Industry Returns in Global Value Chains: The Role of Upstreamness and Downstreamness[*]

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Abstract

This paper studies how upstreamness and downstreamness affect industry returns in global value chains. Up- and downstreamness measure the average distance from final consumption and primary inputs, respectively, and are computed from world input-output tables. We show that downstreamness is a key driver of expected returns around the globe, whereas upstreamness is not. Industries that are farthest away from primary inputs earn approximately 5% higher returns per year than industries that are closest. The effect is found within countries and business sectors and suggests that investors perceive supplier-dependence in global value chains as an important source of risk.

Keywords: Asset Pricing · Input Output Table · International Financial Markets · International Trade · Stock Returns · Supply Chain

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1 Introduction

"The supply chain stuff is really tricky."

— Elon Musk, CEO of Tesla Inc., Code Conference 2016

Modern-day value chains are notoriously long and increasingly global. Tesla, as one example, witnessed first hand how challenging the management of automotive value chains has become: It had to shut down its production line for several days because, according to CEO Elon Musk, some of its suppliers were hit by natural disasters and, consequently, were unable to deliver parts. Automobile manufacturers in general have always been at the forefront of innovation in efficiently organizing the flow of goods and services from raw materials to final consumers. For example, Ford was among the first to introduce an assembly line and Toyota pioneered just-in-time production in order to avoid hold-ups in production. The sourcing of raw materials, however, is just one side of the coin; delivery to final consumers is the other. Value chains have lengthened substantially in both directions and have become increasingly global over past decades, such that firms have become more and more dependent on their international trade partners. These dependencies may turn out to be very costly, as in the case of Tesla. The question, therefore, arises: Do investors care about these risks? Do they expect higher returns on investments in firms that are particularly exposed to shocks that propagate through upstream or downstream value chains? Which direction matters most? These are the questions our paper aims to address.

We measure the length of upstream and downstream value chains using two industry-level metrics that are well-established in input-output economics: upstreamness and downstreamness. Upstreamness quantifies the average distance of industries from final consumers, i.e. it focuses on downstream value chains, while downstreamness reflects the average distance from primary inputs and is based on upstream value chains. We compute both measures from world input-output tables that contain data on global inter-industry trade flows as well as primary inputs and final consumption. These tables allow us to account for the fact that value chains are not confined to nations, but often cross borders several times, and are increasingly international (Baldwin and Lopez-Gonzalez (2015)). Our analysis discriminates between up- and downstreamness. That is, we explicitly take on two perspectives, from primary inputs and from final consumption, and jointly study the lengths of both branches of global value chains. For this reason, we are able to examine return differences of industries that are relatively independent, dependent on their suppliers, dependent on their customers, or generally dependent on their trade partners (Miller and Blair (2009), Miller and Temurshoev (2017)). Our final sample contains 15 years of data on 33,308 firms that belong to 767 industries, are located in 27 countries, and operate in 53 business sectors. Given our large, multidimensional sample, we can investigate whether the observed return differences are the result of cross-sector or cross-country variation and, for example, account for the fact that entire countries specialize in certain production stages of global value chains (Antràs and Chor (2018)).

We run portfolio sorts and panel regressions in order to examine how up- and downstreamness affect industry returns in global value chains. We find that downstreamness is a key driver of the expected returns of industries around the globe, whereas upstreamness is not. The cross-sectional return difference between industries that are farthest away from primary inputs and those that are closest amounts to approximately 5% per year. Our empirical results are robust to including control variables and equal-weighting firms within an industry. The effect of downstreamness on returns is mostly linear and comes from both cross-sector and cross-country variation. Our analysis shows that investors expect higher returns on investments in industries that are particularly exposed to shocks that propagate through upstream value chains.

This paper brings together input-output economics and asset pricing. Following the emergence of global value chains, economists have made great effort to measure the structure of global production and to grasp its implications for individual economic units as well as the aggregate economy (Carvalho (2014)). Over recent years, empiricists have gained a better understanding of global trade patterns since they have made considerable progress in linking national accounts across countries to form high-quality global input-output tables (Johnson (2018)). While this new data evoked a large number of studies in the domain of macroeconomics, very few studies emerged that explore asset prices on international financial markets in relation to the structure of global production, despite the tight link between asset returns and macroeconomic risks (Cochrane (2007)).[1] Our paper sheds light on this particular relation and shows that investors perceive supplier-dependence in global value chains as an important source of risk, presumably because it increases the risk of costly hold-ups in production.

The remainder of this paper is organized as follows. Section 2 reviews the related literature. Section 3 presents the empirical methodology, the data, and robust evidence from portfolio sorts and panel regressions. Section 4 concludes.

2 Related Literature

This section relates our paper to three strands of literature.

Shock Propagation in Economic Networks The first strand explores the propagation of microeconomic shocks in economic trade networks and has grown substantially over recent years. Lucas (1977) held the view that microeconomic shocks average out and thus have negligible effects on the aggregate economy. Recent studies by Gabaix (2011), Carvalho and Gabaix (2013), Contreras and Fagiolo (2014), and Acemoglu et al. (2016b) challenge this view and argue that the heterogeneity of firms, sectors, or countries can give rise to economy-wide fluctuations and tail risk.[2] Other theoretical and empirical studies identify asymmetric trade linkages between economic units, often industries, as the reason why microeconomic shocks amplify. On the theoretical side, Acemoglu et al. (2012) argue that productivity shocks are transmitted not only to first-order, but also to second- or higher-order connected downstream sectors, eventually affecting the whole economy. Atalay (2017) shows that the amplification of microeconomic shocks is driven by the input specification level of downstream customer sectors. Miranda-Pinto (2019) finds that countries in which sectors have strong

[1]A small literature investigates the asset pricing implications of global production and trade. Examples include Bretscher (2018), Barrot et al. (2019), Jiang and Richmond (2019), and Richmond (2019).

[2]See Carvalho and Tahbaz-Salehi (2019) for an overview of studies on the role of production networks for aggregate macroeconomic fluctuations.

supplier dependencies experience higher output volatility. On the empirical side, Barrot and Sauvagnat (2016) show that natural disaster shocks which hit suppliers cause sales drops at customers and, in addition, propagate to firms which share such customers. Boehm et al. (2019) provide evidence that shocks are transmitted across countries, from globally operating Japanese firms to their U.S. affiliates. Acemoglu et al. (2016a) document that demand-side (supply-side) shocks propagate upstream (downstream) and build up to more than five times the direct effect. We contribute to this strand of literature by showing that shock propagation through global trade linkages matters for asset pricing. We study industries' input demand chains from primary inputs and output supply chains toward the final consumer. We show that investors perceive supply-side shocks that propagate downstream and amplify when passing suppliers as an important source of risk. As a consequence, investors expect higher future returns on investments in industries that are particularly supplier-dependent.

Value Chain Positioning The second strand of literature focuses on measuring the position of firms or industries in value chains, especially in a global context. If shocks propagate up- or downstream, the positions of industries can have major effects on their economic situations. Industries' positions are typically measured relative to primary inputs and final consumption as the upstream and downstream ends of value chains. Antràs et al. (2012) introduce two metrics, up- and downstreamness, which quantify the distance from final consumption, i.e. the length of the downstream output supply chain, and the distance from primary inputs, i.e. the length of the upstream input demand chain, respectively. Antràs and Chor (2018) find a puzzling positive correlation between up- and downstreamness, both at the country and the industry level.[3] Moreover, McNerney et al. (2018) show that industries with higher downstreamness realize greater productivity fluctuations, because upstream supply-side shocks accumulate while propagating downstream. We add to this literature by explicitly distinguishing between up- and downstreamness and simultaneously analyzing the effects of both variables. Our evidence from financial markets implies that downstreamness is of greater relevance for investors than upstreamness.

[3]They built on earlier work from Fally (2012), Antràs and Chor (2013), and Miller and Temurshoev (2017).

Trade Networks and Asset Prices The third strand examines the role of trade linkages for asset prices. Cohen and Frazzini (2008) and Menzly and Ozbas (2010) find that economic links between suppliers and customers generate lead-lag effects in stock and industry returns and reason that these effects are the result of investors' unawareness of trade linkages. Herskovic (2018) proposes two measures that are derived from the distribution of intersectoral linkages – network sparsity and concentration – and represent macroeconomic risks that are priced in the cross-section of stock returns. The study most closely related to ours is Gofman et al. (2019), who calculate an upstreamness-like metric for U.S. firms. They find that upstream firms are more exposed to aggregate productivity shocks and therefore carry a risk premium. In contrast to the existing literature, our paper takes a global view on the role of up- and downstreamness for asset returns. This is important because modern-day value chains are increasingly international. Our paper combines global input-output data with international financial market data. We take into account that value chains can cross borders several times when computing up- and downstreamness and investigate their role for stock returns on 27 financial markets around the globe.

3 Empirical Evidence

This section presents empirical evidence on how up- and downstreamness affect industry returns in global value chains. Up- and downstreamness measure the distance from final consumption and primary inputs, respectively, and are computed from world input-output tables that report trade flows between industries around the globe. In portfolio sorts and panel regressions, we present robust evidence that downstreamness has a strong positive effect on expected returns, whereas upstreamness has no clear effect. Our results imply that an industry's risk of facing a hold-up in production due to supply shortages is the greater, the longer its upstream value chain. Since investors fear production downtimes, they demand a compensation for providing capital to firms that are prone to such risk and expect higher future returns on their investments.

3.1 Methodology

World Input-Output Tables Input-Output tables have long been of great interest to economists. They illustrate the trade relations between suppliers of goods and services and their customers within an economy and are an essential component of national accounting. Harmonized input-output tables of different countries can be linked together to form a so-called world input-output table (WIOT) that represents the entire world economy. WIOTs allow us to study cross-border trade flows that have grown significantly over past decades as a result of globalization. Table 1 depicts the schematic structure of a WIOT for a given year. The rows (columns) represent the supply (use) of goods and services. The core of the table contains the square matrix $\mathbf{Z}$ collecting trade in intermediates between industries. Entry $Z_{i,j}$ $(i, j = 1, \ldots, N)$ denotes the dollar value of intermediate goods and services produced by industry $i = i(s, c)$, classified as business sector s $(s = 1, \ldots, S)$ located in country c $(c = 1, \ldots, C)$, and purchased by industry j. The column vector $\mathbf{GO}$ at the very right side collects gross output by industry and has entry GO_i for industry i. The part of an industry's gross output that is not sold to any other industry but is rather consumed by households, governments, investments, or changes in inventories is referred to as final consumption and collected in the column vector $\mathbf{F}$ with entries F_i.[4] The relation between gross output, intermediate inputs, and final consumption is formalized in the output-side accounting identity

$$GO_i = F_i + \sum_{j=1}^{N} Z_{i,j}. \tag{1}$$

Industries not only rely on intermediate inputs provided by other industries but, in addition, employ primary inputs, such as labor and capital, in their production. The value of these primary inputs is defined as (gross) value added and collected in the column vector $\mathbf{VA}$ with entries VA_i. Since an industry's gross output must equal its total inputs, which can be divided into intermediate and primary, an input-side accounting identity arises which relates

[4] In the original table, final consumption is broken down by country. We construct a column vector by collapsing the country dimension and aggregating each industry's final consumption across all countries.

gross output to intermediate inputs and value added

$$GO_i = VA_i + \sum_{j=1}^{N} Z_{j,i}. \tag{2}$$

Global Value Chains WIOTs can be interpreted as a collection of global value chains. Each industry is embedded in many paths that lead through the table and start at primary inputs and end at final consumption. In a recent contribution, Miller and Temurshoev (2017) highlight that one can take two different perspectives on each value chain: from the output-side and the input-side, as reflected by the two accounting identities. They stress that an industry's average position in value chains can hence be measured for the output supply chain and therefore relative to final consumption, and for the input demand chain, i.e. relative to primary inputs. They argue that this distinction is important because an industry's structure of its output sales is different from its structure of input purchases. We follow their approach and use "output upstreamness" (henceforth upstreamness) and "input downstreamness" (henceforth downstreamness) as our measures of industries' average positions in global value chains.

Upstreamness We start by taking on the output-side perspective and compute an industry's average distance from final consumption as proposed by Antràs et al. (2012). We define the input coefficient $a_{i,j} = \frac{Z_{i,j}}{GO_j}$, which reflects the share of industry j's total inputs that are supplied by industry i, and rewrite Equation (1) as

$$GO_i = F_i + \sum_{j=1}^{N} a_{i,j} GO_j. \tag{3}$$

Next, by iterating over Equation (3) and replacing industries' gross outputs (GO_j, GO_k, and so on), we obtain the infinite sequence

$$GO_i = F_i + \sum_{j=1}^{N} a_{i,j} F_j + \sum_{j=1}^{N} \sum_{k=1}^{N} a_{i,j} a_{j,k} F_k + \dots \tag{4}$$

which reflects the use of industry i's output at different positions in global value chains. The right hand side points out that industry i sells part of its output directly to the final consumer (first term), provides intermediate inputs to industry j, which itself sells part of its output to the final consumer (second term), provides intermediate inputs to industry j, which then supplies goods and services to industry k, which itself finally sells part of its output to the final consumer (third term), and so on. Following Antràs et al. (2012), the weighted average position of industry i's output in global value chains, i.e. industry i's upstreamness, can then be computed by dividing the terms on the right hand side of Equation (4) by gross output and multiplying each term by the distance from final consumption plus one

$$U_i = 1 \cdot \frac{F_i}{GO_i} + 2 \cdot \frac{\sum_{j=1}^{N} a_{i,j} F_j}{GO_i} + 3 \cdot \frac{\sum_{j=1}^{N} \sum_{k=1}^{N} a_{i,j} a_{j,k} F_k}{GO_i} + \ldots \tag{5}$$

which is an infinite power series. Large values of U_i imply that industry i is far upstream, i.e. its output goes through many production stages before reaching final consumption, whereas small values indicate that a large share of output goes directly to the final consumer (Miller and Temurshoev (2017)). If $F_i \geq 0 \; \forall \; i$, U_i has a lower bound of one. Note that if, for example, $U_i > U_j$, this does not necessarily mean that industry i's output is employed in industry j's production. Rather, industry i enters global value chains at production stages farther away from final consumption on average, considering all value chains that industry i is embedded in (Antràs and Chor (2018)).

Downstreamness Next, we take on the input-side perspective and calculate an industry's average distance from primary inputs following Miller and Temurshoev (2017). We define the output coefficient $b_{j,i} = \frac{Z_{j,i}}{GO_j}$, which gives the share of industry j's gross output that is supplied to industry i, and reformulate Equation (2) as

$$GO_i = VA_i + \sum_{j=1}^{N} GO_j b_{j,i}. \tag{6}$$

We iterate over Equation (6) and replace industries' gross outputs to obtain

$$GO_i = VA_i + \sum_{j=1}^{N} VA_j b_{j,i} + \sum_{j=1}^{N} \sum_{k=1}^{N} VA_k b_{k,j} b_{j,i} + \dots \tag{7}$$

which, again, is an infinite sequence. We divide the terms on the right hand side of Equation (7) by gross output and multiply each term by the distance from primary inputs plus one and arrive at the infinite power series

$$D_i = 1 \cdot \frac{VA_i}{GO_i} + 2 \cdot \frac{\sum_{j=1}^{N} VA_j b_{j,i}}{GO_i} + 3 \cdot \frac{\sum_{j=1}^{N} \sum_{k=1}^{N} VA_k b_{k,j} b_{j,i}}{GO_i} + \dots \tag{8}$$

which defines industry i's downstreamness. Industry i is considered to be far downstream when D_i is large because primary inputs are first used in many other industries before reaching industry i's production as intermediate inputs. Small values, on the other hand, imply that a great share of primary inputs is directly used in the production and does not come from other industries (Miller and Temurshoev (2017)). D_i has a lower bound of one if $VA_i \geq 0 \; \forall \; i$.

Computation Equations (5) and (8) require computing infinitely many terms. Following standard input-output analysis (see Miller and Blair (2009)), we circumvent this problem by switching to matrix notation and using simple matrix inversions to compute up- and downstreamness. Appendix A.1 provides a detailed derivation. Let $\mathbf{A} = \mathbf{Z} \; diag(\mathbf{GO})^{-1}$ and $\mathbf{B} = diag(\mathbf{GO})^{-1} \; \mathbf{Z}$ collect the input and output coefficients, respectively, where $diag(\cdot)$ is the diagonal matrix. With the famous Leontief-inverse matrix $\mathbf{L} \equiv (\mathbf{I} - \mathbf{A})^{-1}$ (Leontief (1936), Leontief (1941)) and the Ghosh-inverse matrix $\mathbf{G} \equiv (\mathbf{I} - \mathbf{B})^{-1}$ (Ghosh (1958)), we can calculate up- and downstreamness as

$$\mathbf{U} = \mathbf{G} \; \boldsymbol{\iota} \tag{9}$$

$$\mathbf{D}' = \boldsymbol{\iota}' \; \mathbf{L}, \tag{10}$$

where $\mathbf{U}$, $\mathbf{D}$, and $\boldsymbol{\iota} = (1, 1, \dots, 1)'$ are column vectors. As a result, we can easily calculate industries' upstreamness as row sums of the Ghosh-inverse matrix and industries' downstreamness as column sums of the Leontief-inverse matrix.

Recursive Representation For a better understanding of our measures, we express up- and downstreamness recursively following Fally (2012). In particular, it holds that

$$\mathbf{U} = \boldsymbol{\iota} + \mathbf{B}\ \mathbf{U} \tag{11}$$

$$\mathbf{D}' = \boldsymbol{\iota}' + \mathbf{D}'\ \mathbf{A} \tag{12}$$

as shown in Appendix A.2. This recursive representation illustrates that industries which are important input suppliers to customer industries that have a high upstreamness are themselves far away from final consumption. Analogously, industries which purchase large shares of their inputs from supplier industries that have a high downstreamness are themselves far away from primary inputs.

3.2 Data and Descriptive Statistics

The sample period covers January 2001 to December 2015 and is dictated by the availability of international trade data.

Trade Data We obtain data on global inter-industry trade flows of goods and services from the 2016 release of the World Input-Output Database.[5] The database provides annual WIOTs which are constructed from harmonized national supply and use tables as well as bilateral trade data.[6] WIOTs are available from 2000 to 2014 and cover 44 countries (including "Rest of the World") with 56 business sectors each. Sectors are classified according to revision 4 of the International Standard Industrial Classification (ISIC) scheme and are consistently defined over time and across countries. The tables cover more than 85% of total global GDP (Timmer et al. (2016)) and therefore include the bulk of global value chains. To give an example, Figure 1 shows all global inter-industry trade flows, i.e. the full $(44 \times 56) \times (44 \times 56)$ $\mathbf{Z}$ matrix, in 2014. We can identify four salient features of global

[5] See Timmer et al. (2015) and `http://www.wiod.org` for further information.

[6] The tables have recently attracted much attention in macroeconomic research, see e.g. Johnson (2014), Koopman et al. (2014), Timmer et al. (2014), Fajgelbaum and Khandelwal (2016), and Adao et al. (2017).

trade. First, at the given level of aggregation, industries have strong self-loops, i.e. the most important trade partner is typically the industry itself. This can be inferred from the main diagonal and highlights the important role of intra-industry trade. Turning back to our introductory example, we observe that U.S. automobile manufacturers produced goods worth $596 billion in 2014, of which $101 billion (16.9%) were traded with each other. Second, much of the trade takes place within a country. For example, motor vehicles worth $8 billion (1.3%) were supplied to domestic U.S. wholesalers and retailers. Third, cross-border trade is lively and often strongest between industries in the same sector. Notably, Canadian automobile manufacturers purchased goods worth $16 billion (2.7%) from their U.S. counterpart. Fourth, international trade also takes place between different sectors, for example, U.S. automobile manufacturers sold products worth $3 billion (0.5%) to Canadian wholesalers and retailers. These observations motivate us to take the broadest possible perspective on up- and downstreamness, which we compute for every year based on all available global value chains.

Stock Market Data Our analysis builds on daily and monthly stock returns from financial markets around the globe. We limit ourselves to stocks traded on markets that are classified as either developed or emerging by MSCI and represented in the WIOTs.[7] Data for U.S. stocks is obtained from the Center for Research in Security Prices (CRSP) and the CRSP/COMPUSTAT Merged databases, while data for all other countries is taken from Thomson Reuters Datastream and Worldscope. We apply several filters to ensure high data quality. For the U.S., we narrow the stock universe down to common stocks (share codes 10 and 11) which are traded on NYSE, NYSE MKT, or NASDAQ. For non-U.S. stocks, we use Thomson Reuters Datastream constituent lists, in particular, Worldscope lists, research lists, and dead lists to eliminate survivorship bias. We convert data items that are denominated in local currencies into US-$.[8] We identify common stocks through generic and country-specific static screens in the fashion of Ince and Porter (2006), Griffin et al. (2010), and Schmidt et al. (2019) and, furthermore, apply several dynamic screens on stock prices and returns

[7]See `https://www.msci.com/market-classification` for details.

[8]We convert local currencies into US-$ because trade flows in the WIOTs are denominated in US-$, too. We thereby assume the perspective of an U.S. investor who is perfectly hedged against currency risk.

in order to eliminate erroneous and illiquid observations. Appendix B provides a detailed description of our data cleaning procedure. Besides valid returns, we require that stocks have trading volumes greater than zero in the current month and known market capitalizations for the previous month. The risk-free rate is obtained from Kenneth R. French's homepage.[9]

Industry Mapping Our stock market data includes industry affiliations based on the North American Industry Classification System (NAICS), the Standard Industrial Classification (SIC), or the Industry Classification Benchmark (ICB).[10] We assign stocks to industries in the WIOTs, which are based on ISIC codes, using the following mapping scheme. For NAICS codes, we rely on the official concordance table mapping 2007 NAICS codes to ISIC codes as provided by the U.S. Census Bureau.[11] SIC codes cannot be directly mapped to ISIC codes, but rather have to be converted into 2002 NAICS codes and subsequently translated into 2007 NAICS codes, which then finally can be linked to ISIC codes. For each of these steps, we again use official concordance tables available from the U.S. Census Bureau. Mapping ICB codes proves more challenging because official concordance tables are not available. Hence, from our sample of stocks that have both ICB and SIC codes, we first construct our own concordance table mapping ICB to SIC codes based on the most commonly observed combinations, which we then use to map all remaining stocks following the steps outlined above. Given that the mapping procedures have different levels of complexity, we prioritize assignments to industries in the WIOTs based on NAICS codes over those derived from SIC codes, and use ICB codes only as the last option.

Industry Returns Our main empirical analyses are conducted at the industry level. Hence, we aggregate the stock returns of firms that operate in the same industry and calcu-

[9]See http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

[10]For U.S. stocks, we collect NAICS and SIC codes from the CRSP/COMPUSTAT Merged database and complement them with any non-redundant data from the CRSP database. We prefer historical over header information to account for changing industry affiliations. The databases do not disclose which revision of the NAICS they apply. We therefore make the assumption that the reported NAICS codes are based on the 2007 revision. For non-U.S. stocks, Worldscope provides SIC and ICB codes that were most recently reported. We thus have to make the assumption that non-U.S. stocks did not change their industry affiliation within our sample period.

[11]Official concordance tables are available at https://www.census.gov/eos/www/naics/concordances/concordances.html.

late value-weighted industry returns. We impose the restriction that each industry-month observation is backed by at least five firms in order to limit the role of idiosyncratic stock price movements. In addition, we require at least five industries for every country-month, such that countries in our sample have a minimum level of stock market coverage.

Descriptive Statistics Table 2 summarizes our sample selection. We are able to map 4.4 million stock-month observations to industries in the WIOTs. Most of the links are established via NAICS codes for U.S. stocks and via SIC codes for non-U.S. stocks, i.e. our two conservative mapping schemes based on official concordance tables. Our final sample includes 110,699 industry-month observations that represent 767 (out of 2,408 in the WIOTs) unique industries, 53 (56) sectors, and 27 (43) countries. Table 3 reports time-series averages of the properties of the cross-sectional distribution of industry characteristics. On average, industries consist of 37 firms, leading us to conclude that industry returns in our sample are reliably measured and mostly free of idiosyncratic effects. Our two key explanatory variables, up- and downstreamness, both have minima of 1 by definition, maxima of 4.8 and 3.7, and average values of 2.3 and 2.2, respectively. Industries show substantial (lagged) market capitalizations of $10 billion on average and are therefore of great economic importance. Figure 2 sheds light on the evolution of up- and downstreamness as well as their cross-sectional correlation over time. We find widening ranges for both up- and downstreamness. In addition, their correlation is positive throughout the sample period and grows from 0.34 in 2000 to 0.44 in 2014. This finding is in line with previous research (see e.g. Miller and Temurshoev (2017)) and indicates that upstream and downstream global value chains have become longer and longer. Moreover, it implies that up- and downstreamness need to be studied simultaneously in order to identify the true individual effect of any of the two variables. Table 4 provides summary statistics by country, averaged over time. Mexico has only 5 sectors comprising 45 stocks, while the U.S. is best covered in our sample with 49 sectors and 4,032 stocks on average. The U.S. also leads in terms of (lagged) market capitalization; however, our sample includes several major economies that rank just behind the U.S., such as Japan, the United Kingdom, China, France, and Germany. Countries seem to specialize along global value chains to some degree (Antràs and Chor (2018)). For example, Chinese industries tend to be embedded in long global value chains with a high average up- and downstreamness of 2.8 and 2.7, respectively. This motivates us to run within-country analyses in Section 3.3.2. Table 5 reports summary statistics by ISIC sector, averaged over time and sorted by downstreamness in descending order. We can see that the country dimension is less populated than the sector dimension. While 24 countries have a financial service sector, the U.S. is the only country with a listed public administration and defense sector in our sample. The number of stocks varies between 5 for postal and courier activities and 2,402 for mining and quarrying. In line with economic intuition, the latter sector has the largest upstreamness and is therefore the farthest away from the final consumer. Manufacturing sectors, including our introductory example of automobile manufacturers, are positioned far downstream, suggesting that they have many suppliers between themselves and primary inputs. Lastly, Table 6 shows the ten farthest up- and downstream industries in 2014. Confirming our previous observations, many of these sectors are China-based and can be found on both lists. Mining and quarrying sectors rank among the most upstream industries, while manufacturing sectors dominate the list of the most downstream industries. Furthermore, next to Chinese, we find Taiwanese, South Korean, Russian, and Australian industries, highlighting the recursive calculation of up- and downstreamness because these countries maintain strong regional trade relations with China (Baldwin and Lopez-Gonzalez (2015)).

3.3 Results

Having described our empirical methodology as well as our sample composition, we now present empirical evidence on how up- and downstreamness affect industry returns in global value chains.

3.3.1 Portfolio Sorts

For this purpose, we run portfolio sorts in the fashion of Fama and French (1992). At the end of every year, we assign industries to quintile portfolios based on their up- or downstreamness. We consider country-adjusted, value-weighted industry returns. These are based on value-weighting stock returns of firms in every industry and demeaning industry returns by the corresponding country-average return in each month in order to account for cross-country differences in equity premiums.[12] For each quintile portfolio, we compute equal- and value-weighted returns over the subsequent year, rebalanced monthly. We then take time-series averages of all portfolio returns and report them at an annual level.

Single Sorts Table 7 presents results from single sorts. We do not find any clear, monotonic pattern of value-weighted returns for quintiles formed on either up- or downstreamness. The returns of the High-Minus-Low portfolios are not statistically significantly different from zero. Equal-weighted returns produce similar results. A strategy that goes long industries with high downstreamness and shorts those with low downstreamness yields 2.1% p.a. in excess of the respective average country returns, which is slightly below the 10% significance level.

Independent Double Sorts As discussed above, up- and downstreamness are cross-sectionally correlated. To account for this correlation, we run independent double sorts in Table 8. Panel A shows that all 25 portfolios contain a sufficient number of industries.[13] Panel B reports that, if at all, average value-weighted returns increase with downstreamness when controlling for upstreamness. However, only one of the five High-Minus-Low portfolios earns a statistically significant and economically meaningful country-adjusted return. When controlling for downstreamness, upstreamness seems to have a slightly negative effect on returns. Two out of the five High-Minus-Low portfolios yield statistically significant country-adjusted returns. The results are broadly similar when considering equal-weighted returns in Panel C; however, the effect of downstreamness on returns is weaker.

3.3.2 Panel Regressions

Portfolio sorts can be conducted for a small number of variables only. Panel regressions are much more flexible in this respect and allow us to control for many other factors that are

[12] As a robustness exercise, we also consider industry returns that are based on equal-weighted stock returns in panel regressions in Section 3.3.3.

[13] Recall that each industry contains at least five stocks, such that all 25 portfolios are well-diversified.

potential drivers of industry returns. We therefore run panel regressions of monthly value-weighted industry excess returns on annual up- and downstreamness of the previous year. Table 9 reports the results from variants of the following regression model

$$r_{i,t} - r_{f,t} = \lambda_U \, U_{i,t-1} + \lambda_D \, D_{i,t-1} + \lambda_C \, C_{i,t} + \epsilon_{i,t}, \tag{13}$$

where $r_{i,t} - r_{f,t}$ is industry i's monthly value-weighted return in excess of the risk-free rate, $U_{i,t-1}$ and $D_{i,t-1}$ denote industry i's up- and downstreamness at the end of the previous year, respectively, and $C_{i,t}$ collects a set of control variables (including fixed effects). We specify eight different regression models in the spirit of Petersen (2008) to learn more about the dependence structure inherent in our sample. All models are estimated using ordinary least squares (OLS).

Baseline Results Columns (1) and (2) present the results when including one variable at a time. We include country fixed effects in order to control for time-invariant country characteristics that affect stock market outcomes, such as the size and accessibility of the local stock market, and month fixed effects to account for industry-invariant time effects, e.g. global macroeconomic shocks that affect industries across the board.[14] We cluster standard errors by month because residuals from a regression of industry returns are likely to be correlated between industries in the same month (so-called time effect), for example, because industry returns exhibit a factor structure and are driven by the same state variables. We find that upstreamness does not have a statistically significant effect, whereas downstreamness positively affects industry returns. The coefficient on downstreamness amounts to 0.156 (t=2.8) and is statistically significant at the 1% level. Monthly returns therefore increase by 15.6 basis points per layer that is between the industry and primary inputs. Given that the average cross-sectional dispersion of downstreamness is 2.67 (Table 3), this estimate translates into a sizable annual cross-sectional return difference of approximately 5%. In column (3), we include up- and downstreamness at the same time. The estimates on both variables change only little, suggesting that multicollinearity is not a major concern for our sample. Economically speaking, our results imply that the distance from primary inputs is

[14] See Watanabe et al. (2013) for an overview on country characteristics that affect local financial markets.

the driver of expected industry returns in global value chains, as opposed to the distance from final consumption. Risk propagates through global value chains and accumulates when passing supplier industries. Intuitively, an industry's risk of facing a hold-up in production due to supply shortages is therefore the greater, the longer its upstream value chain. Since investors fear production downtimes, they demand a compensation for providing capital to firms that are prone to such risk and expect higher future returns on their capital.

Standard Errors So far, standard errors have been clustered by month in order to account for a potential time effect. However, our data may still exhibit an industry effect, i.e. a time-series correlation of residuals for a given industry, for two reasons. First, industry returns are positively autocorrelated (Moskowitz and Grinblatt (1999)), and, second, up- and downstreamness are annual values and therefore do not change for twelve months in a year. We control for a potential time and industry effect by clustering on both dimensions, month and industry, in column (4). The standard errors are actually smaller and the t-statistics larger compared to column (3). Given that we have a sufficient number of clusters in both dimensions, we can conclude that an industry effect is unlikely to be present in our sample.[15] Hence, we control for a time effect only in the following analyses.

Fama-MacBeth The Fama-MacBeth procedure is specifically designed to control for a time effect (Petersen (2008)) and is commonly applied in empirical asset pricing research. Hence, we now check the robustness of our previous results w.r.t. the applied estimator. For each month, we estimate a cross-sectional regression with country dummies and calculate estimates and standard errors as in Fama and MacBeth (1973). The results are reported in column (5). Again, the very same pattern emerges. Upstreamness does not explain industry returns, whereas downstreamness has a coefficient of 0.152 (t=2.7) which is statistically significant at the 1% level. The estimates are very similar in terms of magnitude and significance compared to those previously obtained. The Fama-MacBeth regressions therefore validate our OLS panel regressions, on which we rely henceforth.

[15] Our sample covers 767 different industries over 180 months, such that the number of clusters in both dimensions is sufficiently large (Petersen (2008)).

Fixed Effects We have previously used country and month fixed effects. In order to find out whether the observed relation between industry returns and downstreamness reflects mostly cross-sector or cross-country variation or both, we specify different fixed effects in columns (6) to (8). When including month fixed effects but omitting country fixed effects in column (6), the adjusted R^2 is 0.36 and almost equal to the one obtained with both fixed effects in column (3). Country dummies thus do not contribute to explaining industry returns. The coefficient on downstreamness is 0.24 (t=2.4) and statistically significant at the 5% level. In column (7), we include country-month fixed effects in order to correct industry returns from any current, nationwide variation that, for example, is the result of the current local economic situation. The explanatory power of the model is large with an adjusted R^2 of 0.62. The coefficient on downstreamness amounts to 0.138 (t=2.5), is statistically significant at the 5% level, and translates into an economically meaningful annual cross-sectional return difference of roughly 4.5%. This estimate suggests that the observed relation between industry returns and downstreamness arises from cross-sector variation within countries. Column (8) includes ISIC sector-month fixed effects. The model's adjusted R^2 is smaller at 0.38 and the coefficient on downstreamness amounts to 0.149 (t=0.7), but is not statistically different from zero at conventional significance levels. Hence, the effect of downstreamness on industry returns vanishes within-sectors, i.e. when studying industries that operate in the same sector but are located in different countries. However, the lack of statistical significance may also be the result of too few observations along the country dimension. We address this issue by conducting firm-level panel regressions in Section 3.3.4.

Overall, we find that downstreamness is a key driver of the expected returns of industries around the globe, whereas upstreamness is not. The cross-sectional return difference between industries that are farthest away from primary inputs and those that are closest amounts to approximately 5% per year. The effect can be mostly attributed to cross-sector variation within countries. Our results suggest that investors perceive supplier-dependence in global value chains as an important source of risk.

3.3.3 Robustness

We now validate our previous empirical results by including control variables in the regressions, exploring potential nonlinearities, and equal-weighting firms within industries.

Control Variables Industry returns may be driven by variables other than up- and downstreamness, even when absorbing all time-varying country-wide variation through country-month fixed effects. For this reason, we add industry returns over the previous month $t-1$ and covering months $t-12$ to $t-2$ to our previous regressions in order to account for positive autocorrelation and time-series momentum in industry returns (Moskowitz and Grinblatt (1999)). In addition, we include the number of stocks per industry in order to control for the fact that firms in some industries are more commonly listed on the stock market than in others. Moreover, we control for industries' exposures toward common risk factors by estimating betas w.r.t. the global Fama-French five factor model (Fama and French (2012), Fama and French (2015)).[16] Table 10 reports the results. Column (1) confirms that upstreamness does not have a significant effect on industry returns. The effect of downstreamness survives including control variables as shown in column (2). The estimate amounts to 0.106 (t=2.1), which is statistically significant at the 5% level. In comparison to our previous estimate of 0.156, the effect is reduced but still economically meaningful because the monthly return spread of 10.6 basis points per layer translates into a sizable cross-sectional return difference of 3.4% per year. In column (3), we include up- and downstreamness at the same time and arrive at similar results; the coefficient on downstreamness is slightly larger with 0.126 (t=2.3).

Nonlinearities We run two additional regressions to explore the existence of potential nonlinear effects. In column (4), we add squared terms of up- and downstreamness but find no support for a quadratic relation with industry returns. Column (5) includes the

[16] We use betas instead of industry-level characteristics because some of the firms in our sample do not report the required accounting variables (e.g. book equity). We compute betas by regressing each industry's daily returns over a rolling window of 12 months on the daily global factors MKT, SMB, HML, RMW, and CMA readily available on Kenneth R. French's homepage `http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html`. Following Welch (2019), we require at least 127 observations per rolling window.

interaction of up- and downstreamness and reports a negative coefficient of -0.07 (t=-1.7), which is marginally statistically significant at the 10% level. The estimate suggests that the positive relation between downstreamness and industry returns wears off with increasing upstreamness. Economically, this finding implies that, given the same distance from primary inputs, investors prefer industries with long downstream value chains and expect lower returns on investments in such industries.

Equal-Weighting In a further robustness exercise, we use equal instead of value weights for firms within industries. Table 11 presents the results. Columns (1) to (3) confirm that downstreamness is a key driver industry returns, whereas upstreamness is not. The coefficient on downstreamness is 0.124 (t=2.5) and therefore very similar to our previous estimates. Column (4) shows once again that nonlinear effects are not present. In contrast to our previous regression, however, the interaction between up- and downstreamness is not statistically significant in column (5).

To sum up, the robustness exercises underline three points. First, our main findings are robust to including control variables in the regressions. Second, the effect of downstreamness on industry returns is mostly linear and, third, the results are almost identical when equal-weighting firms within industries.

3.3.4 Firm-Level Panel Regressions

Our previous analyses indicate that the effect of downstreamness on industry returns is strongest within-country, whereas it seems to vanish within-sector. However, we have only few observations along the country dimension which may explain the lack of significance when including ISIC sector-month fixed effects. In order to shed more light on the question of whether the observed relation comes from cross-sector or cross-country variation or both, we exploit our unique data set and make use of stock returns instead of industry returns. The regression setup is similar to the industry-level case and involves stock returns over the previous month $t-1$, over months $t-12$ to $t-2$, and firm-level betas w.r.t. the global Fama-French five factor model. In addition, we include lagged firm-level characteristics, such as market capitalization, book-to-market ratio, operating profitability, and asset growth as control variables.[17] We cluster standard errors by month and industry because up- and downstreamness are industry-level variables and therefore do not change for firms in the same industry. We report the results in Table 12. Taken as a whole, the firm-level regressions support our previous conclusions. When including month fixed effects in columns (1) to (3), downstreamness is found to be a key driver of stock returns, whereas upstreamness is not. Monthly stock returns increase by 433 basis points per layer that is between the industry in which the firm operates and primary inputs. The effect is statistically significant at the 5% level and translates into an annual cross-sectional return difference of 14.2% between stocks belonging to the industry that is farthest away from primary inputs and the one that is closest.[18] When including country-month fixed effects in column (4), the effect of downstreamness is positive with 0.122 (t=2.0). In addition, we find a strong effect of downstreamness when including ISIC sector-month fixed effects, i.e. when comparing stocks that operate in the same sectors but in different countries, in column (5). The coefficient on downstreamness amounts to 0.602 (t=1.9), is statistically significant at the 10% level, and reflects a sizable annual cross-sectional return spread of 19.9%.

Overall, the firm-level evidence supports and complements our previous results at the industry level. Downstreamness has a strong positive impact on stock returns, whereas upstreamness has no effect. The firm-level regressions show that the effect of downstreamness is found within countries and within business sectors. In light of the previous results from industry-level regressions, which suggest that the effect is strongest within-country, we can therefore conclude that the robust downstreamness effect is not merely a cross-sector or cross-country effect, but rather comes from variation along both dimensions.

[17] The book-to-market ratio, operating profitability, and asset growth are annual characteristics. Following McLean et al. (2009), we winsorize these variables at the 1% and 99% quantile within each country-year in order to limit the impact of possibly spurious outliers.

[18] This number should we viewed in relation to the average annualized cross-sectional standard deviation of stock returns of 52.1% in the entire sample.

4 Conclusion

Value chains have grown in length and become more and more international over past decades. This paper studies how the distance from final consumption and primary inputs, up- and downstreamness, respectively, affect the expected returns of industries in global value chains. Up- and downstreamness are computed from world input-output tables that contain data on global inter-industry trade flows as well as final consumption and primary inputs. A high upstreamness implies a strong customer-dependence because an industry's output goes through many intermediate production stages before reaching final consumption, whereas a low upstreamness indicates that a large share of output goes directly to final consumers. Similarly, an industry that has a high downstreamness is particularly supplier-dependent because primary inputs are first used in many other industries before being employed in this industry's production as intermediate inputs, whereas a low downstreamness signals that a great share of inputs are primary.

For a large, multidimensional sample containing 15 years of data on 33,308 firms that belong to 767 industries, are located in 27 countries, and operate in 53 business sectors, we present robust evidence that downstreamness is a key driver of the expected returns of industries around the globe, whereas upstreamness is not. The cross-sectional return difference between industries that are farthest away from primary inputs and those that are closest amounts to approximately 5% per year. Our empirical results are robust to including control variables and equal-weighting firms within industries. The effect of downstreamness on returns is mostly linear and comes from both cross-sector and cross-country variation. All in all, we show that investors perceive supplier-dependence in global value chains as an important source of risk. Our results imply that risk propagates through upstream value chains and accumulates when passing suppliers.

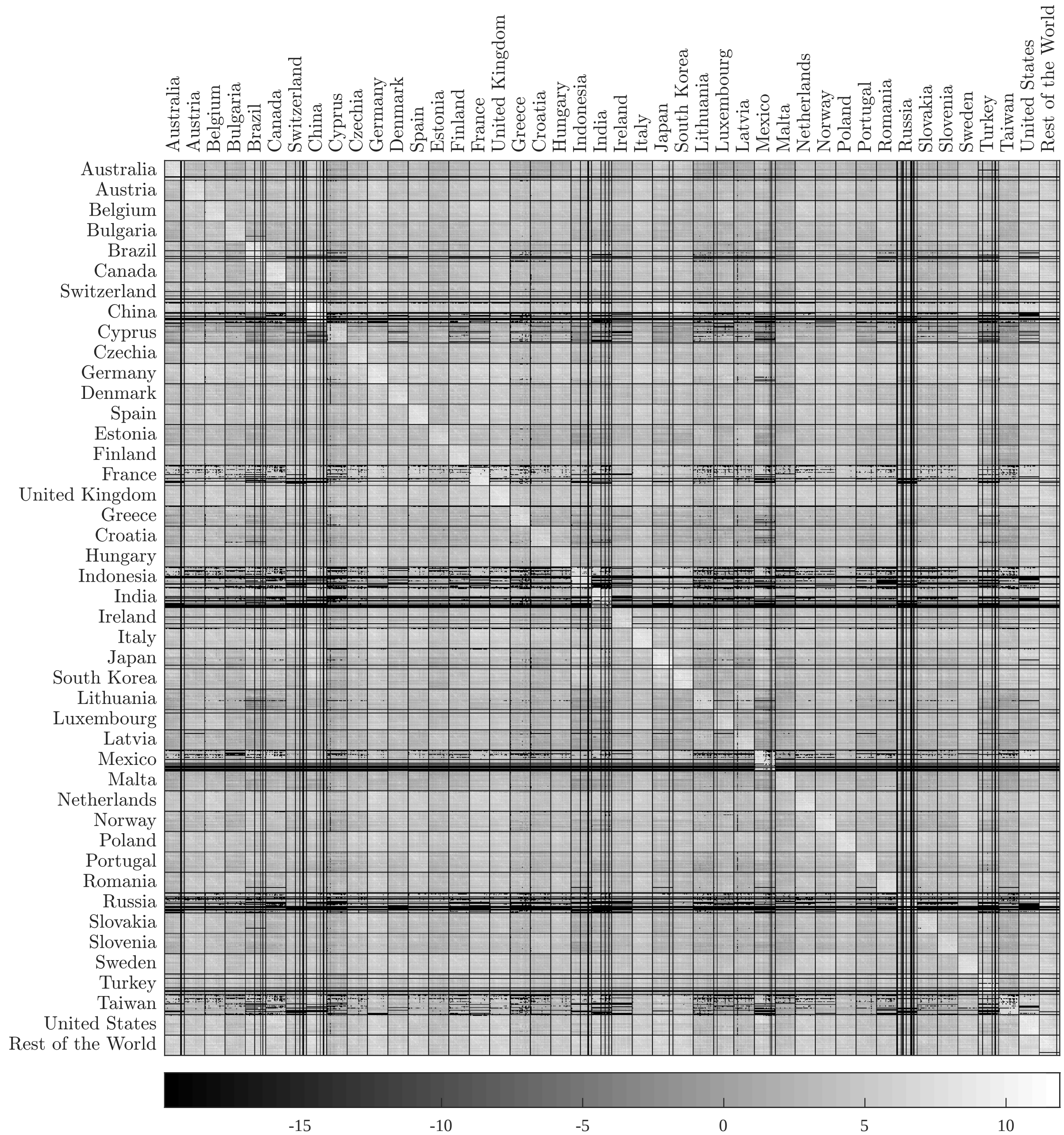

Figure 1: Global Inter-Industry Trade Flows in 2014

This figure depicts global inter-industry trade flows in 2014. Trade flows are denominated in US-$ and reported in logarithms with base 10. Data is taken from world input-output tables available at http://www.wiod.org. The sample includes a total of 2,464 industries that are located in 44 countries (including "Rest of the World") and operate in 56 business sectors. Rows (columns) represent the supplier (consumer) of intermediate goods and services.

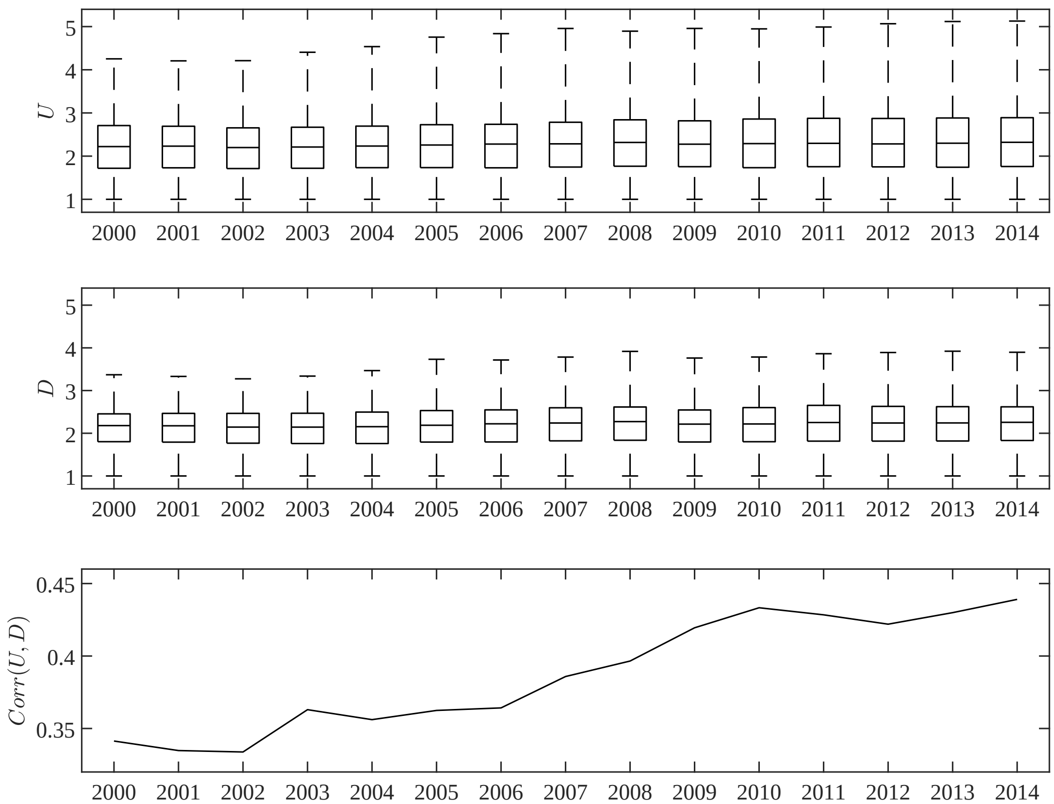

Figure 2: Evolution of Upstreamness and Downstreamness

This figure shows the evolution of up- and downstreamness over time. Up- and downstreamness are computed from annual world input-output tables taken from http://www.wiod.org. The first (second) panel shows box plots of the cross-sectional distribution of upstreamness (downstreamness) for industries in our final sample covering the years 2000 to 2014. The whiskers extend to the minimum and maximum values. The third panel plots the time series of the cross-sectional correlation between up- and downstreamness.

			Input Use										
			Country 1			$\cdots$	Country C			Final Consumption			
			Sector 1	$\cdots$	Sector S	$\cdots$	Sector 1	$\cdots$	Sector S	Country 1	$\cdots$	Country C	Gross Output
		Sector 1											
	Country 1	$\cdots$											
		Sector S											
Input Supply	$\cdots$	$\cdots$				$\mathbf{Z}$					$\mathbf{F}$		$\mathbf{GO}$
		Sector 1											
	Country C	$\cdots$											
		Sector S											
		Value Added				$\mathbf{VA}'$							
		Gross Output				$\mathbf{GO}'$							

Table 1: Schematic Structure of World Input-Output Tables

This table depicts a schematic representation of world input-output tables. Rows (columns) represent the supply (use) of goods and services in the world economy. $\mathbf{Z}$ is a matrix collecting trade in intermediates between industries that operate in business sectors $1, \ldots, S$ located in countries $1, \ldots, C$. $\mathbf{F}$ and $\mathbf{VA}$ are column vectors reflecting final consumption, aggregated across countries, and value added, respectively. Column vector $\mathbf{GO}$ denotes gross output and represents row and column sums.

	U.S.	Ex-U.S.	Total
Stock-month observations after screens	757660	3741166	4498826
Mapped to WIOT industries			
... via NAICS	685879	0	685879
... via SIC	41455	3509447	3550902
... via ICB	0	199784	199784
	727334	3709231	4436565
At least 5 stocks per industry-month	725966	3505162	4231128
At least 5 industries per country-month	725966	3493722	4219688
With control variables	590284	2272090	2862374
No. of unique stocks	7264	26044	33308
Industry-month observations	8944	115086	124030
With control variables	8903	101796	110699
No. of unique industries	52	715	767
No. of unique ISIC sectors	52	51	53
No. of unique countries	1	26	27

Table 2: Sample Selection

This table presents the sample selection process for U.S. and non-U.S. stocks and industries. Data for the U.S. is obtained from the CRSP and CRSP/COMPUSTAT Merged databases, while data for all other countries is taken from Thomson Reuters Datastream and Worldscope. The sample period is from January 2001 to December 2015 (180 months).

	No. of Stocks	U_{t-1}	D_{t-1}	r_{t-1}	$r_{t-12:t-2}$	$\log_{10}(ME_{t-1})$
Mean	37	2.290	2.191	0.009	0.118	10.009
Standard Deviation	80	0.729	0.529	0.072	0.303	0.802
Minimum	5	1.000	1.000	−0.260	−0.617	7.711
Median	16	2.266	2.209	0.007	0.085	9.989
Maximum	1352	4.751	3.670	0.399	1.980	12.216

Table 3: Summary Statistics

This table reports time-series averages of the properties of the cross-sectional distribution of industry characteristics. Characteristics include the number of stocks per industry, upstreamness (U_{t-1}), downstreamness (D_{t-1}), previous-month return (r_{t-1}), momentum return ($r_{t-12:t-2}$), and market capitalization ($\log_{10}(ME_{t-1})$). Up- and downstreamness are measured annually at of the end of the previous year, whereas all other characteristics are measured at monthly frequency. The sample period is from January 2001 to December 2015 (180 months).

Country	No. of ISIC Sectors	No. of Stocks	$\bar{U}_{t-1}$	$\bar{D}_{t-1}$	$r_{C,t} - r_{f,t}$	$\log_{10}(ME_{C,t-1})$
Australia	36	1306	2.322	2.147	0.009	11.906
Belgium	7	73	2.296	2.315	0.008	11.168
Brazil	11	98	1.935	1.958	0.000	11.451
Canada	36	2313	2.301	2.118	0.006	11.973
China	41	1539	2.766	2.683	0.008	12.173
Denmark	8	94	1.968	2.133	0.007	10.826
Finland	7	58	2.552	2.301	0.001	11.114
France	36	727	2.292	2.189	0.004	12.126
Germany	29	721	2.187	2.090	0.005	12.065
Greece	17	178	1.807	1.935	−0.008	10.801
India	40	2497	2.050	2.080	0.013	11.795
Indonesia	16	244	2.155	1.959	0.016	11.041
Italy	20	197	2.269	2.316	0.002	11.639
Japan	47	3451	2.294	2.093	0.002	12.550
Mexico	5	45	1.508	1.748	0.004	11.294
Netherlands	6	46	2.190	2.163	0.005	10.951
Norway	7	87	2.317	2.041	0.008	10.980
Poland	20	326	2.324	2.292	0.007	10.848
Russia	10	162	2.592	2.007	−0.004	11.776
South Korea	38	1503	2.590	2.375	0.011	11.766
Spain	8	71	2.240	2.249	0.004	11.545
Sweden	25	340	2.399	2.149	0.008	11.495
Switzerland	14	159	2.140	2.226	0.005	11.956
Taiwan	32	1257	2.422	2.490	0.007	11.750
Turkey	23	264	2.244	2.340	0.013	11.074
United Kingdom	41	1354	2.279	2.074	0.004	12.397
United States	49	4032	2.106	1.965	0.004	13.128

Table 4: Summary Statistics by Country

This table reports time-series averages of country characteristics. Characteristics include the total number of ISIC sectors per country, the total number of stocks per country, average industry upstreamness ($\bar{U}_{t-1}$), average industry downstreamness ($\bar{D}_{t-1}$), the value-weighted country excess return ($r_{C,t} - r_{f,t}$), and the total market capitalization per country ($\log_{10}(ME_{C,t-1})$). Up- and downstreamness are measured annually at of the end of the previous year, whereas all other characteristics are measured at monthly frequency. The sample period is from January 2001 to December 2015 (180 months).

ISIC Sector	No. of Countries	No. of Stocks	$\bar{U}_{t-1}$	$\bar{D}_{t-1}$	$r_{S,t} - r_{f,t}$	$\log_{10}(ME_{S,t-1})$
Manufacture of motor vehicles, trailers and semi-trailers	13	373	1.946	2.996	0.007	11.904
Manufacture of other transport equipment	5	77	1.977	2.831	0.007	11.452
Manufacture of basic metals	14	312	3.545	2.823	0.008	11.223
Manufacture of rubber and plastic products	9	194	2.980	2.795	0.008	10.999
Manufacture of electrical equipment	16	496	2.362	2.740	0.006	11.484
Manufacture of chemicals and chemical products	18	951	3.193	2.670	0.007	12.094
Manufacture of paper and paper products	14	239	3.258	2.635	0.006	11.198
Manufacture of fabricated metal products, except machinery and equipment	14	354	2.755	2.632	0.008	11.072
Manufacture of machinery and equipment n.e.c.	19	1147	2.067	2.626	0.006	12.010
Manufacture of food products, beverages and tobacco products	23	801	1.726	2.588	0.008	12.187
Manufacture of textiles, wearing apparel and leather products	16	677	2.013	2.559	0.009	11.387
Manufacture of computer, electronic and optical products	21	2095	2.234	2.541	0.003	12.399
Manufacture of coke and refined petroleum products	11	263	2.868	2.537	0.005	12.103
Manufacture of wood and of products of wood and cork, except furniture	7	70	2.857	2.514	0.007	10.321
Manufacture of furniture; other manufacturing	14	364	1.798	2.504	0.008	11.422
Water transport	8	81	2.739	2.448	0.005	10.861
Manufacture of other non-metallic mineral products	13	331	2.685	2.410	0.008	11.238
Construction	22	1096	1.450	2.398	0.007	11.748
Printing and reproduction of recorded media	15	475	2.992	2.375	0.003	11.189
Electricity, gas, steam and air conditioning supply	16	391	2.888	2.352	0.004	12.122
Manufacture of basic pharmaceutical products and pharmaceutical preparations	14	822	1.878	2.346	0.005	12.348
Air transport	4	43	2.202	2.303	0.002	10.829
Water collection, treatment and supply	2	23	2.397	2.236	0.011	10.358
Land transport and transport via pipelines	9	179	2.545	2.166	0.006	11.565
Accommodation and food service activities	12	332	1.584	2.120	0.008	11.524
Warehousing and support activities for transportation	9	129	2.910	2.078	0.007	11.171
Crop and animal production, hunting and related service activities	8	98	2.308	2.030	0.006	10.497
Sewerage; waste collection, treatment and disposal; materials recovery	5	43	2.568	1.978	0.004	10.800
Telecommunications	16	411	2.231	1.948	0.002	12.170
Wholesale and retail trade and repair of motor vehicles and motorcycles	19	834	2.016	1.925	0.004	11.800
Publishing activities	11	421	2.046	1.912	0.006	12.040
Other service activities	19	426	1.595	1.882	0.006	11.505
Computer programming, consultancy and related activities	18	830	2.196	1.881	0.004	11.685
Advertising and market research	6	93	2.673	1.879	0.004	10.883
Insurance, reinsurance and pension funding, except compulsory social security	13	235	1.910	1.878	0.003	12.087
Motion picture, video and television programme production, music publishing	10	244	2.188	1.874	0.004	11.754
Administrative and support service activities	14	510	2.776	1.863	0.006	11.438
Fishing and aquaculture	1	8	1.813	1.852	0.014	9.082
Mining and quarrying	13	2402	3.686	1.826	0.006	12.240
Postal and courier activities	1	5	2.884	1.812	0.005	10.710
Wholesale trade, except of motor vehicles and motorcycles	4	113	2.340	1.755	0.007	11.213
Scientific research and development	12	229	1.913	1.751	0.005	11.065
Legal and accounting activities; management consultancy activities	7	127	2.690	1.744	0.004	10.871
Retail trade, except of motor vehicles and motorcycles	19	802	1.865	1.720	0.006	12.116
Other professional, scientific and technical activities; veterinary activities	1	9	2.268	1.702	0.005	9.599
Human health and social work activities	9	170	1.116	1.687	0.006	11.182
Architectural and engineering activities; technical testing and analysis	10	140	2.230	1.663	0.006	10.838
Financial service activities, except insurance and pension funding	24	1603	2.486	1.656	0.003	12.655
Public administration and defence; compulsory social security	1	7	1.188	1.626	0.003	9.644
Activities auxiliary to financial services and insurance activities	16	586	2.105	1.517	0.005	11.843
Education	4	73	1.140	1.472	0.000	10.549
Real estate activities	12	239	1.465	1.438	0.008	10.998
Repair and installation of machinery and equipment	3	26	1.188	1.263	0.009	10.219

Table 5: Summary Statistics by ISIC Sector

This table reports time-series averages of ISIC sector characteristics. Characteristics include the total number of countries per sector, the total number of stocks per sector, average industry upstreamness ($\bar{U}_{t-1}$), average industry downstreamness ($\bar{D}_{t-1}$), the value-weighted sector excess return ($r_{S,t} - r_{f,t}$), and the total market capitalization per sector ($\log_{10}(ME_{S,t-1})$). Up- and downstreamness are measured annually at of the end of the previous year, whereas all other characteristics are measured at monthly frequency. The sample period is from January 2001 to December 2015 (180 months).

Panel A: Upstreamness			
Rank	Country	ISIC Sector	U
1	China	Mining and quarrying	5.128
2	Taiwan	Manufacture of chemicals and chemical products	4.699
3	China	Electricity, gas, steam and air conditioning supply	4.641
4	South Korea	Mining and quarrying	4.562
5	China	Manufacture of coke and refined petroleum products	4.481
6	China	Manufacture of chemicals and chemical products	4.476
7	China	Manufacture of paper and paper products	4.413
8	Russia	Mining and quarrying	4.335
9	Australia	Mining and quarrying	4.330
10	South Korea	Manufacture of chemicals and chemical products	4.228
Panel B: Downstreamness			
Rank	Country	ISIC Sector	D
1	China	Manufacture of electrical equipment	3.897
2	Taiwan	Manufacture of chemicals and chemical products	3.886
3	China	Manufacture of computer, electronic and optical products	3.871
4	China	Manufacture of motor vehicles, trailers and semi-trailers	3.849
5	China	Manufacture of rubber and plastic products	3.742
6	China	Manufacture of other transport equipment	3.735
7	China	Manufacture of chemicals and chemical products	3.730
8	China	Manufacture of fabricated metal products, except machinery and equipment	3.714
9	China	Manufacture of basic metals	3.650
10	Taiwan	Manufacture of basic metals	3.645

Table 6: Industry Ranking in 2014

This table lists the ten industries with the largest upstreamness (Panel A) and largest downstreamness (Panel B) in 2014. The rankings are based on industries with return data. Upstreamness (U) and downstreamness (D) are computed based on all industries in the 2014 world input-output table.

Panel A: Average Value-Weighted Country-Adjusted Returns							
	1 Low	2	3	4	5 High	High−Low	t-statistic
U	0.025	0.006	−0.020	0.005	0.006	−0.019	(−1.034)
D	0.004	−0.013	0.003	0.012	0.019	0.015	(1.314)
Panel B: Average Equal-Weighted Country-Adjusted Returns							
	1 Low	2	3	4	5 High	High−Low	t-statistic
U	0.022	0.028	0.012	0.025	0.025	0.003	(0.273)
D	0.018	0.007	0.019	0.026	0.039	0.021	(1.621)

Table 7: Single Sorts

This table presents time-series average returns of portfolios formed by sorting industries based on their upstreamness (U) or downstreamness (D). Portfolio returns are computed over the subsequent year and are weighted by industries' lagged market capitalizations (Panel A) or equal-weighted across industries (Panel B). Portfolios are rebalanced monthly. Industry returns are calculated by value-weighting stock returns of firms in the industry and are demeaned by the corresponding country-average return. The sample period is from January 2001 to December 2015 (180 months). Newey and West (1987) t-statistics for the High-Minus-Low portfolios are reported in parentheses.

Panel A: Average No. of Industries

	1 Low D	2	3	4	5 High D
1 Low U	51	29	21	12	9
2	19	23	25	28	28
3	25	32	23	22	22
4	16	23	32	29	22
5 High U	12	17	21	31	43

Panel B: Average Value-Weighted Country-Adjusted Returns

	1 Low D	2	3	4	5 High D	High−Low	t-statistic
1 Low U	0.016	0.021	0.028	0.082	0.023	0.007	(0.266)
2	0.019	−0.009	0.033	0.004	0.036	0.017	(0.710)
3	−0.020	−0.021	−0.007	0.013	0.040	0.060	(2.780)
4	0.005	0.007	0.008	0.011	0.011	0.006	(0.209)
5 High U	−0.010	0.013	−0.011	0.020	0.016	0.026	(0.929)
High−Low	−0.026	−0.008	−0.039	−0.062	−0.007		
t-statistic	(−0.850)	(−0.229)	(−2.214)	(−2.280)	(−0.246)		

Panel C: Average Equal-Weighted Country-Adjusted Returns

	1 Low D	2	3	4	5 High D	High−Low	t-statistic
1 Low U	0.007	0.014	0.052	0.060	0.018	0.011	(0.519)
2	0.038	0.004	0.017	0.033	0.048	0.010	(0.515)
3	0.013	0.002	0.002	0.013	0.045	0.032	(1.590)
4	0.039	0.009	0.018	0.031	0.035	−0.004	(−0.141)
5 High U	0.011	0.020	0.006	0.018	0.041	0.030	(1.101)
High−Low	0.004	0.006	−0.046	−0.042	0.023		
t-statistic	(0.158)	(0.327)	(−2.545)	(−2.144)	(1.148)		

Table 8: Independent Double Sorts

This table presents time-series average characteristics of portfolios formed by independently sorting industries based on their upstreamness (U) and downstreamness (D). Panel A shows the average number of industries in each portfolio. Portfolio returns are computed over the subsequent year and are weighted by industries' lagged market capitalizations (Panel B) or equal-weighted across industries (Panel C). Portfolios are rebalanced monthly. Industry returns are calculated by value-weighting stock returns of firms in the industry and are demeaned by the corresponding country-average return. The sample period is from January 2001 to December 2015 (180 months). Newey and West (1987) t-statistics for the High-Minus-Low portfolios are reported in parentheses.

	$r_{i,t} - r_{f,t}$							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$U_{i,t-1}$	0.012		−0.030	−0.030	−0.040	−0.013	−0.055	0.077
	(0.284)		(−0.689)	(−0.745)	(−0.929)	(−0.280)	(−1.294)	(1.043)
$D_{i,t-1}$		0.156***	0.170***	0.170***	0.152***	0.240**	0.138**	0.149
		(2.786)	(2.950)	(3.429)	(2.661)	(2.427)	(2.503)	(0.703)
Observations	110699	110699	110699	110699	110699	110699	110699	110699
Adjusted R^2	0.361	0.361	0.361	0.361	0.406	0.360	0.615	0.381
Country FE	Yes	Yes	Yes	Yes	Yes	No	No	No
Month FE	Yes	Yes	Yes	Yes	No	Yes	No	No
Country × Month FE	No	No	No	No	No	No	Yes	No
ISIC Sector × Month FE	No	No	No	No	No	No	No	Yes
Estimator	OLS	OLS	OLS	OLS	FMB	OLS	OLS	OLS
Standard Errors	Month	Month	Month	Month & Industry	FMB	Month	Month	Month

Table 9: Regressions

This table reports coefficients from panel regressions of industries' monthly excess returns on their upstreamness ($U_{i,t-1}$) and downstreamness ($D_{i,t-1}$). Industry returns are calculated by value-weighting stock returns of firms in the industry and expressed in excess of the risk-free rate. Up- and downstreamness are measured at the end of the previous year and centered on their sample means. The sample period is from January 2001 to December 2015 (180 months). All coefficients are multiplied by 100. t-statistics are reported in parentheses. ***, **, or * indicate statistical significance at the 1%, 5%, or 10% level.

	$r_{i,t} - r_{f,t}$				
	(1)	(2)	(3)	(4)	(5)
$U_{i,t-1}$	-0.011		-0.041	-0.037	-0.040
	(-0.302)		(-1.074)	(-0.992)	(-1.046)
$D_{i,t-1}$		0.106^{**}	0.126^{**}	0.124^{**}	0.116^{**}
		(2.099)	(2.327)	(2.279)	(2.080)
$U^2_{i,t-1}$				-0.010	
				(-0.231)	
$D^2_{i,t-1}$				0.030	
				(0.482)	
$U_{i,t-1} \times D_{i,t-1}$					-0.070^{*}
					(-1.720)
$r_{i,t-1}$	0.662	0.653	0.652	0.651	0.648
	(0.527)	(0.520)	(0.518)	(0.518)	(0.516)
$r_{i,t-12:t-2}$	1.083^{***}	1.078^{***}	1.077^{***}	1.076^{***}	1.075^{***}
	(3.683)	(3.667)	(3.661)	(3.665)	(3.656)
$\beta_{MKT,i,t-1}$	-0.295	-0.305	-0.297	-0.299	-0.302
	(-0.961)	(-0.991)	(-0.967)	(-0.976)	(-0.983)
$\beta_{SMB,i,t-1}$	0.050	0.055	0.055	0.055	0.061
	(0.487)	(0.534)	(0.536)	(0.530)	(0.589)
$\beta_{HML,i,t-1}$	0.163	0.166	0.169	0.169	0.168
	(1.467)	(1.490)	(1.520)	(1.515)	(1.507)
$\beta_{RMW,i,t-1}$	0.002	-0.003	-0.003	-0.003	-0.003
	(0.019)	(-0.028)	(-0.037)	(-0.036)	(-0.029)
$\beta_{CMA,i,t-1}$	0.138	0.138	0.137	0.137	0.137
	(1.468)	(1.477)	(1.463)	(1.465)	(1.462)
No. of Stocks	-0.000	-0.000	-0.000	-0.000	-0.000
	(-1.310)	(-1.444)	(-1.387)	(-1.416)	(-1.533)
Observations	110699	110699	110699	110699	110699
Adjusted R^2	0.616	0.616	0.616	0.616	0.616
Country × Month FE	Yes	Yes	Yes	Yes	Yes
Estimator	OLS	OLS	OLS	OLS	OLS
Standard Errors	Month	Month	Month	Month	Month

Table 10: Regressions with Controls

This table reports coefficients from panel regressions of industries' monthly excess returns on their upstreamness ($U_{i,t-1}$), downstreamness ($D_{i,t-1}$), squared and interacted terms, and control variables. Industry returns are calculated by value-weighting stock returns of firms in the industry and expressed in excess of the risk-free rate. Up- and downstreamness are measured at the end of the previous year and centered on their sample means. Control variables include the previous-month return ($r_{i,t-1}$), momentum return ($r_{i,t-12:t-2}$), previous-year betas w.r.t. the global Fama-French five factor model ($\beta_{MKT,i,t-1}$,$\beta_{SMB,i,t-1}$,$\beta_{HML,i,t-1}$,$\beta_{RMW,i,t-1}$,$\beta_{CMA,i,t-1}$), and the number of stocks per industry. The sample period is from January 2001 to December 2015 (180 months). All coefficients are multiplied by 100. t-statistics are reported in parentheses. ***, **, or * indicate statistical significance at the 1%, 5%, or 10% level.

	$r^{ew}_{i,t} - r_{f,t}$				
	(1)	(2)	(3)	(4)	(5)
$U_{i,t-1}$	-0.013		-0.043	-0.032	-0.042
	(-0.389)		(-1.206)	(-0.943)	(-1.195)
$D_{i,t-1}$		0.103^{**}	0.124^{**}	0.116^{**}	0.120^{**}
		(2.212)	(2.505)	(2.317)	(2.391)
$U^2_{i,t-1}$				-0.035	
				(-0.932)	
$D^2_{i,t-1}$				0.025	
				(0.465)	
$U_{i,t-1} \times D_{i,t-1}$					-0.027
					(-0.752)
$r^{ew}_{i,t-1}$	1.579	1.568	1.565	1.563	1.564
	(1.380)	(1.372)	(1.370)	(1.368)	(1.369)
$r^{ew}_{i,t-12:t-2}$	1.338^{***}	1.334^{***}	1.333^{***}	1.334^{***}	1.333^{***}
	(6.207)	(6.193)	(6.191)	(6.198)	(6.190)
$\beta^{ew}_{MKT,i,t-1}$	-0.245	-0.254	-0.249	-0.249	-0.250
	(-1.056)	(-1.096)	(-1.072)	(-1.076)	(-1.076)
$\beta^{ew}_{SMB,i,t-1}$	-0.070	-0.065	-0.063	-0.062	-0.062
	(-0.682)	(-0.628)	(-0.615)	(-0.604)	(-0.606)
$\beta^{ew}_{HML,i,t-1}$	0.037	0.036	0.039	0.038	0.039
	(0.495)	(0.483)	(0.517)	(0.508)	(0.510)
$\beta^{ew}_{RMW,i,t-1}$	0.040	0.039	0.038	0.038	0.038
	(0.658)	(0.637)	(0.634)	(0.632)	(0.634)
$\beta^{ew}_{CMA,i,t-1}$	0.020	0.019	0.018	0.018	0.018
	(0.347)	(0.335)	(0.316)	(0.310)	(0.315)
No. of Stocks	-0.000	-0.000	-0.000	-0.000	-0.000
	(-0.032)	(-0.179)	(-0.097)	(-0.082)	(-0.148)
Observations	110699	110699	110699	110699	110699
Adjusted R^2	0.711	0.711	0.711	0.711	0.711
Country $\times$ Month FE	Yes	Yes	Yes	Yes	Yes
Estimator	OLS	OLS	OLS	OLS	OLS
Standard Errors	Month	Month	Month	Month	Month

Table 11: Regressions with Equal-Weighting

This table reports coefficients from panel regressions of industries' monthly excess returns on their upstreamness ($U_{i,t-1}$), downstreamness ($D_{i,t-1}$), squared and interacted terms, and control variables. Industry returns are calculated by equal-weighting stock returns of firms in the industry and expressed in excess of the risk-free rate. Up- and downstreamness are measured at the end of the previous year and centered on their sample means. Control variables include the previous-month return ($r^{ew}_{i,t-1}$), momentum return ($r^{ew}_{i,t-12:t-2}$), previous-year betas w.r.t. the global Fama-French five factor model ($\beta^{ew}_{MKT,i,t-1}$,$\beta^{ew}_{SMB,i,t-1}$,$\beta^{ew}_{HML,i,t-1}$,$\beta^{ew}_{RMW,i,t-1}$,$\beta^{ew}_{CMA,i,t-1}$), and the number of stocks per industry. The sample period is from January 2001 to December 2015 (180 months). All coefficients are multiplied by 100. t-statistics are reported in parentheses. ***, **, or * indicate statistical significance at the 1%, 5%, or 10% level.

	$r_{i,t} - r_{f,t}$				
	(1)	(2)	(3)	(4)	(5)
$U_{i,t-1}$	0.041		-0.052	-0.084	-0.025
	(0.422)		(-0.582)	(-1.471)	(-0.220)
$D_{i,t-1}$		0.413^{**}	0.433^{**}	0.122^{**}	0.602^{*}
		(2.383)	(2.512)	(2.007)	(1.874)
$r_{i,t-1}$	-0.838	-0.855	-0.855	-2.878^{***}	-1.585^{**}
	(-1.088)	(-1.111)	(-1.111)	(-4.351)	(-1.990)
$r_{i,t-12:t-2}$	0.350^{***}	0.343^{***}	0.344^{***}	0.239^{***}	0.288^{**}
	(2.882)	(2.843)	(2.853)	(2.788)	(2.559)
$\beta_{MKT,i,t-1}$	0.421^{*}	0.483^{**}	0.485^{**}	0.501^{***}	0.548^{**}
	(1.865)	(2.126)	(2.133)	(2.636)	(2.526)
$\beta_{SMB,i,t-1}$	0.022	0.003	0.004	0.016	-0.001
	(0.237)	(0.027)	(0.042)	(0.181)	(-0.011)
$\beta_{HML,i,t-1}$	-0.063	-0.061	-0.061	-0.040	-0.035
	(-0.743)	(-0.724)	(-0.724)	(-0.566)	(-0.443)
$\beta_{RMW,i,t-1}$	-0.004	-0.013	-0.013	0.005	-0.041
	(-0.062)	(-0.217)	(-0.216)	(0.099)	(-0.742)
$\beta_{CMA,i,t-1}$	-0.035	-0.035	-0.036	-0.015	-0.036
	(-0.500)	(-0.487)	(-0.513)	(-0.288)	(-0.569)
$Size_{i,t-1}$	-0.583^{***}	-0.591^{***}	-0.593^{***}	-0.517^{***}	-0.629^{***}
	(-4.663)	(-4.701)	(-4.692)	(-5.541)	(-5.045)
$Book\text{-}to\text{-}Market\ Ratio_{i,t-1}$	0.029^{*}	0.026	0.026	0.025^{*}	0.031^{**}
	(1.673)	(1.561)	(1.571)	(1.917)	(1.969)
$Operating\ Profitability_{i,t-1}$	0.307^{***}	0.297^{***}	0.293^{***}	0.242^{***}	0.274^{***}
	(4.478)	(4.041)	(4.186)	(4.217)	(4.275)
$Investment_{i,t-1}$	-0.028	-0.026	-0.025	-0.023	-0.020
	(-1.176)	(-1.144)	(-1.139)	(-1.407)	(-1.100)
Observations	2862374	2862374	2862374	2862374	2862374
Adjusted R^2	0.120	0.120	0.120	0.228	0.147
Month FE	Yes	Yes	Yes	No	No
Country × Month FE	No	No	No	Yes	No
ISIC Sector × Month FE	No	No	No	No	Yes
Estimator	OLS	OLS	OLS	OLS	OLS
Standard Errors	Month & Industry	Month & Industry	Month & Industry	Month & Industry	Month & Industry

Table 12: Firm-Level Regressions

This table reports coefficients from panel regressions of firms' monthly excess returns on their upstreamness ($U_{i,t-1}$), downstreamness ($D_{i,t-1}$), and control variables. Stock returns of firms are expressed in excess of the risk-free rate. Up- and downstreamness are measured at the end of the previous year, assigned to firms based on firms' industry affiliations, and centered on their sample means. Control variables include the previous-month return ($r_{i,t-1}$), momentum return ($r_{i,t-12:t-2}$), previous-year betas w.r.t. the global Fama-French five factor model ($\beta_{MKT,i,t-1}$,$\beta_{SMB,i,t-1}$,$\beta_{HML,i,t-1}$,$\beta_{RMW,i,t-1}$,$\beta_{CMA,i,t-1}$), as well as lagged market capitalization (in logarithm with base 10, $Size_{i,t-1}$), book-to-market ratio, operating profitability, and asset growth ($Investment_{i,t-1}$). The last three characteristics are annual and winsorized at the 1% and 99% quantile within each country-year. The sample period is from January 2001 to December 2015 (180 months). All coefficients are multiplied by 100. t-statistics are reported in parentheses. ***, **, or * indicate statistical significance at the 1%, 5%, or 10% level.

Appendix A Derivations

A.1 Matrix Representation

Equations (5) and (8) require computing infinitely many terms. Following standard input-output analysis (see Miller and Blair (2009)), we circumvent this problem by switching to matrix notation and using simple matrix inversions to compute up- and downstreamness. The two accounting identities in Equations (1) and (2) read as

$$\mathbf{GO} = \mathbf{F} + \mathbf{Z}\,\boldsymbol{\iota} \tag{14}$$

$$\mathbf{GO}' = \mathbf{VA}' + \boldsymbol{\iota}'\,\mathbf{Z}, \tag{15}$$

in matrix notation, where $\boldsymbol{\iota} = (1, 1, \ldots, 1)'$ is a column vector of ones. Let

$$\mathbf{A} = \mathbf{Z}\,diag(\mathbf{GO})^{-1} \tag{16}$$

collect the input coefficients, where $diag(\cdot)$ is the diagonal matrix. It then holds

$$\mathbf{GO} = \mathbf{F} + \mathbf{A}\,\mathbf{GO}, \tag{17}$$

the matrix analogue of Equation (3), which can be written as

$$\mathbf{GO} = (\mathbf{I} - \mathbf{A})^{-1}\;\mathbf{F} = \mathbf{L}\,\mathbf{F} \tag{18}$$

with the famous Leontief-inverse matrix $\mathbf{L} \equiv \mathbf{I} + \mathbf{A} + \mathbf{A}^2 + \ldots = (\mathbf{I} - \mathbf{A})^{-1}$ (Leontief (1936), Leontief (1941)). Similarly, with output coefficient matrix

$$\mathbf{B} = diag(\mathbf{GO})^{-1}\,\mathbf{Z}, \tag{19}$$

we have

$$\mathbf{GO}' = \mathbf{VA}' + \mathbf{GO}'\,\mathbf{B} \tag{20}$$

as the matrix equivalent to Equation (6), which can be expressed as

$$\mathbf{GO}' = \mathbf{VA}' \ (\mathbf{I} - \mathbf{B})^{-1} = \mathbf{VA}' \ \mathbf{G} \tag{21}$$

with the Ghosh-inverse matrix $\mathbf{G} \equiv \mathbf{I} + \mathbf{B} + \mathbf{B}^2 + \ldots = (\mathbf{I} - \mathbf{B})^{-1}$ (Ghosh (1958)). The Leontief- and Ghosh-inverse matrices are related by

$$\mathbf{G} = diag(\mathbf{GO})^{-1} \ \mathbf{L} \ diag(\mathbf{GO}) \tag{22}$$

as shown in Appendix A.3. Up- and downstreamness are defined analogous to Equations (5) and (8) as

$$\mathbf{U} = diag(\mathbf{GO})^{-1} \ (\mathbf{I} + 2\mathbf{A} + 3\mathbf{A}^2 + \ldots) \ \mathbf{F} \tag{23}$$

$$\mathbf{D}' = \mathbf{VA}' \ (\mathbf{I} + 2\mathbf{B} + 3\mathbf{B}^2 + \ldots) \ diag(\mathbf{GO})^{-1}, \tag{24}$$

where $\mathbf{U}$ and $\mathbf{D}$ are column vectors. Following Miller and Temurshoev (2017), we can write

$$\mathbf{U} = diag(\mathbf{GO})^{-1} \ \mathbf{L} \ \mathbf{L} \ \mathbf{F} \tag{25}$$

$$\mathbf{D}' = \mathbf{VA}' \ \mathbf{G} \ \mathbf{G} \ diag(\mathbf{GO})^{-1}, \tag{26}$$

because $(\mathbf{I} + 2\mathbf{A} + 3\mathbf{A}^2 + \ldots) = (\mathbf{I} + \mathbf{A} + \mathbf{A}^2 + \ldots)(\mathbf{I} + \mathbf{A} + \mathbf{A}^2 + \ldots) = \mathbf{L} \ \mathbf{L}$ and, similarly, $(\mathbf{I} + 2\mathbf{B} + 3\mathbf{B}^2 + \ldots) = \mathbf{G} \ \mathbf{G}$. From Equations (18) and (21), $\mathbf{GO} = diag(\mathbf{GO}) \ \boldsymbol{\iota}$, and Equation (22) it then follows that

$$\mathbf{U} = \mathbf{G} \ \boldsymbol{\iota} \tag{27}$$

$$\mathbf{D}' = \boldsymbol{\iota}' \ \mathbf{L}, \tag{28}$$

i.e. upstreamness can be easily computed as row sums of the Ghosh-inverse matrix and downstreamness as column sums of the Leontief-inverse matrix.

A.2 Recursive Representation

An equivalent, recursive representation is proposed by Fally (2012). Following Antràs et al. (2012), we rewrite Equations (27) and (28) as

$$(\mathbf{I}-\mathbf{B})\ \mathbf{U}=\boldsymbol{\iota} \tag{29}$$

$$\mathbf{D}'\ (\mathbf{I}-\mathbf{A})=\boldsymbol{\iota}' \tag{30}$$

by replacing the Leontief- and Gosh-inverse matrices with $\mathbf{L}\equiv(\mathbf{I}-\mathbf{A})^{-1}$ and $\mathbf{G}\equiv(\mathbf{I}-\mathbf{B})^{-1}$, respectively. Further matrix manipulations leave us with

$$\mathbf{U}=\boldsymbol{\iota}+\mathbf{B}\ \mathbf{U} \tag{31}$$

$$\mathbf{D}'=\boldsymbol{\iota}'+\mathbf{D}'\ \mathbf{A}, \tag{32}$$

where $\mathbf{U}$ and $\mathbf{D}$ are defined recursively, because they are represented on the left and right hand sides of the equations. The recursive representation in Equation (31) highlights that industries which are important input suppliers to customer industries that have a high upstreamness are themselves far away from final consumption. Analogously, Equation (32) implies that industries which purchase large shares of their inputs from supplier industries that have a high downstreamness are themselves far away from primary inputs.

A.3 Relation between Leontief- and Ghosh-inverse matrices

The Leontief- and Ghosh-inverse matrices are closely related as shown by Miller and Blair (2009). Plugging Equation (19) in Equation (16) gives

$$\mathbf{A}=diag(\mathbf{GO})\ \mathbf{B}\ diag(\mathbf{GO})^{-1}. \tag{33}$$

Equivalently, it holds

$$\mathbf{I}-\mathbf{A}=\mathbf{I}-diag(\mathbf{GO})\ \mathbf{B}\ diag(\mathbf{GO})^{-1}, \tag{34}$$

which can be expressed as

$$\mathbf{I} - \mathbf{A} = diag(\mathbf{GO})\ (\mathbf{I} - \mathbf{B})\ diag(\mathbf{GO})^{-1} \tag{35}$$

since $\mathbf{I} = diag(\mathbf{GO})\ \mathbf{I}\ diag(\mathbf{GO})^{-1}$. Inverting gives

$$(\mathbf{I} - \mathbf{A})^{-1} = diag(\mathbf{GO})\ \ (\mathbf{I} - \mathbf{B})^{-1}\ \ diag(\mathbf{GO})^{-1}. \tag{36}$$

With the definitions of the Leontief-inverse matrix $\mathbf{L} \equiv (\mathbf{I} - \mathbf{A})^{-1}$ and the Ghosh-inverse matrix $\mathbf{G} \equiv (\mathbf{I} - \mathbf{B})^{-1}$, we can write

$$\mathbf{L} = diag(\mathbf{GO})\ \mathbf{G}\ diag(\mathbf{GO})^{-1}, \tag{37}$$

which is equivalent to Equation (22).

Appendix B Additional Tables

Country	List	Country	List	Country	List
Australia	DEADAU	Greece	DEADGR	Poland	DEADPO
	FAUS		FGREE		FPOL
	WSCOPEAU		FGRMM		WSCOPEPO
Belgium	DEADBG		FGRPM	Russia	DEADRU
	FBEL		FNEXA		FRTSCL
	FBELAM		WSCOPEGR		FRUS
	FBELCM	India	DEADIND		FRUSUP
	WSCOPEBG		FBSE		WSCOPERS
Brazil	DEADBRA		FINDIA	South Korea	DEADKO
	FBRA		FINDNW		WSCOPEKO
	WSCOPEBR		FINDUP		FKOR
Canada	DEADCN1		FNSE		FKONEX
	DEADCN2		WSCOPEIN	Spain	DEADES
	DEADCN3	Indonesia	DEADIDN		FSPN
	DEADCN4		FINO		WSCOPEES
	DEADCN5		WSCOPEID	Sweden	DEADSD
	DEADCN6	Italy	DEADIT		FAKTSWD
	FTORO		FITA		FSWD
	FVANC		WSCOPEIT		WSCOPESD
	LTTOCOMP	Japan	DEADJP	Switzerland	DEADSW
	WSCOPECN		FFUKUOKA		FSWA
China	DEADCH		FJASDAQ		FSWS
	FCHINA		FOSAKA		FSWUP
	WSCOPECH		FTOKYO		WSCOPESW
Denmark	DEADDK		JAPOTC	Taiwan	DEADTW
	FDEN		WSCOPEJP		FTAIQ
	WSCOPEDK	Mexico	DEADME		WSCOPETA
Finland	DEADFN		FMEX	Turkey	DEADTK
	FFIN		MEX101		FTURK
	WSCOPEFN		WSCOPEMX		FTURKUP
France	DEADFR	Netherlands	DEADNL		WSCOPETK
	FFRA		FHOL	United Kingdom	DEADUK
	WSCOPEFR		WSCOPENL		FBRIT
Germany	DEADBD1	Norway	DEADNW		LSETSCOS
	DEADBD2		FNOR		LSETSMM
	DEADBD3		WSCOPENW		LUKPLUSM
	DEADBD4				WSCOPEJE
	DEADBD5				WSCOPEUK
	DEADBD6				
	FGER1				
	FGER2				
	FGERIBIS				
	FGKURS				
	WSCOPEBD				

Table 13: Constituent Lists

This table contains the Thomson Reuters Datastream constitutent lists, in particular Worldscope, research, and dead lists, used for the sample of non-U.S. stocks.

Panel A: Generic Keywords	
Type	Keywords
Duplicates	1000DUPL, DULP, DUP, DUPE, DUPL, DUPLI, DUPLICATE, XSQ, XETa
Depository Receipts	ADR, GDR
Preferred Stock	PF, 'PF', PFD, PREF, PREFERRED, PRF
Warrants	WARR, WARRANT, WARRANTS, WARRT, WTS, WTS2
Debt	%, DB, DCB, DEB, DEBENTURE, DEBENTURES, DEBT
Unit Trusts	.IT, .ITb, TST, INVESTMENT TRUST, RLST IT, TRUST, TRUST UNIT, TRUST UNITS, TST, TST UNIT, TST UNITS, UNIT, UNIT TRUST, UNITS, UNT, UNT TST, UT
Exchange Traded Funds	AMUNDI, ETF, INAV, ISHARES, JUNGE, LYXOR, X-TR
Expired Securities	EXPD, EXPIRED, EXPIRY, EXPY
Miscellaneous (mainly taken from Ince and Porter (2006))	ADS, BOND, CAP.SHS, CONV, DEFER, DEP, DEPY, ELKS, FD, FUND, GW.FD, HI.YIELD, HIGH INCOME, IDX, INC.&GROWTH, INC.&GW, INDEX, LP, MIPS, MITS, MITT, MPS, NIKKEI, NOTE, OPCVM, ORTF, PARTNER, PERQS, PFC, PFCL, PINES, PRTF, PTNS, PTSHP, QUIBS, QUIDS, RATE, RCPTS, REAL EST, RECEIPTS, REIT, RESPT, RETUR, RIGHTS, RST, RTN.INC, RTS, SBVTG, SCORE, SPDR, STRYPES, TOPRS, UTS, VCT, VTG.SAS, XXXXX, YIELD, YLD
Panel B: Country-Specific Keywords	
Country	Keywords
Australia	PART PAID, RTS DEF, DEF SETT, CDI
Belgium	VVPR, CONVERSION, STRIP
Brazil	PN, PNA, PNB, PNC, PND, PNE, PNF, PNG, RCSA, RCTB
Canada	EXCHANGEABLE, SPLIT, SPLITSHARE, VTG\\., SBVTG\\., VOTING, SUB VTG, SERIES
Denmark	\\)CSE\\)
Finland	USE
France	ADP, CI, SICAV, \\)SICAV\\), SICAV-
Germany	GENUSSCHEINE
Greece	PR
India	FB DEAD, FOREIGN BOARD
Italy	RNC, RP, PRIVILEGIES
Mexico	'L', 'C'
Netherlands	CERTIFICATE, CERTIFICATES, CERTIFICATES\\), CERT, CERTS, STK\\.
South Korea	1P
Sweden	CONVERTED INTO, USE, CONVERTED-, CONVERTED - SEE
Switzerland	CONVERTED INTO, CONVERSION, CONVERSION SEE
United Kingdom	PAID, CONVERSION TO, NON VOTING, CONVERSION 'A'

Table 14: Keywords

This table lists the generic (Panel A) and country-specific keywords (Panel B) that are searched for in the names of firms in the sample of non-U.S. stocks. If a keyword is found in a firm's name, the firm is removed from the sample.

Panel A: Static Screens

No.	Description	Reference
(1)	We only consider the firm's security that has the largest market capitalization and liquidity (MAJOR=Y).	Schmidt et al. (2019)
(2)	Securities must be of type equity (TYPE=EQ).	Ince and Porter (2006)
(3)	Quotations of securities must be primary (ISINID=P).	Fong et al. (2017)
(4)	Firms must be located in the respective countries (GEOGN=country).	Ince and Porter (2006)
(5)	Securities must be listed in the respective countries (GEOLN=country).	Griffin et al. (2010)
(6)	Securities must be quoted in the currencies of the respective countries (PCUR=currency of the country).[a]	Griffin et al. (2010)
(7)	Securities must have the ISIN country codes of the respective countries (GGISN=country).	Annaert et al. (2013)
(8)	Securities' names must not contain any of the keywords given in Panel A of Table 14 that indicate non-common equity (NAME, ENAME, ECNAME).	Ince and Porter (2006), Campbell et al. (2010), Griffin et al. (2010), Karolyi et al. (2012)

Panel B: Dynamic Screens

No.	Description	Reference
(1)	We delete observations associated with zero returns at the end of the time series, because Thomson Reuters Datastream reports constant stock prices after a delisting.	Ince and Porter (2006)
(2)	We delete observations associated with abnormal stock prices that exceed $1,000,000.	Schmidt et al. (2019)
(3)	We delete monthly (daily) observations if returns exceed 990% (200%).	Griffin et al. (2010), Schmidt et al. (2019)
(4)	We delete monthly (daily) observations in case of strong return reversals, defined as $(1 + r_{t-1})(1 + r_t) - 1 < 0.5$ given that either r_{t-1} or $r_t \geq 3.0$ $((1 + r_{t-1})(1 + r_t) - 1 < 0.2$ with r_{t-1} or $r_t \geq 1.0)$.	Ince and Porter (2006), Griffin et al. (2010), Jacobs (2016)
(5)	We delete observations if a firm's market capitalization in month $t - 1$ is below the 5% quantile of all firms in the respective country.	Chui et al. (2010)
(6)	We delete observations in case a firm's market capitalization is greater than 90% of the country's total market capitalization.	Jacobs (2016)
(7)	We delete observations of stocks that show non-zero price changes in less than 50% of the traded months in the prior year.	Griffin et al. (2010), Griffin et al. (2011)
(8)	We delete all observations of firms that have fewer than 12 monthly stock returns within the sample period.	Hou et al. (2011)
(9)	We winsorize all monthly and daily returns at the 0.1% and 99.9% quantile within each country-month.	Jacobs (2016)

Table 15: Screens

This table describes the static (Panel A) and dynamic screens (Panel B) that are applied to the sample of non-U.S. stocks. Screens (5) to (9) in Panel B are also applied to U.S. stocks. [a]Pre-Euro currencies are accepted for Euro-zone countries; US-$ and Russian ruble are accepted for Russia.

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