Can Global Sourcing Strategy Predict Stock Returns?

Nitish Jain
London Business School, London NW1 4SA, United Kingdom, njain@london.edu

Di (Andrew) Wu
Ross School of Business, University of Michigan, Ann Arbor, Michigan 48109, andydiwu@umich.edu

Problem definition: While firms are increasingly relying on sourcing globally as a key constitute of their supply chain strategy, there is no empirical evidence on whether investors of these firms adequately reflect firms' global sourcing strategy (GSS) in their stock valuation process. In this paper, we empirically test whether stock market participants are efficient in doing so.

Methodology/results: Using the empirical asset pricing framework, we find that information concerning firms' GSS strongly predicts their future stock returns. We compile a transaction-level imports database for US-listed firms and construct measures for five widely studied GSS aspects in the Operations Management literature: the extent of global sourcing; supplier relationship strength; supplier concentration; sourcing lead time; and sourcing countries' logistical efficiency. For each measure, 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% (6% to 13.9%) with value (equal)-weighted portfolios. Their return predictability is incremental over other operations-and-cost-arbitrage motivated predictors such as inventory turnover, cash conversion cycle and gross profitability, is persistent across different supply chain positions, and is robust to alternate risk models, subsamples, and empirical specifications. Together, our results indicate that the GSS measures embody independent information about firms' future profitability, and this information is mispriced by market participants, leading to predictable returns. In accordance with this mechanism, we find that the GSS measures strongly predict both firms' future earnings and the surprise in market reactions around the earnings announcement days.

Managerial implications: The robust return predictability of our GSS measures suggests that investors are not fully incorporating GSS-related information in their stock valuation frameworks. Therefore, our results calls for greater investor education on global sourcing and better dissemination of global sourcing information so as to mitigate valuation inefficiency.

Key words: global sourcing strategies, asset pricing, empirical operations management

---

1. Introduction

In the last three decades, firms have increasingly tapped into the *global* side of their supply chain, leading to a steady growth in global trade in spite of periodic instances of disruptions and crises.[1]

[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. Preliminary data suggest that the growth trend continues after the temporary decline due to the COVID-19 pandemic: https://www.wto.org/english/news_e/pres21_e/pr889_e.htm

Not surprisingly, scholars in operations management have extensively studied firms' global sourcing strategy (GSS) to understand its relation with firm cash flows and profitability, primarily using theoretical models. For example, Boute and Van Mieghem (2015) provides guidance on strategic sourcing allocation between the global and domestic suppliers that balances the global suppliers' cost-advantage and the domestic suppliers' shorter lead time. Hamad and Gualda (2014) study relation between a multi-echelon global supply network and cash flow optimization. Dong et al. (2010) relate firms' multi-location global supply network to exchange-rate uncertainties and pricing responsiveness. Berry and Kaul (2015) study firms' ability to tap into knowledge pool of global suppliers network to develop new capabilities.

Despite the wealth of theoretical studies that relate GSS to firms' own profit-linked outcomes, there is no empirical study about whether *market participants* could in fact realize this relation and adequately reflect firms' GSS choices in their valuation process to price the firms' stocks. Two factors may hinder market efficiency in pricing global sourcing strategies. One, the firm-level information on GSS choices is not as easily accessible as other operational measures such as inventory and trade credits,[2] limiting how market participants might quantify and comprehend global sourcing. Second, even if such information is available, processing it and adequately incorporating it into stock valuation would require domain-specific knowledge in supply chain management and the related theories in global sourcing, which typical market participants might not possess.

Adequately pricing firms' GSS choices is further challenged by the fact that these choices often embed competing benefits, as documented in the extant Operations Management literature. For example, consider the postulated benefits of supplier portfolio choices. A large and diversified supplier base offers the advantages of greater competition (Li 2013) and resilience (Sheffi 2005) but poses organizational challenges (Belavina and Girotra 2012). In contrast, a smaller concentrated base renders economies of scale benefits (Cachon and Harker 2002) but increases disruption likelihood (Tomlin 2006). Not surprisingly, firms within a same industry often employ wide varying supplier portfolio strategies. For instance, as shown in Table A18, the supplier management strategies for the US firms in the apparel industry vary from low to high concentration. On the one hand, Cato Fashions sources no more than 5% of its total procurement from any of its supplier. On the other hand, Aeropostale Inc sources 81% of total sourcing from its top five suppliers.

In this paper, we bridge this research gap by examining the market efficiency in pricing firms' GSS choices. We do so using the empirical asset pricing framework, which is widely used by scholars in multiple fields including in Operations (e.g., Wu and Birge 2014, Alan et al. 2014). In a recent research setting article on the future directions of the operations-finance interface research,

[2]For instance, see Jain et al. (2014) for challenges in compiling GSS information.

Babich and Kouvelis (2018) note the emerging importance of supply chains "as a source of new systematic factors" to identify factors that explain systematic variation in prices. Our study directly contributes to this emerging stream.

We begin our analysis by systematically quantifying different aspects of the global sourcing strategies of US-based nonfinancial firms [3] using transaction-level data on their import activities. To do so, we first compile a comprehensive import dataset that combines (1) 130 million product-level import shipment data from from Standard & Poor's Panjiva database from January 2008 to December 2019, which we further match to 3,000 publicly-traded firms in the US, with (2) product-level unit pricing data from PIERS and (3) additional data on logistics processing efficiency from World Bank, and port-to-port sea distances. Our database captures almost all US imports over the sea route, which accounts for 90% of world trade (IMO 2008). It captures rich details of each import transaction, including the identities of the buyer and supplier, country of origin, nature of imported product, and quantity imported.

Next, we use our imports dataset to construct firm-level measures of five aspects of firms' global sourcing strategies that are studied in the theoretical and practitioner OM literature: (1) the extent of global sourcing level, which we denote as GL (Jain et al. 2014); (2) supplier concentration, SC (Cachon and Harker 2002, Jain et al. 2022, Sheffi 2005); (3) the frequency of repeat business in a buyer-supplier relationship, RB (Sheffi 2005, Belavina and Girotra 2012, Jain et al. 2022); (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). While existing studies typically agree that global sourcing, as quantified by these measures, affects firm profitability, they have not yet prescribed a consistent view on the direction of the relation, 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 determinant of firms' profitability (Cachon and Terwiesch 2008, Kesavan and Mani 2013). Furthermore, when these measures are further reflected in equity prices, their relation with future stock returns remains unknown.

Our tests investigate the return predictability of each of the five GSS measures, both in the time series and in the cross section of stocks. We first do so in the time series by employing the classical zero-cost investment strategy. Using 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.

[3] 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.

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) 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 (significant at the 5% to 1% level) imply an abnormal return of 6% to 9.6% (6% to 13.9%). Furthermore, we find that these results are not driven by a specific risk model or a specific subperiod of our study. For all the four variables, our zero-cost portfolio strategy generates positive raw returns for at least nine of the 11 return years.

The strong return predictability of GSS variables are also present in the cross section, where all four measures are significantly positively related (at the 0.1% level) to future returns in standard Fama and MacBeth (1973) regressions with a host of additional return predictors such as size, book-to-market and profitability ratios, leverage, investment, R&D and inventory policies. In a "horcerace" with all four GSS variables in the same predictive regression, we find that the GL and RS measures retain the highest relative predictive power.

Furthermore, we also find that the return predictability of the GSS variables is persistent for firms' across different supply chain positions, in subsample analyses that separately examine the GSS-return relation among manufacturers, wholesalers, and retailers. In the second part of the analysis, we rule out whether the observed predictability might simply reflect the measures' relatedness with inventory turnover (IT) and Cash Conversion Cycle (CCC), two extensively documented operations-derived return predictors (Chen et al. 2005, 2007, Alan et al. 2014, Wang 2019). We test for the incremental return predictability of the GSS measures above and beyond both IT and CCC using both time series (i.e., double-sorts) and cross section tests,and we continue to find strong support for our main findings, with statistically significant and economically sizable estimates for all four key GSS measures.

The results so far suggests that GSS is not a proxy of other operations-related metrics such as inventory policies, and its return predictability might be attributable to new information embedded in our GSS measures. Return predictability of a given signal generally arises either from exposure to the risks that it captures, or from market mispricing of the new information that it embeds (for a recent example see Wang (2019)). Our next set of tests further examines this mechanism in more depth by testing the risk- vs. mispricing-based explanations of the GSS-return predictability. We first show that both standard and emerging risk models such as the five-factor (Fama and French 2015) or q-factor (Hou et al. 2015) models do not fully explain the relation between GSS and returns, as evidenced by the low or negative risk loadings and significantly positive alphas persisting in these models. More importantly, using a standard earnings prediction model Fama and

French (2000) incorporating our GSS measures, we find a significant incremental predictive power of the GSS variables for future earnings, after controlling for past earnings and other standard earnings predictors. Furthermore, we find that GSS-predicted earnings surprises lead to abnormal stock returns around the five-day window when these earnings are announced in each quarter, which explains between 10% and 25% of the annual zero-cost GSS alphas. Collectively, these results suggest that market participants do not fully incorporate the incremental information in the GSS variables into their stock valuation framework, thereby leading to surprise reactions when the earnings are realized.

In totality, these results suggest that the GSS variables' return predictability is likely explained by the mispricing mechanism—market inefficiency in processing firms' global sourcing information in an adequately and timely fashion—rather than the exposure to risk encapsulated in the standard factor models. Further delving into this mechanism, we examine whether GSS is indicative of the firms' ability to exploit cost arbitrage and optimize cash flows across the sourcing locations. We first assess (1) whether GSS indeed embeds signals on firms' cost arbitrage and cash flow optimization actions, and if so, (2) whether the GSS-return relation can be fully—or at least partially—explained by cost arbitrage. Not surprisingly, we find evidence that the GSS variables are predictive of cost-arbitrage and cash flow measures, indicating that global sourcing could be related to the cost-reduction component of firm profitability. On the stock return front, we again document incremental predictability in new double-sort analyses featuring standard cost proxies, which further suggest that investors do not fully account for this information in their pricing.

Finally, we examine the robustness of the GSS measures' return predictability using a series of tests including: (1) alternate risk models (unadjusted, CAPM-only, the five-factor, and the q-factor); (2) subsamples by difficulty of arbitrage (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); (3) alternate portfolio rebalancing and holding periods, (4) variable construction (double-sort analysis with measures of inventory level (Jones and Tuzel 2013) and the modified gross margin return on inventory), and alternate choices of portfolio sorting and investment strategy. In all, across all these tests, we find strong support for our main finding with sign- and significance-consistent results for 69 out of 74 alpha estimates of the zero-cost portfolio.

Our study contributes to both the OM literature and the practice of supply chain management. First, it expands the stream of research that identifies operations-motivated return predictors (Hendricks and Singhal 2005, Chen et al. 2007, Alan et al. 2014). We show that GSS is likely a key return driver, with its return predictability *incremental* to other operations-related predictors, and persistent across supply chain locations. Second, we document the relative importance of the GSS variables in predicting returns. Our results indicate that, if managers and investors have to prioritize from the four GSS variables due to limited processing time and capacity, it would be most informative to first analyze firms' overall global sourcing level, as well as the relative strength (e.g., degree of repeat business) of their sourcing relationships. Finally, our study highlights the value of using granular, transaction-level data in deriving new supply chain insights: Compared to relationship-level data such as FactSet, the granularity of transaction-level data allows us to further quantify the intricacies of sourcing management, which as shown in our study is significantly predictive of both firms' future profitability, cost optimization outcomes, and future equity returns.

2. Literature Review

Our paper, which is one of the few studies in the nascent empirical literature on global supply chains and sourcing practices (Jain et al. 2014, Hertzel et al. 2021), contributes to the broader operations-finance interface literature that links operational measures with financial performance and asset pricing outcomes. Earlier studies include Chen et al. (2007), who show the association between stock returns and inventory turnover measures using a cross-sectional regression analysis, and Hendricks and Singhal (2005) who examine the impact of information on supply chain disruptions on stock returns using the event studies methodology. Subsequent studies such as Wu and Birge (2014) and Bellamy and Osadchiy (2020) find association between firms' supply-chain network characteristics and their stock returns, while Wang et al. (2021) document that the firms' exposure to risk is dominated by the tier-2 supplier network structure. Schmidt and Raman (2022) further establish internal control systems as a supply chain disruption mitigator. In terms of other financial metrics, Kesavan and Mani (2013) relate firms' inventory performance to retailers' future earnings.

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. Likewise, Wang (2019) finds a strong return predictability of cash conversion cycle 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 measures is complementary to the other widely studied operational measures such as firms' inventory (Chen et al. 2005, 2007, Alan et al. 2014), and trade credits (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.

3. Data and Variable Construction

In this section, we first describe our dataset that is complied by carefully linking three distinct proprietary and public data sources. We then provide details of the GSS variables construction.

3.1. 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 and 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 of imports data and updates data tables with daily frequency and makes trade data available with a latency of 1 to 7 days. 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 A2 in the Appendix 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 data with the dollar value of imported goods. We merge the import values into Panjiva 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 values 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 (HS, see Table A17 for HS definition).

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

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	0.384	1.114	0.114	0.049	0.070
Median	627.26	0.332	0.908	0.076	0.034	0.001
SD	8377.35	0.273	3.940	0.126	0.051	0.203
P25	88.82	0.217	0.288	0.008	0.017	0.000
P75	2893.43	0.567	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	0.366	0.840	0.081	0.052	0.051
Median	198.32	0.324	0.676	0.023	0.031	0.001
SD	7237.28	0.230	3.954	0.115	0.062	0.154
P25	24.98	0.204	0.082	0.000	0.013	0.000
P75	1388.68	0.512	1.777	0.122	0.065	0.033
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 A17 (in the Appendix) for construction details.

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 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 Jain et al. (2014), we find that our sample firms are larger in size compared to the average firm in Compustat universe[4].

3.2. GSS Variables: Measure Construction

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

[4] In Appendix F we present results using Factset Revere dataset compiled supplier information of our sample firms.

associated GSS measures (Jain et al. 2022). 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.

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, 2022). 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 in Introduction) but also by product-category specific factors such as design complexity and supplier availability (Jain et al. 2022). 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. 2022). 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

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

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

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

3.3. Rationale Behind the Construction of GSS Variables

Our GSS metrics correspond to facets of global sourcing that are extensively studied by the OM scholars as drivers of firm performance, and are also actively considered by the practitioners while formulating their sourcing strategies (Table A18 in Appendix list examples of the managers' voluntarily disclosures for these metrics). Additionally, these aspects of global sourcing are logical targets of asset pricing studies, as the existing literature often theorize divergent cash flow implications to each aspect of GSS.

Global Sourcing Level. A key driver of firms shifting to global sourcing is the global suppliers' cost advantage (Boute and Van Mieghem 2015) as a result of low cost labor , cheaper material and, often, export incentives. Other advantages such as knowledge sharing, cash flow management, and responsive pricing (Dong et al. 2010, Hamad and Gualda 2014, Berry and Kaul 2015) also accrue more with a higher level of global sourcing. But at the same time, global sourcing also makes firms vulnerable to larger sourcing interruptions likelihood (Sheffi 2005, Jain et al. 2022), higher investments in inventory (Jain et al. 2014), and challenges in implementing efficient closed loop supply chains (Guide et al. 2003); all these factors impose higher financial burden on firms (cf. Tomlin (2006), Jain et al. (2014)).

Supplier Concentration. A firm's choice of splitting its orders among suppliers effect performance in many ways including sourcing cost, reliability, and lead times. 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) and effective supplier improvement strategies (Kalkanci 2020). 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 improved supply reliability and lower cost through competition (cf. Klotz and Chatterjee (1995), Iyer et al. (2005)).

Relationship Strength. Sheffi (2005) notes that a firm can develop relatively strong or weak relationships with suppliers, irrespective of how diversified the supplier base is. Stronger long-term relationships results in aligned incentives that encourage suppliers to invest in value-enhancing investments, such as for information sharing (Ren et al. 2010). Furthermore, such relationships are often associated with a high frequency of repeat business which renders various value-inducing benefits, including that of cooperative behavior (Belavina and Girotra 2012), strategic capacity investments (Taylor and Plambeck 2007), lower supplier default risk (Swinney and Netessine 2009) and curtailed agency issues (Plambeck and Taylor 2006). Despite these many advantages to long-term repeated sourcing, at times such relationships can be value destroying for a firm. For one, long-term relationships can lead to supplier complacency (Anderson and Jap 2005), resulting in unreliable sourcing. Also, long-term contracts often bind a firm with a minimum or maximum purchase quantity per period which may constrain the buying firm's supply agility.

Logistical Efficiency. Based on a survey response of one hundred and five managers, Fugate et al. (2010) find that firms' logistical efficiency positively correlates with organizational performance. Supplier countries worldwide differ in their infrastructure quality, customs procedures, and bureaucratic requirements (Hausman et al. 2005). These differences shape the sourcing firm's logistical efficiency. On the one hand, an efficient and lean system typically deliver superior economic value in normal times. On the other hand, such systems may be less equipped to deal with periods of disruptions as compared to those with buffered (or redundant) resources (Hollnagel 2009).

Sourcing Shipment Lead Time. Boute and Van Mieghem (2015) note that a firm's optimal allocation of sourcing from global shares is moderated by the shipping lead time. Using a survey of 402 firms, Christensen et al. (2007) find that a firm's financial performance is sensitive to variance

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
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

in shipping lead times. 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).

As such, except for the SL measure that *ceteris paribus* is associated with higher cost, the remaining four measures embed competing considerations to profitability and equity returns, and likely work in tandem to create value for the firm. This leaves the examination of these relationships an open empirical question, which we address in this study.

Table 2 shows in-sample correlation between the GSS variables. 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.

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 A17 provides the definition of these control variables and details of the data fields used in constructing these control variables.

4. 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.

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

The time series tests are in the form of a trading strategy where we sort our 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. 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.

4.1.1. Analysis Using Sorted Portfolios. 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} $(= 1 \ldots 5)$ GSS measure $GSS_k \in \{GL, SC, SL, LE, RS\}$ in annual frequency as follows: on January 1 of year t $(= 2009 \ldots 2019)$, 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. Put differently, the sourcing choices in period $t-1$ corresponds to fit data and the portfolio returns in period t corresponds to test data in our analysis. While the frequency gap between Panjiva data (real time) and accounting data (quarterly) may raise concerns of look-ahead bias in our analysis. Appendix B establish the robustness of our results with 6- and 12-month lagged GSS measures to mitigate such concerns.

Note that, similar to other operational measures such as inventory productivity, global sourcing is also presumably influenced by firms' industry-specific business environment. For example, Jain et al. (2022) 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 A1, we find that the firms in the business equipment makers industry and pharmaceutical industry in the Fama-French 12-industries classification (see Table A17 in appendix for industry classification details) exhibit, on average, substantially 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.[5] We therefore 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

[5] 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.

quintile of our sample stock universe. As illustrated in panel B of Figure A1 in the appendix, this nonparameteric sorting procedure results in a symmetric industry representation across each of the quintile portfolios. Table A18 list examples of firms allocated to highest and lowest quintiles and those firms public disclosures on selected aspects of their GSS. The assigned quintiles based on our imports-data constructed GSS metrics are largely consistent with the disclosures. We perform our main analysis using these industry-adjusted quintiles, and present the results based on the unadjusted quintiles as a robustness check in Section G.

Next, using stocks assigned to each GSS_k quintile, we form two portfolios: an equal-weighted (EW) portfolio and a value-weighted (VW) portfolio. 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. 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:

$$R_{k,p,t} - R_{f,t} = \alpha_{k,p} + \beta^M_{k,p}(MKT_t - R_{f,t}) + \beta^S_{k,p}SMB_t + \beta^H_{k,p}HML_t + \beta^U_{k,p}UMD_t + \epsilon_{k,p,t}, \qquad (10)$$

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.[6] 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 ($R_{k,EX,t} = R_{k,5,t} - R_{k,1,t}$). 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, which we report and discuss 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.

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

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 qunitle portfolios, from lowest quintile (indexed: 1) to the highest (5). Column 'H-L' shows the alpha estimates of the zero-cost investment portfolio. 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%).

As per our conjecture, we find a negative correlation between future stock returns and the SL measure. For each of the remaining three significant variables, we find a positive correlation with returns. This suggest that in these variables, on average, the embedded positive channels dominate the negative ones. For example, in the case of GL measure, the benefits of cost-arbitrage, knowledge sharing and efficient cash flow management dominate the associated effect of increase in inventory investment (Jain et al. 2014) which negatively correlates with returns (Alan et al. 2014). Likewise, for the SC (RS) variable the benefits associated with high SC (RS) level such as economies of scale and modest organizational efforts in supplier management (benefits of cooperative behavior, lower supplier default risk, curtailed agency issues) dominate the negative effects such as increased sourcing interruption likelihood (reduced complacency). It is conceivable that the overall relationship of these variables with returns is of non-monotone nature as they embedded competing factors. As such, at the most granular level, the relation between GSS and returns might not be monotone, while in the data the positive effect of one side might on average dominate the negative side. Additionally, investors might have difficulty processing the value signals embedded in GSS, thus resulting in predictably positive returns. Alternatively, firm-level moderators may strengthen one set of factors over another, resulting in heterogeneous effects. Future empirical research can explore these possibilities.

Next, in Figure 1, 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), for each year 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

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 3.2 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.

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. Importantly, 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. This indicates that the return predictability of our GSS measures, including its individual components, are not driven by any particular sub-period in our study sample. The results of the time-series tests, therefore, provide strong evidence towards the return predictability of four key GSS variables.

4.1.2. Return Predictability by Supply Chain Position. Past studies have documented inconsistency in return predictability of operations-motivated predictor by a firm's supply chain position. For example, Chen et al. (2005, 2007) document inconsistency in the return predictability of equal-weighted portfolios formed on inventory. Specifically, they find that while for retailers lower-quintile portfolios yield abnormal returns, for wholesalers, middle-quintile portfolios yield

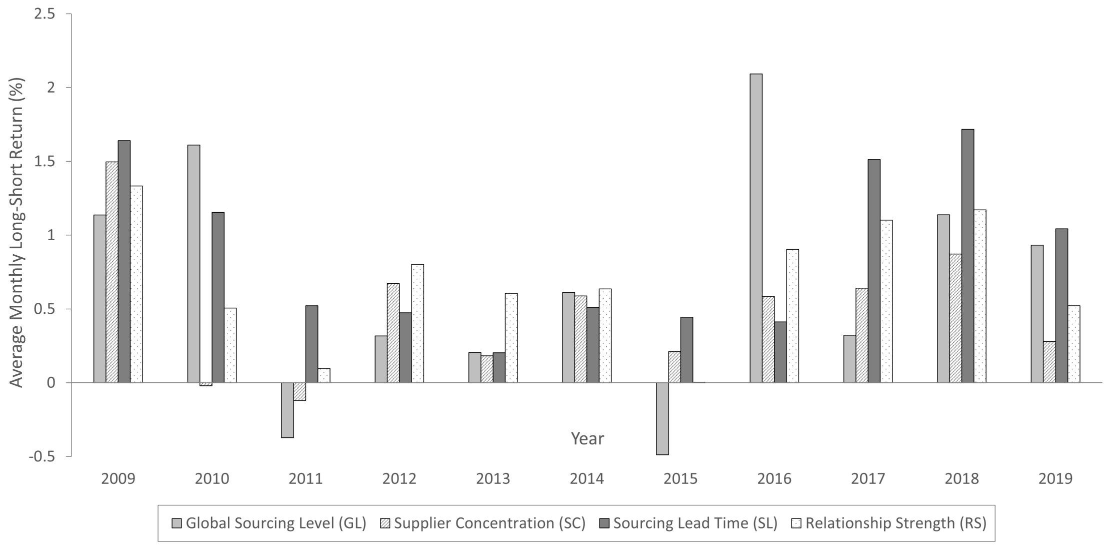

Figure 1 **Average Monthly Zero-Cost Returns for Key Global Sourcing Strategy Measures**

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. Motivated by these observations, we examine whether the GSS variables' return predictability persist across firms at different supply chain locations. We do so by repeating our Fama-French-Carhart four-factor analysis (as described in Section 3) for subsamples of retailers (SIC two-digit codes: 52–59), wholesalers (50–51), and manufacturers (20–39).

Table 4 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.

4.2. 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. 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 ($\mathrm{R}_{[t-1,t]}$) and return in the last 12 months but one ($\mathrm{R}_{[t-12,t-2]}$); (3) inventory investment levels (Inventory); (4)

Table 4 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	1.109	1.255	0.178	0.524	0.346	-0.123	0.611	0.734
		(-0.71)	(2.93)	(3.39)	(0.80)	(1.01)	(0.64)	(-1.38)	(1.42)	(1.61)
	EW	1.015	0.904	-0.111	0.169	3.166	2.997	0.279	1.825	1.546
		(1.89)	(1.26)	(-0.13)	(0.85)	(2.94)	(2.74)	(1.79)	(4.29)	(3.49)
Supplier Concentration (SC)	VW	-0.098	0.952	1.051	0.371	0.596	0.225	0.114	0.881	0.767
		(-0.35)	(2.88)	(2.67)	(1.67)	(1.51)	(0.53)	(1.12)	(3.58)	(2.61)
	EW	0.055	3.096	3.040	0.356	4.478	4.122	0.619	2.456	1.837
		(0.13)	(3.40)	(3.13)	(1.45)	(3.73)	(3.37)	(3.66)	(6.67)	(4.72)
Sourcing Lead Time (SL)	VW	0.912	-0.390	-1.302	0.423	0.428	0.005	0.570	-0.105	-0.674
		(3.27)	(-1.44)	(-3.42)	(0.93)	(2.28)	(0.01)	(2.07)	(-1.16)	(-2.24)
	EW	2.694	0.032	-2.662	3.873	0.110	-3.763	2.624	0.261	-2.362
		(2.90)	(0.09)	(-2.77)	(3.07)	(0.50)	(-2.98)	(6.66)	(1.85)	(-5.72)
Relationship Strength (RS)	VW	-0.175	1.380	1.556	0.500	0.345	-0.155	0.011	0.742	0.731
		(-0.70)	(3.79)	(4.09)	(2.29)	(0.72)	(-0.31)	(0.11)	(2.92)	(2.56)
	EW	0.332	1.918	1.586	0.563	4.191	3.628	0.447	2.577	2.130
		(0.83)	(2.47)	(1.89)	(0.86)	(3.43)	(2.43)	(2.69)	(6.38)	(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.

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 A17, provides details of the construction procedure for these control variables.

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.

Table 5 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)
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)
Controls	No	Partial	Yes	Yes	No	Partial	Yes	Yes
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)
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)
Controls	No	Partial	Yes	Yes	No	Partial	Yes	Yes
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. Full results with all controls are reported in Appendix Table A20.

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 5 reports the estimation results of the cross-section tests and Table A20 in the appendix reports the full estimates including all control variables. 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 5.1, 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).

4.2.1. Relative return predictability of GSS variables. Additionally, we examine the relative importance of GSS variables in predicting returns, which could further shed light on which GSS metric would be more informative for investors and managers. Since the managers and investors typically have limited time and attention to process firm-level operations information (Hirshleifer et al. 2011), this analysis could help them prioritize their attention on the GSS metrics that have the highest relative predictability for future returns.

To do so, we conduct a horserace between our GSS metrics by modify our Fama-MacBeth cross-sectional regressions. Specifically, instead of using each GSS measure in isolation, we incrementally add each of the four GSS variables to the regression. Table A15 of the Appendix reports the results. Starting with the GL measure, adding RS does not reduce the statistical significance of either measure. However, when all four measures are included in the same regression (Column 4), the GL and RS variables retain their significant prediction power while the estimates for SL and SC become marginally significant. This suggests the GL and RS variables likely incorporate some information embedded in the SL and SC variables. Our results thus indicate that, if managers/investors have to prioritize from the four GSS variables due to limited processing time and capacity, it would be most informative to first analyze firms' overall global sourcing level, as well as the relative strength (e.g., time of doing business together) of their sourcing relationships.

5. Sources of Return Predictability

In this section, we examine potential sources of observed return predictability of GSS variables. First, in Section 5.1, we examine whether the return predictability is due to incremental information embodied in these variables or is driven by alternative return predictors that are conceptually related to GSS. Next, we note that 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). Given this, 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. Results in Section 5.2 strongly indicate that the return predictability of GSS is consistent with the mispricing mechanism.

5.1. Incremental Information in GSS Relative to Alternative Predictors

We group alternative return predictors that are conceptually related to GSS in three primary categories. The first category comprises of unmeasured risk exposures, for instance to 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 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. We discuss these results in Appendix C.

The third 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 our measures are not proxies for these operational levers, 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 measures.

First, in the time series, we use a double-sort analysis to examine the GSS variables' incremental return predictability *conditional* on inventory and CCC, denoted as $\mathtt{R}$ for brevity. 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 $\mathtt{R}$ 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 $\mathtt{R}$-tercile portfolio, we sort the firms on the one-year lagged value of the selected GSS measure $\mathrm{GSS}_k \in \{\mathrm{GL}, \mathrm{SC}, \mathrm{SL}, \mathrm{RS}\}$ 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 6 (panels labeled "All Firms") shows the alpha estimates obtained from the double-sort analysis using the inventory turnover (IT) measure, computed 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 result using the adjusted inventory turnover (Alan et al. 2014), and inventory level (Jones and Tuzel 2013) measures which are presented in Appendix G. Results using CCC are presented in Table A14 of the Appendix. 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 decrease in IT measure. The average monthly (annual) abnormal return of the zero-cost portfolio across the four sourcing measures increases from 0.28% for the stocks with the highest IT to 0.78% for the stocks with the lowest IT. This implies that there is a complementary association between the GSS and IT variables, with the information embedded in the GSS variables exhibiting higher predictive power for inventory-inefficient firms. Results conditioning on CCC are similar. Collectively, these results strongly suggest that the GSS choice variables embed incremental information over and above the information captured in the firms' inventory and trade credit policies as reflected in IT and CCC.

5.1.1. Incremental return predictability by supply chain position. Additionally, existing papers such as Chen et al. (2005, 2007) show that inventory-based measures exhibit inconsistent return predictability across retailers, wholesalers, and manufacturers. Therefore, we implement an additional test on top of this by conducting the inventory-based double-sorting procedure on the manufacturer and retailer subsamples. Essentially, we triple-sort the portfolios according to (1) whether the firm is a retailer or manufacturer (there are not enough observations in the wholesaler sample), (2) its inventory turnover measure, and (3) each of the four GSS measures.

Alpha estimates for the long-short GSS portfolios are reported in Table 6 (panels labeled "Manufacturers" and "Retailers"). We continue to find strong support for persistent return predictability of three out of the four GSS variables (namely, for GL, SL, and RS): In both the retailer and manufacturer subsample, the alpha estimates of the long-short GSS portfolios have mostly consistent magnitude and statistical significance as their full-sample counterparts.

Table 6 Double Sort Results: Inventory Turnover, IT

	Global Sourcing Strategy Measure Terciles											
	Global Sourcing Share (GL)						Supplier Concentration (SC)					
	All Firms				Retailers	Manufac.	All Firms				Retailers	Manufac.
InvT Terciles	1	2	3	3-1	3-1	3-1	1	2	3	3-1	3-1	3-1
1	-0.330	0.171	0.294	0.625	1.314	0.683	-0.215	-0.457	0.685	0.900	0.474	0.531
	(-3.33)	(1.15)	(1.45)	(4.88)	(5.12)	(2.64)	(-1.83)	(-2.91)	(4.78)	(9.63)	(1.77)	(2.08)
2	0.034	0.53	0.476	0.441	0.502	0.409	0.125	0.149	0.204	0.078	-0.085	0.048
	(0.34)	(3.44)	(1.65)	(2.57)	(4.08)	(1.22)	(1.11)	(1.25)	(1.29)	(0.80)	(-0.21)	(0.30)
3	0.275	0.444	0.599	0.324	1.257	0.691	0.28	0.251	0.408	0.128	0.332	0.152
	(2.51)	(2.70)	(2.32)	(2.24)	(2.93)	(2.07)	(2.12)	(1.50)	(2.19)	(1.04)	(1.45)	(1.19)
Avg of InvT 1-3	-0.007	0.382	0.456	0.463	1.024	0.594	0.064	-0.019	0.432	0.369	0.240	0.244
	(-0.11)	(4.35)	(2.36)	(2.31)	(3.46)	(2.53)	(0.80)	(-0.24)	(4.24)	(3.14)	(0.98)	(1.04)
InvT Terciles	Sourcing Lead Time (SL)						Relationship Strength (RS)					
	All Firms				Retailers	Manufac.	All Firms				Retailers	Manufac.
	1	2	3	3-1	3-1	3-1	1	2	3	3-1	3-1	3-1
1	0.545	-0.091	-0.321	-0.866	-0.984	-0.700	-0.318	-0.104	0.417	0.735	1.183	0.831
	(3.68)	(-0.65)	(-2.86)	(-8.60)	(-2.01)	(-3.52)	(-2.75)	(-0.84)	(3.06)	(7.35)	(2.29)	(3.07)
2	0.353	0.343	-0.011	-0.364	-0.353	-0.245	-0.024	0.306	0.534	0.558	0.520	0.335
	(2.07)	(2.66)	(-0.10)	(-3.67)	(-2.60)	(-2.96)	(-0.23)	(2.55)	(2.94)	(4.88)	(2.44)	(2.16)
3	0.552	0.456	0.190	-0.362	-0.191	-0.289	0.223	0.279	0.534	0.311	0.197	0.125
	(2.13)	(2.78)	(1.63)	(-2.62)	(-1.15)	(-2.41)	(1.90)	(1.80)	(2.29)	(2.28)	(1.82)	(1.51)
Avg of InvT 1-3	0.483	0.236	-0.047	-0.531	-0.509	-0.411	-0.040	0.160	0.495	0.535	0.633	0.430
	(3.94)	(2.56)	(-0.66)	(-4.23)	(-2.37)	(-3.14)	(-0.56)	(1.73)	(4.26)	(3.85)	(2.45)	(2.83)

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 3.2 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.

5.2. Market Mispricing of GSS Information

Although researchers in operations acknowledge that GSS could affect firm profitability through various channels, global sourcing remains a highly 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 this mispricing channel with a two-sided approach. First, following Fama and French (2000) 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 begin by estimating 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

Table 7 GSS Variables: Earnings and Abnormal Returns Around Earnings Announcement Days

Panel A. Earnings

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)
Controls	Yes	Yes	Yes	Yes
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

Notes. Full estimates with all control variables are reported in Table A16 in the Appendix.

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 $AC_{i,t}$ is accruals.

Panel A of Table 7 shows the estimation results. Full estimates with all control variables are reported in Table A16 in the Appendix. 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 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 are instead *surprised* by the subsequent earnings realizations. We do so using a widely-used test that examines abnormal stock returns around earnings announcements (Sloan 1996, 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 4.2) 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 5.

Panel B of Table 7 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. Inline with our main analysis, SL estimates continue to show opposite sign to that obtained with GL, SC, and RS variables. 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.

5.2.1. GSS and the Cost Component of Earnings In this section, we further investigate the channels behind GSS variables' predictability of earnings and investigate whether GSS is related to the cost component of earning, i.e., firms' ability to exploit cost arbitrage and optimize cash flows across the sourcing locations—two commonly acknowledged global sourcing gains and core contributors to firms' earnings.

We do so in two steps. First, we examine whether a firm's GSS choices indeed embeds signals on its cost arbitrage and cash flow management actions, proxied using three metrics: (i) Gross Profit Margin (GPM), (ii) Cost of Goods Sold (COGS), and (iii) Cash Conversion Cycle. Modifying the earnings prediction model (Eq 11) with these cost-arbitrage measures as dependent variables, we test each of our GSS variables' predictive power of these cost-related measures. Appendix N provides detail on these tests and Panel A of Table A13 reports the results, which provide confirmatory evidence that GSS can indeed predict firms' cost arbitrage and cash flow optimization efforts. Specifically, we find that firms with higher global sourcing level (GL), that source from logistically efficient locations (SL), and engage in relatively more repeat business with suppliers (RS) have a significantly higher margin and simultaneously a significantly lower CCC. Similar findings that a firm's global sourcing decisions relate to its margin implications have been documented in the economics literature (e.g., see the recent work by Antras et al. (2017)).

Next, we turn to the investor side and examine whether cost arbitrage alone is sufficient to fully explain the return predictive power of GSS. To do so, we modify our double-sort analysis using cost proxies and each of the GSS variables. Intuitively, if GSS primarily affect profitability through the cost channel and investors are attentive to this relation, then we would expect the GSS portfolio alphas to have substantially lower magnitudes and statistical insignificance in double sorts, particularly for firms with better cost positions. Our results, as shown in Panel B of Table A13 indicate that firms' cost-arbitrage gains, as reflected in the gross margins and COGS measures, could explain some of the GSS variables' predictability, slightly more so than inventory-related policies. For example, com- pared to inventory double sorts, the alphas are moderately lower in magnitude for the GPM terciles of SC, SL and RS variables. Importantly, the incremental return predictability of GSS after controlling for these potential cost arbitrage metrics remain statistically significant. These results thus suggest that cost arbitrage and cash flow optimization actions could be important elements in the GSS-return relation, and global sourcing could be related to the cost-reduction component of firm profitability. However, investors do not fully account for such relation in their pricing, likely due to constraints in processing and measuring the relatively specialized global sourcing information, and this leads to predictable returns.

6. Robustness Tests

This section discusses the robustness of our results with respect to model specifications, sample selection, portfolio choice, and empirical setup. First, in our main analysis, we use the 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 A4 shows results of alternative risk models for each of the four GSS variables that show significant return predictability in our main analysis, and Appendix D) provide additional discussions. We show that the significant alphas persist without any risk adjustment, as well as under alternative risk models such as the Fama and French (2015) five-factor and the Hou et al. (2015) q-factor models. Additionally. we also examine the sensitivity of our results to (a) an alternate shorter quarterly portfolio rebalancing frequency (see Appendix I), (b) a longer two-year holding period (Appendix J), (c) alternate inventory double-sort analysis (Appendix G), (d) small firm size and stock illiquidity (Appendix L), (e) stock sorting choice for portfolio formation (Appendix H), (f) alternate net-long investment strategy (Appendix K), and (g) omission of the non-sea based imports in our transactions data (Appendix E). Across this group of robustness tests, we find sign- and significance-consistent results, with our main analysis, for 57 out of 62 alpha estimates. Finally, we examine the GSS variables' preliminary returns predictability during the onset of the COVID period as many firms faced challenges in sourcing from the global suppliers (Table A12 in Appendix M). Using the GSS metrics constructed from end-of-2019 Panjiva data, we continue to find significantly positive average monthly long-short returns for each of the four significant

GSS variables during 2020 and 2021, which are comparable in magnitude to those before 2019. This suggests that the market mispricing of sourcing-related information did not materially change during the onset of the COVID pandemic.

7. Conclusion and 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, there is scant empirical evidence that investors adequately reflect firms' global sourcing strategy (GSS) in their valuation process to price stocks. On the one hand, a detailed view of firms' GSS choices is generally less accessible than other operations-related data such as inventory 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 global sourcing is part of the a firm's overall supply chain strategy, other operations-motivated return predictors (such as inventory turnover, IT, and cash conversion cycle, CCC) may already embody information embedded in the firm's GSS choices. In this study, we find strong evidence of incremental return predictability—above and beyond IT and CCC—of key GSS components including: the extent of global sourcing; supplier concentration; relationship strength; and sourcing lead time. We find that the predictive power of these variables persists across firms, and is independent of their supply chain positions. Importantly, our analysis suggest that GSS measures' return predictability is more likely explained by their informational value on respective firms' future profitability (for example, through cost-arbitrage and cash flow optimization components) than by exposure to aggregate risk factors. The robust return predictability of our GSS measures suggests that investors are not fully incorporating GSS-related information in their stock valuation frameworks, leading to mispricing of the firms' stocks. Therefore, our results calls for greater investor education on global sourcing and supply chain-related topics, and increasing the quantity and timeliness of firms' sourcing decision disclosures, so as to mitigate valuation inefficiency.

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 such a causal inference is a fruitful direction for future 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—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). Intuitively, our findings rests on three primary factors, which are likely to persist within and outside of our sample period: (i) the importance of sourcing choices to serve demand, (ii) the market participants' limited ability to adequately reflect the GSS signal into prediction of future profitability, and (iii) the information embedded in sourcing choices is incremental to that in other operational measures such as IT and CCC. Nevertheless, unique and unforeseen volatilities and disruptions of global trade in the future might alter the GSS-return relationship, and therefore may 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 the standard risk models to incorporate other operations-focused levers, such as contract structures,and trade-credit provisioning.

Acknowledgments

We acknowledge the generous research support from Ripple Labs, Inc. Any opinions, findings, conclusions, or recommendations expressed here are those of the authors and do not necessarily reflect the views of the sponsors.

References

Alan Y, Gao GP, Gaur V (2014) Does inventory productivity predict future stock returns? A retailing industry perspective. *Management Science* 60(10):2416–2434.

Anderson E, Jap SD (2005) The dark side of close relationships. *MIT Sloan Management Review* 46(3):75.

Antras P, Fort TC, Tintelnot F (2017) The margins of global sourcing: Theory and evidence from us firms. *American Economic Review* 107(9):2514–64.

Babich V, Kouvelis P (2018) Introduction to the special issue on research at the interface of finance, operations, and risk management (iform): Recent contributions and future directions. *Manufacturing & Service Operations Management* 20(1):1–160.

Bansal R, Wu D, Yaron A (2022) Socially responsible investing in good and bad times. *The Review of Financial Studies* 35(4):2067–2099.

Belavina E, Girotra K (2012) The relational advantages of intermediation. *Management Science* 58(9):1614–1631.

Bellamy M, Osadchiy N (2020) Supply network drivers of risk and performance. *The Oxford Handbook of Supply Chain Management* .

Belo F, Lin X (2012) The inventory growth spread. *The Review of Financial Studies* 25(1):278–313.

Berk JB (1995) A critique of size-related anomalies. *The Review of Financial Studies* 8(2):275–286.

Berry H, Kaul A (2015) Global sourcing and foreign knowledge seeking. *Management Science* 61(5):1052–1071.

Boute RN, Van Mieghem JA (2015) Global dual sourcing and order smoothing: The impact of capacity and lead times. *Management Science* 61(9):2080–2099.

Cachon G, Terwiesch C (2008) *Matching supply with demand* (McGraw-Hill Publishing).

Cachon GP, Harker PT (2002) Competition and outsourcing with scale economies. *Management Science* 48(10):1314–1333.

Carhart MM (1997) On persistence in mutual fund performance. *The Journal of finance* 52(1):57–82.

Chen H, Frank MZ, Wu OQ (2005) What actually happened to the inventories of american companies between 1981 and 2000? *Management science* 51(7):1015–1031.

Chen H, Frank MZ, Wu OQ (2007) US retail and wholesale inventory performance from 1981 to 2004. *Manufacturing & Service Operations Management* 9(4):430–456.

Christensen WJ, Germain RN, Birou L (2007) Variance vs average: Supply chain lead-time as a predictor of financial performance. *Supply Chain Management: An International Journal* .

Cohen L, Frazzini A (2008) Economic links and predictable returns. *The Journal of Finance* 63(4):1977–2011.

Dong L, Kouvelis P, Su P (2010) Global facility network design with transshipment and responsive pricing. *Manufacturing & Service Operations Management* 12(2):278–298.

Engelberg J, McLean RD, Pontiff J (2018) Anomalies and news. *The Journal of Finance* 73(5):1971–2001.

Fama EF, French KR (1992) The cross-section of expected stock returns. *the Journal of Finance* 47(2):427–465.

Fama EF, French KR (1993) Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics* 33(1):3–56.

Fama EF, French KR (2000) Forecasting profitability and earnings. *The Journal of Business* 73(2):161–175.

Fama EF, French KR (2015) A five-factor asset pricing model. *Journal of financial economics* 116(1):1–22.

Fama EF, MacBeth JD (1973) Risk, return, and equilibrium: Empirical tests. *Journal of political economy* 81(3):607–636.

Fillat JL, Garetto S (2015) Risk, returns, and multinational production. *The Quarterly Journal of Economics* 130(4):2027–2073.

Fugate BS, Mentzer JT, Stank TP (2010) Logistics performance: Efficiency, effectiveness, and differentiation. *Journal of business logistics* 31(1):43–62.

Guide VDR, Harrison TP, Van Wassenhove LN (2003) The challenge of closed-loop supply chains. *Interfaces* 33(6):3–6.

Hamad R, Gualda NDF (2014) Global sourcing approach to improve cash flow of agribusiness companies in brazil. *Interfaces* 44(3):317–328.

Harvey CR, Liu Y, Zhu H (2016) ... and the cross-section of expected returns. *The Review of Financial Studies* 29(1):5–68.

Hausman WH, Lee HL, Subramanian U (2005) *Global logistics indicators, supply chain metrics, and bilateral trade patterns* (The World Bank).

Hendricks KB, Singhal VR (2005) Association between supply chain glitches and operating performance. *Management science* 51(5):695–711.

Hertzel MG, Peng J, Wu J, Zhang Y (2021) Global supply chains and cross-border financing. Available at SSRN 3289212.

Hirshleifer D, Lim SS, Teoh SH (2011) Limited investor attention and stock market misreactions to accounting information. *The Review of Asset Pricing Studies* 1(1):35–73.

Hollnagel E (2009) *The ETTO principle: efficiency-thoroughness trade-off: why things that go right sometimes go wrong* (Ashgate Publishing, Ltd.).

Hou K, Xue C, Zhang L (2015) Digesting anomalies: An investment approach. *The Review of Financial Studies* 28(3):650–705.

IMO (2008) International shipping and world trade: Facts and figures. International Maritime Organization, Maritime Knowledge Centre, London.

Iyer AV, Deshpande V, Wu Z (2005) Contingency management under asymmetric information. *Operations Research Letters* 33(6):572–580.

Jain N, Girotra K, Netessine S (2014) Managing global sourcing: Inventory performance. *Management Science* 60(5):1202–1222.

Jain N, Girotra K, Netessine S (2022) Recovering global supply chains from sourcing interruptions: The role of sourcing strategy. *Manufacturing & Service Operations Management* 24(2):846–863.

Jones CS, Tuzel S (2013) Inventory investment and the cost of capital. *Journal of Financial Economics* 107(3):557–579.

Kalkanci B (2020) Supply risk mitigation via supplier diversification and improvement: An experimental evaluation. Working Paper, Scheller College of Business.

Kesavan S, Mani V (2013) The relationship between abnormal inventory growth and future earnings for us public retailers. *Manufacturing & Service Operations Management* 15(1):6–23.

Klotz DE, Chatterjee K (1995) Dual sourcing in repeated procurement competitions. *Management science* 41(8):1317–1327.

Li C (2013) Sourcing for supplier effort and competition: Design of the supply base and pricing mechanism. *Management Science* 59(6):1389–1406.

Osadchiy N, Schmidt W, Wu J (2021) The bullwhip effect in supply networks. *Management Science* 67(10):6153–6173.

Pan A, Ramasesh R, Hayya J, Ord J (1991) Multiple sourcing: The determination of lead times. *Operations research letters* 10(1):1–7.

Plambeck EL, Taylor TA (2006) Partnership in a dynamic production system with unobservable actions and noncontractible output. *Management Science* 52(10):1509–1527.

Ren ZJ, Cohen MA, Ho TH, Terwiesch C (2010) Information sharing in a long-term supply chain relationship: The role of customer review strategy. *Operations research* 58(1):81–93.

Schmidt W, Raman A (2022) Operational disruptions, firm risk, and control systems. *Manufacturing & Service Operations Management* 24(1):411–429.

Sheffi Y (2005) *The resilient enterprise: overcoming vulnerability for competitive advantage*, volume 1 (The MIT Press).

Sloan RG (1996) Do stock prices fully reflect information in accruals and cash flows about future earnings? *Accounting review* 289–315.

Swinney R, Netessine S (2009) Long-term contracts under the threat of supplier default. *Manufacturing & Service Operations Management* 11(1):109–127.

Taylor TA, Plambeck EL (2007) Supply chain relationships and contracts: The impact of repeated interaction on capacity investment and procurement. *Management science* 53(10):1577–1593.

Tomlin B (2006) On the value of mitigation and contingency strategies for managing supply chain disruption risks. *Management Science* 52(5):639–657.

Wang B (2019) The cash conversion cycle spread. *Journal of Financial Economics* 133(2):472–497.

Wang Y, Li J, Wu D, Anupindi R (2021) When ignorance is not bliss: An empirical analysis of subtier supply network structure on firm risk. *Management Science* 67(4):2029–2048.

Wu J, Birge JR (2014) Supply chain network structure and firm returns. Available at SSRN 2385217.

Zhao G, Webster K, Yin Luo C, Wang S, Elledge D, Alvarez MA, Wang A (2015) The logistics of supply chain alpha. Deutche Bank Market Research.

Online Appendix: Can Global Sourcing Strategy Predict Stock Returns?

Appendix A: Portfolio 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: 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.[7]

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 A2 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

[7] 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 A2 Robustness Test: Alternative Portfolio Formation

Portfolio Formation Techniques	Long-Short (1) GL	(2) SC	(3) SL	(4) RS
GSS_{t-1}	0.718	0.631	-0.868	0.729
	(2.72)	(3.19)	(-6.46)	(4.78)
$GSS_{t-1.5}$	0.660	0.417	-0.666	0.742
	(2.83)	(1.99)	(-3.01)	(4.25)
GSS_{t-2}	0.566	0.570	-0.754	0.694
	(2.10)	(3.68)	(-5.85)	(4.79)

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 C: 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.

Table A3 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)

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 A3 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 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.

Appendix D: Alternative Risk Model Specifications

In our main analysis, we use the 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 A4 shows results of alternative risk models for each of the four GSS variables that show significant return predictability in our main analysis.

We first present results without any risk adjustment. In row 1 of Table A4, we report the average unadjusted monthly excess returns (portfolio return minus the risk-free rate) of different quintiles (columns 1 to 5), and the zero-cost investment portfolio (column H-L). Not surprisingly, the unadjusted portfolio returns are slightly higher than the factor model alpha returns, and remains monotonically changing as one moves from lowest to highest quintile.

Rows 2 and 3 reports 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 four-factor model remains the mainstay of asset pricing, 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 market, SMB and HML factors are augmented by the 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 and size factors are augmented with two factors based on investment over assets (the I/A factor) and return on equity (the ROE factor).

Our results are little changed with these adjustments, which further 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.

Appendix E: Alternate Subsample 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.

Table A5 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)

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 A5, we find consistent support—both in sign and significance—to our main findings.

Appendix F: GSS Measure Construction: Using Factset Revere Dataset

In this section, we evaluate the usefulness of Factset Revere data on supply-chain linkages in constructing the studied GSS metrics which exhibit strong return predictability. To begin, we note that Factset Revere dataset differs from Panjiva dataset in two key aspects.

1. *Missing information on goods' value.* FactSet sparsely report information on transacted goods' value over a supply-chain link. The transacted value data is available for approx. 10% of the links. This severely limits the quality of GSS measures since one cannot infer the strength of a supply-chain link, which is needed for four of the five GSS measures that use import values as weights.

In contrast, for Panjiva dataset, as shown by Jain et al. (2014) one can use the Journal of Commerce Port Import Export Reporting Service (PIERS) to supplement the Panjiva data with the dollar value of imported goods. PIERS provide the dollar value of imported goods by combining multiple sources at the industry, supplier country, and product level. Though these measures are good for controlling cross-industry or cross-product differences, they might not be helpful in studying firm-level margins advantage in sourcing. For the latter, one would require importing firms' truthful reporting on the value of imported goods for each transaction.

2. *Relatively sparse coverage of buyers.* One of the main sources of primary linkage data in FactSet is Compustat Segments. The Compustat Segments dataset relies on the Statement of Financial Accounting Standards No. 14 requirement that public firms disclose customers that account for at least 10 percent of their total sales. Factset complements this source by manual searching of supplier names from various sources including firms' financial filings (see Zhao et al. (2015)). While the manual search results in much wider coverage of supply chain links compared to Compustat Segments dataset, the coverage is still parse relative to supply chain links covered by Panjiva. Furthermore, the ten percent threshold rule introduces a truncation bias as customers below this threshold are not reported, and those right around this threshold would appear to enter and exit the data arbitrarily. Such a truncation can lead to mismeasurement of the studied GSS variables, which require the *untruncated* history of imports from all suppliers.

Given the aforementioned differences, we conduct a quasi-falsification analysis by constructing an alternative series of the GSS measures using only the FactSet data, and examine any possible changes in return predictability. We obtain from the FactSet Supply Chain database all relationships labeled as suppliers and merge them with our sample firms by GVKEY. Next, for each focal firm i in the merged data, we compute the GSS metrics using i's Factset-derived supplier list. We make two changes in constructio of GSS measures. First, since no goods' value is reported, we construct an alternative GL measure as *(total number of non-US suppliers)/(total number of suppliers)*. Second, all other metrics (SC, SL and RS) are constructed by weighting all suppliers equally rather than by their specific annual imported values. Finally, since FactSet-covered suppliers contain both US and international firms, we compute two versions of the FactSet-based GSS measures. One version uses all available links (essentially treating all reported suppliers as a "global" supplier; GL is trivially one in this case and only SC and RS varies between firms)[8]. The second version only uses non-US supply links.

Table A6 shows prediction results using FactSet-based GSS measures. We find that these measures exhibit either an insignificant or very weak predictive power. Only 1 out of the 10 Factset-based GSS measures exhibit weak return predictability. Specifically, the RS variable based on both the international and domestic links exhibits a marginally positive return association at 10% p-value (Column 5 in Row 3). In summary, although the FactSet-based supplier dataset is well-suited for studying risk propagation along known chains of firms (e.g., the bullwhip effect as examined by (Osadchiy et al. 2021) and subtier risk propagation (Wang et al. 2021)), it seems not rich enough (compared to Panjiva) to construct import-based global sourcing variables, thus leading to lower return predictability.

[8]We do not construct SL and LE measures due to the lack of lead time and logistical efficiency measures for domestic suppliers.

Table A6 GSS measures using Factset supply-linkages data

	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)
Firms with FactSet Coverage	N/A	-0.097	N/A	N/A	0.311
(Metrics constructed using all available links)	N/A	(-0.55)	N/A	N/A	(1.90)
Firms with FactSet Coverage	-0.188	0.075	-0.123	-0.107	0.252
(Metrics constructed using non-US links only)	(-0.38)	(0.98)	(-1.21)	(-0.20)	(1.36)

Appendix G: 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. In Table A7 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 $IL = \text{INVT}/\text{AT}$ (Belo and Lin 2012) and (ii) 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 A7 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. In summary, across this group of robustness tests, we find sign- and significance-consistent results, with our main analysis, for 8 out of 8 alpha estimates.

Appendix H: Alternate Stock Sorting Approach

In our main analysis, 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 A1). In Table A8, 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 8 out of 8 alpha estimates.

Appendix I: Alternative Portfolio Rebalancing with Quarterly Frequency

In the main analysis, we do an annual rebalancing of portfolios to reflect the changes in samples firms' GSS choices over time. Row 3 in Table A9 show results of an alternate quarterly rebalancing approach. Compared to main analysis results (Row 1), the alphas for the quarterly-rebalanced portfolios remain similarly significant and are of similar economic magnitudes. For three of the four GSS measures, the quarterly-rebalanced portfolios have a slightly larger size of the alphas (for example, 0.68% vs. 0.64% in annually rebalanced GL portfolio), but the difference is likely not statistically significant. In summary, across this group of robustness tests, we find sign- and significance-consistent results, with our main analysis, for 4 out of 4 alpha estimates.

Table A7 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) Global Sourcing Share			(2) Supplier Concentration			(3) Weighted Lead Time			(4) 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 Adjusted Inventory Turnover, AIT

	(1) Global Sourcing Share			(2) Supplier Concentration			(3) Weighted Lead Time			(4) 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 6 for details on the otherwise identical empirical specification.

Table A8 Unadjusted Sorting Results

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

Notes. This table reports monthly four-factor alphas of 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 specification.

Appendix J: Longer Holding Periods

Row 2 in Table A9 reports the alphas of our GSS portfolios with a longer, two-year holding period (compared to one-year holding period in the main analysis). Two observations stand out. First, for each of the four GSS

Table A9 Robustness Test: Alternative Choices for Portfolio Rebalancing and Holding Period

Portfolio Formation Techniques	Long-Short or Net Long Alphas			
	(1) GL	(2) SC	(3) SL	(4) RS
Main analysis	0.637	0.494	-0.769	0.597
	(2.44)	(2.55)	(-5.76)	(3.90)
Quarterly Rebalanced	0.682	0.590	-0.733	0.715
	(2.91)	(3.08)	(-3.34)	(3.63)
2-Year Holding Period	0.315	0.243	-0.512	0.498
	(1.56)	(1.41)	(-2.66)	(3.92)
Net-long (annual quintile weights)	0.374	0.283	0.397	0.301
Note: Weights reversed for SL measure	(2.43)	(1.47)	(2.80)	(4.11)

variables, the longer investment horizon yield substantially smaller alphas (e.g., 0.315% vs. 0.637% for the GL portfolio). Moreover, only two of the four GSS variables–SL and RS–retain their statistical significance. These results thus indicate a decay in return predictability between year 1 and year 2, and suggest that, over a longer holding period, all GSS variables provide weaker abnormal returns.

Appendix K: Eliminating Short Selling

We further investigate the mispricing channel by examining whether mispricing is primarily driven by the short leg. The rationale is that, if the GSS variables do embed incremental information, then the alphas should not be concentrated on either leg of the trade. This could be examined using a net-long portfolio construction approach (Bansal et al. 2022), which also examines whether the GSS-based trading strategies can be applied in the practical setting of portfolio management. Specifically, our main analyses use value- and equal-weighted long-short portfolios. This approach might require shorting a large number of small stocks. As an alternative, we construct a GSS-tilted, net-long portfolio by (1) buying the entire sample universe of stocks, but (2) weighting them by their annual GSS quintile scores:

$$w_{i,t} = \frac{\mathrm{GSS}_{i,t}}{\sum_{I} \mathrm{GSS}_{i,t}}, \tag{12}$$

where $GSS_{i,t}$ is the quintile score for each of the four sourcing metrics (GL, SC, SL and RS. This portfolio weighting scheme is also employed in the finance literature (e.g., Bansal et al. 2022) and ensures that (1) the weights sum up to one and (2) stocks in the highest GSS quintile (reversed for the LE measure) receives five times the portfolio allocation of those in the lowest quintile. We estimate the alphas of this net-long portfolio and present them in Row 4 of Table A9. These results are broadly consistent with the previous results using long-short portfolios, and thus indicate that market mispricing of GSS-related information is not concentrated in stocks of any specific leg.

Appendix L: Alternate Subsample Analysis: The Effect of Size and Liquidity

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 using value-weighted portfolios, to further investigate whether our results are robust in predicting stocks of different liquidity profiles, we separately analyze the predictability of GSS in subsamples of small and large firms. Consistent with Fama and French (1993), we classify a stock as small or big depending on whether it is below (above) the 30^{th} (70^{th}) percentile of the size distribution. Accounting for the low number of observations, we repeat our time-series test in these subsamples using tercile portfolios (and above/below median for the SC measure). We form the zero-cost portfolios accordingly from these terciles.

Table A10 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	n/a	1.658	0.549	2.470	n/a	3.263	0.793
	(-0.46)	(1.58)	(4.49)	(8.03)	(-0.05)	(1.66)	(3.56)	(7.60)	(1.98)	n/a	(3.45)	(1.41)	(3.67)	n/a	(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.

Table A10 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 A11, 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 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. Following the convention, we define penny stocks as those that have a monthly closing price of below \$3 a share.

Collectively across these subsample analyses, we find sign- and significance-consistent results, with our main analysis, for 22 out of 24 alpha estimates. These results provide strong evidence that the return

Table A11 Eliminating Penny Stocks

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

predictability of the four GSS variables is robust and not driven by difficulty of arbitrage due to the presence of either small-size firms or penny stocks.

Appendix M: GSS Portfolio Returns During the Onset of COVID

In this section, we examine the premilinary return predictability of the GSS variables during the onset of the COVID pandemic, which has led many firms to rethink the pros and cons of the global sourcing due to the ongoing supply chain disruptions. At the same time, it is unknown whether the pricing value of the information embedded the GSS signals itself is significantly altered by the pandemic. That is, it is unknown whether market participants are more or less efficient in pricing GSS information during the COVID pandemic. We examine this by computing the average COVID-period monthly returns of pre-COVID GSS portfolios (i.e., portfolios formed at the end of 2019). We plot the unadjusted long-short returns for each of the four GSS portfolios during the extended period of 2020-21 in Table A12 below. Overall, the positive average monthly long-short returns persist for the main GSS variables during 2020 and 2021. The magnitude of these returns are similar to those before 2019, suggesting that the market mispricing of sourcing-related information did not materially change, and market participants did not fully incorporate the GSS-embedded pricing signals, during the onset of the COVID pandemic.

Table A12 Long-Short GSS Returns During COVID Onset

Year	Average Monthly Long-Short Returns			
	(1)	(2)	(3)	(4)
	GL	SC	SL	RS
2020	0.751	0.330	0.856	1.189
2021	1.040	0.294	1.404	1.375

Appendix N: Market Pricing of Cost Arbitrage and Efficient Cash Flow Management

Table A13 report results of estimating earnings prediction model with measures of the cost-arbitrage actions—GPM and COGS—and that of Cash Conversion Cycle action, CCC, as the dependent variables

Table A13 Predicting Cost-Related Earnings Components with GSS Measures

Panel A. Predicting Cost Arbitrage-Related Earnings Components with GSS

Cost-related Measures:	GPM_{t+1}				CCC_{t+1}				$COGS_{t+1}$			
	(1) GL	(2) SC	(3) SL	(4) RS	(5) GL	(6) SC	(7) SL	(8) RS	(9) GL	(10) SC	(11) SL	(12) RS
GSS(H)	0.063	0.002	-0.070	0.059	-3.597	-0.751	0.461	-1.854	0.007	0.015	-0.000	0.015
	(6.49)	(0.75)	(-6.46)	(2.61)	(-2.38)	(-0.82)	(0.23)	(-1.90)	(1.53)	(1.80)	(-0.11)	(2.03)
GSS(L)	-0.089	-0.052	0.035	-0.056	4.027	1.480	-3.860	-0.675	-0.001	0.001	0.006	-0.001
	(-3.58)	(-7.92)	(0.97)	(-5.00)	(1.96)	(1.59)	(-3.02)	(-1.14)	(-0.10)	(0.48)	(1.14)	(-0.40)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Average R^2	0.160	0.154	0.157	0.156	0.735	0.736	0.735	0.735	0.813	0.812	0.810	0.820

Panel B. Double-Sorting with COGS then GSS

	(1) GL			(2) SC			(3) SL			(4) RS		
COGS Tercile	H	M	L	H	M	L	H	M	L	H	M	L
GSS(H-L)	0.419	0.405	0.671	0.032	0.406	0.313	-0.388	-0.192	-0.600	0.735	0.521	0.487
	(1.78)	(2.47)	(3.30)	(0.71)	(3.80)	(3.48)	(-2.21)	(-1.60)	(-3.74)	(5.23)	(4.02)	(4.76)
GPM Terciles	H	M	L	H	M	L	H	M	L	H	M	L
GSS(H-L)	0.377	0.393	0.708	0.114	0.276	0.351	-0.285	-0.234	-0.481	0.369	0.660	0.514
	(2.36)	(2.70)	(3.87)	(0.50)	(1.78)	(2.99)	(-2.03)	(-2.25)	(-3.14)	(4.51)	(4.40)	(4.09)

and the lagged GSS values as predictors. We include all of the control variables used in earnings prediction, Eq 11. Also, similar to the overall earnings prediction analysis, we include lagged values of these measures in the regression to isolate the incremental effect of GSS on these actions. First, Columns (1) to (8) provide confirmatory evidence that global sourcing strategies can indeed predict firms' cash flow management and cost arbitrage efforts. Intuitively, firms that conduct more global sourcing (Columns 1 and 5), source from logistically efficient locations (Columns 3 and 7), and engage in relatively more repeat business with suppliers (i.e., have higher relationship strength with suppliers, Columns 4 and 8) have a significantly higher margin and simultaneously a significantly lower CCC. Collectively, our results show that GSS-embedded information is likely related to the cost component of earnings.

Next, we repeat our double sort analysis with cost-arbitrage measures to examine whether the cost-arbitrage alone is sufficient to fully explain the return predictive power of GSS. Intuitively, if GSS primarily affect profitability through the cost channel and investors are attentive to this relation, then we would expect the GSS portfolio alphas to have substantially lower magnitudes and statistical insignificance in double sorts analysis, particularly for firms with better cost positions (e.g., lower COGS and higher GPM). Table A13 reports the long-short portfolio alphas of double sort analysis with COGS and GPM measures. First, compared to inventory double sorts, the alphas are moderately lower in magnitude (e.g., when averaged across the high, medium and low GPM terciles, the monthly SC/SL/RS alpha is 0.247%/-0.333%/0.514%, compared to 0.369%/-0.531%/0.535% of the inventory-sorted portfolios; results using COGS are similar to inventory double sorts). These results indicate that firms cost-arbitrage gains, as reflected in the gross margins and COGS measures, could explain some of the GSS variables' predictability, a bit more so than inventory-related policies. At the same time, the incremental return predictability of GSS after controlling for these potential cost arbitrage metrics remain statistically significant: most of the long-short alphas remain significant in each of the COGS, GPM and/or CCC terciles.

Table A14 Double Sort Results: Cash Conversion Cycle, CCC

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)

Appendix O: Additional Figures and Tables

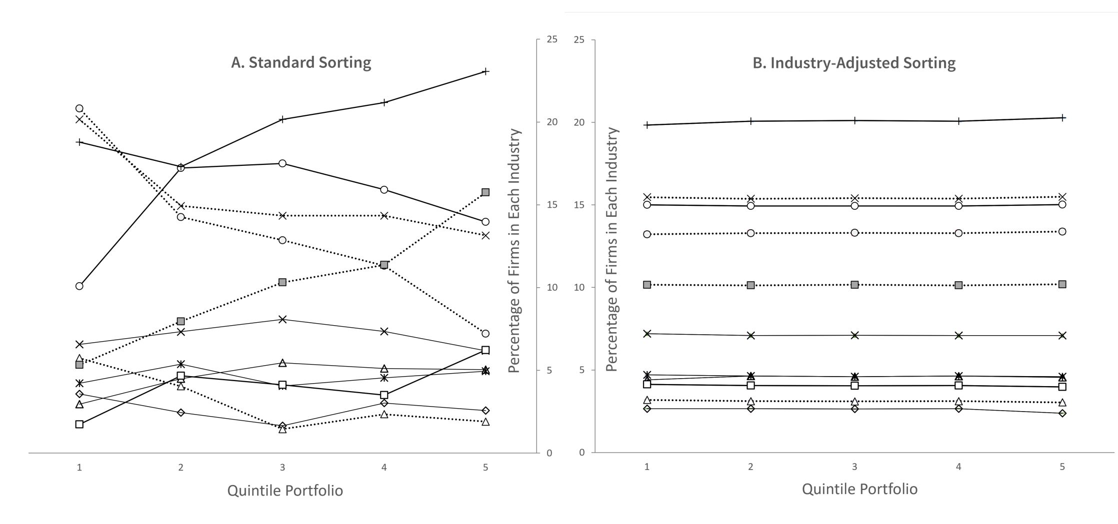

Figure A1 Sorting on Global Sourcing Level (GL): Industry Distribution Within Each Quintile Portfolio

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 A2 **Example of A Panjiva Entry**

Table A15 **Return Predictability Controlling for Other GSS Measures**

	Adding Additional GSS Measures			
	(1)	(2)	(3)	(4)
GL	0.594	0.568	0.579	0.561
	(2.77)	(2.69)	(2.70)	(2.60)
RS		0.487	0.465	0.391
		(3.41)	(3.04)	(2.83)
SL			-0.115	0.380
			(-2.11)	(1.88)
SC				-0.060
				(-1.64)
Full Controls	yes	yes	yes	yes
Average R^2	0.047	0.050	0.050	0.051

Table A16 **Full Table: 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

Table A17 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 (1996) 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
12 industries	Based on SIC codes we 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.
HS	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).

Table A18 Examples of GSS Measures in Sample Firms

Firm	Year	Quintile	Discussion
A. Global Sourcing Level (GL)			
FRESH DEL MONTE PRODUCE INC	2013	High(5)	We have a diverse **product line that is sourced globally**. We hold commanding positions in several product categories and we have a powerful distribution network that enables us to meet growing worldwide demands.
FASTENAL CO	2018	High(5)	Fastener products have a very **high content of imported products** and a lot of that is coming out of China. So if you think about that 1/3 of our business, **a big piece of that is sourced globally**. And most of that had moved outside of North America, heck, before we even started in business back in the late '60s. And so on that 35% it's a pretty big piece. On the non-fasteners, it's also a quite large piece.
GIBRALTAR INDUSTRIES INC	2008	Low(1)	And I know you've **traditionally sourced domestically**. Anything you are seeing that's attractive from overseas? Right now...the **only part we source overseas** has been the very light gauge material that we use in the building products business. Many of the U.S. mills preferred not to run those light gauges. Again, we continue to purchase that way.
WABASH NATIONAL CORP	2018	Low(1)	As you know, the updates from Washington regarding trade and tariffs seem to be changing weekly, if not more frequently... The majority of Wabash's **materials and components are sourced domestically**, so the direct impact of tariffs to Wabash is not significant.
B. Supplier Concentration (SC)			
ABERCROMBIE & FITCH	2014	High(5)	During fiscal 2014, we sourced approximately **81% of our merchandise from our top five** merchandise vendors.
AEROPOSTALE	2014	Low(1)	During Fiscal 2014, the Company sourced merchandise through approximately 150 vendors located throughout the world...The Company **did not source more than 10% of its merchandise from any single** factory or supplier.
C. Sourcing Lead Time (SL)			
MILLER INDUSTRIES INC	2017	High(5)	Now we're looking at purchasing effectiveness. We **haven't done a great job historically at managing supplier lead times**. We're now very focused on making sure we have accurate supplier lead times in the system, making sure that we have a really strong discipline process around back order management as well.
RALPH LAUREN CORP	2016	Low(1)	Together, we will...**cut supplier lead times**. This will allow our customers to buy much closer in and improve the flexibility to chase in season...working in collaboration with our partners, we will reduce and close the tail of our distribution
D. Relationship Strength (RS)			
AK STEEL HOLDING CORP	2011	High(5)	Kind of at the end of the day though, I think what's most important is to develop **meaningful, long-lasting supplier arrangements** and hopefully, in our case, equity arrangements that position us well to endure the ebbs and flows of the market.
GROCERY OUTLET HLDNG CORP	2018	Low(1)	We also continue to invest more time and resources in establishing and developing **new opportunistic relationships**...with a focus on new supplier acquisitions...This positions us well to efficiently identify and develop new relationships with suppliers of all sizes. In many cases, new partnerships begin with a **smaller initial purchase order**.

Table A20 Full Table: 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.