) firms than CPI (control) firms.

quantities and prices until 2011. Specifically, we try to answer two pertinent questions related to the above disclosure. First, what additional information does the disclosure of product-level quantities and prices provide? Second, does this additional information improve or deteriorate stock price efficiency?

Disclosing product-level quantities and prices can help disaggregate revenue growth into growth due to 'shifts in demand' and growth due to 'movement along demand curve.' We find that the revenue growth component attributed to demand shocks provides crucial information about the persistence of revenues.

Next, we examine the efficiency with which additional information about the persistence of revenues is incorporated into stock prices. Theory shows that pubic disclosure of information can either improve or worsen informational efficiency. We test this hypothesis empirically using two different measures of market efficiency: accuracy of analysts' revenue forecasts and abnormal stock returns to earnings announcements. Our results show that the information contained in public disclosures of product-level quantities and prices improves the informational efficiency of stock prices.

Thus, we find a unique case where an attempt by an emerging economy to follow globally established standards reduces the informational efficiency of stock prices. Our results suggest that investors in India are likely to be better served by reverting to the pre-2011 regime with respect to quantity and price disclosures. Global regulators may also want to consider making product and price disclosures mandatory for all firms, subject to the usual caveats associated with the difficulty of adjudicating policy decisions from one setting and from archival studies of this kind without a full consideration of social costs and benefits from mandatory disclosure.

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Figure 1: IMPULSE RESPONSE- QUANTITY

The figure plots the association between revenue growth in a year and the quantity growth during the five preceding years.

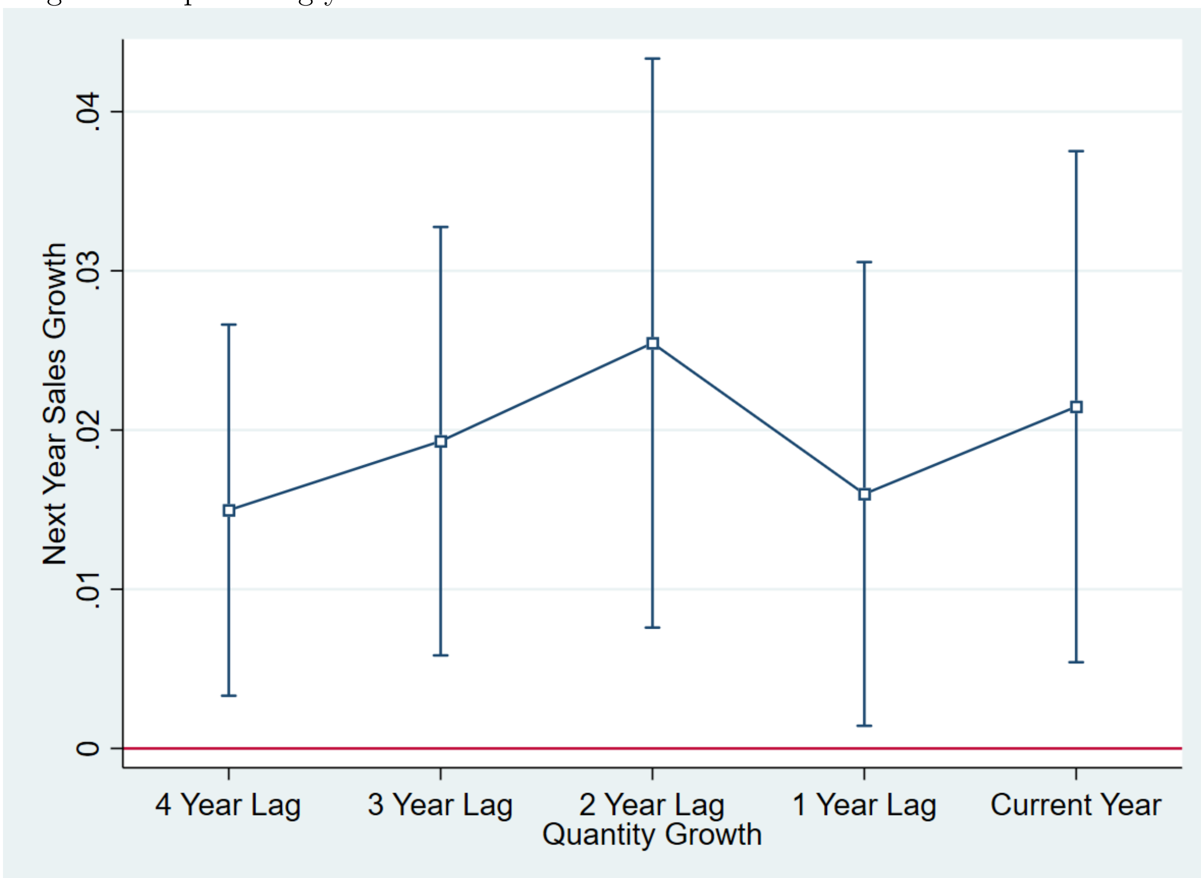

Figure 2: Impulse Response- Sales

The figure plots the association between revenue growth in a year and the revenue growth during the five preceding years.

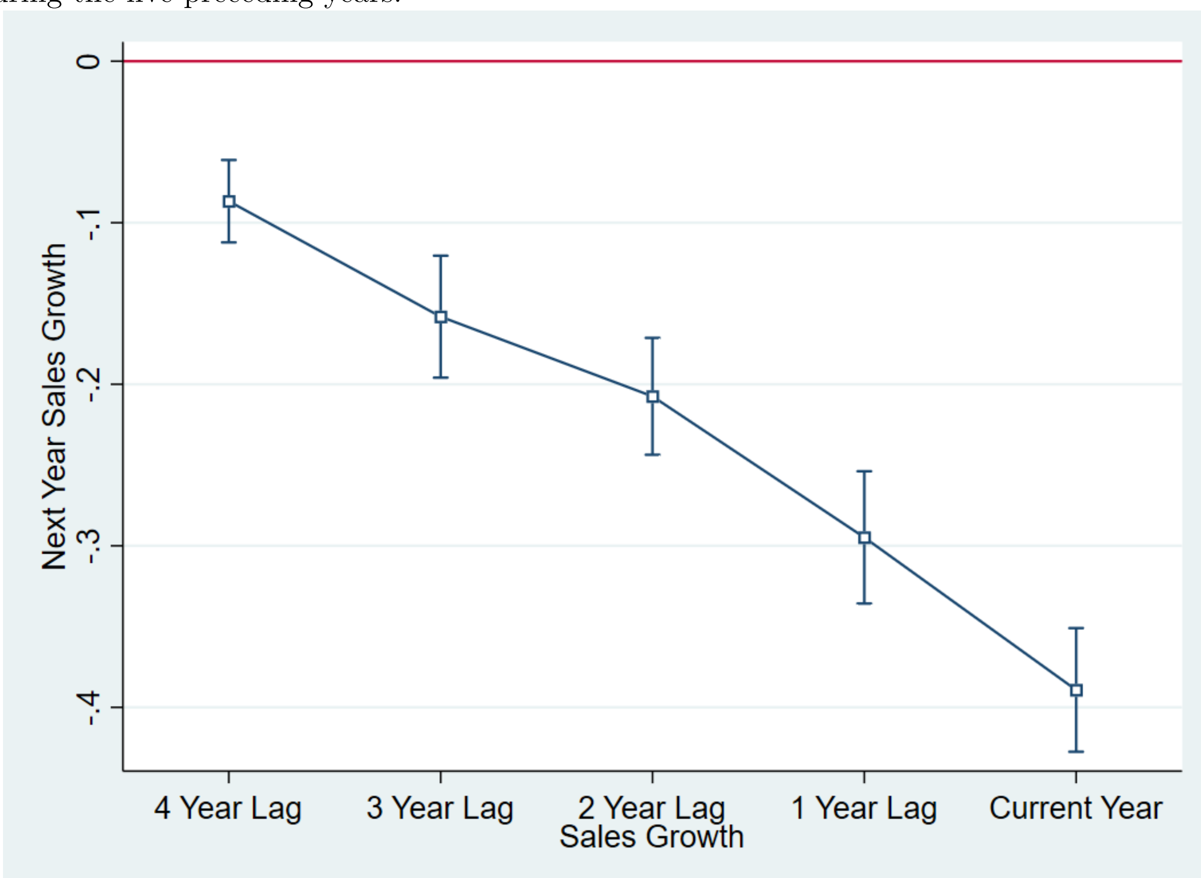

TABLE 1: VARIABLE DEFINITION

Variable Name	Definition
ΔSales	The percentage change in sales of a firm's product in a year compared to the previous year.
ΔQ	The percentage change in the quantity of a firm's product sold in a year compared to the previous year.
ΔP	The percentage change in the selling price of a product of a firm in a year.
q^f	The variable stands for 'quantity growth factor.' It is the ratio of quantity growth over the sum of price growth and quantity growth for a firm's product in a year.
CAR[-1,1]	It denotes the cumulative abnormal return of the stock over the three days around an earnings announcement. That is, the excess of the 3-day buy and hold return of stock around the earnings announcement date over the 3-day expected return. The expected return is calculated using four methods: Market index return, CAPM model, 3-factor model, and 5-factor model. We calculate the CAPM expected return by calculating the CAPM beta of the stock from the previous 360 days of stock return and market return. Similarly, we also calculate the expected returns of the 3-Factor and 4-Factor models using the risk factor betas from the previous 360 days.
abs(CAR[-1,1])	The absolute value of the CAR[-1,1] is expressed in percentages.
Rev surprise	It is calculated as the difference between the actual revenue of the firm in the year and the mean consensus revenue estimate of the firm, divided by the mean consensus revenue estimate of the firm. Revenue surprise is expressed in percentages.
abs(Rev surprise)	The absolute value of *Rev surprise* expressed in percentage. A higher value of abs(Rev surprise) indicates that the analysts fared poorly in predicting the revenues of the firm.
Size	Natural logarithm of the total assets of the firm in a year.
Profitability	The operating profit margin of the firm in the year.
log(HHI)	The logarithm of the HHI of the industry calculated in the year. HHI stands for the Herfindahl-Hirschman index (HHI) of the industry in the year. Here, HHI is calculated as the sum of squares of the market share of firms' revenues in the industry in the year. A lower value of HHI indicates higher competition in the industry.
Market share	The ratio of assets of the firm to the total of the industry the firm belongs to in a year.

TABLE 2: SAMPLE CONSTRUCTION

This table shows the steps to arrive at the sample used in the study.

Panel A: Sample Construction For Tests Examining The Association Between Variables	
Sample Period	2000-2011
Number of firm-product-year observations with product level information	2,70,614
Less: observation where annual sales growth cannot be calculated	81,639
Number of firm-product-year observations in final sample	1,88,975
Less: observations for which subsequent year's annual sales growth cannot be calculated	52,922
Number of observations available for regression	1,36,053
Number of firms	11,807
Number of products	22,672
Number of firm-product pairs	33,272
Number of firm-year pairs	58,423

Panel B: Sample Construction: Market Reaction	
Sample Period	2007-2016
Number of firms with stock returns information for at least one year	3,522
Number of manufacturing firms with stock returns information for at least one year in both the pre- and post-treatment period	2,166
Number of observations with stock returns information	13,036

Panel C: Sample Construction: Revenue forecast error	
Sample Period	2007-2016
Number of firms with Revenue forecast information for at least one year	425
Number of treated firms with Revenue forecast information for at least one year	310
Number of observations with Revenue forecast information	2,452

TABLE 3: Summary Statistics

This table shows the descriptive statistics for the variables used in the study.

Variables	**Q1**	**Median**	**Q3**	**Mean**	**Std Dev**
Δ*Sales (%)*	-17.28	9.57	44.50	68.32	288.48
ΔQ *(%)*	-20.57	5.02	38.52	91.35	461.59
ΔP *(%)*	-8.22	3.23	18.22	24.77	130.40
q^f	0.25	0.85	1.14	0.72	2.63
Market adjusted abs(CAR[-1,1]) in %	1.47	3.29	6.37	4.64	4.46
CAPM adjusted abs(CAR[-1,1]) in %	1.36	3.21	6.14	4.49	4.34
3 Factor adjusted abs(CAR[-1,1]) in %	1.33	3.13	5.96	4.34	4.19
4 Factor adjusted abs(CAR[-1,1]) in %	1.30	3.12	5.93	4.32	4.17
abs(Rev Surprise) in %	2.00	4.68	9.10	9.07	19.31
Log(size)	5.11	6.32	7.75	6.48	2.01
Profitability in %	4.18	9.44	16.09	9.87	18.15
Log(HHI)	5.44	5.86	6.46	5.97	0.76
Market share in %	0.02	0.10	0.50	1.10	4.06

TABLE 4: Mean Reversion of Sales Growth

This table tests the association between sales growth in a year and its subsequent year at a firm-product level. The data are organized at a firm-product-year level for the period 1997 to 2011. The dependent variable is "$\Delta \text{Sales}_{i,j,t+1}$," which is the one-year lead value of growth in sales of a product of a firm under consideration. The independent variable "$\Delta \text{Sales}_{i,j,t}$" is the current period growth in sales of a product of a firm in a year. Both variables are expressed in percentages. We include a set of four control variables – size, profitability, industry competition, and market share of the firms – in the even-numbered columns. We use firm and product level fixed effects in columns 1 and 2, firm $\times$ product level fixed effects in columns 3 and 4, firm $\times$ product and product $\times$ year level fixed effects in columns 5 and 6, respectively. We also include year-level fixed effects in columns 1 to 4. We cluster the standard error at the NIC 5-digit industry level. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable			$\Delta \boldsymbol{Sales}_{i,j,t+1}$			
$\Delta Sales_{i,j,t}$	-0.1560***	-0.1523***	-0.1788***	-0.1757***	-0.1626***	-0.1583***
	[0.0070]	[0.0072]	[0.0068]	[0.0071]	[0.0122]	[0.0131]
Observations	130,112	112,351	128,329	110,775	47,749	41,253
R-squared	0.2572	0.2549	0.2830	0.2797	0.4515	0.4480
Controls	No	Yes	No	Yes	No	Yes
Firm Fixed Effects	Yes	Yes	No	No	No	No
Product Fixed Effects	Yes	Yes	No	No	No	No
Year Fixed Effects	Yes	Yes	Yes	Yes	No	No
Firm x Product Fixed Effects	No	No	Yes	Yes	Yes	Yes
Product x Year Fixed Effects	No	No	No	No	Yes	Yes

TABLE 5: QUANTITY GROWTH AND FUTURE SALES GROWTH

In this table we test whether sales growth driven by shifts in demand shock predicts persistence of sales growth. The data are organized at a firm-product-year level for the period 1997 to 2011. The dependent variable is "$\Delta\text{Sales}_{i,j,t+1}$," which is the one-year lead value of growth in sales of a product of a firm. The independent variable "$\Delta\text{Sales}_{i,j,t}$" is the current period growth in sales of a product of a firm in a year. The variable "$q^f_{i,j,t}$" is the quantity growth factor, which is calculated as the ratio of growth in quantity to the sum of the growth in quantity and growth in price of a product of the firm in the current year. We include a set of four control variables – size, profitability, industry competition, and market share of the firms – in the even numbered columns. We use firm and product level fixed effects in columns 1 and 2, firm × product level fixed effects in columns 3 and 4, firm × product and product × year level fixed effects in columns 5 and 6, respectively. We also include year-level fixed effects in columns 1 to 4. We cluster the standard error at the NIC five digit industry level. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable			$\Delta \boldsymbol{Sales}_{i,j,t+1}$			
$\Delta Sales_{i,j,t}$ * $q^f_{i,j,t}$	0.0914***	0.0893***	0.0897***	0.0866***	0.0950***	0.0886***
	[0.0118]	[0.0122]	[0.0115]	[0.0119]	[0.0191]	[0.0231]
$q^f_{i,j,t}$	0.9729***	0.9848***	0.9715***	0.9695***	1.2597***	1.0243**
	[0.2515]	[0.2392]	[0.2306]	[0.2219]	[0.4118]	[0.4061]
$\Delta Sales_{i,j,t}$	-0.2235***	-0.2185***	-0.2448***	-0.2397***	-0.2357***	-0.2278***
	[0.0113]	[0.0115]	[0.0108]	[0.0111]	[0.0177]	[0.0208]
Observations	129,738	112,043	127,959	110,471	47,601	41,150
R-squared	0.2591	0.2565	0.2852	0.2816	0.4554	0.4514
Controls	No	Yes	No	Yes	No	Yes
Firm Fixed Effects	Yes	Yes	No	No	No	No
Product Fixed Effects	Yes	Yes	No	No	No	No
Year Fixed Effects	Yes	Yes	Yes	Yes	No	No
Firm x Product Fixed Effects	No	No	Yes	Yes	Yes	Yes
Product x Year Fixed Effects	No	No	No	No	Yes	Yes

TABLE 6: REVENUE FORECAST ERROR

This table estimates the impact of product level disclosures on accuracy of analysts' revenue forecast using a DID design. The data are organized at a firm-year level span between 2007 to 2016. The dependent variable is *"abs(Rev surprise)"*, which is the absolute value of the revenue forecast error, that is calculated as the difference between actual revenue and the average value of analyst forecasts of revenue divided by the average value of analyst forecasts of revenue. The variable *"Post"* is set to one for the years 2012 and after and zero for the years before that. The variable *"Treated"* denotes manufacturing firms. In columns 3 and 4, we include interaction terms between $Treated$ and each year relative to the treatment year. For instance, $Year[+1]$ and $Year[-1]$ represent the first year before and after the treatment, respectively. We include the set of four control variables - size, profitability, industry competition, and market share of the firm - in the even numbered columns. We also include firm and year fixed effects across all the columns. The standard errors are adjusted for heteroskedasticity and clustered at the NIC five digit industry level. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)
		abs(Rev surprise)		
*Post * Treated*	14.2602**	13.4321**		
	[6.1131]	[5.7143]		
*Year[-5] * Treated*			-23.1345	-22.4453
			[16.4969]	[16.1592]
*Year[-4] * Treated*			-12.6930	-11.8014
			[13.8964]	[13.6176]
*Year[-3] * Treated*			-11.8255	-11.0249
			[13.4168]	[13.1830]
*Year[-2] * Treated*			3.5240	4.1286
			[5.9516]	[5.8128]
*Year[+1] * Treated*			6.6152*	6.4664*
			[3.8682]	[3.8857]
*Year[+2] * Treated*			7.1881	6.7713
			[4.4140]	[4.3776]
*Year[+3] * Treated*			7.9118*	7.5837*
			[4.1480]	[4.0782]
*Year[+4] * Treated*			8.1745*	7.7918*
			[4.3492]	[4.2614]
*Year[+5] * Treated*			8.6105*	8.7273*
			[4.6123]	[4.5558]
Controls	No	No	No	No
Firm Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Observations	2,405	2,404	2,405	2,404
R-squared	0.3229	0.3288	0.3402	0.3455

TABLE 7: Event Study - Earnings Announcements (Treated Firms)

In this table, we compare the abnormal price reaction of stocks to earnings announcements before and after the discontinuation of product level disclosures. We presents the event study for firms belonging to the manufacturing industry. The return window provides the length of the window around the earnings announcement date, for which the cumulative abnormal return (CAR) of the stock is calculated. CAR is calculated by subtracting the benchmark return from the holding period return of the stock during the return window. We use four different types of benchmark rates to calculate CAR; (i) Market return; (ii) CAPM return; (iii) 3-Factor model return (Fama and French (1996); and (iv) 4-Factor model return (Carhart (1997)). $CAR[-1, 1]$, $CAR[0, 2]$, $CAR[0, 4]$, and $CAR[-2, 2]$ denotes the CAR of the stock for the days -1 to 1, 0 to 2, 0 to 4, and -2 to 2 with respect to the earnings announcement date, respectively. The pre-preiod (post-period) *"Mean abs CAR"* is the average of the absolute value of the CARs for all the observations during years 2007 to 2011 (2012 to 2016). We test whether the difference between pre- and post-period *"Mean abs CAR"* is statistically different from zero.

Manufacturing industry firms								
			Pre period		*Post period*			
Benchmark	*Return window*	*N*	*Mean abs (CAR)*	*N*	*Mean abs (CAR)*	*Difference*	*t-stat*	*p-value*
Market return	CAR[0, 2]	3,828	0.0449	5,419	0.0475	0.0026***	2.73	0.01
Market return	CAR[0, 4]	3,828	0.0570	5,419	0.0600	0.0030**	2.54	0.01
Market return	CAR[-1, 1]	3,828	0.0444	5,419	0.0486	0.0042***	4.49	0.00
Market return	CAR[-2, 2]	3,828	0.0530	5,419	0.0569	0.0039***	3.42	0.00
CAPM	CAR[0, 2]	3,828	0.0434	5,419	0.0462	0.0028***	3.01	0.00
CAPM	CAR[0, 4]	3,828	0.0552	5,419	0.0583	0.0031***	2.67	0.01
CAPM	CAR[-1, 1]	3,828	0.0432	5,419	0.0470	0.0038***	4.12	0.00
CAPM	CAR[-2, 2]	3,828	0.0516	5,419	0.0549	0.0032***	2.94	0.00
3-Factor	CAR[0, 2]	3,828	0.0420	5,419	0.0447	0.0026***	2.89	0.00
3-Factor	CAR[0, 4]	3,828	0.0539	5,419	0.0562	0.0023**	2.04	0.04
3-Factor	CAR[-1, 1]	3,828	0.0419	5,419	0.0452	0.0033***	3.70	0.00
3-Factor	CAR[-2, 2]	3,828	0.0490	5,419	0.0523	0.0033***	3.14	0.00
4-Factor	CAR[0, 2]	3,828	0.0420	5,419	0.0445	0.0025***	2.83	0.00
4-Factor	CAR[0, 4]	3,828	0.0539	5,419	0.0559	0.0020*	1.77	0.08
4-Factor	CAR[-1, 1]	3,828	0.0418	5,419	0.0450	0.0031***	3.53	0.00
4-Factor	CAR[-2, 2]	3,828	0.0490	5,419	0.0521	0.0031***	2.95	0.00

TABLE 8: Event Study - Earnings Announcements (control firms)

In this table, we compare the abnormal price reaction of stocks to earnings announcements before and after the discontinuation of product level disclosures. We presents the event study for firms belonging to the service industry. The return window provides the length of the window around the earnings announcement date, for which the cumulative abnormal return (CAR) of the stock is calculated. CAR is calculated by subtracting the benchmark return from the holding period return of the stock during the return window. We use four different types of benchmark rates to calculate CAR; (i) Market return; (ii) CAPM return; (iii) 3-Factor model return (Fama and French (1996); and (iv) 4-Factor model return (Carhart (1997)). $CAR[-1,1]$, $CAR[0,2]$, $CAR[0,4]$, and $CAR[-2,2]$ denotes the CAR of the stock for the days -1 to 1, 0 to 2, 0 to 4, and -2 to 2 with respect to the earnings announcement date, respectively. The pre-preiod (post-period) *"Mean abs CAR"* is the average of the absolute value of the CARs for all the observations during years 2007 to 2011 (2012 to 2016). We test whether the difference between pre- and post-period *"Mean abs CAR"* is statistically different from zero.

Service industry firms

Benchmark	*Return window*	*N*	*Pre period Mean abs (CAR)*	*N*	*Post period Mean abs (CAR)*	*Difference*	*t-stat*	*p-value*
Market return	CAR[0, 2]	1,619	0.0454	2,170	0.0432	-0.0022	1.62	0.11
Market return	CAR[0, 4]	1,619	0.0556	2,170	0.0554	-0.0001	0.09	0.93
Market return	CAR[-1, 1]	1,619	0.0447	2,170	0.0451	0.0004	0.32	0.75
Market return	CAR[-2, 2]	1,619	0.0540	2,170	0.0537	-0.0003	0.19	0.85
CAPM	CAR[0, 2]	1,619	0.0444	2,170	0.0419	-0.0024*	1.79	0.07
CAPM	CAR[0, 4]	1,619	0.0543	2,170	0.0542	-0.0001	0.05	0.96
CAPM	CAR[-1, 1]	1,619	0.0435	2,170	0.0433	-0.0002	0.12	0.91
CAPM	CAR[-2, 2]	1,619	0.0530	2,170	0.0516	-0.0014	0.86	0.39
3-Factor	CAR[0, 2]	1,619	0.0424	2,170	0.0411	-0.0013	1.02	0.31
3-Factor	CAR[0, 4]	1,619	0.0525	2,170	0.0526	0.0000	0.03	0.98
3-Factor	CAR[-1, 1]	1,619	0.0420	2,170	0.0422	0.0002	0.14	0.89
3-Factor	CAR[-2, 2]	1,619	0.0506	2,170	0.0497	-0.0008	0.51	0.61
4-Factor	CAR[0, 2]	1,619	0.0422	2,170	0.0408	-0.0014	1.09	0.28
4-Factor	CAR[0, 4]	1,619	0.0524	2,170	0.0522	-0.0003	0.16	0.87
4-Factor	CAR[-1, 1]	1,619	0.0420	2,170	0.0421	0.0002	0.13	0.90
4-Factor	CAR[-2, 2]	1,619	0.0505	2,170	0.0492	-0.0013	0.81	0.42

Internet Appendix

TABLE A1: Financial Reporting Changes

The table presents the key changes brought about by the adoption of newer reporting format adopted by Indian companies.

Attribute	**Old Schedule VI**	**New Schedule VI**
Product level disclosures for manufacturing firms	Manufacturing companies need to disclosure product level break up of quantities sold and purchases purchase and their related revenues.	Manufacturing companies now need to disclose revenue from operation under three sub-heads: (i) sales from products, (ii) sales from services, and (iii) other operating revenues.
Format of balance sheet presentation	Horizontal or vertical format of presentation is allowed	Only vertical format of presentation is allowed
Rounding off of figures in financial statements	For companies with sales turnover of more than Rs 1 billion, round off to nearest hundreds, thousands, lakhs, millions	For companies with sales turnover of more than Rs 1 billion, round off to nearest lakhs, millions or crores
Presentation of current or non-current balance sheet items	Does not require companies to classify asset or liability items into current and non-current items.	Companies need to report asset and liability items under current and non-current subheadings. Thus, the revised reporting makes it easier to assess the current and non-current portions of assets and liabilities.
Presentation of borrowing	Short and long term borrowings are presented as different line items under the common head 'Loan funds'	Short and long term borrowings now presented under different sub-heads.
Presentation of disintegrated information	Has the concept of 'schedules', where disintegrated and detailed information about each line items of income statement and balance sheet are provided.	Switches to the concept of 'notes to accounts, where detailed information of each line item is provided
Trade creditors	Trade credit information provided under the head 'Sundry Creditors'	Renamed as Trade payables

TABLE A2: ABNORMAL MARKET RETURNS TO EARNINGS ANNOUNCEMENTS

In this table, we estimate the impact of product level disclosures on market reaction to earnings announcements using a DID design. The data are organized at a firm-year level span between 2007 to 2016. The dependent variable is *"abs(CAR[-1,1])"*, which is the absolute value of the cumulative abnormal return of the stock for the three day window around the earnings announcement. In columns 1 and 2 (3 and 4), *"abs(CAR[-1,1])"*, is calculated by adjusting the stock index return (CAPM expected return) during the same time frame. The variable *Post* is set to one for the years 2012 to 2016, zero otherwise. The variable *Treated* is set to one for manufacturing industry firms, and zero for service industry firms. We include the set of four control variables - size, profitability, industry competition and market share - in columns 2 and 4. We use firm fixed effects and year fixed effects across all columns.

	(1)	(2)	(3)	(4)
	Market adjusted		CAPM adjusted	
	abs(CAR[-1,1])			
*Post * Treated*	0.0041*	0.0043*	0.0040*	0.0042*
	[0.0022]	[0.0022]	[0.0022]	[0.0023]
Controls	No	Yes	No	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Observations	12,999	12,854	12,999	12,854
R-squared	0.2239	0.2264	0.2303	0.2327

TABLE A3: ALTERNATE IDENTIFICATION USING CPI/PPI INDUSTRIES

In this table, we estimate the impact of product level quantity disclosures on market reaction to earnings announcements and analysts' revenues forecast errors in a DID design using an alternate definition of treated/control firms. Here we consider the firms belonging to industries that primarily cater to PPI (CPI) products as the treated (control) industries. In columns 1 and 2 the dependent variable is the absolute value of the revenue forecast error. In columns 3 - 4 (5 -6) the dependent variable is market adjusted (CAPM adjusted) "$abs(CAR[-1,1])$." We include firm and year fixed effects across all columns. We include the set of four control variables - size, profitability, industry competition, and market share of the firm - in the even numbered columns. The standard errors are adjusted for heteroskedasticity and clustered at the NIC five digit industry level. ***, **, and * represent statistical significant at the 1%, 5%, and 10% levels respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
			Market adjusted		*CAPM adjusted*	
	abs(Rev surprise)		***abs(CAR[-1,1])***			
*Post * Treated*	16.6165***	15.9508***	0.0044**	0.0044**	0.0053**	0.0053**
	[2.9722]	[3.1479]	[0.0022]	[0.0022]	[0.0023]	[0.0023]
Controls	No	Yes	No	Yes	No	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,379	2,378	12,839	12,742	12,839	12,742
R-squared	0.3299	0.3367	0.2239	0.2262	0.2307	0.2326

TABLE A4: EVENT STUDY - EARNINGS ANNOUNCEMENTS (TREATED FIRMS (PPI))

In this table, we compare the abnormal price reaction of stocks to earnings announcements before and after the discontinuation of product level disclosures. We presents the event study for firms belonging to the PPI industry. The return window provides the length of the window around the earnings announcement date, for which the cumulative abnormal return (CAR) of the stock is calculated. CAR is calculated by subtracting the benchmark return from the holding period return of the stock during the return window. We use four different types of benchmark rates to calculate CAR; (i) Market return; (ii) CAPM return; (iii) 3-Factor model return (Fama and French (1996); and (iv) 4-Factor model return (Carhart (1997)). $CAR[-1,1]$, $CAR[0,2]$, $CAR[0,4]$, and $CAR[-2,2]$ denotes the CAR of the stock for the days -1 to 1, 0 to 2, 0 to 4, and -2 to 2 with respect to the earnings announcement date, respectively. The pre-preiod (post-period) *"Mean abs CAR"* is the average of the absolute value of the CARs for all the observations during years 2007 to 2011 (2012 to 2016). We test whether the difference between pre- and post-period *"Mean abs CAR"* is statistically different from zero.

PPI industry firms - Absolute cumulative abnormal returns around earnings announcement

Benchmark	*Return window*	*N*	*Pre period* *Mean abs (CAR)*	*N*	*Post period* *Mean abs (CAR)*	*Difference*	*t-stat*	*p-value*
Market return	CAR[0, 2]	3,792	0.0456	5,274	0.0481	0.0025***	2.61	0.01
Market return	CAR[0, 4]	3,792	0.0573	5,274	0.0610	0.0036***	3.03	0.00
Market return	CAR[-1, 1]	3,792	0.0448	5,274	0.0474	0.0043***	4.55	0.00
Market return	CAR[-2, 2]	3,792	0.0534	5,274	0.0579	0.0045***	3.88	0.00
CAPM	CAR[0, 2]	3,792	0.0441	5,274	0.0469	0.0028***	2.96	0.00
CAPM	CAR[0, 4]	3,792	0.0556	5,274	0.0596	0.0040***	3.37	0.00
CAPM	CAR[-1, 1]	3,792	0.0435	5,274	0.0477	0.0042***	4.48	0.00
CAPM	CAR[-2, 2]	3,792	0.0522	5,274	0.0559	0.0037***	3.29	0.00
3-Factor	CAR[0, 2]	3,792	0.0426	5,274	0.0453	0.0027***	2.99	0.00
3-Factor	CAR[0, 4]	3,792	0.0541	5,274	0.0574	0.0033**	2.91	0.00
3-Factor	CAR[-1, 1]	3,792	0.0421	5,274	0.0459	0.0038***	4.18	0.00
3-Factor	CAR[-2, 2]	3,792	0.0495	5,274	0.0530	0.0035***	3.33	0.00
4-Factor	CAR[0, 2]	3,792	0.0425	5,274	0.0452	0.0027***	2.92	0.00
4-Factor	CAR[0, 4]	3,792	0.0540	5,274	0.0571	0.0031***	2.73	0.01
4-Factor	CAR[-1, 1]	3,792	0.0420	5,274	0.0457	0.0037***	4.10	0.00
4-Factor	CAR[-2, 2]	3,792	0.0496	5,274	0.0528	0.0033***	3.10	0.00

Table A5: Event Study - Earnings Announcements (Control Firms (CPI))

In this table, we compare the abnormal price reaction of stocks to earnings announcements before and after the discontinuation of product level disclosures. We presents the event study for firms belonging to the CPI industry. The return window provides the length of the window around the earnings announcement date, for which the cumulative abnormal return (CAR) of the stock is calculated. CAR is calculated by subtracting the benchmark return from the holding period return of the stock during the return window. We use four different types of benchmark rates to calculate CAR; (i) Market return; (ii) CAPM return; (iii) 3-Factor model return (Fama and French (1996); and (iv) 4-Factor model return (Carhart (1997)). $CAR[-1,1]$, $CAR[0,2]$, $CAR[0,4]$, and $CAR[-2,2]$ denotes the CAR of the stock for the days -1 to 1, 0 to 2, 0 to 4, and -2 to 2 with respect to the earnings announcement date, respectively. The pre-preiod (post-period) *"Mean abs CAR"* is the average of the absolute value of the CARs for all the observations during years 2007 to 2011 (2012 to 2016). We test whether the difference between pre- and post-period *"Mean abs CAR"* is statistically different from zero.

CPI industry firms - Absolute cumulative abnormal returns around earnings announcement

Benchmark	*Return window*	*N*	*Pre period* *Mean abs (CAR)*	*N*	*Post period* *Mean abs (CAR)*	*Difference*	*t-stat*	*p-value*
Market return	CAR[0, 2]	1,590	0.0446	2,218	0.0419	-0.0027**	1.97	0.05
Market return	CAR[0, 4]	1,590	0.0551	2,218	0.0534	-0.0017	1.00	0.32
Market return	CAR[-1, 1]	1,590	0.0444	2,218	0.0440	-0.0004	0.28	0.78
Market return	CAR[-2, 2]	1,590	0.0538	2,218	0.0523	-0.0015	0.84	0.40
CAPM	CAR[0, 2]	1,590	0.0431	2,218	0.0406	-0.0026*	1.90	0.06
CAPM	CAR[0, 4]	1,590	0.0537	2,218	0.0519	-0.0019	1.10	0.27
CAPM	CAR[-1, 1]	1,590	0.0431	2,218	0.0419	-0.0012	0.88	0.38
CAPM	CAR[-2, 2]	1,590	0.0523	2,218	0.0500	-0.0023	1.35	0.18
3-Factor	CAR[0, 2]	1,590	0.0412	2,218	0.0397	-0.0016	1.19	0.23
3-Factor	CAR[0, 4]	1,590	0.0518	2,218	0.0497	-0.0021	1.27	0.20
3-Factor	CAR[-1, 1]	1,590	0.0416	2,218	0.0409	-0.0007	0.50	0.61
3-Factor	CAR[-2, 2]	1,590	0.0494	2,218	0.0482	-0.0012	0.78	0.44
4-Factor	CAR[0, 2]	1,590	0.0410	2,218	0.0393	-0.0017	1.29	0.20
4-Factor	CAR[0, 4]	1,590	0.0519	2,218	0.0493	-0.0026	1.60	0.11
4-Factor	CAR[-1, 1]	1,590	0.0415	2,218	0.0407	-0.0009	0.66	0.50
4-Factor	CAR[-2, 2]	1,590	0.0493	2,218	0.0477	-0.0016	1.03	0.30

TABLE A6: Matched Sample Tests

In this table, we estimate the impact of product level quantity disclosures on market reaction to earnings announcements and analysts' revenues forecast errors after controlling for the differences between the two group of firms using entropy balancing technique. We obtain a matched sample of treated and control firms on the basis of size, operating performance, financial leverage, and ROA by employing the entropy balancing technique. In columns 1 and 2 the dependent variable is the absolute value of the revenue forecast error. In columns 3 - 2 (5 -6) the dependent variable is market adjusted (CAPM adjusted) "$abs(CAR[-1,1])$." We include firm and year fixed effects across all columns. We include the set of four control variables - size, profitability, industry competition, and market share of the firm - in the even numbered columns. The standard errors are adjusted for heteroskedasticity and clustered at the NIC five digit industry level. ***, **, and * represent statistical significant at the 1%, 5%, and 10% levels respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
			Market adjusted		*CAPM adjusted*	
	abs(Rev surprise)			***abs(CAR[-1,1])***		
*Post * Treated*	8.7210*	8.0826*	0.0043*	0.0045*	0.0043*	0.0046*
	[1.9140]	[1.9222]	[0.0026]	[0.0025]	[0.0026]	[0.0025]
Controls	No	Yes	No	Yes	No	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,392	2,391	12,193	12,137	12,193	12,137
R-squared	0.3642	0.3696	0.2327	0.2343	0.2401	0.2409