Systematic Risk and the Bullwhip Effect in Supply Chains

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Abstract

The variance of demand can be divided into two components, a systematic risk component that occurs due to economic factors, and an idiosyncratic noise component. Operational hedging addresses the total variance of demand, whereas financial hedging is useful against systematic risk. We investigate the systematic risk component of demand uncertainty using industry-level data for the manufacturing, wholesale trade, and retail trade sectors of the U.S. economy, and applying sales as a proxy for demand. We show that the degree of systematic risk increases substantially from retailers to wholesalers to manufacturers. Investigating two potential sources of this phenomenon, amplification of production series as predicted by the bullwhip effect and aggregation of orders placed by downstream industries, we find evidence supporting the latter. Our result have implications for the relative values of different operational and financial hedging strategies chosen by a firm. It is particularly relevant to events such as the 2008-09 economic recession and the post-recession recovery.

Key words: Systematic risk, order aggregation, empirical analysis, supply webs, hedging.

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1. Introduction

The variance of demand can be divided into two components. A *systematic risk* component refers to the variance that occurs due to economic factors. It can be measured using the correlation coefficient of demand uncertainty with the return on a broad financial market index. An *idiosyncratic noise* or white noise component refers to the variance that is independent of economic factors. Recent research on the operations-finance interface shows that firms can invest in different types of strategies to mitigate the cost impact of the systematic risk and idiosyncratic noise components of the variance of demand. In particular, Chod et al. (2010) show that financial hedging can be used to mitigate systematic risk whereas operational hedging can be used to mitigate idiosyncratic noise. Moreover, these two types of strategies can be complements or substitutes depending on the operational parameters of the firm and the type of operational hedging employed.

Building on this literature, we can further say that the relative values of operational and financial hedging will depend on the amount of systematic risk in demand. For example, suppose that a firm with two products, identical in demand distributions and price-cost parameters, is considering an investment in flexible capacity that can produce either product. This mechanism will provide a hedge against demand uncertainty, and is known in the literature as a type of risk pooling (Cachon and Terwiesch (2009), Jordan and Graves (1995)) or product flexibility (Chod et al. 2010). First, let both products have correlation coefficients of 0.9 with the financial market return. Then, risk pooling will be less valuable for these products because their systematic risk is high and their demands will tend to move together, thus providing little benefit from pooling. Moreover, a high systematic risk implies a high cost of capital, so that the net present value of the investment in flexible capacity will be low. However, the firm will be able to hedge away the systematic risk in demand using traded instruments in the financial market. In comparison, suppose that the products have correlation coefficients of 0.0 with the financial market return. Then, risk pooling will be more valuable because the demand for each product has higher idiosyncratic noise which can be canceled out by risk pooling. A lower systematic risk also implies a lower cost of capital, and a higher net present value of the investment in flexible capacity. However, the firm will not be able to employ financial hedging to any benefit. These implications of systematic risk can be derived from existing theory. Other types of operational hedging can also be similarly compared with financial hedging. However, there is no empirical work that estimates the degree of systematic risk in demand for different industries in the economy. Therefore, the relative benefits of operational versus financial
hedging strategies for different industries are not known. This motivates the main research question of our paper: what is the degree of systematic risk in demand for industries in the manufacturing, wholesale trade, and retail trade sectors of the U.S. economy?

We conduct our analysis at the industry level using monthly data from the U.S. Census Bureau for the period 1992-2007. Following common practice in empirical research in operations management, we use sales as a proxy for demand, and use these two terms interchangeably throughout the paper. Thus, we define the systematic risk in sales as the correlation coefficient of sales uncertainty with the return on a broad financial market index, i.e., the market return. We measure market return as the return on the value weighted market index (VWMI) for the U.S. stock markets, which is commonly used as a proxy for market portfolio in asset pricing research. To compute sales uncertainty, we use price-adjusted and deasonalized sales data. Price adjustment is done to express production and sales data in comparable units, and deseasonalizing is done to remove the predictable component of sales due to seasonality.

The main result of our paper is that the correlation coefficient between sales uncertainty and market return increases from retailers to wholesalers to manufacturers, with average values of 0.331, 0.415 and 0.502, respectively, for industries in the retailing, wholesaling and manufacturing sectors. We conduct our analysis for time windows of different lengths varying from 3 months to 54 months, and find that the increase in correlation coefficient across the three sectors is robust with respect to the length of time window; the above estimates are for a 12-month time window. Analysis at the three- or four-digit NAICS code level reveals some variability across industries in each sector, but the main result remains the same: retail industry segments on average have the lowest correlation between sales uncertainty and market return, and manufacturers have the highest.

For retailers, we expect sales uncertainty to be correlated with market return because end-consumer demand depends on the wealth of consumers, which in turn, varies with market return. This argument follows from the permanent income hypothesis of Milton Friedman, and has been tested in several papers in macroeconomics, such as Ando and Modigliani (1963), Ludvigson et al. (1998). One might expect the same logic to hold for wholesalers and manufacturers as well because they supply products to retailers. However, their correlation coefficients will be modulated by supply chain dynamics. The question is why does the correlation increase upstream in the supply chain? It is not obvious a priori whether the correlation should increase or decrease. Mathematically, since the correlation coefficient is inversely proportional to the standard deviation of sales, the bullwhip effect (Lee et al. (1997)) should cause the correlation to decrease if the covariance between
sales uncertainty and market return remains constant or grows slower than the standard deviation of sales. However, if the covariance in the numerator of the correlation coefficient grows faster than the standard deviation of sales in the denominator, then the effect would be the opposite. For instance, the covariance at the upstream levels of a supply chain could increase if upstream firms react faster and more strongly to changes in economic conditions when placing their orders than downstream firms. We test this hypothesis. Interestingly, we find that for the majority of the industries, order processes have higher variability than sales but are less correlated with market returns. In other words, industries on average decrease the systematic risk in their order processes even as they increase idiosyncratic noise and total variance. Still, we observe that the correlation increases upstream in supply chains!

To understand the operational phenomenon producing this effect, it is important to recognize that supply chains are in fact supply webs. Each agent in the supply chain receives orders from many customers. The shipments from an industry represent a response to the aggregate stream of orders. Is there any reason to believe that the correlation of the aggregate order stream with the market is higher than the correlation of the each of the orders that it consists of? The answer is yes, and the reason is purely statistical: if one sums up random variables each having some positive correlation with the market and some independent noise, the noise will cancel and the correlated components will add up. We test this hypothesis by using the Leontief matrices for the U.S. economy which provide the bill of input materials. We reconstruct the order streams to each industry from the production levels of its downstream industries. Remarkably, we find that the correlation of the aggregated order processes with market return is an unbiased and statistically significant predictor of the correlation of sales uncertainty with market return. This allows us to conclude that it is the order aggregation process and the noise cancelation effect that is responsible for the observed increase in correlation.

Finally, we test whether the pricing of equity in financial markets is consistent with the systematic risk in sales, resulting in higher risk premia for firms in industries with higher correlation of sales uncertainty and market returns. For this purpose, we build equity portfolios for each industry and estimate their risk premia, i.e., portfolio betas. We observe that there is a positive and statistically significant relationship between the portfolio betas and the correlation coefficient of sales uncertainty with market return. Thus, the systematic risk in sales is indeed correlated with the stock return betas of firms. In other words, the location of a firm in its supply chain is a determinant of its systematic risk and cost of capital.
In summary, our paper has four main insights: (i) the degree of systematic risk in sales increases upstream in the supply chain, (ii) unlike the bullwhip effect in supply chains, this increase in systematic risk is not explained by within-firm production planning and inventory replenishment processes because production time-series data have lower systematic risk than sales for each industry, (iii) the increase is explained by aggregation of flows, and (iv) the systematic risk in sales is correlated with the risk premium of stock portfolios in industries. Our results imply that different types of actions will be desirable along the supply chain to manage the risks due to demand uncertainty. Retailers will favor actions involving operational hedging, such as leadtime reduction, risk pooling, and diversification of product portfolio, compared to financial hedging. On the other hand, upstream players, especially manufacturers, will find it easier to justify methods based on financial hedging. Our results are especially relevant for manufacturing firms in the context of the bullwhip effect. While the bullwhip effect causes the variance of demand to be the highest for the manufacturers in a supply chain, our results imply that manufacturers have a way out because they also have the highest ability to hedge their risk using financial instruments.

2. Literature review

Many methods for reducing and managing demand uncertainty have been developed in the operations management literature under the umbrella of risk pooling, operational flexibility and operational hedging strategies. These methods include flexible capacity (Jordan and Graves (1995), Van Mieghem (1998), Goyal and Netessine (2007)), delayed differentiation (Lee et al. 1993), and geographical pooling (Eppen and Schrage 1981). Their value has been demonstrated in case studies, and their concepts are an integral part of textbooks. For example, Cachon and Terwiesch (2009) (Chapter 12) define risk pooling as redesigning the supply chain, the production process or the product to reduce or hedge demand uncertainty. They describe methods of risk pooling such as location pooling, capacity pooling, and lead time reduction. While risk pooling focuses on the correlation structure in demand across products and locations, which is internal to the firm, researchers have also studied the value of operational flexibility under external risks such as exchange rate or price fluctuations, see for example, Huchzermeier and Cohen (1996), Kogut and Kulatilaka (1994), Li and Kouvelis (1999).

The more recent literature has evolved around joint models of operational and financial hedging. Gaur and Seshadri (2005) use examples from the retailing industry to develop the idea that the
demand for an item can be correlated with the return on a financial market asset, and show that this can be useful in financial hedging of the demand risk; Caldentey and Haugh (2006) study a continuous time model of financial hedging and stocking decisions; Chen et al. (2007), Kouvelis et al. (2009), and Devalkar et al. (2010) study inventory, pricing, and financial hedging decisions in a multi-period setting. The concepts of operational hedging and financial hedging are evaluated in greater depth by Chod et al. (2010). These authors model the correlation of demand across products as well as with the financial market, and investigate whether operational and financial hedging are complements or substitutes. Considering two types of operational hedging—product flexibility, i.e., creating flexible capacity to produce two or more different items, and postponement flexibility, i.e., creating the resources to reduce lead time so that production can take place with a more accurate demand forecast—these authors show that product flexibility and financial hedging strategies are complements or substitutes depending on the correlation structure between the demands for the items, whereas postponement flexibility and financial hedging are always substitutes. Van Mieghem (2008), Chapter 9, discusses various types of risk and their mitigation through operational and financial means.

Our paper contributes to this literature by analyzing systematic risk, which plays a role in operational and financial hedging. A crucial assumption of risk pooling is the uncorrelatedness of the demand components being pooled. When demands have a systematic market-associated risk component, i.e., when the correlation of demand uncertainty with market returns is high, it means that a larger proportion of the variance of demand is correlated with economic factors. In such cases, there will be little idiosyncratic noise in demand which could be hedged by risk pooling. Thus, operational hedging strategies will diminish in value, and financial hedging will become more valuable. Our results show that the systematic risk in sales uncertainty varies across the supply chain, so that the values of financial and operational hedging will depend on the location of a firm in its supply chain.

The variance of demand in supply chains has also been studied in the context of the bullwhip effect. The theoretical research on the bullwhip effect predicts an increase in the variance of demand upstream in the supply chain. Investigating this effect empirically in industry-level data, Cachon et al. (2007) discover that most industries smooth seasonality. They find evidence for the bullwhip effect in deseasonalized data, but not in seasonally unadjusted data, which leads them to conclude that the bullwhip effect is mitigated by seasonality. Bray and Mendelson (2010) study the bullwhip effect in firm-level data from Compustat. By using a forecast evolution model to decompose the
effect by lead time lags, they find that there is evidence for the existence of the bullwhip effect for wholesaling, manufacturing and resource extraction, but not for retailing.

Our paper uses similar data set and methodology as Cachon et al. (2007), but focuses on the correlation coefficients of sales and production time-series with market return, not their variances. Cachon et al. (2007) identify the need to construct supply webs (page 466) in order to evaluate amplification ratios at a finer level of granularity. We conduct such analysis by using input-output matrices and investigating the effect of aggregation on systematic risk. Because market returns are not seasonal, our results remain qualitatively the same regardless of whether seasonally unadjusted or adjusted data are used. In the paper, we present results using seasonally adjusted data. Moreover, we conduct our analysis using industry-level data from the U.S. Census Bureau as well as firm-level data from Compustat. The results of firm-level analysis support the findings using industry-level data. This paper presents the results using industry-level data because input-output matrices are available only at the industry-level.

Besides the bullwhip effect, recent empirical research in operations has examined inventory productivity using data at the industry level (Rajagopalan and Malhotra 2001), and at the firm level (e.g., Gaur et al. (2005), Kesavan et al. (2010), Rumyantsev and Netessine (2007), and Cachon and Olivares (2010)). We draw upon these papers by using sales as a proxy for demand. Rumyantsev and Netessine (2007) use historical quarterly sales to compute sales uncertainty; in a similar manner, Cachon and Olivares (2010) compute positive and negative sales trends using annual data of automotive sales, and we compute sales uncertainty using historical monthly sales.

We employ input-output analysis to reconstruct supply chain flows. The framework for input-output analysis, developed by Wassily Leontief (Leontief 1986), has been instrumental for studies in macroeconomics. The use of input-output models and data in operations management is limited. Barker and Santos (2009) use input-output data to model production breakdowns and investigate the effect of inventory on the speed of recovery, and Kananen et al. (1990) use it in a scenario-based analysis of Finnish economy. Outside operations management, input-output models have been used for the optimal resource allocation (Gale 1967), assessing environmental impact of products and materials (Hendrickson et al. 1998), and evaluating the impact of trade agreements (Kehoe 2002).

While the operations management literature focuses on maximizing the profits for a firm, in the finance and accounting literature, systematic risk has a direct effect on the cost of capital of the firm. Therefore, systematic risk and its determinants have long been studied in this literature. For stock returns, the systematic, market-associated risk is usually represented by the parameter
beta. Beaver et al. (1970) study how firms’ betas are associated with accounting parameters, such as dividends payout, asset size, earnings variability, and earnings covariability. Mandelker and Rhee (1984) test the relationship between operational and financial leverage and firms’ betas and find both to be significant determinants. Citing the need for theoretical models relating betas to the accounting numbers, Bowman (1979) derives the relationship between betas, leverage, and the accounting (earnings-based) beta. In the context of real options, Dixit and Pindyck (1994) and McDonald and Siegel (1985) provide a framework for estimating the risk premium for a firm whose cash flow is correlated with market return. Armstrong et al. (2009) investigate the effect of market-wide and firm-specific information on the firms’ betas. Analysts’ forecasts have also been studied in the context of systematic risk. Diether et al. (2002) find that firms with higher dispersion in analysts’ earnings forecasts have lower returns, and Johnson (2004) posits that the dispersion in earnings forecasts amounts to a proxy for idiosyncratic risk, and therefore lower returns follow from the standard asset pricing theory.

Although many potential determinants of systematic risk have been studied in the literature, to the best of our knowledge, this paper is the first that relates systematic risk to the placement and operations of a company within a supply chain. Given advanced supply chain management techniques developed recently, it is important to understand their relevance and impact on the systematic risk faced by the firm. Our paper contributes to the literature by documenting systematic risk as an important implication of supply chains. Our paper is based in part on the U.S. Census data. While not the focus of our study, the bullwhip effect is still present in our data, and in that sense, our results confirm the findings of Cachon et al. (2007) for deseasonalized sales data. We also address an important limitation mentioned by Cachon et al. (2007), namely, we are able to reconstruct the supply-chain web at the industry level. This allows us to test the role of aggregation in transmitting systematic risk in a supply chain.

3. Data

We use data for the U.S. economy obtained from the following sources:

(i) monthly surveys of manufacturing, wholesale trade, and retail trade sectors conducted by the U.S. Census Bureau (US Census Bureau (2010c), US Census Bureau (2010e), US Census Bureau (2010d));

(ii) estimated annual gross margins reported by the U.S. Census Bureau for manufacturing, whole-
sale trade, and retail trade sectors;

(iii) price deflators data (Bureau of Economic Analysis (2010b));

(iv) input output matrices from the Bureau of Economic Analysis (BEA) benchmark input-output accounts (Bureau of Economic Analysis (2002));

(v) historical daily and monthly returns on the value-weighted market index (VWMI) from CRSP;

(vi) historical daily returns and closing market capitalizations of U.S. public-listed firms in manufacturing, wholesale trade, and retail trade sectors, also obtained from CRSP.

We treat the first three data types in the same way as described by Cachon et al. (2007). All the analysis presented in this paper is conducted at the industry level. We have estimated the systematic risk in sales at firm-level as well for public-listed firms in manufacturing, wholesale trade and retail trade; these analyses confirm our results, but are not reported in this paper because input output matrices are available only at the industry level. In general, we assume throughout this paper that the wholesale sector lies upstream of the retail sector in the supply chain, and the manufacturing sector lies upstream of the wholesale sector. The data on input output matrices enable us to formally map supply chain flows across industries in various sectors.

The monthly surveys of manufacturing, wholesale trade, and retail trade sectors conducted by the U.S. Census Bureau (US Census Bureau (2010c), US Census Bureau (2010e), US Census Bureau (2010d)) provide industry level data on raw and seasonally-adjusted sales and inventories at the industry level.\textsuperscript{1} We use data from January 1992 to December 2007, yielding 192 monthly data points in each time series. U.S. Census classifies data for each sector into industry segments, using the M3 classification for manufacturing and the NAICS classification for retail and wholesale trade. The mapping from M3 to NAICS segments is one-to-one in some instances, one-to-many in others, and many-to-one in the rest. That is, some of the M3 segments directly correspond to NAICS segments, some represent a combination of several disjoint NAICS segments, and still some others represent a decomposition of NAICS segments.\textsuperscript{2} This mapping is provided in US Census Bureau (2010a). Table 1 lists the industry segments in our study: they include non-overlapping segments, their aggregates, and in some cases subsegments. For manufacturing, the non-overlapping segments are reported on the industry-segment level (M3 codes for such segments end with ‘S’), see

\textsuperscript{1}For manufacturers, the report provides the volume of shipments.

\textsuperscript{2}NAICS is a tree-like classification system, disjoint means that the segments belong to non-overlapping subtrees.
column 2, Table 1). For some industry segments, the M3 survey gives more detailed data, e.g, for the Beverage and Tobacco Products segment 12S, separate series for sub-segments 12A (Beverage Manufacturing) and 12B (Tobacco Manufacturing) are available. We use them in the input-output analysis.

Inventories and sales are valued at different prices for each industry segment. We adjust the sales data using estimated annual gross margins to control for this difference. Gross margins are available for retail and wholesale trade for the years 1993-2007 (US Census Bureau (2008a), US Census Bureau (2008b)). For manufacturers, we compute the margins from the sales and COGS data available from the year 1997 and 2002 Economic Census (US Census Bureau (2002, 1997)). When price margin data for a year are missing, we use data from the closest year. The comparison of values computed from year 1997 and 2002 Economic Census shows that the margins for manufacturing segments are fairly stable over time.

We collect the price deflators data (Bureau of Economic Analysis (2010b)) for the years 1992-2007 to adjust each time series for inflation and/or price fluctuations in order to conduct comparisons across years.\(^3\) Price deflators are provided according to the NAICS classification. We use price deflators rather than price inflation indices because price deflators vary with changes in the product mix produced by an industry, whereas price inflation indices do not. There is an exact match between price deflators segments and segments of retailers and wholesalers, but some judgement is needed to assign a corresponding price deflator to M3 manufacturing segments. Our approach to account for margins and inflation is similar to that used by Cachon et al. (2007).

We obtain the make and use input output (IO) matrices from the Bureau of Economic Analysis (BEA) benchmark input-output accounts for year 2002 (Bureau of Economic Analysis (2002)). The make matrix lists the amounts in dollars of different commodities produced by each industry, with the diagonal representing the amount of primary commodity output for each industry. There is a one-to-one correspondence between an industry and a primary commodity output, with two additional commodity rows in the IO matrices, Scrap and Second-hand Goods, and Non-comparable Imports. The use matrix provides the amount of commodities used as inputs by industries and in final consumption. Final consumption is represented as an industry with zero output and a non-zero column in the use matrix. IO matrices are available at three levels of detail: sector, summary, and detailed. We work with the IO matrices at the summary level that span 135 commodities and 133

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\(^3\)BEA provides monthly price deflator data in NIPA tables 2AUI and 2BUI. Table 2AUI covers years 1967-1996 and Table 2BUI covers years from 1997 onwards.
industries. The industries are defined using the NAICS classification: the summary level roughly corresponds to four-digit NAICS segment. The summary level is the most suitable for our purposes because it most closely (but, still, imperfectly) matches the M3 manufacturing segments. Unfortunately, the IO matrices do not break down the retail and wholesale trade sectors into segments at either the summary or the detail level. This precludes us from reconstructing order streams from individual segments of retail and wholesale trade to other industry segments. Therefore, for this part of our analysis, we treat retail and wholesale trade at the sector level.

Note that the sales, inventory, and orders data for manufacturing are classified by M3 segments, but the input output data are according to NAICS classification. Thus, we aggregate the make and use matrices using the mapping between M3 and NAICS segments (US Census Bureau (2010a)). During this aggregation, we add up rows of the matrices with 4-digit NAICS codes corresponding to an M3 segment, and replace them with one aggregate row. The same is done for commodities. Since our primary focus is on the retail, wholesale and manufacturing sectors, we collapse the parts of the matrix that are not related to retail, wholesale and manufacturing sectors into one row (for industries) and one column (for commodities). The aggregated industries are agriculture, mining, construction, utilities, financial, professional services, information technology, and other industries. The elements in the row are the amounts of commodities produced or used by all other industries; the column represents the amount of all other aggregate commodities produced or used by each industry. The aggregated make and use matrices contain 44 industries and 44 commodities, corresponding to 41 industries in manufacturing, plus wholesale trade, retail trade, and all other industries. We then compute the industry-by-industry requirements matrix, which for each industry shows the requirement of inputs from each industry per $1 output. Section 4.2 describes the calculation of the requirements matrix. To account for the final consumption, we augment the requirements matrix by one row and one column, representing the final consumption ‘industry’. The total consumption volume is obtained from the GDP quarterly series (US Census Bureau (2010b)) and the structure of consumption is obtained from the IO use matrix. The same approach is used to compute the sales of all other industries: we compute it from the GDP series using the make matrix to obtain the ratio of all other industries production and GDP. GDP series is adjusted for price using GDP deflators (Bureau of Economic Analysis (2010a)).

Annualized GDP volume is reported quarterly. We transform this into monthly series by dividing the GDP volume by 12 and assigning it to the 3 respective months. Monthly GDP deflators are then applied.
In addition to the operational data, we collect daily and monthly data on historical returns for VWMI from January 1992 to December 2007. This index is a value-weighted composition of closing prices of all stocks traded at NYSE, AMEX, and NASDAQ, adjusted for dividends and distributions. We use it as the broadest financial indicator available; it is commonly used as a proxy for market portfolio in research in asset pricing. Monthly data are used to estimate the covariance of sales with market returns, and daily data are used to compute beta in order to study the relationship between systematic risk and beta. To compute beta, we further collect historical daily stock returns for public firms in retail trade, wholesale trade, and manufacturing for the years 1992-2007. Then we compute the returns on value weighted portfolios of companies from each industry segment. Closing market capitalization on the previous trading day is used as the weight. Returns on these industry segment portfolios are used to compute the beta for each industry segment and test the relationship between betas and correlation coefficients. All financial data are obtained from the CRSP database accessed through Wharton Research Data Services (WRDS).

Figure 1 describes our data at the industry level. It plots the seasonally and price-adjusted sales and the VWMI price as a function of time for retailers, wholesalers, and manufacturers. Three observations are evident from a visual inspection of the plots confirmed by the formal computations: 1) The range of variation in the sales time-series, i.e., the difference between the maximum and minimum values, widens as we move upstream. 2) The volatility of the sales trajectory is higher for wholesalers than for retailers, and is the highest for manufacturers. 3) The sales trajectory follows the financial index progressively closer for the upstream sectors. Thus, even from a cursory examination of Figure 1, it is apparent that the correlation coefficients goes up for the industries that are upstream in the supply chain.

4. Amplification of correlation

In this section, we estimate the correlation between sales uncertainty and market return for various sectors and industry segments in our data set. We start by analyzing industry segments one by one and summarizing the estimates by levels of the supply chain. We establish that the correlation increases for the upper levels of supply chains and test for the potential sources of this amplification. First, motivated by the rationale for the bullwhip effect, we compute the correlation of uncertainty in orders placed by an industry and the market returns. We proxy orders with the industry’s production and test whether this correlation is greater than the correlation of sales uncertainty
Figure 1: Sales and the VWMI market index. For display purposes the time trends are removed from both sales and VWMI trajectories.
with market returns. If confirmed, this individual industry-by-industry correlation amplification could be a source of the correlation increase upstream. Second, we test whether the increase in the correlation upstream can be attributed to the aggregation of orders from downstream industries. We discuss an intuition for that source of amplification and present the theoretical justification behind the empirical analysis.

4.1 Individual industry analysis

We define sales uncertainty as the deviation of sales from their past values over a fixed time-horizon, i.e., \( SU_{i,t:T} = S_{i,t+T} - S_{i,t} \), where \( i \) denotes the sector or industry segment index of a time-series, \( S \) denotes seasonally and price adjusted sales, \( t \) denotes time measured in months, and \( T \) is the time horizon parameter. Typically, we measure sales uncertainty over 12 months by setting \( T = 12 \), but for robustness tests, we vary \( T \) to assess how our results change with the length of the time period over which sales uncertainty is measured. By working with seasonal and price-adjusted data, we ensure that the correlation of sales uncertainty with market return is not caused by seasonal or price volatility.

We estimate the correlation of sales uncertainty with the return on VWMI realized over the time window \((t, t+T]\) for each industry \( i \) using the following regression equation:

\[
SU_{i,(t,t+T]} = S_{i,t+T} - S_{i,t} = a_i + b_i r_{(t,t+T]} + \epsilon_{i,t+T}.
\]

(1)

Here, \( r_{(t,t+T]} = \ln(VWMI_{t+T}/VWMI_t) \) is the rate of return on VWMI from \( t \) to \( T \), \( a_i \) and \( b_i \) are regression coefficients, and \( \epsilon_{i,t+T} \) denotes random error. We use ordinary least squares (OLS) to estimate (1). The error terms in our model can be correlated for each industry segment. Moreover, the Breusch and Pagan tests reveal a mild presence of heteroskedasticity for some industry segments. In the presence of heteroskedasticity and autocorrelation, OLS is still consistent, but standard errors need to be adjusted in order to provide correct inference. A standard approach is to use the Newey-West standard error estimator which can account for an arbitrary heteroskedasticity and autocorrelation structure (Greene 2003, Chapter 10). In our specification, we use an autocorrelation structure with up to \( T \) lags.

Let \( \rho_s \) be the correlation coefficient under consideration, i.e., for industry \( i \),

\[
(\rho_s)_i = \text{Corr}(SU_{i,(t,t+T]}, r_{(t,t+T]}).
\]

Also let \( (\sigma^2_s)_i = \text{Var}(SU_{i,(t,t+T)}) \).

The first column of Table 1 presents the estimates of \( \rho_s \) for \( T = 12 \) months. The value of \( \rho_s \) is
equal to 0.331 for the retail trade sector, 0.415 for wholesale trade, and 0.502 for manufacturing. All three estimates are statistically significant at $p < .05$. Note the increase in estimates of $\rho_s$ from retail to wholesale trade to manufacturing sectors. It is possible to build confidence intervals and test for statistical significance in differences between correlation coefficients using Fisher’s transformation of $\rho$ to $z$-scores (see Chen and Popovich (2002) for details). The difference between the correlation coefficient estimates for the retail and manufacturing sectors is significant at $p = .05$ level. The difference between the wholesale and retail sectors, and wholesale and manufacturing sectors has weak statistical significance. One possible explanation to this is that the retailers place orders directly to manufacturers, bypassing the wholesale level. In the next section, we use input-output analysis to reconstruct the flows between industry segments. It turns out that 95.6% of orders placed by retailers are placed directly to manufacturers or all other industries, and only 4.4% are placed to wholesalers. When we consider the segment-by-segment estimates, we find that the model is significant at $p = .05$ for 2 out of 6 retail, 9 out of 18 wholesale, and 12 out of 25 manufacturing non-overlapping segments. The increasing number of segments demonstrating the statistically significant relationship is not surprising given the increase in $\rho_s$ on the sector-level. The $p$-values of the $F$-tests of statistical significance of model (1) are reported in the third column in Table 1.

The key result of increasing $\rho_s$ is robust for a wide range of values of $T$ (see Figure 2 for the plot of correlation coefficients for $6 \leq T \leq 18$ on top, and the long-term effects for $3 \leq T \leq 54$ on the bottom). The difference between correlation coefficients for retailers and wholesalers is significant at $p = .05$ for $T \geq 14$, and the difference for retailers and manufacturers is significant for $T \geq 10$. The significance level for the difference between wholesalers and manufacturers is about $p = .25$ for $9 \leq T \leq 18$ and increases to $p = .05$ for $T \geq 24$. Notice that for $T \geq 24$ the $\rho_s$ reaches the highest level for manufacturers at $\approx 0.85$, followed by wholesalers at $\approx 0.65$, and retailers at $\approx 0.2$. In the case of retailers $\rho_s$ exhibits a downward trend and declines from $\approx 0.35$ to $\approx 0.10$ for $30 \leq T \leq 54$.

The increasing trend in $\rho_s$ as a function of $T$ for wholesalers and manufacturers suggests that the correlation is consistently present over smaller periods of time within the time window $(t, t+T]$ for these sectors. Indeed, the sales uncertainty over $(t, t+T]$ can be represented as a sum of $SU_{it}$ over a partition of $(t, t+T]$. If each of the terms of the sum is similarly correlated with the market, the correlation of the sum will increase. The fact that the correlations stabilize at some level of $T$ indicates that the industries adapt to the market with time. In fact, changes in retail sales over a long term window are weakly correlated with the market, meaning that either long
term consumption is very stable, or retailers adjust their product mix in response to the market conditions.

The second measure of interest is the covariance of sales uncertainty with market returns, see Table 1, column two. As expected from the increasing $\rho_s$, as well as the bullwhip effect, the covariance estimates increase from lower, to upper levels of supply chains. The result is robust with respect to the length of the time window $T$, as evident from Figure 2 (right panel). For $T = 12$, the difference between the covariance estimates for manufacturers and retailers, and manufacturers and wholesalers is significant at $p = .05$. All three pairwise differences between the covariance estimates for retailers, wholesalers and manufacturers, are statistically significant at at least $p = .05$ level for $T \geq 18$.

Model (1) relates the difference in sales to the market return. In addition to this specification, we estimate the specification based on ratios of sales, i.e., $S_{i,t+T}/S_{i,t} = a_i + b_i r_{t,t+T} + \epsilon_i,t+T$, where
\( S_{i,t} \) and \( r_{(t,t+T)} \) are defined in the same way as before. An advantage of this specification is that it is mirrors the equation of the Capital Asset Pricing Model (CAPM), with the stock return on the left hand side replaced by the sales uncertainty (we discuss the relationship between \( \rho_s \), the key component of model (1), and beta the key component of CAPM in Section 5). The results under the differences and ratio specifications are qualitatively the same. Details on the estimation of the ratio model are presented in the Appendix.

Given the evidence of increasing correlation, we investigate possible reasons for its increase. Our first analysis is based on the existence of the bullwhip effect. In this effect, the variance of production or volume of orders placed by an industry is higher than the variance of sales due to reasons such as demand forecast updating and order batching. In our case, it is possible that companies and industries respond to the performance of the aggregate financial market and the associated change in sales when updating their demand forecasts. Thus, they would make greater changes in production or volume of orders. This increased response in production would be consistent with the bullwhip effect. It would lead to an amplification of the correlation coefficient of production with market returns. We test for this effect in the data.

Cachon et al. (2007) use a similar within industry analysis to test for the presence of the bullwhip effect. Following their work, we define the production of an industry \( i \) in period \( t \) as

\[
P_{i,t} = S_{i,t} + I_{i,t} - I_{i,t-1},
\]

(2)

where \( S_{i,t} \) is the volume of price-adjusted sales (shipments) out of industry \( i \) in month \( t \) and \( I_{i,t} \) is the end-of-month inventory of industry \( i \) for month \( t \). The production represents the inflow of material in industry \( i \). Similar to the discussion following (1), define \( \rho_p = \text{Corr}(P_{i,t+T} - P_{i,t}, r_{(t,t+T)}) \). We wish to test if \( \rho_p > \rho_s \) on average.

Table 1 presents the estimates of \( \rho_p \) alongside the corresponding estimates of \( \rho_s \). Note that \( \rho_p < \rho_s \) based on the aggregate estimates for retail, wholesale and manufacturing sectors, with estimates of 0.172, 0.290 and 0.443, respectively. Moreover, at a finer level of detail, using data for non-overlapping segments, we find that \( \rho_p < \rho_s \) for all six retail segments, 13/18 wholesale segments, and 20/25 manufacturing segments. These represent more than 50% of the segments in each case with \( p < .05 \). In fact, retailers, wholesalers, and manufacturers all attenuate \( \rho_p \) compared to \( \rho_s \) by an average of 30%. Thus, the hypothesis that \( \rho_p > \rho_s \) is not supported by the data.

We plot \( \rho_p \) as a function of \( \rho_s \) for non-overlapping segments in Figure 3. A linear fit of \( \rho_p \) on \( \rho_s \) shows that the slope coefficient is significantly less than 1 (\( p < .05 \)) and thus confirms statistical
Figure 3: Correlation of industry production ($\rho_p$) vs. correlation of sales uncertainty with market returns ($\rho_s$) for non-overlapping segments in retail, wholesale trade, and manufacturing.

significance of the attenuation. Also the intercept is not statistically significant (at $p = .05$), showing that there is no bias in the linear fit for $\rho_p$.

Further analysis reveals that $\text{Var}(P_{i,t+T} - P_{i,t}) > \text{Var}(S_{i,t+T} - S_{i,t})$. This is consistent with the findings of Cachon et al. (2007), who document the presence of the bullwhip effect in the seasonally-adjusted industry-level data. At the same time, $\text{Cov}(P_{i,t+T} - P_{i,t}, r_{(t,t+T)})$ is on average of the same order as $\text{Cov}(S_{i,t+T} - S_{i,t}, r_{(t,t+T)})$: a simple regression of $\text{Cov}(P_{i,t+T} - P_{i,t}, r_{(t,t+T)})$ on $\text{Cov}(S_{i,t+T} - S_{i,t}, r_{(t,t+T)})$ reveals that one is an unbiased predictor of the other, i.e., statistically, the regression has zero intercept and the unity slope. The overall effect of these two values is that $\rho_p$ is less than $\rho_s$ for most industries. Therefore, we reject the hypothesis that industrial production responds to the performance of the aggregate financial market through forecast updating. In the next section, we turn to the other potential source of correlation amplification, namely, order aggregation.

4.2 Input-output analysis

It is important to understand that the correlation of production with the market by itself does not necessarily mean that the sales for the industry upstream will be more correlated with the market. It can lead to an increase in the correlation upstream only if the supply chain is sufficiently serial, i.e., the impact of orders placed by other firms or industries is negligible. Generally, this is not the case. Supply chains have a network structure, with suppliers serving multiple customers. We investigate the aggregation effect of this network structure on systematic risk in sales in this section.

An intuitive explanation of the aggregation effect is as follows. Each industry serves orders from
many other industries, and orders coming from each of those industries are potentially correlated with market returns in the sense described in Section 4.1. Therefore, order volume, a random variable, can be decomposed into two parts: one perfectly correlated with the market, and the other orthogonal to market returns. By pooling all these orders, the standard deviation of the correlated components increases linearly whereas the standard deviation of the orthogonal components increases as $\sqrt{N}$, where $N$ is the number of industries from which orders are pooled. This can lead to an increase in the correlation of the pooled orders with the market if the correlation of each order stream with the market is positive. Therefore, we expect sales at the upstream industry, which are obtained by pooling all these orders together, to have a higher correlation with market returns than sales at downstream industries. We formalize this explanation and test it empirically.

4.2.1 Modeling justification

Consider a simplified two-level supply chain as in Figure 4. Let there be a single industry at the top level (Industry 0) and $N > 1$ industries at the lower level, placing orders to Industry 0. For each industry $i = 1..N$ at the lower level, let $S_{i,t}$ denote the sales in period $t$, $P_{i,t}$ denote the production in period $t$. Empirically we found that the difference in production $T$ months apart is correlated with the market return over this period (see Section 4). Let $\Delta P_{i,t} \triangleq P_{i,t+T} - P_{i,t}$. Then

$$\Delta P_{i,t} = a_i + b_i r_{(t,t+T)} + \epsilon_{i,t},$$

where $r_{(t,t+T)}$ is the same as in (1). It is easy to see that

$$\text{Corr}(\Delta P_{i,t}, r_{(t,t+T)}) = \frac{b_i \sigma_r}{\sqrt{(b_i)^2 \sigma_r^2 + \sigma_i^2}},$$

where $\sigma_r^2 = \text{Var}(r_{(t,t+T)})$, and $\sigma_i^2 = \text{Var}(\epsilon_{i,t})$. 
Consider Industry 0 located in the upstream of the supply chain. Each of the downstream industries places orders to Industry 0 to support their production. Assume that the amount of orders from industry \( k \) in period \( t \) is equal to \( M_{k0}P_{k,t} \), i.e., industry \( k \) has to order \( M_{k0} \) worth of materials from Industry 0 to produce \$1 \) worth of output. Then the sales at Industry 0 in period \( t \) are

\[
S_{0,t} = \sum_{k=1}^{N} M_{k0}P_{k,t},
\]

and the sales uncertainty

\[
\Delta S_{0,t} = S_{0,t+T} - S_{0,t} = \sum_{k=1}^{N} a_{k}M_{k0} + r_{(t,t+T)}\sum_{k=1}^{N} b_{k}M_{k0} + \sum_{k=1}^{N} M_{k0}\epsilon_{k,t}.
\]

Then

\[
\text{Corr}(\Delta S_{0,t}, r_{(t,t+T)}) = \frac{\sigma_{r}\sum_{k=1}^{N} b_{k}M_{k0}}{\sqrt{\sigma_{r}^{2}(\sum_{k=1}^{N} b_{k}M_{k0})^{2} + \sum_{k=1}^{N} (M_{k0}\sigma_{r})^{2}}}.
\]

The correlation at the upstream level is amplified with respect to industry \( i \), i.e., \( \text{Corr}(\Delta S_{0,t}, r_{(t,t+T)}) > \text{Corr}(\Delta P_{i,t}, r_{(t,t+T)}) \) if and only if

\[
\left(\sum_{k=1}^{N} b_{k}M_{k0}\right)^{2} > \left(\sum_{k=1}^{N} b_{k}M_{k0}\right)^{2} + \sum_{k=1}^{N} \left(M_{k0}\frac{\sigma_{r}}{\sigma}\right)^{2}
\]

To provide a simple illustration of the correlation amplification, assume that industries 1..\( N \) are identical in their response to market and production structure, i.e., \( \sigma_{k} = \sigma \), \( b_{k} = b \), and \( M_{k0} = M_{0} \) for all \( k \). Then (4) can be rewritten as:

\[
1 \geq \frac{1 + \frac{\sigma^{2}}{b^{2}\sigma_{r}^{2}}}{1 + \frac{\sigma^{2}}{\sigma_{r}^{2}}},
\]

which holds trivially. Indeed, in this case

\[
\text{Corr}(\Delta S_{0,t}, r_{(t,t+T)}) = \frac{Nb\sigma_{r}^{2}}{\sigma_{r}\sqrt{(Nb)^{2}\sigma_{r}^{2} + N\sigma^{2}}} = \frac{Nb\sigma_{r}^{2}}{\sigma_{r}\sqrt{(b)^{2}\sigma_{r}^{2} + \sigma^{2}/N}} > \frac{b\sigma_{r}^{2}}{\sigma_{r}\sqrt{(b)^{2}\sigma_{r}^{2} + \sigma^{2}}}
\]

\[
= \text{Corr}(\Delta P_{i,t}, r_{(t,t+T)}),
\]

i.e., the correlation of the change in sales and market return upstream is higher than that of the change in production and the market return downstream. Note that \( \text{Corr}(\Delta S_{0,t}, r_{(t,t+T)}) \) is increasing in \( N \) and \( \lim_{N \to \infty} \text{Corr}(\Delta S_{0,t}, r_{(t,t+T)}) = 1 \). Therefore, it is possible for the correlation between sales upstream and market return to exceed the correlation between sales downstream.
and market return. Furthermore, we would expect to see higher correlation if \( N \) is large, i.e., for industries that serve demand from a large pool of industries.

Two observations are in order. First, \( \text{Corr}(\Delta S_{0,t}, r_{(t,t+T)}) \) can be less than \( \text{Corr}(\Delta P_{i,t}, r_{(t,t+T)}) \) if \( b_i \)’s have different signs. In principle, this suggests a way for a company to avoid a high correlation between the sales for their products and the market return: produce and sell a mix of products, the sales for which have different signs for \( b_i \). In reality, the industries with negative \( b_i \) are rare as seen in Table 1. Similar to finance, such industries would play a role of insurance against drops in the financial market.

Second, there can be many industries at the top level, therefore, we use the IO matrix to obtain the proportion of each industry’s production being sales for each other industry. The input-output matrices can be used to reconstruct the flows of raw materials and products between industries and consumers. We derive the material requirements matrix \( M \), in which the \( i \)-th row shows the amount of inputs from all industries required to produce $1 output of industry \( i \). Let \( q \) denote a column vector of total commodity output, \( g \) denote a column vector of total industry output, \( U \) be the intermediate portion of the use matrix, and \( V \) be the make matrix. The intermediate portion of the use matrix shows the amounts of commodities used by the industries as intermediates. \( U \) is commodity by industry matrix, and \( V \) is industry by commodity matrix. The matrices \( U, V, q, g \) are supplied by the U.S. Census. Our notation follows United Nations Statistical Office (1968), see also Chentrens (2007). Then the material requirements matrix can be derived as:

\[
M = (V \text{ diag}^{-1}(q) \ U \text{ diag}^{-1}(g))'.
\]

(6)

The \( ij \) element of \( M \) shows the amount of input from industry \( j \) to industry \( i \) as

\[
M_{ij} = \frac{1}{g_j} \sum_{k \in I} \frac{V_{ik}}{q_k} U_{kj},
\]

where \( I \) represents the set of all industries.

We make two assumptions in using the IO matrices. First, in the calculation of \( M \), each industry splits an order for a commodity between all industries that produce it, proportionally to their production shares of that commodity. Second, we assume that the structure of IO matrices does not change with time. The first assumption is standard in input-output analysis. The second assumption is driven by data availability: IO matrices are issued every 5 years for reference Census years. We use the IO tables from 2002 benchmark year U.S. Census, which are the most recent available tables at the time of the study. Alternatively, one could linearly interpolate between tables from different reference years to obtain approximate IO matrices for each year.
We account for the final consumption of products produced by each industry by introducing an extra row and column into matrix $M$. The last row represents the break-down of $1 of the final consumption, and the last column is all zeros, representing the fact that no final product that is consumed can be used as an intermediate.

Using the requirements matrix, if industry $i$ produces $x of output, then it should order $M_{ij}x$ of raw materials from industry $j$. Therefore, the total orders to industry $j$ in period $t$ are given by $\sum_{i \in I} M_{ij}P_{i; t}$. Let $\rho_{IO}$ denote the correlation coefficient between total orders to each industry and market returns. We compute this correlation coefficient as follows:

$$(\rho_{IO})_i = \text{Corr} \left( \sum_{i \in I} M_{ij}(P_{i; t+T} - P_{i; t}), r_{(t; t+T)} \right).$$

We then compare it to $\rho_s$. If $\rho_{IO}$ is statistically found to be a good predictor of $\rho_s$ and is of the same order of magnitude, then we would conclude that aggregation is a cause of amplification of correlation upstream in the supply chain.

This analysis can be cross-validated using a different way of measuring aggregation. From (5) we would expect to see high $\rho_s$ for an industry that serves a large number of approximately the same demands coming from other industries, i.e., for an industry with low concentration of customers. A commonly used measure of concentration is the Herfindahl index or its inverse, see, e.g., Libecap and Wiggins (1984). The inverse Herfindahl index for industry $j$’s customer base is given by:

$$H_j^{-1} = \left( \sum_i \left( \frac{M_{ij}g_i}{\sum_i M_{ij}g_i} \right)^2 \right)^{-1}.$$

Here, we choose the inverse Herfindahl index, rather than the direct Herfindahl index, because $H^{-1}$ is more sensitive when customers are relatively small and the number of customers is large. Consistent with the aggregation hypothesis, we expect to see a positive, statistically significant relationship between $H^{-1}$ and $\rho_s$.

### 4.2.2 Empirical results

Table 2 shows the estimates of $\rho_{IO}$ alongside those for $\rho_s$. The first column of the table lists the names of all 41 non-overlapping manufacturing segments and the aggregate wholesale trade, retail trade and manufacturing sectors, the second column gives the corresponding NAICS codes, and the third column gives the M3 classification codes. We use the mapping between M3 and NAICS systems, and where required, we aggregate the M3 series for shipments and production data to match the NAICS classification. Note that this mapping varies from the NAICS system in a few
places. Segment 336 is split into two parts denoted as 336A and 336B.

We find that the estimates of $\rho_{IO}$ and $\rho_s$ are 0.340 and 0.331, respectively, for retail trade and 0.441 and 0.415, respectively, for wholesale trade. We recall that the estimates of $\rho_p$ were 0.172 for retail and 0.290 for wholesale trade. Thus, we see from these two sets of observations that $\rho_{IO}$ is a far more accurate predictor of $\rho_s$ than $\rho_p$ is. In Figure 5, we plot $\rho_s$ against $\rho_{IO}$ and fit a linear regression model. The coefficient of determination ($R^2$) is 0.59. At $p = .05$, the intercept is not significantly different from zero and the slope coefficient is not significantly different from unity. These results indicate that $\rho_{IO}$ is an unbiased and statistically significant predictor of $\rho_s$, i.e., the two methods of individual industry analysis and input-output analysis give generally consistent results. This contrasts to the results based on individual production series presented in Section 4.1, where attenuation of the correlation of the production with market return was observed. Thus, we note that even though the correlation of the production is attenuated, the superposition of the production series leads to a higher correlation due to the aggregation effect.

Table 3 shows the results of a regression of $\rho_s$ on $H^{-1}$. We find that there is a positive, statistically significant relationship between $\rho_s$ and $H^{-1}$ at $p = .05$. Overall, the aggregation effect seems to explain well the increased correlation between sales and market returns for the industries upstream supply chains.

**Table 3:**

<table>
<thead>
<tr>
<th>$\rho_s$</th>
<th>Coef.</th>
<th>Std.Err</th>
<th>95% C.I.</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\rho_{IO}$</td>
<td>0.950***</td>
<td>0.125</td>
<td>0.699 - 1.202</td>
</tr>
<tr>
<td>Intercept</td>
<td>-0.044</td>
<td>0.044</td>
<td>-0.134 - 0.045</td>
</tr>
</tbody>
</table>

$N = 43$, $Prob. > F = 0$, $Adj.R^2 = 0.577$
5. Implications for the market price of risk

The correlation between sales uncertainty and market return shows the presence of the systematic, market-associated risk in sales revenue. For the most companies in retail, wholesale and manufacturing sales revenue is the primary component of cash flow. In this section, we test whether the increased correlation between sales uncertainty and return on the market portfolio translates into increased beta for the associated industry portfolio. The larger betas in turn would imply higher co-variability of the portfolio with the market, therefore, risk averse investors would demand higher risk premium for holding it (see Danthine and Donaldson 2002, Section 3.4). The risk premium takes form of a higher expected return on the portfolio. The Capital Asset Pricing Model connects the risk premium of an asset and its co-variability with the market.

Under the Capital Asset Pricing Model:

\[
E(R_i) = R_f + (E(R_m) - R_f) \beta_i,
\]

where, \( R_i \) is the return on industry \( i \) portfolio, \( R_m \) is the return on the market portfolio, \( R_f \) is the risk free rate, and \( \beta_i = \frac{\text{Cov}(R_m, R_i)}{\text{Var}(R_m)} \) is the beta of the portfolio of industry \( i \). Equation (7) can be rewritten as

\[
E(R_i) = R_f + \left( \frac{E(R_m) - R_f}{\sigma_m} \right) \text{corr}(R_i, R_m) \sigma_i,
\]

where \( \sigma_i \) and \( \sigma_m \) are standard deviations of \( R_i \) and \( R_m \) respectively.

There are obvious similarities between (8) and (1). Indeed, (1) can be rewritten as:

\[
E(SU_{i,(t,t+T)}) = a_i + \frac{E(r_{(t,t+T)})}{\sigma_m} (\rho_s)_i (\sigma_s)_i.
\]

The former characterizes the effect of the market on expected return, and the latter the effect on the market on expected sales uncertainty. It is likely that sales uncertainty and returns are also correlated. In fact, if \( R_{i,(t,t+T)} \) is perfectly correlated with \( SU_{i,(t,t+T)} \), then \( \beta_i \sim (\rho_s)_i (\sigma_s)_i \).

This motivates us to test statistical relationship between \( \rho_s \), \( \sigma_s \), and beta. We proceed as follows. First, we construct portfolios that include every public company in each industry segment on any given day from Jan. 1992 to Dec. 2007, i.e., over the same period used for computation of \( \rho_s \) and \( \sigma_s \). The composition of portfolio on a given day is determined by public companies which are in business on that day and does change over time. The share of each company in the portfolio is proportional to its market capitalization on the previous trading day. We use value weighted portfolios because the estimates of \( \rho_s \) are based on the aggregate sales data where sales of all companies in an industry are

\[^{5}\text{For example, Kim et al. (2009) use a linear relationship between sales growth and company's equity.}\]
summed. Then we compute daily returns on the portfolios and estimate betas using (7) daily returns on VWMI (see Cochrane 2001, Section 12.1) and assuming constant risk free rate. Estimates of beta for industry portfolios are presented in Table 2. As expected, among manufacturers, wholesalers, and retailers, manufacturers have the highest beta of 1.010. Somewhat unexpectedly retailers have the second highest beta of 0.986, and beta for wholesalers is 0.731. The differences between betas are statistically significant at $p = .05$. The lower beta for wholesalers may be due to the fact that public companies represent just 11% of the sales volume in wholesale trade (this percentage is 32% and 76% for retailers and manufacturers respectively, based sales data for year 2005), so that the wholesalers beta is computed over a small fraction of companies in wholesale trade. Underrepresentation of industry segments in public companies is less of the problem among retailers and manufacturers.

With the estimates of beta in hand we use OLS to estimate the following models:

$$\beta_i = a + b_1(\rho_s)_i + \epsilon_i,$$

and

$$\beta_i = a + b_1(\rho_s)_i + b_2(\sigma_s)_i + b_3(\rho_s\sigma_s)_i + \epsilon_i.$$  

(9)
(10)

Model (10) directly corresponds to CAPM, as it includes the multiplicative effect $\rho_s\sigma_s$. We also control for the direct effects of $\rho_s$ and $\sigma_s$. In (10), $\sigma_s$ has units of sales, whereas all other variables are unitless. To be consistent, we use the percentage sales uncertainty (SU) to compute $\sigma_s$. The results are presented in Table 4.

Both models (9) and (10) are highly statistically significant according to the $F$-test. Coefficient on $\rho_s$ in model (9) is positive and statistically significant at $p = 0.05$. The model explains approximately 10% of variance in betas. Model (10) explains more than 40% of variance in betas. The coefficient on $\rho_s\sigma_s$ is positive and highly significant. At the same time the coefficients on $\rho_s$ and $\sigma_s$ are weakly significant and negative, which suggests that while $\rho_s\sigma_s$ is a major predictor of beta, a more complex relationship between $\rho_s$ and beta than prescribed by a simple analogy to CAPM is possible. Overall, the results of both models support the hypothesis that financial markets price-in the systematic risk in sales revenue.

The statistically significant relationship between $\rho_s$ and beta is remarkable. Given that the correlation between sales uncertainty and market return is one of many potential factors of financial systematic risk, it is reassuring to observe this relationship in the data. It should be noted that
our approach involves noisy estimates on both sides of the regression equation.\(^6\) In that sense, the adjusted \(R^2\) of 0.434 in the estimate of (10) is noteworthy.

6. Discussion and Limitations

The operations management literature on risk pooling has developed methods to manage demand uncertainty. While the focus of these methods is on the total variance of demand and the correlation of demand across products, the recent literature on operations-finance interface suggests that systematic risk in demand also affects the value of operational and financial hedging strategies. Our paper investigates this aspect of the variance of demand. The contribution of the paper is to show, using industry-level sales as a proxy for demand, that systematic risk is an important phenomenon in supply chains and that the supply chain location of a firm is a determinant of the degree of systematic risk in its sales uncertainty. This implies that operational hedging (risk pooling) strategies would be less effective for the upper layers of supply chains. Such strategies provide a hedge against idiosyncratic noise because noise in the demand of products or across geographical locations will cancel out on average. But such strategies are not useful against systematic risk, which will not cancel out. Since systematic risk increases upstream in supply chains, the usefulness of operational hedging will decline, as opposed to financial hedging which will gain in effectiveness.

Our result is relevant for firms in the context of the financial crisis in 2008-09 and the ensuing economic recession. Since demand for all products dips during the recession, flexibility strategies that seek to hedge against idiosyncratic noise are less valuable. For example, Toyota hedges variability in global demand by meeting excess demand from a flexible plant in Japan (see Iyer et al. 2009). The plant was forced to remain idle when the global economy slumped. Operational flexibility is advantageous in such situations only if it provides a hedge against the systematic risk component of demand uncertainty. For example, postponement flexibility, i.e., lead time reduction, can be more beneficial than flexible production capacity to mitigate the increase in systematic risk. Moreover, firms that produce products with different degrees of systematic risk will benefit more from operational flexibility.

Our result is analogous to the bullwhip effect, but different. The analogy arises because the variance of demand also increases upstream in the supply chain. The difference is that we find the systematic risk in production time series to be smaller than that in the sales time series on

\(^6\)A part of the noise is eliminated through aggregation firm’s individual return into portfolios. However, on the firm-level data (9) and (10) also produce statistically significant estimates.
average, whereas the bullwhip effect predicts that the variance of production time series will be larger than the variance of sales time series due to reasons such as demand forecast updating and order batching. It is this prediction which has been tested by Cachon et al. (2007) and Bray and Mendelson (2010). Our paper contributes to this stream of research by investigating the effect of aggregation in supply chain flows. Our result that industries have less systematic risk in their production time series than in sales time series is similar to the finding of Cachon et al. (2007) that firms smooth seasonality. Together, these two findings suggest that firms might be taking some sensible actions in their supply chains, whereas the theory on the bullwhip effect seeks to educate firms against self-inflicted wounds that exacerbate the bullwhip effect.

It is possible to replicate parts of our analysis on firm-level data. Upon doing this analysis, we continue to observe that the correlation between sales uncertainty and market return is higher for firms in upper levels of supply chains, i.e., it increases from retailers to wholesalers to manufacturers. We also observe that the firms with higher correlation coefficients have higher betas. Unfortunately, it is not possible to test for the role of aggregation in the amplification of correlation with firm-level data because this would require input-output matrices at the firm-level to construct supply chain relationships among firms. In the recent past, firms are required by the Securities Exchange Commission to report their major customers in annual reports. At present, these data are unstructured, sparse, and, thus, of limited value. Nonetheless, as they become richer with time, it would be useful to replicate the input-output study at the firm-level.

References


Table 1: Correlation measures for industry groups, years 1992-2007. Aggregate segments and subsegments are marked with asterisks and are excluded from the analysis of $\rho_s$ and $\rho_p$ to avoid double counting.

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<thead>
<tr>
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<th>$\text{Cov}_s$</th>
<th>$P_s$</th>
<th>$\rho_p$</th>
<th>$\text{Cov}_p$</th>
<th>$P_p$</th>
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<td><strong>Retail trade industries</strong>*</td>
<td>44,45</td>
<td>0.331</td>
<td>174.285</td>
<td>0.022</td>
<td>0.172</td>
<td>116.385</td>
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<td>Retail trade industries (excl motor veh)*</td>
<td>44,45 excl.</td>
<td>0.196</td>
<td>72.160</td>
<td>0.142</td>
<td>0.103</td>
<td>48.836</td>
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<td>Motor vehicle and parts dealers</td>
<td>441</td>
<td>0.252</td>
<td>105.240</td>
<td>0.035</td>
<td>0.171</td>
<td>75.714</td>
</tr>
<tr>
<td>Furniture, furnishings, electronics, and appliance stores</td>
<td>442,443</td>
<td>0.152</td>
<td>11.930</td>
<td>0.252</td>
<td>0.145</td>
<td>14.927</td>
</tr>
<tr>
<td>Building material and garden equipment and supplies dealers</td>
<td>444</td>
<td>0.108</td>
<td>8.818</td>
<td>0.114</td>
<td>0.078</td>
<td>8.666</td>
</tr>
<tr>
<td>Food and beverage stores</td>
<td>445</td>
<td>0.159</td>
<td>8.833</td>
<td>0.309</td>
<td>0.117</td>
<td>7.654</td>
</tr>
<tr>
<td>Clothing and clothing accessories stores</td>
<td>448</td>
<td>0.291</td>
<td>10.514</td>
<td>0.011</td>
<td>0.044</td>
<td>3.336</td>
</tr>
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<td>General merchandise stores</td>
<td>452</td>
<td>-0.166</td>
<td>-14.142</td>
<td>0.324</td>
<td>-0.227</td>
<td>-29.649</td>
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<td>Department stores*</td>
<td>4521</td>
<td>0.168</td>
<td>10.179</td>
<td>0.277</td>
<td>0.014</td>
<td>1.340</td>
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<td><strong>Merchant wholesale industries</strong>*</td>
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<td>0.004</td>
<td>0.290</td>
<td>250.125</td>
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<td>Durable goods merchant wholesale industries*</td>
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<td>308.751</td>
<td>0.000</td>
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<tr>
<td>Motor vehicles, parts, and supplies wholesalers</td>
<td>4231</td>
<td>-0.138</td>
<td>-19.537</td>
<td>0.175</td>
<td>-0.156</td>
<td>-30.649</td>
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<tr>
<td>Furniture and home furnishings wholesalers</td>
<td>4232</td>
<td>0.323</td>
<td>6.717</td>
<td>0.000</td>
<td>0.197</td>
<td>5.743</td>
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<td>Furniture and home furnishings wholesalers</td>
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<td>0.079</td>
<td>5.735</td>
<td>0.448</td>
<td>0.038</td>
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<td>Professional and commercial equipment wholesalers</td>
<td>4234</td>
<td>0.290</td>
<td>82.985</td>
<td>0.023</td>
<td>0.270</td>
<td>86.748</td>
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<td>Computers and software wholesalers*</td>
<td>42343</td>
<td>0.212</td>
<td>142.874</td>
<td>0.111</td>
<td>0.207</td>
<td>151.380</td>
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<tr>
<td>Metal and mineral (except petroleum) wholesalers</td>
<td>4235</td>
<td>0.382</td>
<td>21.281</td>
<td>0.008</td>
<td>0.309</td>
<td>22.105</td>
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<tr>
<td>Electrical goods wholesalers</td>
<td>4236</td>
<td>0.470</td>
<td>83.499</td>
<td>0.008</td>
<td>0.428</td>
<td>93.810</td>
</tr>
<tr>
<td>Hardware and plumbing and heating equipment wholesalers</td>
<td>4237</td>
<td>0.373</td>
<td>12.133</td>
<td>0.011</td>
<td>0.247</td>
<td>10.935</td>
</tr>
<tr>
<td>Machinery, equipment, and supplies wholesalers</td>
<td>4238</td>
<td>0.615</td>
<td>70.136</td>
<td>0.000</td>
<td>0.467</td>
<td>68.858</td>
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<tr>
<td>Miscellaneous durable goods wholesalers</td>
<td>4239</td>
<td>0.278</td>
<td>25.541</td>
<td>0.005</td>
<td>0.237</td>
<td>29.846</td>
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<tr>
<td>Nondurable goods merchant wholesale industries*</td>
<td>424</td>
<td>-0.121</td>
<td>-31.121</td>
<td>0.023</td>
<td>-0.086</td>
<td>-32.707</td>
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<tr>
<td>Paper and paper products wholesalers</td>
<td>4241</td>
<td>-0.012</td>
<td>-0.423</td>
<td>0.914</td>
<td>0.035</td>
<td>1.348</td>
</tr>
<tr>
<td>Drugs and druggists' sundries wholesalers</td>
<td>4242</td>
<td>-0.453</td>
<td>-57.084</td>
<td>0.002</td>
<td>-0.402</td>
<td>-63.000</td>
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<tr>
<td>Apparel, piece goods, and notions wholesalers</td>
<td>4243</td>
<td>0.021</td>
<td>0.925</td>
<td>0.885</td>
<td>-0.041</td>
<td>-2.897</td>
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<tr>
<td>Grocery and related products wholesalers</td>
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<td>0.104</td>
<td>12.706</td>
<td>0.582</td>
<td>0.118</td>
<td>16.306</td>
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<tr>
<td>Farm product raw material wholesalers</td>
<td>4245</td>
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<td>-0.479</td>
<td>0.976</td>
<td>0.027</td>
<td>6.546</td>
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<tr>
<td>Chemical and allied products wholesalers</td>
<td>4246</td>
<td>0.066</td>
<td>1.803</td>
<td>0.547</td>
<td>-0.029</td>
<td>1.071</td>
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<tr>
<td>Beer, wine, and distilled alcoholic beverages wholesalers</td>
<td>4248</td>
<td>0.061</td>
<td>1.458</td>
<td>0.600</td>
<td>0.043</td>
<td>1.653</td>
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<tr>
<td>Miscellaneous nondurable goods wholesalers</td>
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<td>0.316</td>
<td>26.452</td>
<td>0.010</td>
<td>0.277</td>
<td>29.298</td>
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<tr>
<td><strong>Total Manufacturing</strong>*</td>
<td>MTM</td>
<td>0.502</td>
<td>727.646</td>
<td>0.012</td>
<td>0.443</td>
<td>662.517</td>
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<td>Food Products</td>
<td>11S</td>
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<td>33.684</td>
<td>0.274</td>
<td>0.241</td>
<td>36.800</td>
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<td>Beverage and Tobacco Products</td>
<td>12S</td>
<td>0.346</td>
<td>16.285</td>
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<td>0.229</td>
<td>17.723</td>
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<tr>
<td>Textiles</td>
<td>13S</td>
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<td>0.860</td>
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<td>Textile Products</td>
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<td>0.349</td>
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<td>0.016</td>
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<tr>
<td>Apparel</td>
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<td>17.276</td>
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<td>Leather and Allied Products</td>
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<td>Wood Products</td>
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<td>12.322</td>
<td>0.102</td>
<td>0.233</td>
<td>15.311</td>
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</table>
Table 2: Correlation of sales uncertainty and market returns computed via: Census data (ρ_s), IO analysis (ρ_{IO}); volatility of SU percentage change (σ_s); Beta of industry portfolios. Aggregate manufacturing estimates are presented for reference but are not included in the analysis of ρ_s and ρ_{IO}, and ρ_s and beta in order to avoid double counting.

<table>
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<tr>
<th>Industry (IO, aggregated)</th>
<th>NAICS (IO)</th>
<th>M3</th>
<th>ρ_s</th>
<th>ρ_{IO}</th>
<th>σ_s</th>
<th>Beta</th>
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<tr>
<td>Paper Products</td>
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<td>0.134</td>
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<td>47.401</td>
<td>0.079</td>
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<td>Chemical Products</td>
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<td>11.570</td>
<td>0.000</td>
<td>0.226</td>
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<td>Plastics and Rubber Products</td>
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<td>Light truck and utility vehicle manufacturing</td>
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<td>Transportation Equipment</td>
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<td>0.188</td>
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<tr>
<td>Ships and Boats</td>
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<td>-3.220</td>
<td>0.684</td>
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<tr>
<td>Furniture and Related Products</td>
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<td>0.236</td>
<td>8.006</td>
<td>0.135</td>
<td>5.227</td>
<td>0.578</td>
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<tr>
<td>Miscellaneous products</td>
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<td>0.790</td>
<td>0.909</td>
<td>0.105</td>
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<tr>
<td>Consumer Durable Goods*</td>
<td>CDG</td>
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<td>0.089</td>
<td>0.790</td>
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<td>0.105</td>
</tr>
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<td>Construction Materials and Supplies*</td>
<td>CMS</td>
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<td>61.910</td>
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<td>CNG</td>
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<td>CNG</td>
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<td>0.208</td>
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<td>Information Technology Industries*</td>
<td>ITI</td>
<td>0.637</td>
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<tr>
<td>Nondurable Goods*</td>
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<td>0.300</td>
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32
<table>
<thead>
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<th>Industry</th>
<th>Coef.</th>
<th>Std.Err</th>
<th>95% C.I. LL</th>
<th>95% C.I. UL</th>
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<tr>
<td>H⁻¹</td>
<td>0.012**</td>
<td>0.005</td>
<td>0.0017</td>
<td>0.022</td>
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<tr>
<td>Intercept</td>
<td>0.187***</td>
<td>0.042</td>
<td>0.102</td>
<td>0.272</td>
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</table>

\[ N = 43, \ Prob > F = 0.023, \ Adj.R^2 = 0.10 \]

<table>
<thead>
<tr>
<th>Model equation</th>
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<th>(10)</th>
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</thead>
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<tr>
<td>( \rho_s )</td>
<td>0.653**</td>
<td>-0.799*</td>
</tr>
<tr>
<td>( \sigma_s )</td>
<td>-0.267</td>
<td>0.407</td>
</tr>
<tr>
<td>( \rho_s \sigma_s )</td>
<td>-1.340*</td>
<td>-0.725</td>
</tr>
<tr>
<td>Intercept</td>
<td>10.916***</td>
<td>2.742</td>
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</tbody>
</table>

\[ N = 43, \ Prob > F = 0.023, \ Adj.R^2 = 0.434 \]
A1. Results for the ratio model

In this appendix we present the estimation results of an alternative specification of model (1). In particular, we replace the left hand side of model (1) by the ratio of sales, i.e., we estimate:

\[ S_{i,t+T}/S_{i,t} = a_i + b_i r_{(t,t+T)} + \epsilon_{i,t+T}. \] (A1)

We fully replicate the analysis of the paper for this alternative specification. Qualitatively, the results remain the same, i.e.,

1. \((\rho_s)_i = \text{Corr}(S_{i,t+T}/S_{i,t}, r_{(t,t+T)})\) increases from retailers, to wholesalers, and to manufacturers (Table A1).

2. \((\rho_p)_i = \text{Corr}(P_{i,t+T}/P_{i,t}, r_{(t,t+T)})\) is statistically smaller than the respective \((\rho_s)_i\), i.e., industries attenuate the correlation of production with the market (Table A1, Figure A2).

3. The correlation of aggregated flow of orders to an industry \((\rho_{IO})_i = \text{Corr}((\sum_{i \in I} M_{ij} P_{i,t+T})/\sum_{i \in I} M_{ij} P_{i,t}, r_{(t,t+T)})\) with the market is statistically the same as the respective \((\rho_s)_i\) (Table A2, Figure A3).

4. The systematic risk, characterized by the coefficient \((\rho_s)_i (\sigma_s)_i\), is priced by the financial market, the relationship between \((\rho_s)_i (\sigma_s)_i\) and beta of the respective industry portfolio is statistically significant (Table A3).

The detailed estimates are presented below.

Table A1: Correlation measures for industry groups, years 1992-2007, ratio model. Aggregate segments and subsegments are marked with asterisks and are excluded from the analysis of \(\rho_s\) and \(\rho_p\) to avoid double counting.
Table A2: Correlation of the sales ratio and market returns computed via: Census data ($\rho_s$), IO analysis ($\rho_{IO}$); volatility of sales percentage change ($\sigma_s$); Beta of industry portfolios. Aggregate manufacturing estimates are presented for reference but are not included in the analysis of $\rho_s$ and $\rho_{IO}$, and $\rho_s$ and beta in order to avoid double counting.

<table>
<thead>
<tr>
<th>Industry (IO, aggregated)</th>
<th>NAICS (IO)</th>
<th>M3</th>
<th>$\rho_s$</th>
<th>$\rho_{IO}$</th>
<th>$\sigma_s$</th>
<th>Beta</th>
</tr>
</thead>
<tbody>
<tr>
<td>Food manufacturing</td>
<td>1 3110</td>
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<td>0.256</td>
<td>0.317</td>
<td>0.034</td>
<td>0.522</td>
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<tr>
<td>Beverage manufacturing</td>
<td>2 3121</td>
<td>12A</td>
<td>0.036</td>
<td>0.124</td>
<td>0.101</td>
<td>0.462</td>
</tr>
<tr>
<td>Tobacco manufacturing</td>
<td>3 3122</td>
<td>12B</td>
<td>0.498</td>
<td>0.281</td>
<td>0.185</td>
<td>0.504</td>
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<tr>
<td>Textile mills</td>
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<td>13S</td>
<td>0.012</td>
<td>0.303</td>
<td>0.065</td>
<td>0.652</td>
</tr>
<tr>
<td>Textile product mills</td>
<td>5 3140</td>
<td>14S</td>
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<td>0.200</td>
<td>0.067</td>
<td>0.826</td>
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<td>Apparel manufacturing</td>
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<td>0.387</td>
<td>0.080</td>
<td>0.919</td>
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<tr>
<td>Leather and allied product manufacturing</td>
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<td>16S</td>
<td>0.441</td>
<td>0.273</td>
<td>0.111</td>
<td>0.777</td>
</tr>
<tr>
<td>Wood product manufacturing</td>
<td>8 3170</td>
<td>17S</td>
<td>0.215</td>
<td>0.275</td>
<td>0.063</td>
<td>0.850</td>
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<tr>
<td>Pulp, paper, and paperboard mills</td>
<td>9 3212</td>
<td>22A</td>
<td>0.147</td>
<td>0.230</td>
<td>0.066</td>
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<td>Converted paper product manufacturing</td>
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<td>22B,C</td>
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<td>0.353</td>
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<td>Printing and related support activities</td>
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<td>23S</td>
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<td>0.036</td>
<td>0.440</td>
</tr>
<tr>
<td>Petroleum and coal products manufacturing</td>
<td>12 3240</td>
<td>24S</td>
<td>0.257</td>
<td>0.217</td>
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<td>0.615</td>
</tr>
<tr>
<td>Basic chemical Agg</td>
<td>13 325X</td>
<td>25D</td>
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<td>Agricultural chemical manufacturing</td>
<td>14 3253</td>
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<td>-0.017</td>
<td>0.074</td>
<td>0.109</td>
<td>0.634</td>
</tr>
<tr>
<td>Pharmaceutical and medicine manufactur</td>
<td>15 3254</td>
<td>25B</td>
<td>-0.026</td>
<td>0.149</td>
<td>0.074</td>
<td>0.821</td>
</tr>
<tr>
<td>Paint, coating, and adhesive manufactur</td>
<td>16 3255</td>
<td>25C</td>
<td>0.201</td>
<td>0.249</td>
<td>0.055</td>
<td>0.818</td>
</tr>
</tbody>
</table>

Note: Table A2 presents the correlation of the sales ratio and market returns computed via Census data ($\rho_s$), IO analysis ($\rho_{IO}$), volatility of sales percentage change ($\sigma_s$), and Beta of industry portfolios. The table includes aggregate manufacturing estimates for reference but excludes them from the analysis of $\rho_s$ and $\rho_{IO}$, and $\rho_s$ and Beta to avoid double counting.
Plastics and rubber products manufacturing 17 3260 26S 0.335 0.338 0.045 0.828  
Nonmetallic mineral product manufacturing 18 3270 27S 0.352 0.306 0.049 0.778  
Iron Agg 19 331X 31A 0.205 0.349 0.125 0.941  
Foundries 20 3315 31C 0.276 0.316 0.105 0.654  
Fabricated metal Agg 21 332X 32S 0.420 0.343 0.063 0.686  
Agriculture, construction, and mining machinery manufacturing 22 3331 33A-D 0.264 0.296 0.158 0.878  
Industrial machinery Agg 23 333X 33E 0.212 0.372 0.124 0.569  
HVAC and commercial refrigeration equipment manufacturing 24 3334 33H 0.261 0.271 0.122 0.659  
Metalworking machinery manufacturing 25 3335 33I 0.152 0.378 0.133 0.939  
Engines and other machinery Agg 26 333Y 33F,G,J,K-N 0.329 0.452 0.172 1.444  
Computer and peripheral equipment manufacturing 27 3341 34A 0.329 0.452 0.172 1.444  
Audio, video, and communications equipment manufacturing 28 334A 34D,E,F 0.488 0.567 0.255 1.655  
Semiconductor and other electronic component manufacturing 29 3344 34C 0.467 0.595 0.230 1.771  
Electronic instrument manufacturing 30 3345 34K 0.316 0.320 0.093 0.904  
Manufacturing and reproducing magnetic and optical media 31 3346 34B 0.425 0.296 0.203 1.192  
Electric lighting equipment manufacturing 32 3351 35A 0.160 0.235 0.127 0.818  
Household equipment manufacturing 33 3352 35B 0.042 0.296 0.080 0.883  
Electrical equipment manufacturing 34 3353 35C 0.344 0.378 0.096 0.921  
Other electrical equipment and component manufacturing 35 3359 34H, 35D 0.522 0.519 0.157 1.151  
Motor vehicle manufacturing 36 3361 36A,B,C -0.032 0.124 0.116 1.124  
Motor vehicle body, trailer, and parts manufacturing 37 336A 36D,E 0.123 0.062 0.088 0.810  
Aerospace product and parts manufacturing 38 3364 36F-J 0.143 0.164 0.631 0.870  
Other transportation equipment manufacturing 39 336B 36K-N 0.149 0.159 0.120 0.691  
Furniture and related product manufacturing 40 3370 37S 0.218 0.428 0.060 0.759  
Misc Agg 41 3399 39S 0.046 0.360 0.038 0.789  
Wholesale trade 42 42 - 0.452 0.428 0.024 0.731  
Retail trade 43 44-45 - 0.407 0.342 0.019 0.986  
Manufacturing Aggregate* 44 31-33 MTM 0.488 0.000 0.044 1.010

Table A3: Estimates of relationship between Beta, $\rho_s$ (ratio model), and $\sigma_s$.

<table>
<thead>
<tr>
<th>Model equation</th>
<th>(9)</th>
<th>(10)</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\rho_s$</td>
<td>0.541*</td>
<td>-0.700*</td>
</tr>
<tr>
<td></td>
<td>0.282</td>
<td>0.409</td>
</tr>
<tr>
<td>$\sigma_s$</td>
<td>-</td>
<td>-0.998</td>
</tr>
<tr>
<td></td>
<td>-</td>
<td>0.7249052</td>
</tr>
<tr>
<td>$\rho_s * \sigma_s$</td>
<td>-</td>
<td>10.334***</td>
</tr>
<tr>
<td></td>
<td>-</td>
<td>2.915</td>
</tr>
<tr>
<td>Intercept</td>
<td>0.731***</td>
<td>0.853***</td>
</tr>
<tr>
<td></td>
<td>0.084</td>
<td>0.104</td>
</tr>
<tr>
<td>N</td>
<td>43</td>
<td>43</td>
</tr>
<tr>
<td>$Prob &gt; F$</td>
<td>0.062</td>
<td>0.0</td>
</tr>
<tr>
<td>$Adj.R^2$</td>
<td>0.06</td>
<td>0.374</td>
</tr>
</tbody>
</table>
Figure A1: Left: Correlation between sales uncertainty (ratio model) and the VWMI return as a function of $T$: point estimates (top), long term effects and 90% confidence intervals (bottom). Right: Covariance between sales uncertainty (ratio model) and the VWMI return as a function of $T$: point estimates (top), long term effects and 90% confidence intervals (bottom).

Figure A2: Correlation of industry production ($\rho_P$) vs. correlation of sales uncertainty with market returns ($\rho_s$) for non-overlapping segments in retail, wholesale trade, and manufacturing, ratio model. Linear fit is reported.
Figure A3: Correlation of sales uncertainty with the market ($\rho_s$) vs. correlation of orders implied from the production series and IO matrix with market returns ($\rho_{IO}$) for 43 industries and industry segments, ratio model. Linear fit is reported.

<table>
<thead>
<tr>
<th>$\rho_s$</th>
<th>Coef.</th>
<th>Std.Err</th>
<th>95% C.I.</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\rho_{IO}$</td>
<td>0.877***</td>
<td>0.152</td>
<td>0.570</td>
</tr>
<tr>
<td>Intercept</td>
<td>-0.017</td>
<td>0.050</td>
<td>-0.119</td>
</tr>
</tbody>
</table>

$N = 43$, $Prob. > F = 0$, $Adj.R^2 = 0.434$