Can Global Sourcing Strategy Predict Stock Returns?

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In this study, we empirically test the proverbial notion that global supply chains are associated with shareholder value creation as they enable firms' to better serve demand by combining the best of offshore and onshore suppliers. We find that information concerning firms' global sourcing strategy (GSS) strongly predicts their future stock returns. Using a transaction-level imports dataset for the period 2008 to 2019, we measure US public firms' five GSS choices: the extent of global sourcing; supplier relationship strength; supplier concentration; sourcing lead time; and sourcing countries' logistical efficiency. For each of the five measures, we examine returns of a zero-cost investment strategy of buying from the highest and selling from the lowest quintile of that measure. Collectively these investment strategies yield an average annual four-factor alpha of 6% to 9.6% with value-weighted portfolios, and 6% to 13.9% with equal-weighted portfolios. These measures exhibit incremental return predictability over other operations-motivated return predictors such as inventory turnover and cash-conversion cycle and their return predictability is persistent across different supply chain positions, and their predictive power is robust to alternate risk models, sample construction, inventory measures, and empirical specifications. Together, these results indicate that the GSS measures embody independent information about firms' future profitability, a likely explanation for their return predictability power. In accordance, we find that the GSS measures are predictive of firms' future earnings surprises and abnormal returns around the earnings announcement days.

Key words: sourcing strategies, global sourcing, supplier concentration, sourcing lead time, relationship strength, asset pricing, stock returns, empirical operations management

1. Introduction

In the last three decades, firms have increasingly tapped into the *global* side of their supply chain to unlock value, with an increasing degree of their inputs sourced from international suppliers (Dong and Kouvelis 2020). Modern managers leverage global supply chains not only for cost savings but also increasingly for their unique knowledge and skill advantages relatively to a purely domestic supplier base (Frayer et al. 2016). This shift has propelled a steady long-term growth in global trade in spite of periodic instances of disruptions and crises such as the Asian financial crisis, the

Great Recession, the Tohoku earthquake and tsunami, the Eurozone debt crisis, as well as the ongoing COVID pandemic and ongoing trade war between the US and China.[1]

Consequently, the academic operations literature has postulated a wide spectrum of channels through which global sourcing could be related to value creation. For example, Hamad and Gualda (2014) illustrate relation between a multi-echelon global supply network and cash flow optimization. Likewise, Dong et al. (2010) show how a multi-location global supply network can mitigate exchange-rate uncertainties and improve pricing responsiveness. Berry and Kaul (2015) conjecture that firms may tap into knowledge pool of global suppliers network to develop new capabilities, and Jain et al. (2014) document how aspects of firms' global sourcing strategy can affect value drivers such as investment in inventory (Alan et al. 2014). Reflecting on the importance of global suppliers, Cohen and Lee (2020) note that they offer " ··· *new opportunities that render more flexibility and potentially new value-creating paths that smart supply chain designs can take advantage of*."

Despite the wealth of studies on these potential channels of value creation through global sourcing, there is no empirical study that directly examine the association between firms' global sourcing strategies and shareholder value, as reflected in the equity returns of publicly-traded firms. In this study, we aim to fill this important gap in the literature. Specifically, we examine whether information on firms' global sourcing strategy (GSS) is predictive of its future stock returns — a key metric of shareholder value creation (Banz 1981). As managers incentives are often linked to stock-market performance (Alan et al. 2014), quantifying the relation between GSS and future stocks returns is an important step in incentivizing managers to carefully implement GSS and align these strategies with investor relations (Babich and Kouvelis 2018). We do so in this paper with an empirical asset pricing framework that is widely used by scholars in multiple fields including in Operations Management (OM) (e.g., Alan et al. 2014, Wu and Birge 2014).

In the first step of our analysis, we quantify different aspects of the global sourcing strategies of US-based nonfinancial firms [2] using transaction-level data on their import activities. We compile a comprehensive import dataset covering a 12-year period between January 2008 and December 2019 that combines (1) 130 million product-level import shipment data from from Standard & Poor's Panjiva database with (2) product-level unit pricing data from PIERS and (3) additional data

[1]For example, during the period 2000–2018 global trade has grown with annual rate of 6.3 %, with a total trade of \$19.5 trillion in 2018 (O'Connell 2019). In the post-COVID era, it is expected that many factors will lead to reconfiguration of global supply chains including national priorities in critical sectors such as Healthcare (McCarthy 2020). After a brief slump period, global trade is experiencing signs of a robust recovery (as per statistics shared by World Trade Organization, http://bit.ly/2NFib0h, last accessed February 18, 2021). This indicates that, similar to the previous instances of global crisis, in the post-COVID era firms would continue to seek and expand engagement with global suppliers to make most of the value-enhancing and cost arbitrage opportunities (Beattie 2020).

[2]We analyze all public firms in the US, except for those in the financial services and public administration sectors (SIC code: 6000-6999, and $\geq$ 9000). The Standard Industrial Classification (SIC) is a four-digit code system for classifying US industries.

on logistics processing efficiency from World Bank, and port-to-port sea distances. The dataset captures imports over sea route that accounts for 90% of world trade (IMO 2008).[3] It includes rich details of each import transaction, including the identities of the buyer and supplier, country of origin, nature of imported product, and quantity imported. Compared to the previous studies using sea-based imports data such as Jain et al. (2014, 2020), our study considerably expands the time period and industry coverage, and thus allows for both time-series and cross-sectional asset pricing tests.

We then use our imports dataset to construct measures of five aspects of firms' global sourcing strategies that are commonly studied in the theoretical and practitioner OM literature: (1) the extent of global sourcing level, GL (Jain et al. 2014); (2) supplier concentration, SC (Cachon and Harker 2002, Jain et al. 2020, Sheffi 2005); (3) the frequency of repeat business in a buyer-supplier relationship, RB (Sheffi 2005, Anderson and Jap 2005, Belavina and Girotra 2012, Jain et al. 2020); (4) the degree of logistical efficiency in sourcing, LE (Hollnagel 2009, Jain et al. 2014), and (5) sourcing lead time, SL (Pan et al. 1991, Cachon and Terwiesch 2008). Existing studies have not yet prescribed a consistent view on the relation between these measures and stock returns, as firms often face competing considerations when deciding on various GSS choices. For example, Jain et al. (2014) notes the competing factors embedded in SC and GL strategies with respect to firms' inventory decisions, a key predictor of stock returns (Alan et al. 2014).

As such, we investigate the return predictability of each of the five GSS measures. We first do so in the time series by employing the classical zero-cost investment strategy. In particular, we perform an annual sort of our sample stock universe into quintiles using the previous-year value of a GSS measure and form a zero-cost portfolio by buying stocks from the highest and selling stocks from the lowest quintile of that GSS measure. Following Alan et al. (2014), we apply an industry-neutral sorting to mitigate the concern of difference in returns across quintiles being associated with asymmetric industry distribution rather than difference in the GSS choice levels. Combining this approach with annual rebalancing, we study return outcomes of both the value- and equal-weighted portfolios of about 3,000 publicly traded firms over the 132-month period of January 2009 to December 2019.

We find that except for the logistical efficiency measure, all of our GSS measures exhibit significant and consistent stock return predictability across multiple tests. For instance, the monthly Carhart (1997) four-factor alphas generated from the zero-cost value-weighted (equal-weighted)

[3]US firms also engage in land-based imports from Canada and Mexico. The relative share of land-based imports vary considerably based on sectors. For instance, during the period 2008-19, though the median annual share of Canada and Mexico imports aross sectors is 23%, a few sectors in agriculture and textile industries show an outsized share of above 50%.

portfolio across the four measures is as follows: GL 0.64**% (1.05***%); SC 0.49**% (-0.25%); RB 0.60***% (0.55**%); and SL -0.77***% (-1.09***%). On an annual level, these estimates imply an abnormal return of 6% to 9.6% (6% to 13.9%). The observed abnormal return yield of the GSS variables is comparable to other operations-motivated return predictors. For example, Alan et al. (2014) find monthly abnormal return of equal-weight portfolios in the range of 0.83% to 1.08% with inventory turnover measures. Furthermore, we find that these results are not driven by a specific subperiod of our study. For all the four variables, our zero-cost portfolio strategy generates positive returns for at least nine of the 11 return years. Importantly, we also find that the return predictability of the GSS variables is persistent for firms' across different supply chain positions, in a subsample analyses that examines manufacturers, wholesalers, and retailers.

Furthermore, as GSS constitutes a crucial part of a firm's overall supply chain strategy, the observed return predictability of the GSS measures could be driven by either (a) new information embedded in these variables or (b) simply reflect their relatedness with other operations-motivated return predictors, including inventory turnover (IT, Alan et al. (2014)) and cash conversion cycle (CCC, Wang (2019)). We therefore test for the incremental return predictability of the GSS measures above and beyond these related predictors in two ways. First, we use a double-sort analysis framework in which we form portfolios by sorting our sample stock universe first on a operations measure (IT or CCC) and then on a GSS measure. We find strong sign- and significance-consistent support for our main findings; both within the tercile ranks of the operations measure and when averaged across the tercile ranks. Second, we speficically control for these measures in the Fama and MacBeth (1973) cross-section test, which enables control for numerous other well-documented return predictors including size, book-to-market ratio, profitability, leverage, investment, and inventory measures. We continue to find strong support for our main findings under this cross-sectional test, with the coefficient estimates being sign- and significant-consistent for all four key GSS measures.

Our next set of tests examines whether the return predictability of the GSS measures is consistent with mispricing explanation. We first show that both standard and emerging risk models such as the five-factor or q-factor models do not fully explain the relation between GSS and returns, as evidenced by the low or negative risk loadings and significantly positive alphas. Second, we find a significant incremental predictive power of the GSS variables for future earnings after controlling for past earnings, and other standard earnings predictors. This indicates that market participants do not fully incorporate the value relation of GSS into their earnings expectations. As a result, we also find that, GSS-predicted earnings surprises lead to abnormal stock returns around the window when these earnings are announced. Thus, we find consistent evidence that market participants do not fully incorporate the incremental information in the GSS variables into their investment framework, thereby leading to surprise reactions when the earnings are realized. Collectively, these analyses indicate that the GSS variables' return predictability is likely explained by the mispricing mechanism rather than the exposure to risk encapsulated in the standard factor models.

Finally, we examine the robustness of the GSS measures' return predictability using a series of tests including: (1) alternate risk models (unadjusted risk, the Fama and French (2015) five-factor, and the Hou et al. (2015) q-factor); (2) subsamples (small- and large-firm subsamples, the exclusion of difficult-to-trade "penny stocks", sectors with high land-import shares, and publicly disclosed supply chain links in 10-K fillings); and (3) variable construction (double-sort analysis with measures of inventory level (Jones and Tuzel 2013) and the modified gross margin return on inventory (Alan et al. 2014)). In all, across all these tests, we find strong support for our main finding with sign- and significance-consistent results for 86 out of 92 alpha estimates of the zero-cost portfolio.

1.1. Relation to Literature

Our study primarily contributes to the growing OM literature that links operational measures with financial performance. In one of the earlier studies, Gaur et al. (1999) show the association between stock returns and inventory turnover measures using a cross-sectional regression analysis. Focusing on operations-related announcements, Hendricks and Singhal (2005, 2009) examine the impact of information on supply chain glitches and excess inventory on stock returns using the event studies methodology. Schmidt and Raman (2019) find that the impact of operational disruptions on firms' performance is mitigated by the level of operational transparency imparted by the firms to its investors. Wu and Birge (2014) find association between firms' supply-chain network characteristics and their stock returns; relatedly, Wang et al. (2021) find that the firms' exposure to risk is dominated by the tier-2 supplier network structure rather than those suppliers own risk. Within this literature, our paper is most closely related to the studies by Chen et al. (2005, 2007), Cohen and Frazzini (2008), Alan et al. (2014) and Wang (2019). These studies examine the predictability of operations-related measures on stock returns using portfolio-based tests. Using a parametric approach to sort portfolios, Chen et al. (2005, 2007) find that the return predictability of the inventory measure varies across the manufacturing, wholesale, and retail industries. In comparison, using a non-parametric approach, Alan et al. (2014) uncover evidence of robust return predictability of inventory measures in the retail industry. Cohen and Frazzini (2008) find a strong relation between returns of customer-supplier pairs using publicly disclosed links of major customers (accounting for at least 10% of revenue) in 10-K filings. The authors term this return predictability as "customer momentum". Likewise, Wang (2019) finds a strong return predictability of cash conversion cycle (CCC) measure that embeds firms' payment practice (trade credit) information – a topic of avid interest in the OM-Finance interface literature.

Our paper complements and extends the aforementioned studies in three ways. First, to the best of our knowledge, it provides the first rigorous evidence towards the return predictability of firms' GSS choices, an important constitute of a firm's overall supply chain strategy. Second, we show that the information embedded in the GSS choices is complementary, in predicting returns, to the other widely studied operational measures such as firms' inventory (Chen et al. 2005, 2007, Alan et al. 2014), and CCC (Wang 2019). Our study also complements Cohen and Frazzini (2008), which is based on domestic economic links data, by examining return predictability of a firm's extent and nature of upstream relationships, using micro-transaction level data on global suppliers of all sizes. Third, our study demonstrates that operational measures can predict stock returns across the wide range of US industries and for firms in different locations of the supply chain.

Our paper also relates to the literature that examines potential economic factors that result in value creation through global sourcing. For instance, Xiao et al. (2015) study how taxation policies across sourcing locations effect firms' global supply network decisions, Blanchard et al. (2017) study interaction between trade policies and firms' global value chains, Kohler and Smolka (2009) discover the relation between organizational form in global sourcing (e.g., vertical integration versus arms-length sourcing) and value creation through improved productivity, and Antras et al. (2017) documents that firm's sourcing decisions exhibit complementarities across markets which, in turn, renders value. In this study, we document association between widely employed sourcing strategies, which are typically an amalgamation of multiple factors, and stock returns. In this way, our findings lay foundation for future theoretical and empirical work to identify economic factors behind the global sourcing–firm value relationship.

2. Data and Variable Construction

In this section, we first describe our dataset that is complied by linking three distinct data sources: (i) proprietary transaction-level dataset on all US sea-based imports; (ii) a publicly available dataset on firms' stock prices and accounting data; and (iii) a publicly available country-level dataset on logistics performance compiled by the World Bank. Next, we provide details of the GSS variables construction.

2.1. US Sea-based Imports Data

We use a proprietary dataset by Panjiva Inc to compile data on sea-based imports by US firms, which are legislatively required to report all physical imports to US Customs and Border Protection (CBP). Firms report transactional details using the Bill of Lading Manifest, which captures rich transaction details including the supplier's and buyer's names and addresses, a description of the goods, the quantity imported, and additional transaction-specific information. Panjiva Inc, a subsidiary of S&P's Global Market Intelligence, is one of the largest commercial data aggregator

Bill of Lading Number	Redacted	**Consignee**	GE GENERATORS PENSACOLA
Arrival Date	5/16/18	**Consignee Ultimate Parent**	General Electric Company
Shipment Origin	Germany	**Shipper Ultimate Parent**	Esm Energie- Und Schwingungstechnik Mitsch Gmbh
Transport Method	Maritime	**Port of Lading**	Bremerhaven, Germany
Vessel	VECCHIO BRIDGE	**Shipment Destination**	The Port of Charleston, Charleston, SC
Volume (TEU)	0.07	**HS Code**	8483.40
Weight (kg)	840	**Description**	TRANSMISSION SHAFTS

Figure 1 Example of A Panjiva Entry

of imports data and updates data tables with daily frequency and makes trade data available with a latency of 1 to 7 days (source: https://bit.ly/37dRrvd, last accessed Feb 26, 2020). Effectively, this enables almost real time access to information on firms' GSS choices. In addition, Panjiva comprehensively processes the raw data to provide structure, impute missing values, and link the supplier and buyer entities with identifiers that are common with S&P's Capital IQ and Compustat databases.

Figure 1 shows an example of a shipment reported in the Panjiva database. We note that though firms self-report information about the value of imported goods, the CBP redacts corresponding fields while sharing data with commercial vendors like Panjiva. Following Jain et al. (2014), we use the Journal of Commerce Port Import Export Reporting Service (PIERS) to supplement the Panjiva import data with the dollar value of imported goods. PIERS impute dollar value of each transaction based on imported goods' product category and country.[4] We merged the import values by PIERS into Panjiva dataset using the unique bill of lading numbers. We were able to obtain dollar value of 93.2% of transactions in our data set. We impute the remaining transactions' dollar value using the average per-unit import value at the supplier-country$\times$product-category level. Like, Jain et al. (2014) we define product category using the 4-digit Harmonized Commodity Description and Coding System.[5]

Our sample covers all sea-based imports into the US during the 12-year period starting January 2008, the first full-year coverage by Panjiva, to December 2019. It contains more than 130 million unique import records of US firms from 244 supplier countries. We match these records to 243,156 unique public and private entities covered by the Capital IQ database. Next, we aggregate these entities to the ultimate parent company level. This enables us to attribute to the associated parent company all the import transactions executed by multiple entities. Following standard asset pricing practice (Fama and French 1992), we exclude from our sample financial services (SIC code: 6000-6999) and public administration (SIC code: 9000 and above) firms, as they have different accounting conventions than industrial firms. Finally, we merge the parent-level company to 4,262

[4] See PIERS FAQ on imports value at https://bit.ly/38GkO91.

[5] The Harmonized Commodity Description and Coding System is an internationally standardized system of names and numbers for classifying traded products. It is developed and maintained by the World Customs Organization (WCO)

publicly traded companies in the US. We obtain monthly stock returns of these companies from the Compustat North America Security Monthly file. During our study period, we find that 2,950 of these firms have continuous reporting of accounting variables in Compustat, which is about a third of the Compustat universe in the same period. In Table 1, we present key summary statistics of firms in our sample. Similar to Basker and Van (2010), we find that our sample firms are larger in size compared to the average firm in Compustat universe.

Table 1 Sample Summary Statistics

Panel A. Panjiva-matched Sample						
Statistics	Size	Profitability	Leverage	Investment		
	Total Assets AT	Gross Margin GPM	Debt-to-Equity D/E	Inventory INVT/AT	Capital CAPEX/AT	R&D XRD/AT
Mean	3861.71	-1.074	1.114	0.114	0.049	0.070
Median	627.26	0.328	0.908	0.076	0.034	0.001
SD	8377.35	9.549	3.940	0.126	0.051	0.203
P25	88.82	0.203	0.288	0.008	0.017	0.000
P75	2893.43	0.493	1.984	0.176	0.063	0.044
No. of Firms			2,950			

Panel B. Overall Compustat Sample						
Statistics	Size	Profitability	Leverage	Investment		
	Total Assets AT	Gross Margin GPM	Debt-to-Equity D/E	Inventory INVT/AT	Capital CAPEX/AT	R&D XRD/AT
Mean	2702.15	-2.519	0.840	0.081	0.052	
Median	198.32	0.333	0.676	0.023	0.031	
SD	7237.28	13.003	3.954	0.115	0.062	
P25	24.98	0.167	0.082	0.000	0.013	
P75	1388.68	0.542	1.777	0.122	0.065	
No. of Firms			9,177			

Notes. This table presents the cross-sectional distribution of the average annual levels of firm size, gross margins, leverage, inventory, and capital and R&D investment levels during the sample period of 2008–2019. Refer to Table A5 (in the Appendix) for construction details.

2.2. GSS Variables: Theory and Measure Construction

In this section, we first discuss the theoretical constructs that motivates strength and sign of the five studied GSS variables' return predictability. We next provide construction details of these variables respective measures.

2.2.1. Return Predictability of GSS variables? A supply chain bridges the demand and supply sides to create economic value (Lee et al. 2004, Cachon and Terwiesch 2008). Global sourcing strategy (GSS) has increasingly became a key constitute of firms' supply chain management strategy. Firms, however, often face competing considerations when deciding on various GSS choices. For example, consider the choice of supplier base size and relative concentration of sourcing among the suppliers. On the one hand, concentrated sourcing from a small group of suppliers invokes benefits such as reduced unit and fixed costs on account of economies of scale (Cachon and Harker 2002). On the other hand, a diversified (or low concentrated) sourcing from a large group of suppliers provides other benefits, including reduced lead times (Pan et al. 1991), and opportunity to leverage competition to gain better price and other supply terms by dynamically allocating order quantities. Not surprisingly, we find anecdotal evidence of comparable firms within same industry adapting varied supplier concentration choices. For instance, Aeropostale Inc. implements a high SC strategy and sources between 81% and 83% of its merchandise from its top five suppliers. In comparison, Cato Fashions implements a low SC strategy with no supplier accounting for more than 7% of total purchases (data is sourced from 2015 annual reports).

Similar to the just noted example of supplier concentration, a firm's choice of the extent of reliance on global suppliers ('global sourcing level' measure, GL) also embeds competing considerations. Though the higher the GL the greater the associated benefits of lower unit cost and knowledge sharing, but it may also result in higher financial burden through increased inventory investment (Jain et al. 2014). Likewise, the choice of the extent of repetitive business with a supplier is entrenced with competing benefits ('relationship strength' measure, RS). The higher the frequency of repeat business in a buyer-supplier relationship the larger the benefits of cooperative behavior (Belavina and Girotra 2012), but also the greater the threat of supplier complacency (Anderson and Jap 2005). Similarly, sourcing from logistically efficient locations is associated with both advantages and disadvantages ('logistical efficiency' measure, LE). In particular, though the efficient and lean systems typically deliver superior economic value in normal times, these systems may be less equipped to deal with periods of disruptions as compared to those with buffered (or redundant) resources (Hollnagel 2009). Sourcing lead time is the only exception among the five studied GSS aspects that does not seem to embed competing considerations ('Sourcing lead time' measure, SL). Given all else being equal, sourcing from a location with higher lead time not only imply on average higher inventory investment but also exposure to additional costs ensuing through stochastic delays associated with longer lead time (Cachon and Terwiesch 2008).

In summary, the studied GSS measures quantify different aspects of a firm's global sourcing strategy including level, concentration, logistical efficiency, leadtime, and relationship strength. Theoretically, these measures complement each other, and likely work in tandem, to create value for the firm. Thus, the relative importance of these variables in predicting returns is an open empirical query. Furthermore, except for the SL measure that *ceteris paribus* is associated with higher cost, the remaining four measures embed competing considerations. Therefore, we hypothesize a negative association between the SL measure and future stock prices. For the remaining four measures, both the sign and strength of association with future stock prices are open empirical queries. We next discuss measures to operationalize the five GSS variables using our imports dataset.

2.2.2. GSS Measures. We construct our measures of the GSS choices at the firm × year level. Through these measures, we capture the extent and the supplier engagement nature of a firm's GSS. We adjust for the within-firm differences in supplier engagement strategies across product-categories while computing the associated GSS measures (Jain et al. 2020). The year-level operationalization of measures aligns with the annual frequency of portfolio rebalancing in our main asset-pricing analysis. We define product category using the four-digit HS code (e.g., HS code 6402 which denotes "Footwear; waterproof, with outer soles and uppers of rubber or plastics" components, HS code 950 denotes "Yarn of combed wool", etc).

Global Sourcing Level (GL)

Following Jain et al. (2014), we measure a firm's extent of global sourcing as a weighted measure of sourcing from different supplier countries wherein the respective weights are set to equal the average shipment time from the supplier country to the US. We normalize this weighted measure by the firm's cost of goods sold (Compustat field COGS). Formally, we compute the extent of GL employed by firm i in year t as

$$GL_{it} = 100 \times \frac{\sum_{j=1}^{NS_t} ST_j \times IV_{itj}}{\sum_{j=1}^{NS} ST_j} \times \frac{1}{COGS_{it}}, \tag{1}$$

where NS_t is the total number of distinct supplier countries from which firm i has imported goods in year t, ST_j is the average shipment time from the j^{th} supplier country to US, IV_{itj} is the total value of goods imported by firm i from the supplier country j, and $COGS_{it}$ is the corresponding year's cost of goods sold.

We measure the average shipment time between a supplier country and the US as an average of shipment times across all the combinations of the supplier country's sourcing port and destination ports in the US. For each such combination, the shipment time is defined as a sum of (1) the average time required to obtain customs clearance in the supplier country, and (2) the travel time based on the sea distance between ports. We obtain customs clearance time for import transactions from the World Bank's Doing Business dataset. We compute travel time between ports using the sea distance between the US destination port and supplier country sourcing port (obtained from www.sea-distances.com) and an average transport ship speed of 14 nautical mph.

Supplier Concentration (SC)

We measure a firm's concentration of sourcing in its supplier base by the widely used concentration metric: Herfindahl index (Jain et al. 2014, 2020). We note that a firm's choice of sourcing distribution is not only influenced by managerial preference (such as the Aeropostale vs Cato Fashions example cited above) but also by product-category specific factors such as design complexity and supplier availability (Jain et al. 2020). In accordance, we define the degree of supply concentration in firm i's sourcing of goods in year t as a weighted measure of concentration in its supplier bases across all imported product categories, SC_{it} (Jain et al. 2020). For a given product category c, we measure supplier concentration using the Herfindahl index definition, and set its weight to the total value of goods imported in that category by firm i in year t. Formally, we compute SC_{it} as

$$\text{Herfindahl Index}_{itc} = \sum_{j=1}^{NS_{itc}} \left(IV_{itcj}/IV_{itc}\right)^2, \tag{2}$$

$$SC_{it} = \frac{\sum_{c=1}^{NC_{it}} IV_{itc} \times \text{Herfindahl Index}_{itc}}{\sum_{c=1}^{NC_{it}} IV_{itc}}, \tag{3}$$

where NS_{itc} is the total number of suppliers from whom product category c is sourced by firm i in year t, IV_{itcj} is the total value of imports by firm i from supplier j in category c, IV_{itc} is the total value of imports under product category c, and NC_{it} is the total number of product categories imported by firm i in year t.

Buyer Supplier Relationship Strength (RS)

The intensity of repeat business between a buyer and supplier is often considered as a signal of relationship strength between them (Sheffi 2005). Building on this observation, we measure relationship strength of firm i with its suppliers in year t as a weighted average of repeat business intensity with suppliers across product categories. In a given year t, we set the repeat business intensity between firm i and a supplier s to the ratio of the number of months in that year in which product category c is sourced from the supplier to the total number of months in that year in which category c is sourced from any supplier. We set weights for repeat business intensity in category c to the total value of goods imported in that category by firm i in year t. Formally, we compute the relationship strength RS_{it} measure as

$$\text{Repeat Business Intensity}_{itc} = \frac{1}{\text{NS}_{itc}} \sum_{j=1}^{\text{NS}_{itc}} \frac{\text{Count of Nonzero Supplier Imports Month}_{ijtc}}{|\text{Count of Nonzero Imports Month}_{itc}|}, \tag{4}$$

$$RS_{it} = \frac{\sum_{c=1}^{NC_{it}} IV_{itc} \times \text{Repeat Business Intensity}_{itc}}{\sum_{c=1}^{NC_{it}} IV_{itc}}, \tag{5}$$

where NS_{itc} is the total number of suppliers from which category c is imported by firm i in year t, Count of Nonzero Supplier Imports Month$_{ijtc}$ is the total number of months in year t in which firm i imports category c from the supplier j, and Count of Nonzero Imports Month$_{itc}$ is total number of months in year t in which firm i imports category c from any supplier.

Logistical Efficiency in Sourcing (LE)

We measure a supplier country's efficiency in supporting sourcing by the World Bank's Logistics Performance Index (LPI). Hausman et al. (2005) finds this index to successfully capture the explanatory power of multiple logistics indicators and, thus, reflects the efficiency of logistics infrastructure, bureaucratic procedures, and ease of doing business in a supplier country. Using this index, we first measure firm i's degree of logistical efficiency in sourcing a product category c as the weighted average of the supplier countries' LPI score wherein weights are set equal to the total value of category c imports from the respective supplier country. Next, we set the degree of logistical efficiency at the firm-level (LE) sourcing as a weighted average of efficiency across categories with weights set as firm i's total import value in category c. Formally, we compute the firm i's degree of logistical efficiency in year t (LI_{it}) as

$$LE_{itc} = \frac{\sum_{j=1}^{\text{NSC}_{itc}} IV_{itcj} \times \text{LPI}_{jt}}{\sum_{j=1}^{\text{NSC}_{itc}} IV_{itcj}}, \tag{6}$$

$$LE_{it} = \frac{\sum_{c=1}^{NC_{it}} IV_{itc} \times LE_{itc}}{\sum_{c=1}^{NC_{it}} IV_{itc}}, \tag{7}$$

where NSC_{itc} is the number of supplier countries from which firm i imported category c in year t, IV_{itcj} is the total import value of category c goods from the supplier country j, and LPI_{jt} is the performance score value for location j in year t. We use the biannual surveys conducted during the period of 2007 to 2014 by the World Bank to score logistics and ease of business environment in countries worldwide. For a year t, we use the performance score in the latest available survey for computation of LE measure.

Sourcing Shipment Lead Time (SL)

Similar to the LE measure, we compute the measure of sourcing shipment lead time (SL) in two steps to capture lead time at the product-category level and, also, the sourced category's relative importance in the firm's GSS. In particular, for a product category c, we measure the sourcing lead time (SL) of firm i in year t as the weighted average shipment time from different supplier countries where category c is imported from, wherein the weights are set equal to the total value of category c imports from the respective supplier country. Next, we set the level of sourcing lead time at the firm-level sourcing (SL) as a weighted average of lead time across categories with weights set as firm i's total import value in category c. Formally, we compute the firm i's level of sourcing lead time in year t (SL_{it}) as

$$SL_{itc} = \frac{\sum_{j=1}^{\text{NSC}_{itc}} IV_{itcj} \times \text{Shipment Lead Time}_{jt}}{\sum_{j=1}^{\text{NSC}_{itc}} IV_{itcj}}, \tag{8}$$

$$SL_{it} = \frac{\sum_{c=1}^{NC_{it}} IV_{itc} \times SL_{itc}}{\sum_{c=1}^{NC_{it}} IV_{itc}}, \tag{9}$$

where $\text{Shipment Lead Time}_{jt}$ denotes the average shipment time between the supplier country j and US in year t.

These GSS measures capture different aspects of firms' global sourcing. On the one hand, select measures may confound with temporal trend in global trade (like GL) or be inaccurately measured in the absence of non-sea imports in our dataset (like SL). On the other hand, others such as SC and RS are primarily shaped by firms' managerial preferences (as discussed above in the example of Aeropostale vs Cato Fashions) and/or imported category's attributes (Jain et al. 2020). Jointly, these measures complement each other in their relation to return predictability of firms' GSS choices.

In addition to the aforementioned GSS variables, we also construct a set of control variables that cover a variety of publicly available firm-specific operational and financial measures that are often studied in the asset pricing literature. Table A5 provides the definition of these control variables. In Table A5 of Appendix, we provide details of the data fields used in constructing these control variables. In Table 2, we show in-sample correlation among the GSS variables and other financial metrics.

The maximum absolute correlation of the GSS variables with the non-GSS variables is 0.608. This alleviates the concern about GSS variables reflecting mechanical outcomes that are driven by the well-studied non-GSS variables. Among the GSS variables, the maximum absolute correlation is observed between the SL and RS variable (0.688). This is probably driven by ease of coordination with suppliers located nearby, thus, encouraging more repeat business with them. Lastly, inline with intuition, we also observe a moderate positive correlation between the supply concentration and relationship strength variable. It indicates that when purchasing from a small number of suppliers, a firm also typically engages in a higher degree of repeat business with those suppliers.

3. Empirical Methodology, Tests, and Results

Following conventions in the asset pricing literature, we examine the return predictability of our GSS measures, both in the time series and in the cross-section. The time series tests are in the form of a trading strategy where we sort our sample stock universe into different quintiles and then examine the average alphas of each sorted portfolio, and of the zero-investment portfolio over the sample period. For the cross-sectional tests, we use the Fama and MacBeth (1973) two-step procedure. In particular, first for each month of our sample, we regress individual stock returns on the GSS measures together with a host of other potential return drivers spanning the valuation, profitability, leverage, and operations dimensions; and we then compute the time-series averages of these monthly estimates. Below, we first present details of the time-series tests, followed by the description of cross-section tests and, finally, with the analysis on the likely mechanism behind the observed findings.

Table 2 Global Sourcing Measures: Summary Statistics and Correlation with Firm Characteristics

	Statistics				
GSS Measure	Mean	SD	AR(1)	P25	P75
Global Sourcing Dollar Share (%)	7.79	15.77	0.55	0.48	12.72
W-Global Sourcing Share (GL)	1.93	4.60	0.39	0.17	5.53
Supplier Concentration (SC)	0.64	0.30	0.69	0.39	0.94
Sourcing Lead Time (LT)	32.49	7.06	0.67	23.58	37.82
Logistics Efficiency (LE)	3.60	0.29	0.54	3.51	3.73
Relation Strength (RS)	0.41	0.28	0.70	0.22	0.47

	Spearman's Rank Correlations				
	GL	SC	LT	LE	RS
GL	1.00				
SC	0.30	1.00			
LT	-0.17	-0.64	1.00		
LE	0.05	0.17	-0.14	1.00	
RS	0.27	0.67	-0.69	0.16	1.00
Size	-0.61	-0.27	0.41	0.00	-0.32
BM	0.33	0.09	-0.01	-0.17	0.13
GPM	0.09	0.01	-0.04	0.04	0.04
Accrual	0.00	0.00	0.01	0.01	-0.01
InvI	0.11	-0.23	0.16	-0.06	-0.25
InvT	-0.24	0.08	-0.07	-0.03	0.10
Leverage	-0.30	-0.11	0.18	0.00	-0.13
CAPEXI	-0.11	0.00	0.02	-0.06	-0.01
RDI	0.10	0.08	0.01	0.13	0.06

3.1. Time Series Tests: Return Predictability of the GSS Measures

In this section, we first present the details of our zero-cost portfolio analysis to examine the GSS measures' return predictability. Next, we investigate the incremental return predictability of GSS measures relative to other operations-motivated return predictors that may correlate with the studied GSS measures.

3.1.1. Portfolio Analysis: Fama-French-Carhart Four Factor Model We construct our trading strategy in a conservative fashion to minimize portfolio rebalancing and trading costs. Specifically, we form the sorted portfolios for the k^{th} $(= 1 \dots 5)$ GSS measure $GSS_k \in \{GL, SC, SL, LE, RS\}$ in annual frequency as follows: on January 1 of year t $(= 2009 \dots 2019)$, we sort our sample stock universe into five quintiles based on the level of GSS_k in the (previous) year $t-1$. As a result, for example, Jan 1, 2010 portfolio is formed using GSS measures that reflect a firm's sourcing choices between Jan 1, 2009, and Dec 31, 2009.[6]

We note that, similar to other operational measures, such as inventory productivity, the firms' GSS choices are also influenced by their industry-specific business environment. For example, Jain

[6] As noted earlier, Panjiva updates data at a much higher daily frequency compared to the quarterly frequency for accounting data. Though this naturally limits concerns of look-ahead bias in our analysis, we present two additional robustness with 6- and 12-month lagged GSS measures. See appendix C for details.

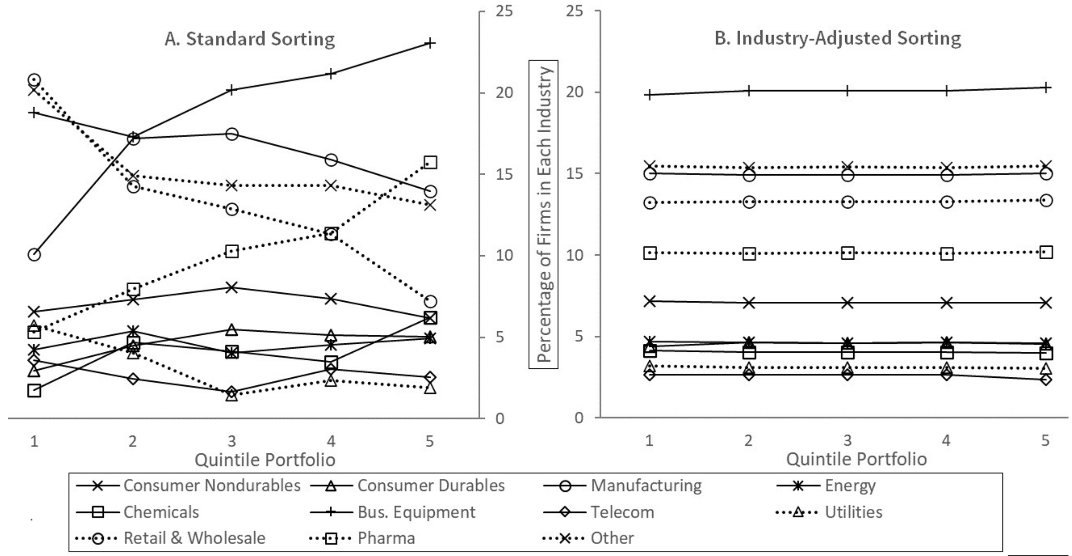

Figure 2 **Sorting on Global Sourcing Level (GL): Industry Distribution within each quintile portfolios**

et al. (2020) reports that wholesalers and retailers source from a relatively less concentrated supplier base compared to manufactures. We find a similar pattern in our sample. For instance, as shown in Figure 2, we find that the firms in the business equipment makers industry and pharmaceutical industry in the Fama-French 12-industries classification[7] exhibit, on average, much higher levels of sourcing from global suppliers than, say, firms in the energy industry. This implies that a simple sorting based on raw GSS measures may result in an asymmetric distribution of industries across the quintile portfolios. If true, such an asymmetric distribution leads to the concern of difference in returns across quintiles being associated with asymmetric industry distribution rather than difference in the GSS choice levels.[8] We therefore follow Alan et al. (2014) and perform an industry-adjusted nonparametric sorting procedure. In particular, we first sort stocks *within* each of the Fama-French 12 industries into five quintiles, and then combine the same index quintile across industries to form our annual portfolios. For example, the lowest quintile of each of the 12 industries are combined to form the lowest quintile of our sample stock universe. As illustrated in panel B of Figure 2, this nonparametric sorting procedure results in a symmetric industry representation across each of the quintile portfolios. We perform our main analysis using these industry-adjusted

[7]This classification is based on SIC codes and assign firms into one of following 12 industries: (1) consumer nondurables such as food, apparel, toys, etc.; (2) consumer durables such as cars and appliances; (3) manufacturing such as machinery, heavy vehicles, etc.; (4) energy such as oil, gas, and coal extraction and products; (5) chemicals and associated products; (6) business equipment such as computers, hardware and software; (7) telecommunications and transmission; (8) utilities; (9) retail and wholesale; (10) healthcare products including pharmaceuticals and medical equipment; (11) finance (excluded from our analysis); and (12) other industries. The classification data is from Ken French's website at https://bit.ly/3cDcaZN.

[8]We note that researchers with a pure focus on maximizing return predictability would be agnostic to standard or industry-adjusted sorting procedures, and, so, include the unadjusted sorting results in the robustness section.

quintiles, and present the results based on the unadjusted quintiles as a robustness check in Section 4.3.

Next, using stocks assigned to each GSS_k quintile, we form two portfolios: an equal-weighted (EW) portfolio and a value-weighted (VW) portfolio.[9] Consistent with Alan et al. (2014), we analyze the alphas of the EW portfolios to avoid giving disproportionately larger weight to mega-sized firms. At the same time, we also present the alphas from the VW portfolios to ensure that our results are not driven predominantly by small firms. In addition to the quintile portfolios, we construct a zero-investment, long-short portfolio by buying from the highest and selling from the lowest quintile of the GSS measure.

We hold each portfolio for one year and liquidate it on 31 December of the year of construction. We capture the monthly returns of our constructed portfolios and label them as $R_{k,p,t}$ where $p = 1, \ldots, 6$ denotes quintile portfolios with index 1 to 5 and the zero-cost investment portfolio with index 6. Effectively, the return of the zero-cost portfolio is $R_{k,6,t} = R_{k,5,t} - R_{k,1,t}$. For each quintile portfolio, we compute the alphas using the standard Carhart (1997) four-factor model using the following regression specification:

$$R_{k,p,t} - R_{f,t} = \alpha_{k,p} + \beta_{k,p}^{MKT}(MKT_t - R_{f,t}) + \beta_{k,p}^{SMB} SMB_t + \beta_{k,p}^{SMB} HML_t + \beta_{k,p}^{MOM} UMD_t + \epsilon_{k,p,t}, \tag{10}$$

where $R_{f,t}$ is the risk-free rate (interest rate on the three-month T-bills), and $MKT - R_f$, SMB, HML and UMD are respectively returns on factors-mimicking portfolios on market, size, book-to-market, and momentum factors.[10] For the estimation of alpha using the returns of zero-cost investment portfolio, the risk-free rate is not deducted from its returns as it is already in the excess-return format ($R_{k,6,t} = R_{k,5,t} - R_{k,1,t}$).

Our regression sample consists of 132 monthly returns observations from January 2009 to December 2019. The beta estimates in Regression (10) capture our portfolios' factor loadings of the market, size, value, momentum risks. We present beta estimates in Table A1 of Appendix. The alpha estimates, $\hat{\alpha}_{k,p}$, capture the factor model alphas of our portfolios — the metric of interest for our analysis. Table 3 shows the estimation results of both the value- and equal-weighted portfolios for each of five GSS measures. In Columns 1 to 5, we present the alpha (abnormal return) estimates for the qunitile portfolios, from lowest quintile (indexed: 1) to the highest (5). Column 'H-L' shows the alpha estimates of the zero-cost investment portfolio.

[9]In a value-weighted portfolio, a fixed dollar amount investment, say \$1, is split across portfolio stocks in proportion to their current market capitalization. In comparison, in an equal-weighted portfolio the investment is split equally among the portfolio stocks.

[10]The factor return series is from Ken French's website at https://bit.ly/3cDcaZN.

We find strong evidence for return predictability of the following four of the five GSS variables: the extent of global sourcing (GL); supplier concentration (SC); relationship strength (RS); and sourcing lead time (SL). We find significant alpha estimates for 7 out of the 8 alpha estimates across these variables. The sign of these significant estimates is consistent between the value- and equal-weighted portfolios. The economic magnitude of the abnormal returns and its spread across portfolios is sizable. Among the value-weighted zero-cost portfolios, the monthly abnormal-return ranges from 0.5% to 0.7% (equivalent of 6% to 9.6% of annualized returns). Likewise, among the equal-weighted zero-cost portfolios, we find monthly (annual) abnormal-return ranges from 0.5% to 1.1% (6% to 12.1%). We also find that, with the exception of the equal-weighted portfolio for the SC variable, the alphas from both the equal- and value-weighted portfolios show a monotonic relationship for all the measures with significant predictability as we move from the lowest to the highest quintile portfolios.

Inline with our intuition, we find a negative correlation between future stock returns and SL measure. Interestingly, we find a positive correlation of returns with the GL measure. We note that Jain et al. (2014) find a firm's inventory increases with the increase in GL, and Alan et al. (2014) document a significant negative correlation between returns and inventory levels. In respect of these studies, our finding indicate that the positive channels of GL measure such as avenues to advance knowledge sharing (Berry and Kaul 2015) and improve cash flow optimization (Hamad and Gualda 2014) dominates the negative channel through increased inventory level in determining future stock returns. Likewise, the positive correlation between returns and SC (resp. RS) variable suggest that benefits associated with high SC (resp. RS) level like economies of scale (resp. benefits of cooperative behavior) dominates those associated with low SC (resp. RS) level such as heightened competition (resp. reduced complacency).

In Figure 3, we present the time series of the average *unadjusted* monthly returns of each of the four zero-cost portfolios in GL, SC, RS, and SL (low-minus-high) between 2009 and 2019. The figure shows that the GSS variables produce consistent results over our study period i.e., our results are not driven by a specific subperiod of our study period. In particular, stocks with high GL outperforms the stocks with low GL in nine out of 11 periods. The GL-based strategy suffers losses in 2011 and 2015, two years corresponding to large disruptions in global trade – the Tohoku earthquake and the height of the Eurozone debt crisis. In these periods, it is natural that stocks with high GL would suffer loss, however, it is interesting to observe that such losses do not persist beyond those years. We find similar consistency in the return predictability of the remaining three GSS variables: stocks with high SC, low SL, and high RS outperform stocks with low SC, high SL, and low RS stocks in 9 of 11, 11 of 11, and 11 of 11 years, respectively.

In summary, the aforementioned results of the time-series tests provide strong evidence towards the return predictability of four key GSS variables.

Table 3 Univariate Portfolio Sorting Results

GSS Measures	Weights	Portfolios 1 (Lowest)	2	3	4	5 (Highest)	**H-L**
Global Sourcing Level (GL)	VW	-0.105	0.462	0.306	0.489	0.532	**0.637**
		(-1.78)	(6.01)	(2.39)	(2.88)	(2.14)	**(2.44)**
	EW	0.164	0.274	0.264	0.437	1.218	**1.054**
		(1.49)	(2.89)	(2.18)	(2.52)	(3.65)	**(3.25)**
Supplier Concentration (SC)	VW	0.068	-0.103	0.184	0.358	0.562	**0.494**
		(0.89)	(-1.35)	(1.92)	(3.33)	(2.98)	**(2.55)**
	EW	0.672	0.549	0.856	1.493	0.423	**-0.249**
		(4.72)	(3.41)	(4.89)	(6.07)	(2.15)	**(-1.39)**
Sourcing Lead Time (SL)	VW	0.644	0.191	0.364	0.273	-0.125	**-0.769**
		(5.35)	(1.76)	(3.38)	(3.00)	(-1.69)	**(-5.76)**
	EW	1.497	1.037	1.022	0.514	0.410	**-1.087**
		(5.42)	(4.88)	(4.99)	(3.45)	(3.08)	**(-4.35)**
Logistical Efficiency (LE)	VW	0.212	0.064	-0.012	0.143	0.192	**-0.021**
		(1.91)	(0.70)	(-0.12)	(1.56)	(1.68)	**(-0.15)**
	EW	0.847	1.273	0.803	0.703	0.888	**0.041**
		(3.97)	(6.08)	(4.45)	(3.93)	(4.95)	**(0.22)**
Relationship Strength (RS)	VW	-0.068	0.028	0.382	0.439	0.529	**0.597**
		(-0.89)	(0.28)	(3.62)	(3.63)	(3.98)	**(3.90)**
	EW	0.584	0.635	1.128	1.090	1.138	**0.553**
		(3.75)	(3.76)	(7.00)	(5.29)	(4.27)	**(2.27)**

Notes. This table reports the monthly four-factor alphas of each sorted quintile portfolio constructed using each GSS measure, described in Section 2.2 above. Portfolio 1 consists of stocks with the lowest measure levels during the previous year and portfolio 5 consists of stocks with the highest measure levels. H–L is the zero-investment portfolio that buys stocks in portfolio 5 and sells stocks in portfolio 1. VW and EW denote that the portfolios are value- and equal-weighted, respectively. The sample period is Jan 2009–Dec 2019. All alphas are expressed in percentage points. The numbers in brackets are t-statistics.

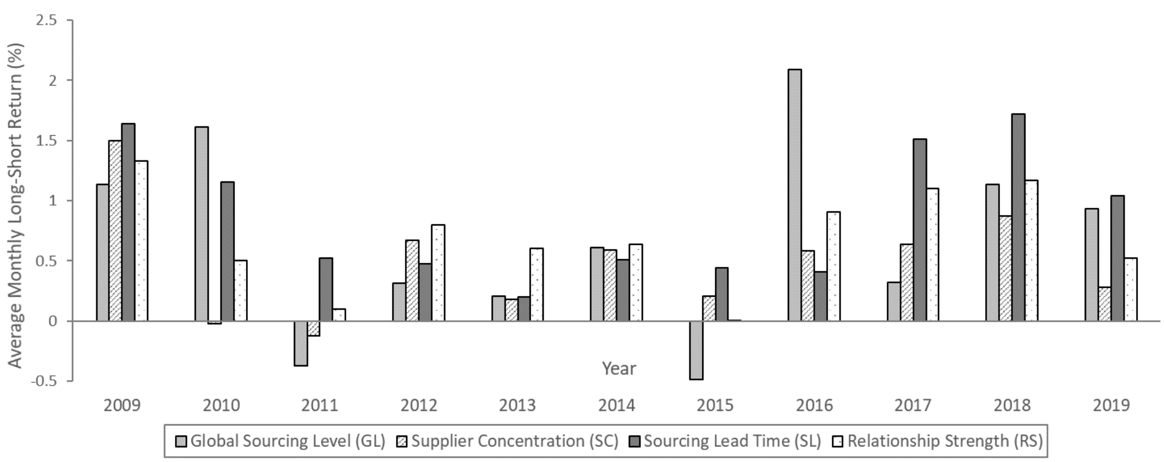

Figure 3 Average Monthly Zero-Cost Returns for Key Global Sourcing Strategy Measures

3.1.2. GSS Variables: Incremental Information Test. In this section, we examine whether GSS variables' return predictability is due to incremental information embodied in these variables or is driven by alternative return predictors that are conceptually related to GSS. We group these predictors in three primary categories.

The first category comprises of global trade policy and/or taxation related risks. Intuitively, these policies typically relate to aggregate, market-level structural changes rather than to firm-level choices such as global sourcing strategies. As a result, the impact of such changes on future returns would more likely be captured in exposure to the common systematic risk factors (i.e. beta loadings on the factor models) rather than the firm-level alphas. Table A1 in the Appendix shows that most of our GSS variables have low or negative loadings on the five principal risk dimensions, while the alphas remain significant. Thus, it is unlikely that policy related structural changes could fully explain our results.

The second category comprises of firms' *operations-linked* measures that (a) are documented to predict future returns, and (b) are related to firms' global sourcing strategy choices. As the *global* part of a firm's overall supply chain strategy, GSS could relate to firms' inventory levels (Jain et al. 2014) and cash conversion cycles (CCC)—two operations-motivated measures which are found to be predictive of future stock returns (Alan et al. 2014, Wang 2019). Therefore, it is important to ensure that GSS choices are not purely proxies for these operational decisions, and the GSS-return relation not being fully subsumed by these measures. Below, we examine whether the GSS measures possess incremental return predictability above and beyond these operational measures.

The third category includes variables related to firms' choice of their supply chain linkages, which again could be related to both global sourcing and are found to be significant predictor for future returns (for example, as a conduit for risk propagation (Wang et al. 2021)). Cohen and Frazzini (2008)'s find a strong relation between returns of customer-supplier pairs based on customer links disclosed in 10-K filings. We find our results remain statistically significant and economically sizable in a sub sample that excludes known supply chain linkages from 10-K filings.[11] We discuss these results in Appendix D.

GSS Incremental Return Predictability: Compared to Inventory Productivity and Cash Conversion Cycle

We use a double-sort analysis to examine the GSS variables' incremental return predictability conditional on the following two return predictors: (a) inventory level and (b) CCC. For exposition brevity below, we denote a measure of these predictors by `R`.

We implement the double-sort procedure in four steps as follows: (i) on 1 January of each year $t = 2010 \ldots 2019$, we first sort our sample stock universe on the accounting values available for `R`

[11] We thank the review team for suggesting this test.

to form tercile portfolios. Inline with the asset-pricing literature, we form the first-sort portfolios with *a minimum time-gap of six months* since the financial information availability. For example, for portfolios formed on Jan 2010, the cut-off date for the accounting values' availability is June 30, 2009; (ii) next, within each R-tercile portfolio, we sort the firms on the one-year lagged value of the selected GSS measure $\text{GSS}_k \in \{\text{GL}, \text{SC}, \text{SL}, \text{RS}\}$ to form tercile portfolios. For example, for portfolios formed in Jan 2010, we compute the GSS measures, regardless of the firms' fiscal-year-end dates, using the information on the sourcing choices made between July 2007 and June 2008 (which effectively maps financial information period of firm with a July fiscal-year end); (iii) next, we use the resultant nine (=3x3) groups to construct value-weighted portfolios that are held for a full year and liquidated on 31 December of year t; (iv) finally, and (iv) using the four-factor model, we examine the monthly abnormal returns (alphas) of these nine value-weighted portfolios, denoted by $r_{k,i,j,t}$ where $i, j \in \{1, 2, 3\}$ are the tercile ranks of the inventory and GSS_k measure respectively, and the three average portfolios with returns set to $\bar{r}_{k,j,t} = \frac{r_{k,1,j,t}+r_{k,2,j,t}+r_{k,3,j,t}}{3}, \forall j \in \{1, 2, 3\}$.

Table 4 show the abnormal return (alpha) estimates obtained from the double-sort analysis using the inventory turnover (IT) measure. Following Alan et al. (2014), we compute the inventory turnover measure as $\text{IT}_{i,t} = (\text{COGS}_{i,t} - \text{LIFO}_{i,t} + \text{LIFO}_{i,t-1})/(\text{INV}_{i,t} + \text{LIFO}_{i,t})$ where LIFO is the LIFO reserve level. We find qualitatively similar results using the gross margin return on inventory GMROI (Alan et al. 2014), adjusted inventory turnover (Alan et al. 2014), and inventory level IL (Jones and Tuzel 2013) measures which are presented in Section 4.3. In Table 5, we show the double-sort analysis results using the CCC measure. Following Wang (2019), we construct the *CCC* measure from Compustat data as a sum of days inventory outstanding, days receivables outstanding, and days payables outstanding.

We find significant return predictability power of the four GSS measures across 23 of the 24 double-sorted portfolios. Interestingly, we find that the return predictability of the GSS measures monotonically increase with the increase in IT measure. The average monthly (annual) abnormal return of the zero-cost portfolio across the four sourcing measures increases from 0.28% (3.37%) for the stocks with the lowest IT to 0.78% (9% annually) for the stocks with the highest IT. This implies that there is a complementary association between the GSS and IT variables. In other words, the information embedded in the GSS variables is more relevant to predicting future stock returns for inventory-efficient firms that exhibit a high inventory turnover.

Collectively, our results provide strong support for the notion that the GSS choice variables embed incremental information over and above the information captured in the firms' inventory turnover and CCC measures.

Table 4 Double Sort Results: Inventory Turnover, IT

InvT Terciles	Global Sourcing Strategy Measure Terciles							
	Global Sourcing Share (GL)				Supplier Concentration (SC)			
	1	2	3	H-L	1	2	3	H-L
1	0.275	0.444	0.599	**0.324**	0.280	0.251	0.408	**0.128**
	(2.51)	(2.70)	(2.32)	**(2.24)**	(2.12)	(1.50)	(2.19)	**(1.04)**
2	0.034	0.530	0.476	**0.441**	0.125	0.149	0.204	**0.078**
	(0.34)	(3.44)	(1.65)	**(2.57)**	(1.11)	(1.25)	(1.29)	**(0.80)**
3	-0.330	0.171	0.294	**0.625**	-0.215	-0.457	0.685	**0.900**
	(-3.33)	(1.15)	(1.45)	**(4.88)**	(-1.83)	(-2.91)	(4.78)	**(9.63)**
Avg of InvT 1-3	-0.007	0.382	0.456	**0.463**	0.064	-0.019	0.432	**0.369**
	(-0.11)	(4.35)	(2.36)	**(2.31)**	(0.80)	(-0.24)	(4.24)	**(3.14)**
InvT Terciles	Sourcing Lead Time (SL)				Relationship Strength (RS)			
	1	2	3	H-L	1	2	3	H-L
1	0.552	0.456	0.190	**-0.362**	0.223	0.279	0.534	**0.311**
	(2.13)	(2.78)	(1.63)	**(-2.62)**	(1.90)	(1.80)	(2.29)	**(2.28)**
2	0.353	0.343	-0.011	**-0.364**	-0.024	0.306	0.534	**0.558**
	(2.07)	(2.66)	(-0.10)	**(-3.67)**	(-0.23)	(2.55)	(2.94)	**(4.88)**
3	0.545	-0.091	-0.321	**-0.866**	-0.318	-0.104	0.417	**0.735**
	(3.68)	(-0.65)	(-2.86)	**(-8.60)**	(-2.75)	(-0.84)	(3.06)	**(7.35)**
Avg of InvT 1-3	0.483	0.236	-0.047	**-0.531**	-0.040	0.160	0.495	**0.535**
	(3.94)	(2.56)	(-0.66)	**(-4.23)**	(-0.56)	(1.73)	(4.26)	**(3.85)**

Notes. This table reports the value-weighted monthly four-factor alphas of each double-sorted tercile portfolios constructed by first sorting on the inventory measure, then on each GSS measure, described in Section 2.2 above. Portfolio 1 consists of stocks with the lowest GSS measure levels during the previous year and portfolio 3 consists of stocks with the highest GSS measure levels. Inventory terciles 1–3 correspond to portfolios with high, medium, and low inventory turnover, respectively. H–L is the zero-investment portfolio that buys stocks in portfolio 5 and sells stocks in portfolio 1. The last row (Avg of 1-3) is the average alpha of across the three inventory terciles. The sample period is Jan 2009–Dec 2019. All alphas are expressed in percentage points. The numbers in brackets are t-statistics.

3.1.3. GSS Variables: Return Predictability by the Supply Chain Position Chen et al. (2005, 2007) find that the return predictability of equal-weighted portfolios formed on inventory (measured in days as INV/COGS*365) varies by the firms' role (position) in a supply chain. For example, while for retailers lower-quintile portfolios yield abnormal returns, for wholesalers, middle-quintile portfolios yield abnormal returns. In comparison, for manufacturers, no significant returns are associated with the low-quintile portfolios, positive returns with middle-quintile portfolios, and negative returns with high-quintile portfolios. Alan et al. (2014) show that, since the operational-linked decisions, such as inventory, naturally vary across industries on account of structural differences in business environment and product characteristics, an alternative industry-adjusted methodology for equal-weighted portfolio construction yields a more consistent return predictability of inventory measures for retail firms.

Similar to inventory, the firms' GSS choices could also exhibit natural variations along the supply chain. For instance, Jain et al. (2020) report that wholesalers and retailers source from a relatively less concentrated supplier base compared to manufactures. Therefore, in this section, we examine whether the observed significant return predictability of the four GSS variables — GL, SC, SL,

Table 5 Double Sort Results: Cash Conversion Cycle, CCC

Finish

CCC Terciles	Global Sourcing Level (GS) Terciles				Supplier Concentration (SC) Terciles			
	1	2	3	H-L	1	2	3	H-L
1	-0.214	0.115	0.604	**0.819**	-0.150	-0.320	0.749	**0.898**
	(-2.31)	(0.77)	(2.59)	**(5.56)**	(-1.40)	(-2.19)	(5.30)	**(8.85)**
2	0.098	0.803	0.484	**0.385**	0.225	0.096	0.484	**0.259**
	(1.22)	(6.30)	(2.34)	**(2.96)**	(2.12)	(0.80)	(3.64)	**(2.83)**
3	0.176	0.369	0.768	**0.592**	0.208	0.194	0.170	**-0.037**
	(1.66)	(2.55)	(2.81)	**(3.70)**	(1.72)	(1.30)	(1.08)	**(-0.35)**
Avg of CCC 1-3	0.020	0.429	0.619	**0.599**	0.094	-0.010	0.468	0.373
	(0.38)	(5.28)	(3.45)	**(3.09)**	(1.23)	(-0.14)	(5.22)	(3.41)
CCC Terciles	Lead Time (SL) Terciles				Relationship Strength (RS) Terciles			
	1	2	3	H-L	1	2	3	H-L
1	0.424	0.086	-0.223	**-0.646**	-0.212	-0.130	0.617	**0.829**
	(2.86)	(0.68)	(-2.07)	**(-6.21)**	(-2.08)	(-0.88)	(4.34)	**(8.79)**
2	0.672	0.254	0.101	**-0.571**	0.089	0.337	0.502	**0.413**
	(4.46)	(2.05)	(1.01)	**(-5.70)**	(0.86)	(2.63)	(3.58)	**(4.08)**
3	0.352	0.379	0.141	**-0.212**	0.123	0.246	0.539	**0.416**
	(1.67)	(2.77)	(1.18)	**(-1.72)**	(1.00)	(2.05)	(2.52)	**(3.18)**
Avg of CCC 1-3	0.483	0.240	0.006	**-0.476**	0.000	0.151	0.553	**0.553**
	(4.88)	(3.01)	(0.09)	**(-4.16)**	(0.00)	(1.72)	(5.17)	**(4.17)**

Notes. This table reports the value-weighted monthly four-factor alphas of each double-sorted tercile portfolios constructed by first sorting on the CCC measure, then on each GSS measure, described in Section 2.2 above. Portfolio 1 consists of stocks with the lowest GSS measure levels during the previous year and portfolio 3 consists of stocks with the highest GSS measure levels. CCC terciles 1–3 correspond to portfolios with high, medium, and low CCC, respectively. H–L is the zero-investment portfolio that buys stocks in portfolio 5 and sells stocks in portfolio 1. The last row (Avg of 1-3) is the average alpha of across the three CCC terciles. The sample period is Jan 2009–Dec 2019. All alphas are expressed in percentage points. The numbers in brackets are t-statistics.

and RS — persist across firms at different supply chain locations. We do so by repeating our Fama-French-Carhart four-factor analysis (as described in Section 2) for subsamples of retailers (SIC two-digit codes: 52–59), wholesalers (50–51), and manufacturers (20–39).

Table 6 shows results. We find strong evidence for persistence of the four GSS variables return predictability across firms, irrespective of their supply chain positions. With the equal-weighted portfolios, we find sign- and significance-consistent estimates for 11 out of the 12 alphas across the three subsamples tests. The value-weighted portfolios show sign- and significance-consistent results for eight tests, with the relative drop driven by the wholesalers subsample. It indicates that the wholesalers' portfolios are more sensitive to the inclusion of large-size firms compared to retailers' and manufactures' subsamples. Interestingly, we find that the GSS variables' return predictability is higher for the retailers' stocks—both in terms of economic magnitudes and statistical significance—than for the manufacturers' stocks. In particular, in comparison to returns observed in the main sample, while the abnormal returns for the manufacturers' portfolios are comparable, with a monthly (annualized) abnormal return of the zero-cost portfolio in the range of 0.6% to 0.8% (7% to 11%), the monthly (annuallized) abnormal returns for the retailers' subsample are considerably higher, in the range of 1.05% to 1.30% (13% to 16%). Likewise, the t-statistics of

Table 6 Return Predictability by Supply Chain Position

GSS Measures	Weights	Top and Bottom Portfolio Alphas								
		Retailers			Wholesalers			Manufacturers		
		1	5	**H-L**	1	5	**H-L**	1	5	**H-L**
Global Sourcing Level (GL)	VW	-0.146 (-0.71)	1.109 (2.93)	**1.255** **(3.39)**	0.178 (0.80)	0.524 (1.01)	**0.346** **(0.64)**	-0.123 (-1.38)	0.611 (1.42)	**0.734** **(1.61)**
	EW	1.015 (1.89)	0.904 (1.26)	**-0.111** **(-0.13)**	0.169 (0.85)	3.166 (2.94)	**2.997** **(2.74)**	0.279 (1.79)	1.825 (4.29)	**1.546** **(3.49)**
Supplier Concentration (SC)	VW	-0.098 (-0.35)	0.952 (2.88)	**1.051** **(2.67)**	0.371 (1.67)	0.596 (1.51)	**0.225** **(0.53)**	0.114 (1.12)	0.881 (3.58)	**0.767** **(2.61)**
	EW	0.055 (0.13)	3.096 (3.40)	**3.040** **(3.13)**	0.356 (1.45)	4.478 (3.73)	**4.122** **(3.37)**	0.619 (3.66)	2.456 (6.67)	**1.837** **(4.72)**
Sourcing Lead Time (SL)	VW	0.912 (3.27)	-0.390 (-1.44)	**-1.302** **(-3.42)**	0.423 (0.93)	0.428 (2.28)	**0.005** **(0.01)**	0.570 (2.07)	-0.105 (-1.16)	**-0.674** **(-2.24)**
	EW	2.694 (2.90)	0.032 (0.09)	**-2.662** **(-2.77)**	3.873 (3.07)	0.110 (0.50)	**-3.763** **(-2.98)**	2.624 (6.66)	0.261 (1.85)	**-2.362** **(-5.72)**
Relationship Strength (RS)	VW	-0.175 (-0.70)	1.380 (3.79)	**1.556** **(4.09)**	0.500 (2.29)	0.345 (0.72)	**-0.155** **(-0.31)**	0.011 (0.11)	0.742 (2.92)	**0.731** **(2.56)**
	EW	0.332 (0.83)	1.918 (2.47)	**1.586** **(1.89)**	0.563 (0.86)	4.191 (3.43)	**3.628** **(2.43)**	0.447 (2.69)	2.577 (6.38)	**2.130** **(4.99)**

Notes. This table reports the monthly four-factor alphas of the top and bottom sorted quintile portfolios for each GSS measure, separately for retailers, manufacturers, and wholesalers. Retailers are firms with SIC codes between 5200 and 5999. Wholesalers are firms with SIC codes between 5000 and 5199. Manufacturers are firms with SIC codes between 2000 and 3999. The sample period is Jan 2009–Dec 2019. Alphas for quintiles 2–4 are omitted to conserve space. All alphas are expressed in percentage points. The numbers in brackets are t-statistics.

the retailers' subsample estimates are also considerably higher than those of the main sample estimates. These results suggest higher heterogeneity in the GSS choices among the firms in the retail sector compared to manufacturers (Jain et al. 2020).

3.2. Cross-sectional Tests: Fama-MacBeth

In this section, we use the Fama and MacBeth (1973) cross-section test to examine the predictive power of the four GSS measures, $GSS_k \in \{GL, SC, SL, RS\}$ while controlling for a variety of return predictors.[12] In particular, we control for the following covariates: (1) standard valuation measures such as market capitalization (Mktcap), book-to-market ratio (BM), and gross profit margin (GPM); (2) two past returns control capturing one-month lagged return ($R_{[t-1,t]}$) and return in the last 12 months but one ($R_{[t-12,t-2]}$); (3) inventory investment levels (Inventory); (4) accounting accruals (Accruals); (5) debt-to-equity ratio (Leverage); (6) investment-related metrics such as capital (Capex Intensity) and R&D (R&D Intensity) investment intensity. Table A5, provides details of the construction procedure for these control variables.

[12]We note that the employed cross-sectional test is different from Fama and French (1993) *two-pass test* of factor models. In Fama and French (1993) time-series test, the first step is to run K time-series regression of each stock return on the proposed factor-mimicking portfolios. In the second step, a single cross-sectional regression is run on the estimated betas to obtain the so-called factor risk premia. We refer readers to Welch (2008) for a detailed discussion on the conceptual relation between the Fama-MacBeth cross-sectional test and the Fama-French time-series test.

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Table 7 Fama-MacBeth Regression Results

	Global Sourcing Strategy Measures							
	Global Sourcing Level (GL)				Supplier Concentration (SC)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Strategy Measure	0.712	0.694	0.703	0.594	1.496	0.541	0.563	0.576
	(4.09)	(3.62)	(3.75)	(2.77)	(7.24)	(4.46)	(4.96)	(4.12)
Mktcap		-0.247	-0.248	-0.359		-0.224	-0.221	-0.306
		(-3.49)	(-3.48)	(-2.91)		(-3.18)	(-3.16)	(-2.95)
BM		0.009	-0.019	-0.054		0.156	0.138	0.157
		(0.05)	(-0.11)	(-0.28)		(0.85)	(0.73)	(0.75)
GPM		0.251	0.229	0.242		0.149	0.126	0.150
		(1.70)	(1.42)	(1.72)		(1.01)	(0.78)	(1.03)
Accruals		1.058	0.916	-0.016		2.234	2.218	1.615
		(1.56)	(1.41)	(-0.03)		(1.79)	(1.79)	(1.43)
Inventory		0.241	0.157			0.258	0.189	
		(1.61)	(1.01)			(1.71)	(1.21)	
CCC				-0.584				-0.851
				(-3.87)				(-4.97)
$R_{t-1,t}$		-5.306	-5.321	-5.887		-5.116	-5.126	-5.718
		(-2.69)	(-2.70)	(-3.08)		(-2.77)	(-2.76)	(-3.21)
$R_{t-12,t-2}$		0.122	0.072	-1.005		0.140	0.102	-0.930
		(0.28)	(0.16)	(-0.98)		(0.45)	(0.32)	(-0.94)
Leverage			-0.109	-0.149			-0.157	-0.183
			(-1.76)	(-2.13)			(-2.42)	(-2.59)
CAPEX Intensity			-0.592	-0.662			-0.477	-0.621
			(-4.52)	(-5.76)			(-3.68)	(-4.96)
R&D Intensity			-0.139	-0.288			-0.186	-0.368
			(-0.95)	(-2.09)			(-1.41)	(-2.63)
Average R^2	0.004	0.044	0.048	0.047	0.001	0.042	0.046	0.046
	Weighted Lead Time (SL)				Relationship Strength (RS)			
	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Strategy Measure	-0.794	-0.247	-0.253	-0.228	1.760	0.518	0.565	0.448
	(-9.95)	(-5.17)	(-5.48)	(-4.52)	(9.64)	(3.19)	(3.70)	(3.08)
Mktcap		-0.294	-0.294	-0.395		-0.214	-0.204	-0.324
		(-3.42)	(-3.37)	(-2.82)		(-2.24)	(-2.15)	(-2.34)
BM		0.207	0.194	0.196		0.160	0.136	0.163
		(1.13)	(1.02)	(0.97)		(0.89)	(0.73)	(0.80)
GPM		0.153	0.142	0.152		0.160	0.129	0.155
		(1.02)	(0.86)	(1.03)		(1.06)	(0.80)	(1.05)
Accruals		2.220	2.174	3.525		2.254	2.254	1.625
		(1.76)	(1.73)	(1.72)		(1.81)	(1.81)	(1.43)
Inventory		0.141	0.073			0.285	0.223	
		(0.99)	(0.50)			(2.09)	(1.57)	
CCC				-0.771				-0.866
				(-4.57)				(-4.91)
$R_{t-1,t}$		-5.313	-5.320	-5.929		-5.122	-5.132	-5.731
		(-2.83)	(-2.82)	(-3.28)		(-2.77)	(-2.76)	(-3.21)
$R_{t-12,t-2}$		0.152	0.116	-0.918		0.132	0.091	-0.943
		(0.50)	(0.37)	(-0.93)		(0.42)	(0.29)	(-0.95)
Leverage			-0.169	-0.202			-0.153	-0.186
			(-2.71)	(-2.88)			(-2.35)	(-2.52)
CAPEX Intensity			-0.439	-0.558			-0.485	-0.619
			(-3.31)	(-4.50)			(-3.72)	(-5.03)
R&D Intensity			-0.115	-0.304			-0.214	-0.370
			(-0.83)	(-2.12)			(-1.75)	(-3.15)
Average R^2	0.000	0.042	0.046	0.048	0.001	0.042	0.047	0.046

Notes. The dependent variable is monthly individual stock returns *in percentage points*. All accounting ratios are winsorized at the 1% level for both tails. All independent variables except past returns are standardized to mean zero and unit standard deviation for ease of coefficient interpretation. The numbers in brackets are t-statistics.

We implement the test in two steps. First, for each month between Jan 2009 and December 2019, we fit a cross-sectional regression of individual stock returns on a GSS measure, GSS_k and a set of the above-listed control variables. We include all of the independent variables in the regression specification with values that are known at the end of the previous month. Specifically, for a firm i in period t, we use the accounting information available as of six months ago $(t-6)$ with the exception of market cap and past returns, which are the values as of the previous month. Further, all independent variables, except the past return variables, are standardized to mean zero and unit standard deviation for ease of coefficient interpretation. We construct the GSS measures using sourcing choices made between the period of $t-24$ and $t-12$ months to ensure full data availability. For example, for the Jan 2010 period, the GSS measures are constructed using information on the sourcing choices made between Jan 2008 and Jan 2009. In the second step, we capture the monthly estimates and compute their time-series average. Consistent with the literature, we include log of BM and size measures and, accordingly, drop negative value observations of these two variables. The standard errors are adjusted using the Newey–West procedure, with up to 12 lags to account for the potentially overlapping accounting, and return periods. A significant average estimate for the GSS measures would indicate that these measures embed incremental information which is relevant for return predictability.

Table 7 reports the estimation results of the cross-section tests. Columns (1), (5), (9), and (13) show estimates of the specification with only the GSS variable, GSS_k. Columns (2), (6), (10), and (14) show results of a specification with commonly studied financial covariates except for Leverage, Capex Intensity, and R&D (R&D Intensity) covariates. We also include inventory turnover as an additional covariate. As discussed in Section 3.1.2, it is an operations measure that is likely to be confounded with a firm's GSS choices and is also documented as a significant predictor of future returns in the cross section. Columns (3), (7), (11), and (15) show estimation results with the full set of financial covariates and inventory turnover. Finally, Columns (4), (8), (12), and (16) show results of the full covariates specification with CCC as the operations-motivated covariate.

The cross-sectional test estimates strongly support our main findings from the time-series tests, both in sign and significance for all four GSS variables. Two additional observations are noteworthy here. One, in the univariate analysis (columns (1), (5), (9), and (13)) we find that each GSS_k variable estimate is strongly significant (all $t-$statistics>3), and has economic magnitude comparable to the monthly abnormal returns observed in the time-series analysis. On average, across the four GSS_k variables, a one-standard-deviation change in the GSS_k variable yields monthly unadjusted returns in range of 0.7% to 1.8%. Second, we observe that all four GSS_k variables retain significant predictive power, even after inclusion of the full set of covariates. The absolute minimum t-statistic in the multivariate regression ranges between 2.77 and 4.52, all of which are significant and of the recommended size as per the recent asset pricing literature norms (Harvey et al. 2016).

3.3. Sources of Return Predictability

Our results in the previous section demonstrate GSS variables' significant predictability of future stock returns. The standard factor models fail to explain this association as we find low or negative loadings on the five principal risk dimension (see Table A1 in the appendix). Intuitively, the observed return predictability could stem from two sources: exposure to latent globalization-related risks not included in the underlying factor model, or market participants' mispricing of GSS variables' relation to future cash flows. Lack of data and representation of globalization risk in factor form prevent us from testing all possible latent risk factors associated with global sourcing (e.g. Fillat and Garetto 2015). Below, we examine whether our results are consistent with the mispricing mechanism.

As discussed in Introduction, global sourcing can create firm value and affect future profitability through various channels, including network effect, cash optimization, cost and knowledge arbitrage, etc. At the same time, global sourcing is a specialized area of supply chain management, and market participants might not possess the requisite domain knowledge to fully account for its implication on future profitability. If so, they might be surprised when future earnings are realized, therefore leading to predictable changes in the observed alphas.

We examine the mispricing channel with a two-sided approach. First, following Fama and French (2000), Hou et al. (2012) and Wang (2019), we examine the GSS variable's predictive power for future earnings using a standard earnings prediction model after controlling for a variety of predictors including past earnings. Second, we test whether investors are surprised by the GSS-related earnings realizations.

We estimate the GSS variable's earning prediction power using the following model

$$\begin{aligned} E_{i,t+1} = \; & \alpha_0 + \alpha_1 GSS(H)_{i,t-1} + \alpha_2 GSS(L)_{i,t-1} + \alpha_3 A_{i,t} + \alpha_4 D_{i,t} + \alpha_5 DD_{i,t} + \alpha_6 E_{i,t} + \\ & \alpha_7 NegE_{i,t} + \alpha_8 AC_{i,t} + \epsilon_{i,t+1}, \end{aligned} \tag{11}$$

where $E_{i,t+1}$ denotes the earnings of firm i in year $t+1$ and is computed as operating income divided by total assets, $GSS(H)$ and $GSS(L)$ are indicator variables that equal 1 for firms in the top and bottom quintiles, respectively, and 0 otherwise, $A_{i,t}$ is the total assets, $D_{i,t}$ is the dividend payment, $DD_{i,t}$ is a dummy variable that equals 1 for dividend payers and 0 otherwise, $NegE_{i,t}$ is a dummy variable that equals 1 for firms with negative earnings and 0 otherwise, and $AC_{i,t}$ is accruals.

Panel A of Table 8 shows the estimation results. For the GL, SC, and RS variables, Rows 1 (2) indicates that high (low) values are positively (negatively) associated with future earnings, compared to the median firms. For the SL variable, high values (longest lead time) are negatively

Table 8 GSS Variables and Earnings

Panel A. Earnings Surprises

Earnings	Global Sourcing Strategy Measure			
	(1) Global Sourcing Level (GL)	(2) Supplier Concentration (SC)	(3) Sourcing Lead Time (SL)	(4) Relationship Strength (RS)
$GSS(H)$	0.060	0.024	-0.080	0.028
	(3.87)	(2.00)	(-5.89)	(2.80)
$GSS(L)$	-0.144	-0.036	-0.001	-0.036
	(-6.40)	(-4.25)	(-0.09)	(-7.14)
AT	0.090	0.081	0.083	0.081
	(6.93)	(6.69)	(6.78)	(6.79)
D	1.086	1.058	1.033	1.048
	(8.28)	(8.20)	(7.85)	(7.84)
DD	-0.139	-0.135	-0.132	-0.135
	(-6.63)	(-6.64)	(-6.32)	(-6.39)
E	0.722	0.727	0.726	0.727
	(8.91)	(8.93)	(8.93)	(8.94)
$NegE$	-0.021	-0.030	-0.028	-0.029
	(-0.60)	(-0.86)	(-0.78)	(-0.83)
AC	-0.043	-0.043	-0.043	-0.043
	(-1.94)	(-1.94)	(-1.94)	(-1.94)
Intercept	-0.560	-0.517	-0.509	-0.524
	(-6.99)	(-6.68)	(-6.95)	(-6.78)
Average R^2	0.590	0.588	0.589	0.588

Panel B. Abnormal Returns Around Earnings Announcement Days

Size-adj. Ret	Global Sourcing Strategy Measure			
	(1) Global Sourcing Level (GL)	(2) Supplier Concentration (SC)	(3) Sourcing Lead Time (SL)	(4) Relationship Strength (RS)
$GSS(H)$	0.600	0.357	-0.268	0.155
	(4.30)	(3.68)	(-3.00)	(2.43)
$GSS(L)$	-0.164	0.042	0.473	-0.084
	(-1.97)	(0.34)	(3.11)	(-2.02)
Average R^2	0.02	0.02	0.02	0.02

associated with the future earnings. These results are directionally aligned with our time-series and cross-sectional findings that show a significant correlation between stock returns and the GSS variables. Collectively, these coefficients indicate that the GSS variables provide incremental information over the commonly studied predictors on firms' future earnings.

Next, having established that GSS variables have predictive power for future earnings, we examine whether investors can expect this or, instead, whether they are surprised by the subsequent earnings realizations. We do so using a widely-used test that examines abnormal stock returns around earnings announcements (Sloan 1996a, Porta et al. 1997, Engelberg et al. 2018). If the GSS-earnings relation is fully incorporated by market participants, then returns on the earnings announcement days (EADs) would be similar to those on other non-earnings announcement days (non-EAD). If, by contrast, investors fail to fully account for information embodied in the GSS variables, then we expect the high (low)-GSS firms to show higher (lower) EAD returns than the non-EAD returns.

We obtain the earnings announcement data from I/B/E/S. We define the cumulative abnormal returns (CAR) in the five days around the EAD as the dependent variable (Wang 2019). Specifically, we measure CAR as the size-decile-adjusted returns from $t-2$ to $t+2$ trading days around the EADs. Finally, we replicate the Fama-MacBeth regression analysis (as discussed in Section 3.2) with the CARs as the dependent variable and $GSS(H)$ and $GSS(L)$ as independent variables, in addition to the same set of controls as in Table 7.

Panel B of Table 8 shows the estimation results in percentage points. In seven out of the eight tests, we find consistent support in the relation between GSS and CARs around the earnings announcement days.[13] The spread between the $GSS(H)$ and $GSS(L)$ estimates suggests that around one tenth to a quarter of the long–short returns in our time-series tests could be realized around EADs, which is sizable and provides a strong indication that investors fail to fully incorporate incremental information that GSS variables sheds on profitability into their forecasts. This, in turn, leads to surprises when the earnings are realized. In totality, results in this section suggest that global sourcing embeds incremental value-relevant information that is not fully incorporated by market participants.

4. Robustness Tests

In this section, we test the robustness of our main findings to alternative risk model specifications, subsample analyses, alternate inventory variable definitions, and alternate stock sorting procedure using eight robustness analyses. In addition to these analyses, in Appendix B we examine whether our findings are sensitive to the omission of non-sea based imports in our dataset.

4.1. Alternative Risk Model Specifications

In our main analysis, we use the Fama-French-Carhart four factor model to estimate a portfolio's monthly abnormal returns while adjusting for the common risk factors. We examine whether our results are sensitive to this specific choice of risk model. Table 9 shows results of alternative risk models for each of the four GSS variables that showed significant return predictability in our main analysis $GSS \in \{GL, SC, SL, RS\}$.

We first present results without any risk adjustment. In row 1 of each individual GSS variable subpanel, we report the average unadjusted monthly excess returns (portfolio return minus the

[13] Inline with our main analysis, SL estimates continue to show opposite sign to that obtained with GL, SC, and RS variables.

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Table 9 Global Sourcing Excess Returns Alphas from Alternative Risk Models

	Sorted Portfolios											
	Global Sourcing Level (GL)						Supplier Concentration (SC)					
	1	2	3	4	5	**H-L**	1	2	3	4	5	**H-L**
Unadjusted Return	0.997	1.618	1.471	1.789	1.680	**0.682**	1.184	1.007	1.311	1.562	1.673	**0.490**
	(3.19)	(4.82)	(4.10)	(4.24)	(4.21)	**(2.76)**	(3.55)	(3.21)	(3.98)	(4.46)	(4.31)	**(2.59)**
FF 5-Factor α	-0.178	0.427	0.267	0.527	0.541	**0.718**	-0.020	-0.171	0.140	0.328	0.611	**0.631**
	(-3.47)	(5.43)	(2.05)	(2.94)	(2.12)	**(2.72)**	(-0.29)	(-2.38)	(1.42)	(2.91)	(3.00)	**(3.19)**
q-Factor α	-0.106	0.546	0.465	0.758	0.931	**1.037**	0.120	-0.087	0.252	0.492	0.799	**0.678**
	(-1.71)	(6.80)	(3.46)	(4.58)	(4.04)	**(4.15)**	(1.64)	(-1.16)	(2.55)	(4.19)	(4.36)	**(3.40)**
	Sourcing Lead Time (SL)						Relationship Strength (RS)					
	1	2	3	4	5	**H-L**	1	2	3	4	5	**H-L**
Unadjusted Return	1.865	1.397	1.496	1.409	0.990	**-0.876**	1.014	1.212	1.512	1.652	1.712	**0.698**
	(5.00)	(3.95)	(4.41)	(4.23)	(3.05)	**(-6.13)**	(3.15)	(3.57)	(4.56)	(4.69)	(4.56)	**(4.18)**
FF 5-Factor α	0.666	0.131	0.318	0.216	-0.202	**-0.868**	-0.155	-0.036	0.299	0.483	0.575	**0.729**
	(5.16)	(1.19)	(2.87)	(2.26)	(-3.00)	**(-6.46)**	(-2.30)	(-0.35)	(2.97)	(3.90)	(4.02)	**(4.78)**
q-Factor α	0.823	0.311	0.552	0.240	-0.071	**-0.894**	-0.060	0.129	0.472	0.630	0.645	**0.706**
	(6.83)	(2.63)	(5.07)	(2.74)	(-1.02)	**(-6.62)**	(-0.83)	(1.20)	(4.57)	(5.20)	(4.82)	**(4.57)**

Notes. The first row of this table reports the monthly unadjusted excess returns (return–risk free rate) of each value-weighted sorted quintile portfolio constructed using each GSS measure. The second and third rows report the alphas of the corresponding portfolios computed using the five-factor (Fama and French 2015) and q-factor (Hou et al. 2015) models. Refer to Table 3 for the otherwise identical empirical specification. The sample period is Jan 2009–Dec 2019. All alphas are expressed in percentage points. The numbers in brackets are t-statistics.

risk-free rate) of different quintiles (columns 1 to 5), and zero-cost investment portfolio (column **H-L**). Not surprisingly, we find that the unadjusted individual portfolio returns are slightly higher than the factor model alpha returns. We continue to find monotonic relationships between the GSS variable and monthly unadjusted returns as one moves from lowest to highest quintile.

In rows 2 and 3, we show estimation results with two emerging risk factor models: the Fama and French (2015) five-factor model and the Hou et al. (2015) q-factor model. Though the Fama-French-Carhart four-factor model (Carhart 1997) remains the mainstay of asset pricing analysis, these alternate models have been found to better capture the risk–return relationship and thus explain a considerably higher number of return anomalies than Carhart (1997). We examine the robustness of our main findings by repeating the time-series analysis using the five-factor model and q-factor models for risk adjustment. In the former risk model, the usual MKTRF, SMB and HML factors are augmented by two additional factors: (i) robust-minus-weak (RMW: stocks with weak earnings minus those with strong earnings) factor that captures profitability risk; and the conservative-minus-aggressive (CMA: stocks with low investments minus those with high investments) factor that captures investment risk. The latter model employs an alternative risk–return framework wherein the market (MKT) and size (ME) factors are augmented with two factors based on investment over assets (the I/A factor) and return on equity (the ROE factor).[14]

Collectively, the results of these alternative specifications indicate that our main findings are robust to both not adjusting the portfolios for risk, and are robust to adjusting for risk using more comprehensive, emerging models. The four GSS variables embed information that is not fully captured by the market, size, value, momentum (past returns), profitability and investment-related risks. Put differently, it is unlikely that the GSS variables' return predictability is fully explained by the exposure to risk encapsulated in the standard factor models.

4.2. Alternate Subsample Analysis: The Effect of Size and Liquidity

In our main analysis, we do not make a distinction between stocks of small and large firms. Berk (1995) notes that, on account of their illiquidity and limited arbitrage opportunities, small firms often have dramatic and outsized returns which dominate the sorted portfolios' returns. While we partially correct for this concern by also examining returns of the value-weighted portfolios, to further investigate whether our results are robust in predicting stocks of different-sized firms, we separately analyze the predictability of GSS in subsamples of small and large firms. Specifically, we classify a stock into the small- or large-firm subsample depending on whether it is below the 30^{th} percentile or above the 70^{th} percentile of the size distribution, respectively. Accounting for the low number of observations, we repeat our time-series test in these subsamples using tercile portfolios. We create the zero-cost investment portfolio by buying from the highest and selling from the lowest tercile of each of the four GSS measures.

Table 10 shows results of the size-based subsample analysis. Due to a clustering issue, we obtain only two portfolios when sorting small-firm sample stocks on the SC measure. Interesting to find that, across all the four GSS variables, the abnormal return of the zero-cost portfolio is higher in the small-firm sample compared to the large-firm sample; even after the use of value-weighting approach to construct portfolios and inclusion of size as a factor in the risk model. Second, the zero-cost portfolio alphas remain significantly positive in both small-firm and large-firm samples, indicating that our results are robust in different firm-size partitions.

Our next test examines whether our results are primarily driven by illiquid stocks that are difficult to trade. In Table 11, we present the GSS four-factor alphas from the sample that excludes "penny stocks" from our stock universe. In the asset pricing literature, many studies have demonstrated that penny stocks, which are thinly traded at low prices, tend to have outsized returns that drive the zero-cost portfolio returns, and so result in many asset pricing anomalies, particularly in the

[14]Factor data is from Ken French's website at https://bit.ly/3cDcaZN, and Lu Zhang's website at https://bit.ly/3bzRfpd.

doing

Table 10 Global Sourcing Excess Alphas from Different Firm-Size Samples

Global Sourcing Strategy Measure Terciles

	Global Sourcing Level Portfolios, GL								Supplier Concentration Portfolios, SC							
Size	VW				EW				VW				EW			
	L	M	H	H-L	L	M	H	H-L	1	2	3	H-L	1	2	3	H-L
Small	-0.116	0.349	1.386	1.502	-0.016	0.557	1.669	1.685	1.110	...	1.658	0.549	2.470	...	3.263	0.793
	(-0.46)	(1.58)	(4.49)	(8.03)	(-0.05)	(1.66)	(3.56)	(7.60)	(1.98)	...	(3.45)	(1.41)	(3.67)	...	(6.02)	(2.10)
Big	-0.138	0.306	0.402	0.540	0.279	0.455	0.161	-0.118	0.063	-0.007	0.256	0.193	0.341	0.363	0.403	0.063
	(-2.02)	(4.34)	(3.23)	(6.23)	(2.91)	(4.74)	(1.85)	(2.20)	(0.79)	(-0.09)	(2.93)	(2.97)	(3.00)	(3.67)	(4.64)	(1.76)

	Sourcing Lead Time Portfolios, SL								Relationship Strength Portfolios, RS							
Size	VW				EW				VW				EW			
	1	2	3	H-L	1	2	3	H-L	1	2	3	H-L	1	2	3	H-L
Small	1.888	2.078	0.769	-1.118	3.301	3.524	2.238	-1.063	0.833	1.688	1.837	1.004	2.261	3.795	2.927	0.666
	(3.09)	(3.14)	(1.60)	(-3.34)	(4.77)	(5.61)	(3.50)	(-2.99)	(1.71)	(3.43)	(2.51)	(2.62)	(3.37)	(6.71)	(4.41)	(2.00)
Big	0.443	0.211	-0.116	-0.559	0.537	0.372	0.200	-0.337	-0.051	0.027	0.463	0.514	0.232	0.380	0.497	0.265
	(4.44)	(2.71)	(-1.56)	(-8.37)	(5.88)	(4.35)	(1.77)	(-5.39)	(-0.64)	(0.29)	(4.61)	(6.51)	(1.91)	(4.14)	(5.09)	(3.23)

Notes. This table reports the monthly four-factor alphas of each sorted tercile portfolios constructed using each GSS measure, for the small firm ($\leq$ 30th percentile in terms of market capitalization) and large firm ($\leq$ 70th percentile in terms of market capitalization), respectively. Refer to Table 3 for details on the otherwise identical empirical specification. All alphas are expressed in percentage points. The numbers in brackets are t-statistics.

short leg (e.g. quintile 1). The return effect of penny stocks might therefore be overstated purely on the account of their illiquidity and the resulting high volatility. See Chu et al. (2017) for a recent summary of these studies. Following the convention, we define penny stocks as those that have a monthly closing price of below \$3 a share.

Table 11 Eliminating Penny Stocks

GSS Measures	Portfolios					
	VW			EW		
	1	5	H-L	1	5	H-L
Global Sourcing Level (GL)	0.068	0.562	0.494	0.280	0.441	0.161
	(0.89)	(2.98)	(2.55)	(4.72)	(2.15)	(1.42)
Supplier Concentration (SC)	0.120	0.655	0.535	0.193	0.621	0.428
	(1.32)	(5.01)	(3.29)	(3.09)	(5.44)	(2.60)
Sourcing Lead Time (SL)	0.571	-0.121	-0.693	0.710	0.156	-0.554
	(4.82)	(-1.51)	(-5.04)	(6.25)	(1.34)	(-3.82)
Relationship Strength (RS)	-0.056	0.500	0.556	0.275	0.596	0.322
	(-0.66)	(4.32)	(3.61)	(2.05)	(5.62)	(1.92)

Notes. This table reports the monthly four-factor alphas of the lowest (1), highest (5) and zero-cost (H–L) portfolios constructed using each GSS measure, for the reduced sample of firms where stocks trading lower than \$3 a share are eliminated. Refer to Table 3 for details on the otherwise identical empirical specification. All alphas are expressed in percentage points. The numbers in brackets are t-statistics.

Collectively across these subsample analyses, we find sign- and significance-consistent results, with our main analysis, for 23 out of 24 alpha estimates. These results provide strong evidence that the return predictability of the four GSS variables is robust and not driven by either the presence of small-size firms or penny stocks.

4.3. Alternate Inventory Variable Definition and Stock Sorting Procedure

In our main analysis, we employ a double-sort analysis to examine the incremental value of the GSS variables in comparison to the inventory turnover (IT) measure that is known for strong return predictability (Alan et al. 2014). In Table 12 we extend the double-sort to further investigate the incremental value of the GSS variables relative to alternative inventory measures: (i) the inventory investment measure $IL = \mathrm{INVT/AT}$ (Belo and Lin 2012); (ii) the gross margin return on inventory $GMROI = (Sales_{i,t} - COGS_{i,t} - LIFO_{i,t} + LIFO_{i,t-1})/(INV_{i,t} + LIFO_{i,t})$ measure defined by Alan et al. (2014); and (iii) the adjusted inventory turnover (AIT) measure that adjusts the IT measure for changes in gross margin, capital intensity, and sales surprise (Alan et al. 2014). Table 12 shows the estimation results of the Fama-French four alphas for the terciles and zero-cost investment portfolios. Note that by construction, inventory investment and inventory turnover measures are inversely related – that is, high inventory investment indicates low inventory turnover. As a result, we find an opposite relationship between the zero-cost portfolio alphas and the inventory investment terciles (the alphas are higher in firms with the lower inventory levels), which is inline with the main analysis.

Finally, in our main analysis, following Alan et al. (2014) we implemented a non-parametric industry-adjusted procedure for portfolio formation. This procedure enables an equal representation of various industries across all quintile portfolios (see Figure 2). In Table 13, we present estimation results of the Fama-French four alphas based on portfolios formed using the conventional industry-unadjusted procedure. Under this analysis, the portfolio returns indicate the GSS variable's informativeness across industries. In summary, across this group of robustness tests, we find sign- and significance-consistent results, with our main analysis, for 71 out of 80 alpha estimates.

5. Discussion

Firms across globe increasingly rely on global sourcing, as a key constitute of their supply chain strategy, to create and capture supply-side value opportunities. At the same time, investors do not seem to fully grasp the implications of global sourcing strategies (GSS) to future firm value. There is scant empirical evidence on association between GSS and stock returns. On the one hand, a detailed view of firms' GSS choices is generally less accessible than other operations-related data such as inventory and cas conversion cycle (CCC), and processing them requires certain domain-specific expertise in supply chain management. As such, market participants might fail to account for information embedded in GSS in pricing stocks. On the other hand, since the GSS choices are part of the a firm's overall supply chain strategy, it is conceivable that other operations-related return predictors already embody information embedded in the firm's GSS choices. In this study, we present rigorous evidence to ascertain whether the firms' GSS choices embed new information

Table 12 Double-Sort Results Using Different Inventory Measures

Panel A. Global Sourcing Strategy Measure Tercile Portfolios Sorted on Inventory Investment, IL

INV Terciles	Measure Terciles											
	(1)			(2)			(3)			(4)		
	Global Sourcing Share			Supplier Concentration			Weighted Lead Time			Relationship Strength		
	1	3	H-L	1	3	H-L	1	3	H-L	1	3	H-L
1	-0.184	0.562	0.746	-0.29	0.704	0.995	0.511	-0.311	-0.823	-0.39	0.615	1.005
	(-1.91)	(2.41)	(5.20)	(-2.21)	(5.03)	(9.31)	(3.67)	(-2.52)	(-7.47)	(-2.97)	(4.20)	(8.55)
3	0.164	0.794	0.63	0.279	0.472	0.193	0.465	0.159	-0.305	0.205	0.516	0.311
	(1.21)	(3.19)	(3.87)	(1.69)	(2.51)	-1.51	(2.29)	(1.16)	(-2.81)	(1.34)	(2.50)	(2.19)
Avg	0.019	0.621	0.602	0.009	0.488	0.479	0.493	-0.059	-0.552	-0.082	0.546	0.628
	(0.31)	(3.66)	(3.17)	(0.12)	(5.37)	(4.12)	(4.99)	(-0.84)	(-4.94)	(-1.06)	(4.97)	(4.29)

Panel B. Global Sourcing Strategy Measure Tercile Portfolios Sorted on Inventory Gross Margin Return, GMROI

	(1)			(2)			(3)			(4)		
	Global Sourcing Share			Supplier Concentration			Weighted Lead Time			Relationship Strength		
	1	3	H-L	1	3	H-L	1	3	H-L	1	3	H-L
1	0.268	0.677	0.409	0.35	0.401	0.051	1.302	0.095	-1.207	0.12	0.918	0.798
	(1.87)	(2.35)	(2.48)	(2.26)	(1.70)	(0.39)	(5.54)	(0.56)	(-8.54)	(0.69)	(4.01)	(5.26)
3	-0.252	0.324	0.576	-0.152	0.599	0.751	0.444	-0.226	-0.67	-0.316	0.365	0.681
	(-3.18)	(1.55)	(4.31)	(-1.68)	(4.50)	(8.45)	(3.27)	(-2.45)	(-7.37)	(-3.31)	(2.61)	(6.71)
Avg	0.055	0.473	0.419	0.088	0.463	0.376	0.681	-0.038	-0.72	-0.062	0.58	0.642
	(0.77)	(2.51)	(2.14)	(1.09)	(4.15)	(3.16)	(5.37)	(-0.47)	(-5.70)	(-0.74)	(4.79)	(4.64)

Panel C. Global Sourcing Strategy Measure Tercile Portfolios Sorted on Adjusted Inventory Turnover, AIT

	(1)			(2)			(3)			(4)		
	Global Sourcing Share			Supplier Concentration			Weighted Lead Time			Relationship Strength		
	1	3	H-L	1	3	H-L	1	3	H-L	1	3	H-L
1	0.224	0.667	0.443	0.323	0.472	0.150	0.533	0.087	-0.446	0.397	0.62	0.223
	(3.01)	(1.93)	(2.05)	(2.30)	(1.84)	(1.59)	(2.50)	(1.11)	(-2.56)	(2.66)	(2.81)	(1.97)
3	-0.162	0.398	0.560	0.070	0.522	0.453	0.501	-0.124	-0.625	0.103	0.538	0.434
	(-2.41)	(2.00)	(3.94)	(1.21)	(4.36)	(4.80)	(3.04)	(-1.71)	(-4.42)	(1.45)	(3.87)	(5.21)
Avg	0.018	0.543	0.525	0.118	0.503	0.386	0.498	0.02	-0.478	0.206	0.618	0.412
	(0.70)	(2.63)	(2.22)	(0.58)	(3.31)	(2.87)	(3.38)	(0.05)	(-3.92)	(0.24)	(3.31)	(4.02)

Notes. This table reports the value-weighted monthly four-factor alphas of each double-sorted tercile portfolio constructed with alternative inventory measures. Refer to Table 4 for details on the otherwise identical empirical specification.

that is associated with future stock returns, above and beyond existing operations-related return predictors such as inventory and cash conversion cycle. We find strong evidence of incremental return predictability of the following GSS variables: the extent of global sourcing; supplier concentration; relationship strength; and sourcing lead time. Also, we find that the predictive power of these variables persists across firms, independent of their supply chain positions. Finally, our analysis suggest that GSS variables' return predictability is more likely explained by these variables' informational value on respective firms' future profitability than by the related market-risk factors.

Our study has two key implications for operations managers. First, we present a potential new channel for operations managers to get the message across to the C-suite by showcasing a strong

Table 13 Unadjusted Sorting Results

GSS Measures	Weights	Portfolios					
		1 (Lowest)	2	3	4	5 (Highest)	**H-L**
Global Sourcing Level (GL)	VW	-0.114 (-1.76)	0.375 (4.94)	0.275 (2.53)	0.482 (2.71)	0.594 (2.40)	**0.709** **(2.71)**
	EW	0.199 (1.78)	0.200 (2.12)	0.304 (2.47)	0.409 (2.50)	1.227 (3.67)	**1.029** **(3.09)**
Supplier Concentration (SC)	VW	0.097 (0.84)	-0.032 (-0.26)	0.093 (0.73)	0.253 (1.76)	0.642 (2.84)	**0.545** **(2.12)**
	EW	0.423 (2.25)	0.538 (2.53)	0.725 (2.56)	1.141 (3.80)	2.137 (5.28)	**1.714** **(4.48)**
Sourcing Lead Time (SL)	VW	0.559 (4.43)	0.398 (3.11)	0.326 (3.11)	0.199 (2.27)	-0.116 (-1.55)	**-0.674** **(-4.96)**
	EW	1.685 (5.51)	1.664 (6.69)	0.788 (4.23)	0.368 (3.13)	0.190 (1.44)	**-1.495** **(-5.02)**
Relationship Strength (RS)	VW	-0.057 (-0.68)	-0.058 (-0.64)	0.242 (2.74)	0.477 (3.96)	0.559 (4.24)	**0.615** **(3.84)**
	EW	0.346 (2.17)	0.553 (3.53)	0.921 (5.30)	1.458 (7.08)	1.412 (4.74)	**1.066** **(3.70)**

Notes. This table reports the monthly four-factor alphas of each sorted quintile portfolio constructed using each GSS measure, where the sorting is done in the standard, unadjusted fashion. Refer to Table 3 for details on the otherwise identical empirical specification. All alphas are expressed in percentage points. The numbers in brackets are t-statistics.

association between GSS and future equity valuation of the firm. It is important for practitioners to document such an association, as managerial incentives are often linked to stock market valuation.

Equally importantly, our findings suggest that managers can enable the market to accurately price their firm's stock by providing timely information about their GSS choices and any changes related to it. Since our results suggest a significant degree of investor mispricing of sourcing strategies, operations managers can reduce the mispricing by increasing the transparency and timeliness of their sourcing decision disclosures and/or providing more investor education on the process behind sourcing and supply chain decisions. Our results, therefore, suggest a higher-profile role for operations managers in investor relations.

Our results should be interpreted with their limitations in mind. First, the empirical asset pricing methodology is apt for examining correlation between the GSS variables and future stock returns, but it does not imply causal relationship between them. Identifying causal inference for the effect of GSS on firms' operational and financial profiles is a fruitful direction for future theoretical and empirical studies.

Second, although we use the most extensive global sourcing data available with the longest possible coverage, our study is limited to the period that the data actually cover, which is the 12-year period between 2008 and 2019. This period is representative of a typical volatile global trade scene, and includes phases of growth (2009-11, 2013-14, and 2016-18), stability (2012-14), and decline (2014-16, 2018-19). Further, intuitively our findings rests on the following three primary factors, all of which are likely to persist within and outside of our sample period: (i) the importance of sourcing choices in capturing supply-side value opportunities, (ii) the market participants' limited ability to correctly capture and incorporate the GSS signal into prediction of the associated future cash flows, and (iii) the information embedded in sourcing choices is incremental to that in other operational measures such as inventory productivity and cash conversion cycles. Nevertheless, unique and unforeseen volatilities and disruptions of global trade in the future might alter the GSS-return relationship, and therefore alter the predictability of the GSS measures in the future.

Third, although our results are consistent with a mispricing-based explanation, we cannot fully rule out the risk-based explanations, particularly if GSS is related to risks that are not fully captured by the principal risk factors in the standard asset pricing models. For instance, in a real-options framework, globalization as a whole is shown to increase the risk faced by importing firms (Fillat and Garetto 2015), which might be further compounded by policy risks at both ends of the trade relationship. As proxying data is not readily available for these risks, they might not be fully reflected in the standard factor portfolios such as HML, CMW, etc. Therefore, in addition to not being fully internalized by market participants, global sourcing strategies could also reflect exposures to new latent risks. These potential risk-based explanations represent a fruitful direction for future research, which could extend our standard risk models to incorporate other operations-focused levers, such as contract structures, supply-chain network structure, and trade-credit provisioning.

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Appendix A: Portfolio Analysis using Time Series Test: Factor Loadings

Table A1 reports the factor loadings — market (MKTRF), size (SMB), book-to-market value (HML), and momentum (UMD) — for the zero-investment portfolios in the five global sourcing strategy (GSS) measures: (i) the extent of global sourcing level (GL); (ii) supplier concentration (SC); (iii) sourcing lead time (SL); (iv) supplier countries' logistical efficiency (LE); and (v) buyer-supplier relationship strength. Note that loadings sign typically reflect the correlation sign reported in Table 2, with the exception of SMB loading for SC variable in the equal-weighted portfolio. The majority of the GSS measures exhibit positive loadings on the SMB factor, consistent with the negative correlation between these measures and firm size in Table 2. Furthermore, GL, SC, and RS have negative loadings on the HML factor, which suggests that stocks with high GSS, SC, and RS tend to be more value-oriented stocks.

Table A1 Factor Loadings

	Global Sourcing Strategy Measures									
Factors	GL	SC	SL	LE	RS	GL	SC	SL	LE	RS
	Value-Weighted Zero-Cost Portfolios					Equal-Weighted Zero-Cost Portfolios				
MKTRF	0.024	0.077	-0.057	0.099	0.004	-0.390	-0.558	0.497	0.099	-0.383
	(0.34)	(1.05)	(-1.57)	(2.61)	(0.08)	(-4.01)	(-4.16)	(5.42)	(1.83)	(-4.29)
SMB	0.208	0.006	-0.274	0.135	0.263	0.204	-0.069	0.065	-0.007	-0.072
	(1.83)	(0.06)	(-4.64)	(2.21)	(3.79)	(1.30)	(-0.37)	(0.44)	(-0.08)	(-0.50)
HML	-0.146	-0.225	0.165	-0.092	-0.242	-0.334	-0.320	0.186	0.077	-0.277
	(-1.41)	(-2.51)	(3.06)	(-1.65)	(-3.81)	(-2.33)	(-1.96)	(1.38)	(0.97)	(-2.11)
UMD	-0.039	-0.101	0.049	0.074	-0.088	-0.172	-0.036	-0.050	0.131	-0.023
	(-0.64)	(-1.95)	(1.55)	(2.28)	(-2.39)	(-2.06)	(-0.38)	(-0.64)	(2.83)	(-0.30)

Notes. This table reports the factor loadings (betas) of the zero-investment (H–L) portfolios for each of the GSS measures. Each column in this table corresponds to beta estimates for the H–L portfolios, whose alpha estimates are presented in the last column of Table 3. The sample period is Jan 2009–Dec 2019. The numbers in brackets are t-statistics.

Appendix B: Robustness Test: Share of non-sea imports

Our imports dataset only captures sea-based imports. This, in turn, constrain us to accurately measure GSS variables, specifically in those sectors which have a disproportionally low share of sea-based imports. For example, sectors that largely rely on land-based routes to import goods from Canada and Mexico. In this section, we present a robustness test that examine whether our findings are sensitive to inclusion or exclusion of such sectors.

We compile the sector-level (4-digit NAICS) share of imports from Canada and Mexico S_{CM} using US census bureau data on total imports by country. For a NAICS sector s, we compute S^s_{CM} as the sample average of annual percentage of its imports that originates from Canada and Mexico compared to the sector's total imports. The median share of Canada and Mexico imports is 23%, which is fairly stable during each of our sample years. However, a small fraction of the sectors (8 NAICS codes)—all related to agriculture and textiles (Grains; Potato; Beef/Cattle; Bakeries/Tortilla; Logging; Sawmills; Paper/Pulp Mills; Limes)—have an outsized Canada and Mexico import share that is above 50%. In our sample, 56 firms (or 1.9%) belong to these sectors. We exclude these firms for our robustness test analysis. As reported in Table A2, we find consistent support—both in sign and significance—to our main findings.

Table A2 Robustness Test: Share of Non-Sea Imports

	Alphas of Long–Short Portfolios				
	(1) GL	(2) SC	(3) SL	(4) LE	(5) RS
Full Sample	0.637	0.494	-0.769	-0.021	0.597
	(2.44)	(2.55)	(-5.76)	(-0.15)	(3.90)
High CAN/MEX Share Removed	0.636	0.500	-0.786	-0.020	0.591
	(2.44)	(2.58)	(-5.90)	(-0.13)	(3.94)

Appendix C: Robustness Test: Further Lagged GSS Measures

In this section, we present two alternate approaches to align the Panjiva-based measures in line with the low-frequency accounting data. These tests examine if our findings, based on univariate sorting tests, are affected by the look-ahead biases.[15]

For each of the four GSS variables that showed significant return predictability, we repeat our zero-cost investment portfolio analysis by forming two sets of quintile-based long–short portfolios with the following lagged measure definitions: (1) as of June of the previous year (denoted as $GSS_{t-1.5}$ in the table); and (2) as of December of the year prior (denoted as GSS_{t-2} in the table). Table A3 shows the results of these robustness tests. Row 1 of each GSS variable sub-panel shows our main analysis estimates for reference. In the main analysis, portfolios in period t are formed using period $t-1$ GSS measures. For example, Jan 1, 2010 portfolio is formed using GSS measures that reflect a firm's sourcing choices between Jan 1, 2009, and Dec 31, 2009. Row 2 shows the results of a 6-month lag analysis in which we form quintile portfolios using sourcing choices information between July 1, 2008, and June 30, 2009. Likewise, Row 3 shows the results of a 12-month lag analysis in which portfolios are formed using sourcing choices information between Jan 1, 2008, and Dec 31, 2008. We continue to find a strong predictive power of all the four GSS variables under both of these lagged measurement approaches.

Appendix D: Robustness: Cohen and Frazzini (2008) – Known supply chain linkages

Cohen and Frazzini (2008) documents a strong return predictability of customer-supplier economic links due to customer momentum phenomenon. In this section, we examine if our findings are a mere reflection of Cohen and Frazzini (2008) or the studied GSS measures capture new incremental information compared to the customer momentum phenomenon. To do so, we repeat our analysis using a sub-sample that excludes firms with disclosed economic links in Compustat 10-K filings. We first obtain all Compustat segments data from 2009 to 2019. Next, we conduct a detailed text search in the Compustat segments data (which are identified with name strings only) with a customized named-entity matching algorithm to match all customer–supplier relations where the (1) disclosed customer names matched to US Compustat–Panjiva linked firms and (2) disclosing firms' names and GVKEYs matched to non-US-headquartered firms.

[15] We note that our double-sort analyses use the GSS measures in the same period as the inventory measures. In particular, all measures are constructed at the end of June of the previous year.

Table A3 Robustness Test: Portfolio Sorting Results with Lagged GSS Measures

	Sorted Portfolios											
	Global Sourcing Level (GL)						Supplier Concentration (SC)					
	1	2	3	4	5	**H-L**	1	2	3	4	5	**H-L**
GSS_{t-1}	-0.178	0.427	0.267	0.527	0.541	**0.718**	-0.020	-0.171	0.140	0.328	0.611	**0.631**
	(-3.47)	(5.43)	(2.05)	(2.94)	(2.12)	**(2.72)**	(-0.29)	(-2.38)	(1.42)	(2.91)	(3.00)	**(3.19)**
$GSS_{t-1.5}$	-0.085	0.097	0.424	0.409	0.575	**0.660**	-0.046	-0.280	0.173	0.427	0.371	**0.417**
	(-1.84)	(0.82)	(1.96)	(3.00)	(1.75)	**(2.83)**	(-0.45)	(-1.93)	(1.38)	(1.50)	(2.87)	**(1.99)**
GSS_{t-2}	-0.167	0.341	0.230	0.512	0.399	**0.566**	-0.019	-0.137	0.105	0.202	0.551	**0.570**
	(-3.24)	(4.62)	(1.76)	(2.62)	(1.52)	**(2.10)**	(-0.27)	(-1.91)	(1.85)	(1.87)	(3.92)	**(3.68)**
	Sourcing Lead Time (SL)						Relation Strength (RS)					
	1	2	3	4	5	**H-L**	1	2	3	4	5	**H-L**
GSS_{t-1}	0.666	0.131	0.318	0.216	-0.202	**-0.868**	-0.155	-0.036	0.299	0.483	0.575	**0.729**
	(5.16)	(1.19)	(2.87)	(2.26)	(-3.00)	**(-6.46)**	(-2.30)	(-0.35)	(2.97)	(3.90)	(4.02)	**(4.78)**
$GSS_{t-1.5}$	0.573	0.296	0.290	0.147	-0.093	**-0.666**	-0.084	-0.120	0.335	0.542	0.658	**0.742**
	(5.70)	(2.88)	(2.61)	(1.80)	(-1.96)	**(-3.01)**	(-1.78)	(-0.45)	(3.50)	(2.78)	(3.37)	**(4.25)**
GSS_{t-2}	0.558	0.345	0.313	0.166	-0.195	**-0.754**	-0.149	-0.068	0.325	0.460	0.545	**0.694**
	(4.31)	(3.26)	(3.23)	(1.92)	(-2.92)	**(-5.85)**	(-2.22)	(-0.69)	(3.17)	(4.10)	(4.14)	**(4.79)**

We identify 53 US firms (1.7% of our sample) that have overlapping disclosure of supply chain links in the Panjiva and Compustat datasets. These firms are dispersed across all GSS quintiles. For instance, in the GL category, 9/5/7/17/15 firms are in GL quintile 1 to 5, respectively. Table A4 shows results of sorting analysis on the sub-sample of firms that excludes these 53 firms. Row 1 shows the results of our main analysis with the full sample of firms for reference. Row 2 shows the sub-sample results. We find consistent results in both sign and significance.

Table A4 Robustness Test: Exclusion of firms' with known economic links in Compustat

	Alphas of Long–Short Portfolios				
	(1) GL	(2) SC	(3) SL	(4) LE	(5) RS
Full Sample	0.637	0.494	-0.769	-0.021	0.597
	(2.44)	(2.55)	(-5.76)	(-0.15)	(3.90)
Segments-Identified Firm Pairs Removed	0.701	0.465	-0.802	-0.014	0.574
	(2.93)	(2.50)	(-5.32)	(-0.06)	(3.85)

Appendix E: Variable Definitions and Compustat Names

Table A5 Construction of Control Variables

Panel A. Description and Construction of Control Variables

Variable Name	Description	Construction
Size	Market capitalization	Closing price of a stock $\times$ total number of shares outstanding
BM	Book-to-market ratio	(Shareholder's equity+deferred taxes–preferred stock)/market capitalization
GPM	Gross profit margin	(Revenue–Cost of goods sold)/Revenue
Leverage	Debt-to-equity ratio	Total liabilities/Shareholders' equity
Accruals	Sloan (1996b) measure	[(ΔCurrent assets–ΔCash & equivalents–ΔCurrent liabilities–ΔDebt in current liabilities–ΔTaxes paid)–Depreciation & amortization]/Total assets
InvI	Inventory investments	Total inventory/Total assets
InvT	Inventory turnover per Alan et al. (2014)	(Cost of goods sold–ΔLIFO reserve)/(Inventory+LIFO reserve)
GMROI	Gross margin return on inventory per Alan et al. (2014)	(Revenue–Cost of goods sold+ΔLIFO reserve)/(Inventory+LIFO reserve)
CAPEXI	Capex intensity	Capital expenditure/Total assets
RDI	R&D intensity	R&D expense/Total assets

Panel B. Related Compustat Variable Names and Description

Variable Name	Compustat description of variables used in the construction of controls
PRCC_F	Closing price of a stock
CSHO	Number of common shares outstanding
SALE	Revenue
COGS	Costs of goods sold
AT	Total assets
LT	Total liabilities
CEQ	Shareholders' equity
ACT	Current assets
CHE	Cash & equivalents
LCT	Current liabilities
DLC	Debt in current liabilities
TXP	Taxes paid
DP	Depreciation & amortization expense
INVT	Total inventory
LIFR	LIFO reserve
CAPEX	Capital expenditure
XRD	R&D expense