Production Networks and Stock Returns: The Role of Vertical Creative Destruction*

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Abstract

We study the relation between firms' risk and their upstreamness in a production network. Empirically, firms' average stock returns and productivity exposures increase monotonically with their upstreamness. We quantitatively explain these novel facts using a multi-layer general equilibrium model. These patterns arise from vertical creative destruction – innovations by suppliers devalue customers' assets-in-place. We confirm several model predictions, and document additional new facts consistent with vertical creative destruction: a diminished value premium among downstream firms and a negative relation between downstream firms' returns and their suppliers' competitiveness. Overall, vertical creative destruction has a sizable effect on cross-sectional risk premia.

Keywords: production networks, stock returns, vertical creative destruction, monopolistic competition, technological innovations

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Production of goods takes place in a complex network comprised of long and intertwined supply chains which produce final consumption goods via multiple intermediary stages.[1] This multi-stage production process, which starts with the most upstream firms and ends with downstream firms that supply directly to consumers, reflects the vertical organization of production. Despite its relevance for economic activity, very little is known about this vertical dimension of production, especially at the firm-level granularity. In particular, several questions regarding the asset pricing implications of this vertical production structure remain unanswered. How do firms' risk exposures to macroeconomic risks vary with their upstreamness? What is the relation between firms' upstreamness and their expected returns? Do supply chain characteristics, such as competitiveness faced by suppliers, impact firms' cost of capital? In this paper, we seek to address these questions both empirically and theoretically.

Intuitively, not all firms along the same production chain benefit equally from technological advancements. Innovations that improve the production of new capital by suppliers can devalue existing capital of customer firms. This yields differential exposures of firms along the production chain to innovations in productivity. These risk exposures are also affected by the competition faced by the firm's suppliers, as suppliers with monopolistic power ration the quantity of new capital they produce. We develop this intuition in this paper, and confirm it in our empirical analysis.

The main empirical challenge to address the aforementioned questions is the availability of comprehensive data that allows one to measure a firm's granular position in the production network over time. To overcome this challenge, we use a novel firm-level database of supplier-customer relationships. This comprehensive database allows us to measure firms' upstreamness in a dynamic production network. To compute firms' upstreamness measures, we decompose a production network into layers of production. All firms in layer j are separated by j supplier-customer links (along the shortest chain) from the bottom layer, which produces final consumption goods. A firm's vertical position corresponds to the layer to

[1] A famous representation of this multi-layer structure of production is the so-called "Hayekian Triangle" (Hayek (1935), page 39).

which it belongs.

The first contribution of this paper is to empirically document two novel stylized facts that highlight a monotonic relation between a firms' vertical position in the production network and their riskiness. First, we show that the further away a firm is from final consumers (i.e., the higher its vertical position is), the higher the average stock return of the firm. An investment strategy that longs firms with the longest distance to consumers (highest vertical position) and shorts firms with the shortest distance (lowest vertical position) generates a return of 105 basis points per month. We refer to this difference in returns as the TMB (Top-Minus-Bottom) spread. Second, we show that a firm's exposure (beta) to aggregate productivity increases monotonically with its vertical position.

Our second contribution is to propose and test a quantitative theory which jointly accounts for the TMB spread, and the monotonic pattern in risk exposures. Our explanation is based on a new form of creative destruction that arises in a multi-layer supply chain economy. In the model, the production economy is comprised of a supply chain, where each layer of production is populated by a representative firm. The output of each layer is sold to the layer below it, which uses that input to produce its own output. The bottom layer, layer zero, produces final consumption goods. We study the asset pricing implications of common productivity shocks, which affect all firms simultaneously.

A positive productivity shock has a dual effect on a firm's valuation. On the one hand, it acts as a positive demand shock for each layer's output, which implies higher future cash flows and improved growth options for firms operating in all layers. This *demand effect*, which appreciates all firms' valuation following a positive shock, exists also in a single sector setup. However, a separate effect exists, which is novel to our multi-layer environment. The same positive shock increases the productivity of the firm's direct suppliers, suppliers of suppliers, and higher-order suppliers. As they all become more productive, the supply curve of the firm's input shifts to the right (i.e., the productivity shock acts as a positive supply shock for the firm's input of capital). This *supply effect* puts a downward pressure on the valuation of firms' assets-in-place: installed capital or inventory stock. In particular, technological improvements make the production of firms' capital input cheaper, which erodes the marginal value of firms' installed capital. We refer to this supply effect as vertical creative destruction.[2]

Importantly, the strength of the supply effect is heterogeneous across layers. A firm at the bottom of the production chain experiences the greatest impact of the supply effect. The reason is that its existing capital is (effectively) built using the capital goods produced by all the layers above it. As each of the intermediate capital goods becomes cheaper to produce, the supply effect cascades downwards cumulatively, and the value of the assets-in-place of the bottom-layer firm experiences the greatest downward pressure, as its replacement cost of capital becomes relatively the cheapest. By contrast, the firm at the top of the production chain is not subject to this vertical creative destruction force, as it has no suppliers. Firms in the middle layers experience some amount of vertical creative destruction following a positive productivity shock, but not as strongly as the bottom layer. This is because middle layers have fewer indirect suppliers, making the cumulative supply effect smaller. Vertical creative destruction acts as a hedge by making the sensitivity of a firm to productivity shocks less positive, as the negative supply effect partially offsets the positive demand effect. This logic explains not only the positive spread between the top and the bottom layers (TMB spread), but also why the productivity beta increases monotonically with the vertical position.

We formalize the intuition above in a production-based asset pricing model. The model provides a quantitative explanation for the spread. It features multiple production layers and a representative household with Epstein and Zin (1989) preferences. The calibrated model yields a monotonic relation between stock returns, productivity risk exposures, and vertical position, and a large TMB spread of 12% per annum, close to its empirical counterpart. We use the calibrated model to derive a number predictions and novel implications of vertical creative destruction and test them empirically.

First, we augment the model to allow for monopolistic power in order to study the implications of competition for the intensity of vertical creative destruction. The augmented

[2]Typically, one thinks of creative destruction as value destroyed by competitors' innovations or new entrants in the spirit of Schumpeter (1942), in what is also called displacement risk. This creative destruction works horizontally. Our creative destruction is different: it works vertically along the supply chain. Innovations by upstream firms devalue the installed capital of downstream firms.

model predicts that the TMB spread is smaller when firms in each layer have greater monopolistic power. Monopolistic rents act as a buffer against any devaluation pressure on the assets-in-place. In addition, following a positive productivity shock, monopolistic suppliers do not increase supply as much as competitive suppliers. As a result, the creative destruction force on their customers' assets-in-place diminishes. To test this prediction, we compute a novel measure of supply chain competition, which accounts not only for the number of competitors that a firm has, but also for the number of competitors of its direct and indirect suppliers. We assign firms into two subsamples based on whether their supply chain competition measure is below or above their layer's median. Consistent with the model prediction, we find that the TMB spread is smaller for the low competition subsample.

Furthermore, we establish empirically a negative relation between firms' cost of capital and competitiveness of their upstream firms. Consumption goods producers whose direct or indirect suppliers (up to five layers above them) have more competitors earn significantly higher expected returns. This novel fact is consistent with the mechanism of the model and highlights the importance of characteristics of the entire supply chain for firms' riskiness.

Third, we confirm the model prediction that the TMB spread is larger for firms that rely more heavily on installed physical assets: value firms, firms with lower capital depreciation rate, firms with lower intangible (organization) capital, and firms carrying more inventory. For these firms, a larger fraction of firm value stems from assets-in-place. This is the component that is subject to vertical creative destruction, which gives rise to the TMB spread.

In addition, we document a novel implication of vertical creative destruction for the within-layer value premium. Within the bottom layers (i.e., consumption goods producers or their direct suppliers), the value premium is much smaller than within the top layers. This finding is consistent with the vertical creative destruction channel. The value premium generally arises because assets-in-place are riskier than growth options. Vertical creative destruction reduces the sensitivity of assets-in-place to aggregate productivity shocks. Given that bottom-layer firms experience vertical creative destruction to the highest extent, their assets-in-place may not be as risky, and the value premium in the bottom layers diminishes.

We confirm the robustness of our empirical findings. The TMB spread remains significant when we (i) use the input-output tables published by the U.S. Bureau of Economic Analysis (BEA) to compute an inter-industry TMB spread from 1973 to 2007, (ii) use industry-based layer-mimicking portfolios to extend the sample period to 1945-2013; (iii) use different rebalancing frequencies or a different methodology to compute the vertical position; (iv) control for known cross-industry spreads.

We also consider several extensions to the model. We solve a model in which each layer is subject to a layer-specific technology shock. The TMB still exists, for a similar logic as in our benchmark model. The extended model further shows that firms have negative (positive) beta to productivity shocks to their direct and indirect suppliers (customers), and that ex-ante heterogeneity between the layers of production is not a quantitatively important driver of the TMB spread. In addition, we study alternative network structures that feature a pyramid or a loop at the top layer and discuss their implications for our results.

Related literature. The paper contributes to three strands of literature: creative destruction, production networks, and production-based asset pricing.

Schumpeter's seminal idea about creative destruction has influenced economic research in many areas.[3] More recently, creative destruction has spurred research in finance. A number of papers exploit the fact that not all firms benefit equally from innovations to derive implications for cross-sectional risk-premia. For example, Gârleanu et al. (2012), Loualiche (2016), Barrot et al. (2016), and Kogan et al. (2017) study displacement risk, which refers to the notion that innovations can benefit new firms or entrants at the expense of incumbent firms.[4] In these papers, creative destruction works horizontally: it is induced by a firm's existing or potential competitors. Our contribution to this literature is that we introduce the concept of vertical creative destruction – suppliers' innovations devalue customer firms. Downstream firms benefit less from aggregate productivity growth due to depreciation of their installed capital and inventory. Our model reveals a seemingly counterintuitive result

[3] See Caballero (2008) for an excellent survey.

[4] Eisfeldt and Papanikolaou (2013) study how creative destruction makes firms with high organization capital more risky. Opp (2016) extends the quality-ladder model of Schumpeterian growth (Grossman and Helpman (1991)) to study the impact of venture capital financing on the macroeconomy.

that increased creative destruction can serve as a hedge, and lower firms' cost of capital.

Our paper is also closely related to the recent literature that connects networks and asset prices. Cohen and Frazzini (2008) and Menzly and Ozbas (2010) study predictability of stock returns via supplier-customer links. In contrast, we are interested in contemporaneous cross-sectional return implications, across different production layers. Ahern (2013) finds that industries with a higher network centrality measure have higher returns. We verify that the TMB spread is not explained by the differences in firms' network centrality. Ozdagli and Weber (2017) find sizable network effects in the propagation of monetary shocks. Our paper focuses on the network effects of aggregate shocks to productivity, which influence all firms at the same time.[5] In a recent paper, Herskovic (2017) derives two risk factors based on the changes in network concentration and network sparsity. By contrast, we focus on the vertical dimension of production by modeling production in a supply chain. We find that the TMB spread increases with the length of the supply chain. However, this is not a result of sparsity or connectivity, but a result of a larger cumulative supply effect.[6]

More broadly, our paper is related to studies that connect investment and other macroeconomic fundamentals to stocks and bonds risk premia (Berk et al. (1999), Boldrin et al. (2001), Gomes et al. (2003), Carlson et al. (2004), Jermann (2010), Van Binsbergen et al. (2012), Ai et al. (2013), Belo et al. (2014), Drechsler et al. (2018)). The novelty of our model is that we explicitly account for the multi-layer nature of the production process, rather than assume a single sector (homogeneous goods). A number of studies examine asset pricing implications in two-sector economies. Gomes et al. (2009) document higher expected returns of durable goods producers relative to non-durables producers. The TMB spread is materially independent of this cross-industry spread. Yang (2013), Papanikolaou (2011), and Garlappi and Song (2017a,b) examine the cross-sectional pricing difference between the

[5]There is a growing literature on propagation of shocks in a production network. These shocks include idiosyncratic productivity shocks (Acemoglu et al. (2012), Atalay (2017)), liquidity shocks (Bigio and La'O (2016)), and natural disasters (Barrot and Sauvagnat (2016), Carvalho et al. (2016)).

[6]Other asset pricing implications of production networks were studied by Buraschi and Porchia (2012); Aobdia et al. (2014); Branger et al. (2017); Rapach et al. (2015); Herskovic et al. (2017), and Richmond (2015). None of these studies has examined the effect of creative destruction on stock returns or the relation between stock returns and firms' vertical position.

consumption sector and the investment sector. We deviate from these studies by using a refined network-based measure of upstreamness, which is more granular than sectoral classifications. Our benchmark results are based on six layers of production. Quantitatively, the majority of the TMB spread stems from *within* the investment sector, not from the return differentials of consumption versus investment firms.

The rest of the paper is organized as follows. In Section 1 we present the data and our measure of the vertical position. Section 2 includes the main empirical results. The model with multiple production layers is presented in Section 3. In Section 4, we perform tests of the model's mechanism. We discuss possible alternative explanations to our findings in Section 5. Section 6 includes robustness checks. Section 7 concludes.

1 An Empirical Measure of Vertical Position

1.1 Data

The data used in our empirical analysis are obtained from several sources. We use CRSP for stock returns, Compustat North America for accounting data, and the FactSet Revere relationships database for information about suppliers, customers, and competitors.

The FactSet Revere database is a novel database that is particularly appealing for our analysis because it has a comprehensive coverage with a start and an end date for each inter-firm relationship.[7] We use this panel data of supplier-customer relationships to measure the vertical position for each firm over time. Alternative data sources for supplier-customer relationships do not allow us to construct the vertical position at this granularity because they either report only a small subset of links between firms (e.g. Compustat segment data reports only names of the most important customers of each firm at an annual frequency), or they do not have a time-series which specifies the start date and end date for each relationship

[7] This database is available from Wharton Research Data Services (WRDS), and it has been used in a number of recent papers that study short-selling behavior (Dai et al. (2017)), network centrality (Wu (2015)), and credit risk propagation (Agca et al. (2017)). The database is also used in the industry for execution of trading strategies (Jussa et al. (2015)).

(e.g. Capital IQ, Bloomberg, Mergent).[8] It is also possible to construct *industry-level* vertical positions using input-output tables published by the BEA. However, this approach disregards any intra-industry supply chains. Not only that FactSet Revere data is more granular, but it also provides further firm-level information that allows us to test our model mechanism. Nonetheless, in Section 2.2.2, we complement our benchmark firm-level findings using BEA input-output tables, and find qualitatively similar results.

FactSet's analysts monitor the relationships data on a daily basis. Similar to Compustat segment data, FactSet collects information from firms' annual reports that include names of customers that generate above 10% of sales (mandatory disclosure according to SFAS No. 131 and Reg S-K item 101 of the SEC).[9] In addition, FactSet collects data from the quarterly filings, press releases, investor presentations, corporate action announcements, and firms' websites. Our sample period is from April 2003, when the database started, to September 2013, when we purchased it from FactSet Revere.[10] To allow for a sufficient time for FactSet's analysts to fully update the supplier-customer relationships, we use only relationships that were present up to December 2012.

1.2 Supplier-Customer Relationships

The unit of observation in the FactSet Revere database is a relationship between two firms. We observe a relationship's start and end dates. To get the most comprehensive information about the network, we utilize information disclosed by both suppliers and customers, and do not require a relationship to be reported by both firms. For example, if Mellanox Technologies Ltd discloses IBM as a customer, we use this relationship even if IBM has not reported Mellanox Technologies Ltd as its supplier.

[8] For comparison, the FactSet Revere relationships database has about 24,000 supplier-customer relationships covering 4,000 customer firms in 2003, the year when the database started, while the Compustat segment database has only 2,300 supplier-customer relationships between less than 1,000 customer firms in 2003. Because of the missing links in the Compustat segment data, the observed supply chains are usually very short, making it impractical to measure a firm's true vertical position.

[9] We do not utilize the data about the strength of the relationship because only a small subset of supplier-customer relationships have this information. Our measure of the vertical position does not require information about the percentage of sales to each customer.

[10] We complement our firm-level analysis with an industry-level analysis, for which the sample period starts in 1973, and with industry-based mimicking portfolios that extend the sample to 1945.

The database includes 433,271 supplier-customer relationships between 193,851 pairs of firms, covering a total of 43,656 firms. We clean it by removing duplicate records and redundant relationships (whose start and end dates fall within the time period of a longer relationship between the same pair of supplier and customer). If two firms appear to re-establish a supplier-customer relationship within six months after their previous relationship ended, we combine the two relationships into one assuming there being no time gap in-between. There are 206,264 supplier-customer relationships after the cleaning.

We merge the FactSet Revere database with the Compustat North America database using firms' CUSIP codes. After excluding financial firms (GICS code: 40) and industrial conglomerates (GICS: 201050), the matched sample has a total of 10,957 firms, including 7,801 firms with at least one supplier-customer relationship.[11]

To incorporate stock return data, we further merge our Revere-Compustat matched database with the CRSP monthly stock database using the CRSP-Compustat linking table, and find 6,721 matched firms. After excluding penny stocks (i.e., stocks with a price of less than $1 in the previous month) and stocks whose CRSP share codes are not 10, 11, or 12, our Revere-Compustat-CRSP matched stock sample includes 5,926 non-penny, non-financial, and non-conglomerate common stocks. Within this sample, 5,624 firms have at least one supplier-customer relationship.

Over the sample period, the total number of non-penny, non-financial, and non-conglomerate common stocks in the CRSP-Compustat merged database is 6,437. Therefore, our matched sample includes about 92% of these stocks. Figure OA.1 in Online Appendix shows the number of stocks in our Revere-Compustat-CRSP matched database versus the number of stocks in the CRSP-Compustat merged database for each industry. It demonstrates that all industries are well-represented in our sample.

[11] We exclude conglomerates because their vertical position in the production network is not precisely measured, and keeping them could introduce a bias into other firms' vertical position measures.

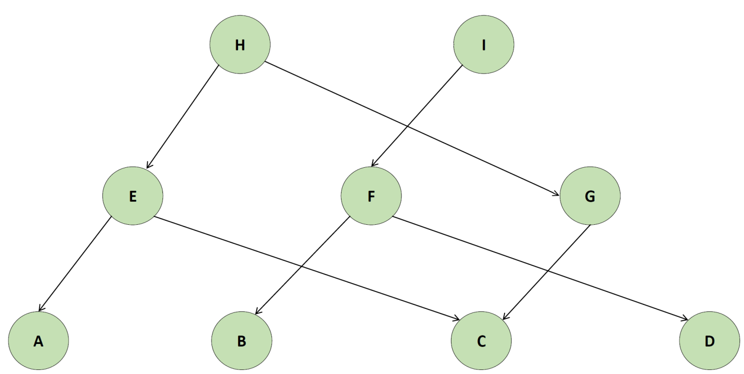
1.3 The Vertical Position Measure

We now describe the main production-based characteristic of interest: a firm's vertical position in a production chain (that is, its upstreamness). We first define and illustrate this measure, and then explain how we compute it.

Production networks can be split into tranches of firms, with firms in the same tranche having a similar distance from consumers (or equivalently, from final consumption good producers). We refer to these tranches as production layers. The firms at the bottom layer of a network produce final consumption goods. All other firms are direct or indirect suppliers to bottom layer firms. We define the vertical position of any firm as the smallest number of supplier-customer links between itself and firms at the bottom layer.

Our methodology of computing vertical positions is based on Gofman (2013). To illustrate this approach, consider the network of firms depicted in Figure 1. If firms A, B, C and D produce final consumption goods, by our definition, they operate at layer zero (the bottom layer). The other firms are connected to the bottom layer by one or more supplier-customer links. We denote the (minimal) number of such links as a firm's vertical position. For instance, Firms E, F and G belong to the same layer, as they have a vertical position of one. Firms H and I, which operate at the top layer, have a vertical position of two.

Figure 1: **Production Network: an Illustration**



The vertical position of each firm is determined endogenously relative to layer zero. Firms in layer one supply to at least one firm in layer zero. Firms in layer i supply to at least one firm in layer $i-1$, and to none of the firms in layers zero to $i-2$. The number of layers of production in each month is endogenous, and depends on the observed supplier-customer relationships.

Formally, consider a distance matrix D_t with n_t rows and m_t columns, where n_t is the total number of firms in the production network in month t, and m_t is the number of final goods producers in month t. An element $D_t(i,j)$ of this matrix measures the minimum number of supplier-customer links between firm i and final goods producer j. Given this distance matrix D_t, the vertical position is defined as the minimum number of supplier-customer relationships to any final goods producer:[12]

$$VP_{i,t} = \min_{j \in \{k: VP_{k,t}=0\}} D_t(i,j). \tag{1}$$

The vertical position measure is a global measure that depends on the entire network structure. A firm's vertical position can change even if its set of direct suppliers and customers does not. Given that the production network is dynamic, the vertical position of firms can change over time. Therefore, we compute our vertical position measures at a monthly frequency by utilizing existing supplier-customer relationships that lasted for at least six months before the measure is computed.

We implement the above methodology using our Revere-Compustat matched sample of 10,957 firms. First, we assign a vertical position of zero to all firms in the Consumer Discretionary (GICS code: 25) and Consumer Staples sectors (GICS code: 30). Second, we use equation (1) to estimate vertical positions of the remaining firms in the sample, using all supplier-customer relationships in which either one or both parties are from this sample.[13] Applying this methodology to our sample of firms, we obtain a comprehensive firm-level panel of vertical positions over time. To the best of our knowledge, this is the first paper to measure upstreamness *dynamically* for the large cross-section of US firms.

[12]We consider several alternatives to measure vertical positions, other than the minimum number of linkages to the bottom-layer. In Section 2.2.2, we compute the vertical position as the weighted average distance to the bottom layer using BEA input-output tables. This measure accounts for the strength of inter-industry linkages. In Section 6.1, we conduct robustness checks using the median distance of firms to the bottom-layer as their vertical position.

[13]To maximize the number of firms available for constructing the production network, we do not require both firms in a supplier-customer relationship to be in the Revere-Compustat matched sample when we estimate the vertical positions, nor do we require a firm to have a match in the CRSP database. Thus, the vertical position measure also utilizes supplier-customer relationships between public and private firms.

2 Stylized Facts: Vertical Position, Risk, and Stock Returns

2.1 Portfolio Formation and Characteristics

We form portfolios by sorting firms according to their vertical positions constructed using the FactSet Revere database, as described in the previous section. When sorting firms into portfolios at the beginning of month t, we utilize the vertical position computed at the end of month $t-2$. We do so to ensure that public information about supplier-customer relationships are known to investors. We skip the first six months of the FactSet Revere sample to make sure that the vertical position is based on supplier-customer relationships lasting for at least six months. The number of production layers and the distribution of firms across these layers are endogenous. In particular, firms need not be allocated equally across the different layers. In fact, as we illustrate below, top layers of production (layers with a high vertical position) include fewer firms. To reduce the amount of noise due to the smaller number of firms at the top layers, we assign firms belonging to layers zero to four into separate portfolios, but combine all firms with a vertical position five or above into a single portfolio. In all, we obtain six portfolios, representing six production layers.

Table 1 reports summary statistics for each layer. It shows a pyramidal shape for the production network: the number of firms decreases almost monotonically from the bottom layer to the top. This endogenous network structure is consistent with the notion of the Hayekian Triangle (Hayek (1935)) used to depict a multi-layer production economy.

One concern about the endogenous pyramidal structure of production is that the layer-based portfolios are not equal in size. For example, the top layer has considerably less firms on average than other layers (although their total market capitalization is a sizable $62 billion). We use several approaches to address this concern. First, in Section 6.1 we verify that the main empirical results are qualitatively robust when we combine the top two layers and form five portfolios instead of six. In that case, the top layer contains about a hundred firms. Second, in Section 6.3 we confirm our main empirical results using layer mimicking portfolios, which are based on well-diversified industry portfolios. Third, in Sections 2.2 and 2.3 we document a monotonic relation between vertical positions and the stock returns (and productivity betas). This monotonicity depends on the returns and exposures across all layers, not just the top or the bottom layer.[14]

Table 1 also shows various characteristics for firms in each layer. There is no significant difference in the book-to-market ratio, financial leverage, bid-ask spread, or dispersion of earnings forecasts by financial analysts between the top and bottom layers. Firms in the bottom layer are relatively more profitable (based on ROA), hold less cash, and have higher operating leverage than firms in other layers. Firms in the top layer are relatively bigger, have a higher asset growth rate and a lower fraction of shares owned by institutional investors, and have lower network centrality than firms in other layers. We discuss the implications of these differences for our results in Section 5.

Due to the dynamic nature of the network, firms can move across layers over time. Table OA.4 in Online Appendix reports monthly transition probabilities of firms across the layers during the sample period. The matrix shows that vertical positions are rather persistent at lower layers (98% for layer 1, which includes direct suppliers to consumption goods producers), but less persistent at the top layer (83%). This suggests that tracking the network structure dynamically is important.[15] Table OA.5 in Online Appendix reports the correlations of the value-weighted portfolio returns across layers. The correlation decreases almost monotonically as the distance between the layers increases, suggesting weaker economic connections between firms that are further away from each other in the chain. The bottom layer has a correlation of 0.89 with the layer 1, but only a correlation of 0.57 with the top layer.

[14]Lastly, we note that our collection of empirical findings in this paper include other related facts regarding stock returns within layers (as opposed to across layers). These results are not affected by heterogeneity in the size of different layers, and are based on a vast number of firms. For instance, in Section 4.1.2, we divide the large sample of bottom layer firms into equally sized groups, showing a negative relation between average returns and upstream competition. In Section 4.3, we show a diminished value premium within the bottom production layers. These results provide support for the vertical creative destruction mechanism without relying on the inter-layer spreads.

[15]In section 6.1, we perform a robustness check by forming portfolios once a year or only at the beginning of the sample period.

Table 1: **Summary statistics by layer**

	N	Market Cap	Book /Market	ROA	Debt /Asset	Cash /Asset	Operating Leverage	Asset Growth	Bid-Ask Spread	Forecast Dispersion	Institutional Ownership	Network Centrality
Layer 5	24	895	0.512	0.094	0.194	0.137	0.645	0.061	0.200	0.123	0.578	0.088
Layer 4	74	558	0.505	0.094	0.173	0.135	0.646	0.046	0.189	0.132	0.570	0.084
Layer 3	252	570	0.471	0.094	0.182	0.149	0.589	0.048	0.181	0.132	0.608	0.232
Layer 2	908	492	0.504	0.094	0.147	0.176	0.693	0.034	0.194	0.135	0.640	2.108
Layer 1	694	598	0.473	0.098	0.117	0.187	0.781	0.024	0.177	0.134	0.653	4.589
Layer 0	1067	477	0.528	0.119	0.219	0.087	1.114	0.016	0.191	0.126	0.642	0.737
TMB			-0.015	-0.025***	-0.024	-0.085	-0.469***	0.044***	0.010	-0.004	-0.064***	-0.648***
t-stat			(-0.45)	(-5.00)	(-1.60)	(-21.54)	(-17.64)	(7.06)	(0.70)	(-0.83)	(-3.09)	(-16.54)

This table presents summary statistics for each production layer, formed using firms in the Revere-Compustat-CRSP matched sample. *N* is the average number of firms in each layer from September 2003 to December 2012. For all other variables, we first calculate the cross-sectional median in a given month, and then report the time series mean. *Market cap* is the market capitalization in million USD; Book/Market is the book-to-market equity ratio; *ROA* is operating income before depreciation divided by total book assets. *Debt/Asset* and *Cash/Asset* are the ratios of total debt, cash and cash equivalents to total book assets, respectively. *Operating Leverage* is calculated as the sum of SG&A (selling, general and administrative expenses) and COGS (costs of goods sold) divided by book assets, following Novy-Marx (2011); *Asset growth* is the real annual growth rate of book assets. *Bid-Ask Spread* is the bid-ask spread scaled by the midpoint stock price. *Forecast Dispersion* is the dispersion of earnings forecasts by financial analysts, calculated using the IBES database. *Institutional Ownership* is the fraction of common shares owned by institutional investors, calculated using the Thomson Reuters Institutional (13f) Holdings database. *Network Centrality* is the eigenvector centrality measure, calculated using the FactSet Revere supplier-customer relationship database. All accounting data are from the Compustat, and stock-related data are from the CRSP. Newey-West t-statistics for the difference between the top and bottom layers (TMB) are reported in the parenthesis.

2.2 Stylized Fact I: Layer Portfolio Returns and the TMB Spread

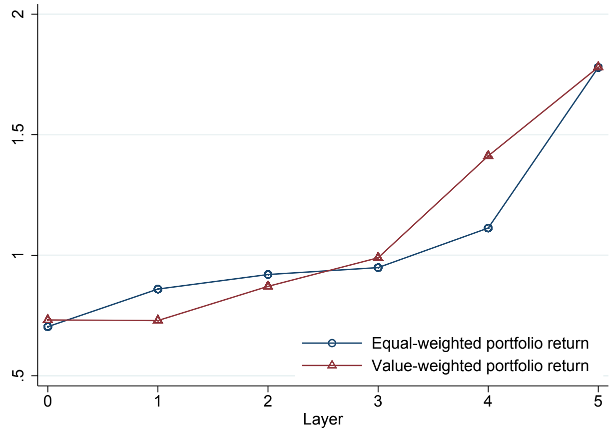
In this section we establish the first stylized fact: a monotonic relation between vertical position and average returns, as well as a sizable return spread between the top and bottom layers of production (the TMB spread). We first document this fact at firm-level granularity using our benchmark FactSet Revere relationship database in Subsection 2.2.1. As previously discussed, this database is used for our benchmark results because it is the most comprehensive database on supplier-customer relationships between US firms. Since it allows to construct firm-level upstreamness measures, we are able to study within-industry supply chains and their contribution to the TMB spread. It also contains crucial data on firms' competitors which we use in Section 4.1 to test the mechanism that we later propose to rationalize our findings. However, the novel benchmark database has a limitation. Due to data availability it covers the period of 2003-2013. For this reason, we demonstrate that the *inter-industry* component of the TMB spread exists in much longer sample periods.[16] We consider two methodologies to examine the long-term TMB spread at the industry level. First, in Subsection 2.2.2 we use industry-level input/output tables to study the relation between industry vertical position and stock returns starting in the 1970s. Second, in Subsection 2.2.3 we utilize an approach of layer-mimicking portfolios to further establish Fact I starting at 1945.

2.2.1 Baseline Results Using Firm-Level Vertical Position

Figure 2 reports our main empirical finding regarding the cross-section of stock returns along the vertical dimension of economy. It shows returns of value-weighted and equal-weighted portfolios formed based on the vertical position. The figure reveals a strong pattern. The higher the vertical position, the higher is the mean return. Firms that produce final consumer goods have a nominal value-weighted (equal-weighted) monthly return of 0.73 (0.70) percent, while firms with a vertical position of five or above have a value-weighted

[16] In Subsection 6.3, we highlight the importance of the intra-sectoral component of the firm-level TMB spread.

Figure 2: **Expected Monthly Returns by Vertical Position**



The figure presents the average monthly returns of the value-weighted and equal-weighted portfolios constructed based on firms' vertical positions. Firms with a vertical position of zero are producers of final goods. The sample period is 11/2003–2/2013.

(equal-weighted) average monthly return of 1.78 (1.78) percent.

Table 2 shows the average returns, along with their respective standard deviations, for each layer. Consistently with Figure 2, the returns increase monotonically from the bottom layer to the top layer. The spread between the top and bottom layers is 105 basis points per month for the value-weighted portfolios and 108 basis points per month for the equal weighted portfolios. Both are economically and statistically significant.

Table 2: **Vertical Position and Stock Returns**

	Value-weighted return		Equal-weighted returns	
	Mean	SD	Mean	SD
Layer 5	1.78	6.54	1.78	7.30
Layer 4	1.41	6.23	1.11	7.11
Layer 3	0.99	5.64	0.95	6.27
Layer 2	0.87	4.93	0.92	6.31
Layer 1	0.73	4.47	0.86	6.36
Layer 0	0.73	3.97	0.70	6.56
spread (5-0)	1.05**	5.36	1.08**	4.54
	(2.07)		(2.51)	

This table presents the means and standard deviations of the monthly raw returns for each layer and the spread between layers 5 and 0 (the TMB spread). The returns are computed from November 2003 to February 2013.

Implied from Table 2, the Sharpe ratios also rise with the vertical position. The annualized Sharpe ratio of the value-weighted (equal-weighted) TMB portfolio is 0.68 (0.82). During the same period, the Sharpe ratio is 0.39 for the market portfolio, 0.28 for the SMB factor, and 0.29 for the HML factor.

In Section 6.2, we show that the TMB spread is a novel empirical finding, as it is largely independent from known production-related and cross-industry spreads including the spread between durables and nondurables (Gomes et al. (2009)), the spread between investment and consumption firms (see Kogan and Papanikolaou (2014)), the book-to-market spread, and others.

2.2.2 Long-Sample Inter-Industry Results Using Input-Output Tables

The BEA periodically publishes Input-Output accounts, which provide an inter-industry analysis snapshot of the economy. Each snapshot is comprised of two tables: Use and Make Tables. The Make table shows the production of commodities by industry. Each row represents an industry, and the columns display the commodities that this industry produces, in dollar value. The Use table shows the use of each commodity by each industry, also in dollar value. Each row in this table presents a commodity, and the columns display the industries using this commodity as an input, as well as the amounts used by final users. We use the combination of Use and Make tables at each point in time to compute industry-level vertical positions. We then confirm the benchmark relation between vertical position and average returns using this data. We use the combination of Use and Make tables at each point in time to compute industry-level vertical positions. We then confirm the benchmark relation between vertical position and average returns using this data.

The advantage of the approach in this subsection is that the I-O tables span a longer period than the FactSet Revere database. They also contain information about the dollar flow of goods between industries. As a result, the vertical positions computed in this subsection alleviate two concerns about our baseline results: (1) the vertical positions in this subsection account for the strength of the links between any two industries, not only for its existence, and (2) the vertical positions in this subsection account for a weighted average of all possible "paths" from one industry to consumers, as opposed to the minimum path as in the baseline results.

However, there are a few shortcoming to using the I-O tables. Most importantly, the results based on I-O tables only reflect across-industry supply chains but not within-industry supply chains. Many production chains extend almost exclusively within sectors. Consequently, firms can have a high vertical position even if their industry (as a whole) does not. For example, long supply chains exist in the health care and information technology industries. This implies that the TMB spread is not purely driven by cross-industry differences. Since the TMB spread is both an inter-industry and an intra-industry result, and since the analysis using only cross-industry information cannot capture any intra-industry contribution to the spread, our hypothesis is that the long-sample TMB spread calculated from I-O tables should be sizable, but diminished in magnitude compared to the benchmark spread. Another limitation of the I-O tables is that the benchmark tables, which classify industries/commodities with sufficient granularity required for our study, are published by the BEA at a relatively low frequency of once every 5 years. For example, benchmark Make and Use tables are available for 2007, 2002, 1997, and so on.

We use the Make and Use tables in the year t to compute the vertical positions of all industries, which are summarized by the vector VP_t^{Ind}. The details of the computation are specified in Section A.1 of the Appendix. We then use vector VP_t^{Ind} to determine firms' vertical positions from year $t-4$ to year t based on their industry affiliations. For example, the vertical position of a firm that belongs to industry i is $VP_{2007}(i)^{Ind}$ from the beginning of 2003 to the end of 2007. The vertical position of the same firm for the previous five years is $VP_{2002}(i)^{Ind}$, and so on. We start our sample in December 1973 as the number of firms in our CRSP database drops significantly prior to this year.[17] We end our sample in December 2007, as this is the last year for which the detailed I-O tables are available.

We sort firms into layer portfolios at each month t based on their vertical positions at

[17]For example, while in December 1972 the number of traded firms having share codes 10, 11 or 12 is about 2,500, it is around 5,000 in December 1973. This is due to the fact that NASDAQ data starts in 1973.

the end of month $t-1$. To parallel with our baseline results, the breakpoints are equidistant on the $[0,5]$ segment. In other words, we use vertical positions $\{1,2,3,4\}$ as breakpoints, and form five portfolios.[18] Firms in layer $i \in \{0..4\}$ have a vertical position score which is between i and $i+1$. The results are reported in Table 3.

Table 3: **Returns of Layer Portfolios Based on Input-Output Tables**

	Value-weighted		Equal-weighted	
	Mean	SD	Mean	SD
Layer 4	1.69	7.08	1.95	7.95
Layer 3	1.19	8.08	1.41	9.16
Layer 2	0.97	6.68	1.40	6.94
Layer 1	0.85	5.27	1.34	6.59
Layer 0	1.10	4.22	1.37	5.29
TMB	0.60**	6.10	0.59*	6.10
t-stat	(2.06)		(1.95)	

The table shows the average and standard deviations of layer portfolio returns, constructed using the BEA Input-Output tables. The sample period is from 1973/12 to 2007/12. Significance at the 5% and 10% levels are indicated by ** and * respectively.

The value-weighted inter-industry TMB spread based is about 60 bps per month, and significant at the 5% level. Under equal weighting the spread is of almost identical magnitude, and significant at the 10% level. By and large (with the exception of layer 0), the average returns increase monotonically with the vertical position.

2.2.3 *Long-Sample Inter-Industry Results Using Mimicking Portfolios*

A separate way to extend the sample period is by constructing layer-mimicking portfolios. This can be achieved in a straightforward way by projecting the layer dimension onto the industry dimension. This approach allows to extend the sample even prior to the availability of BEA I-O tables.

Our approach to rolling the sample backwards using industry-level data (portfolios) is motivated by two facts. First, the results from the previous subsection show that the TMB

[18] We do not construct six portfolios as in the benchmark FactSet Revere database results because the BEA data is less granular (i.e., doesn't account for within-industry supply chains), and consequently, the implied supply chains are shorter on average.

spread exhibits a strong cross-industry component. Second, the association of firms to certain industries is relatively stable over time. As such, the industrial association of firms can be a good indication for their production-layer affiliation over long horizons. By contrast, many firm-level characteristics (e.g., profitability or book-to-market) are not very correlated with the vertical position measure (see Table 1), and are far less persistent than the industry characteristic.

Nonetheless, similarly to the results implied from the BEA I-O database, extending the sample using only cross-industry information implies that we cannot account for intra-industry supply-chains and their contribution to the spread. Moreover, the mimicking portfolio approach is more subject to noise as the mimicking portfolios' parameters are estimated in-sample, and held fixed for a long period prior to estimation (i.e., it implicitly assumes that vertical positions are relatively constant). As a result, we conjecture that the long-sample TMB spread calculated from industry-based layer-mimicking portfolios should be positive, yet quantitatively smaller due to the noisiness of the projected vertical positions.

We use the following procedure for extending the sample period using mimicking portfolios. First, we regress the excess return of each layer portfolio ($j \in \{0..4\}$), available for our sample period, on the excess returns of eleven industry portfolios based on the Fama-French twelve-industry classification.[19] Second, we use the estimated loadings from these projections over our benchmark sample period to construct industry-based layer-mimicking portfolios. The excess return of each mimicking portfolio in each month is equal to the sum of the products of the estimated coefficients and the realized excess returns of the corresponding industry portfolios. We conduct this analysis for the post-war period of 1945-2013. We construct both the value- and equal-weighted layer-mimicking portfolios, using the value- and equal-weighted layer/industry returns, respectively. Table 4 reports the excess returns of these mimicking portfolios.

[19] We collapse layers four and five of the benchmark case to a single layer, denoted as layer four, in order to reduce noise in this estimation procedure by increasing the number of firms in the top layer. We exclude the financial industry because our sample does not include financial firms. Our results are very similar if we include the financial industry, or if we use the Fama-French ten-industry instead of the twelve-industry classification system.

Table 4: **Excess Returns of Layer-Mimicking Portfolios: 1945-2013**

	Value-weighted		Equal-weighted	
	Mean	SD	Mean	SD
Layer 4	0.88	5.08	1.01	5.51
Layer 3	0.85	5.07	1.05	5.81
Layer 2	0.80	4.93	1.00	6.43
Layer 1	0.69	4.50	0.98	6.76
Layer 0	0.67	4.27	0.75	5.55
TMB	0.21**	2.97	0.26***	2.43
t-stat	(2.06)		(3.09)	

The table shows the mean excess return and standard deviation of each layer-mimicking portfolio, constructed using eleven industry portfolios based on the Fama-French twelve-industry classification (the excluded industry is Money and Finance). The value-weighted (equal-weighted) mimicking portfolios are constructed based on the loadings of excess returns of value-weighted (equal-weighted) layer portfolios on excess returns of value-weighted (equal-weighted) industry portfolios. The sample period is from 1945/01 to 2013/02. Significance at the 5% and 1% levels are indicated by ** and ***, respectively.

The value-weighted mean monthly excess returns of the industry-based mimicking portfolios increase monotonically from layer zero to layer four, while the equal-weighted excess returns increase monotonically from layer zero to layer three. In-line with our conjecture, the TMB spread is still positive in the long-run but exhibits a smaller magnitude. The equal-weighted spread between the top and the bottom layer returns is 26.3 basis points per month, or about 3% per annum, statistically significant at the 1% level. The value-weighted spread is 21.4 basis points per month, statistically significant at the 5% level.

As we previously conjectured, the magnitude of the industry-based TMB spread is smaller than the magnitude of the firm-level TMB spread. The drop in magnitude can be explained by two reasons. First, the industry-based spread does not incorporate any intra-industry effect. Consistent with this explanation, in untabulated results we find that within our benchmark sample period the value-weighted inter-industry TMB spread calculated from the mimicking portfolios is only 47 basis points per month. Another reason for the smaller magnitude of the spread is the static nature of the mimicking portfolios. Our construction of the mimicking portfolios is based on the network structure observed within our benchmark sample period, and does not take into account the fact that the production network structure is dynamic. Consistent with this explanation, the TMB spread is generally smaller when we extend the sample further back. For example, the equal-weighted monthly TMB spread is 35 basis points over 1985-2013 (t-stat =2.20), and 21 basis points over 1926-2013 (t-stat = 2.78).

Overall, the results from the two industry-based extended samples highlight that the TMB risk premium is *positive*, and that the monotonic pattern of returns across the layers is not just a short-sample phenomenon.

2.3 Stylized Fact II: Exposure of Layer Portfolios to Productivity Shocks

Section 2.2 established a monotonic relation between vertical position and average returns. In this section we examine whether this relation is a result of exposure to fundamental macroeconomic risk. We establish our second stylized fact: firms in the top layers are more exposed to the aggregate productivity shocks than firms in the bottom layers.

We establish this fact using quarterly portfolio returns obtained from our benchmark analysis, and quarterly labor productivity data published by the U.S. Bureau of Labor Statistics (BLS). We use labor productivity to measure the aggregate productivity because it is presumably less noisy than the total factor productivity, the estimation of which requires an adjustment for seasonal variation in the capital utilization rate.

Panel A of Table 5 reports the regression coefficients (betas) of each layer and of the TMB portfolio with respect to the aggregate productivity. By and large, the productivity beta increases with the vertical position. The beta is 1.2 for the bottom layer, whereas it is 2.9 for the top layer. The beta of the TMB portfolio is 1.6, and marginally significant at the 10% level.

Importantly, the relation between expected returns and productivity may not be linear. This can arise, for example, if the exposure of each layer to the aggregate productivity is time-varying. In fact, this is the case in the model that we use to explain our findings in Section 3. Therefore, in Panel B of Table 5, we change the projection specification to include a quadratic term of productivity. Accounting for model non-linearities, the exposure pattern becomes more pronounced, both economically and statistically. The coefficient of layer portfolio returns on the linear term of productivity increases monotonically with the vertical position (from 2.5 to 10.5). The coefficient of the TMB spread on the linear term is positive and statistically significant. To infer the overall exposure from the non-linear projection, the panel reports the partial derivative of stock returns with respect to productivity shocks. This derivative is based on the estimated coefficients on both the linear and the square terms and the sample mean of changes in the aggregate productivity. This partial derivative shows a monotonic increase in the sensitivity of portfolio returns to productivity shocks from the bottom to the top layer, confirming the prediction of the model.

The monotonic pattern of riskiness is manifested not only when considering the layer portfolios' returns, but also when considering other valuation ratios. Of particular interest is Tobin's Q which highly relates to the valuation of firms' assets-in-place. As we show later in Table 9, our theoretical framework predicts a positive relation between the vertical position and the sensitivity of Tobin's Q to productivity shocks.

We estimate Tobin's Q of each firm using the quarterly Compustat database, and measure its change by the difference in the natural logarithm of the estimated Q. We calculate the quarterly change in Tobin's Q for each layer, $\Delta log(Q_{i,t})$, as the weighted average of changes at the firm level (weighted by lagged book assets). Panel C of Table 5 shows the exposure of each layer in a linear model, while Panel D shows the results for a model with both linear and nonlinear terms. These results echo what we find from stock returns.

One shortcoming of using productivity data is that it is available at a quarterly frequency, resulting in low statistical power. In untabulated results, we regress the daily excess returns of portfolios sorted on vertical position on the daily excess returns of the market. The beta increases monotonically from layer zero to four, and the beta of the TMB portfolio is positive and significant at the 1% level. While the market portfolio is a poor proxy for aggregate productivity because it is influenced by sentiments and other shocks, it allows us to estimate beta of each layer very precisely and it is consistent with the previous result that the exposure to aggregate productivity increases monotonically with the vertical position.

Despite the fact that the betas of layer portfolios to aggregate risk (productivity or

Table 5: **Vertical Position and Exposures to Aggregate Productivity Shocks**

	TMB	Layer 0	Layer 1	Layer 2	Layer 3	Layer 4	Layer 5
Panel A. $R^e_{i,t} = const + \beta\Delta Prod_t + error$							
$\Delta Prod_t$	1.664	1.214	1.306	1.645	2.534	2.072	2.878
	(1.61)	(1.36)	(1.29)	(1.30)	(1.70)	(1.28)	(2.65)
Panel B. $R^e_{i,t} = const + \beta_1\Delta Prod_t + \beta_2\Delta Prod^2_t + error$							
$\Delta Prod_t$	8.044	2.484	4.117	6.609	9.654	10.513	10.528
	(2.76)	(0.86)	(1.39)	(1.91)	(2.44)	(2.65)	(5.32)
$\Delta Prod^2_t$	-1.354	-0.269	-0.596	-1.053	-1.511	-1.791	-1.623
	(-2.65)	(-0.58)	(-1.25)	(-1.90)	(-2.42)	(-2.86)	(-4.90)
$E[\frac{\partial R^e}{\partial \Delta Prod}] = \beta_1 + 2\beta_2 E[\Delta Prod]$	3.254	1.530	2.006	2.882	4.308	4.175	4.784
Panel C. $\Delta log(Q_{i,t}) = const + \beta\Delta Prod_t + error$							
$\Delta Prod_t$	1.194	0.410	0.529	0.920	1.010	1.058	1.603
	(2.10)	(1.20)	(1.26)	(1.93)	(1.76)	(1.50)	(2.42)
Panel D. $\Delta log(Q_{i,t}) = const + \beta_1\Delta Prod_t + \beta_2\Delta Prod^2_t + error$							
$\Delta Prod_t$	5.968	0.257	0.496	2.585	4.103	4.230	6.225
	(3.81)	(0.24)	(0.38)	(1.77)	(2.40)	(1.98)	(3.27)
$\Delta Prod^2_t$	-0.943	0.030	0.007	-0.329	-0.611	-0.627	-0.913
	(-3.22)	(0.15)	(0.03)	(-1.20)	(-1.91)	(-1.57)	(-2.57)
$E[\frac{\partial q}{\partial \Delta Prod}] = \beta_1 + 2\beta_2 E[\Delta Prod]$	2.310	0.373	0.523	1.309	1.733	1.798	2.683

The table shows the sensitivities of the portfolio returns (Panels A and B) and changes in log(Q) (Panels C and D) to percentage changes in the aggregate labor productivity for different layers of production using quarterly data. Layer 0 is a portfolio of firms in consumer discretionary and consumer staples sectors. Layer 5 is a portfolio of firms that have a vertical position of five or higher. T-statistics are reported in parentheses. The Tobin's Q is estimated using the quarterly Compustat database, and the quarterly labor productivity data is from the website of the U.S. Bureau of Labor Statistics.

the market) increase monotonically, we show in Section 6.2 that the TMB spread cannot be explained by common unconditional asset-pricing models, including CAPM, and the Fama and French (1993) three-factor model. As we discuss further in Section 6.2, while this result helps to distinguish TMB from known spreads, it does not suggest that the TMB represents a new risk factor: the evidence in this section shows that the TMB spread can be rationalized through aggregate productivity exposures, to a large extent. Existing factor models fail to fully explain the spread as they are noisy approximations for underlying productivity, and they do not account for time-variation in the risk-exposures (non-linearity). The challenge lies in endogenizing the pattern of layers' risk exposures to aggregate productivity, both qualitatively and quantitatively, in order to match the magnitude of the sizable TMB spread. We provide a model that explains facts I and II in the next section.

3 A General Equilibrium Asset Pricing Model with Multiple Layers of Production

In this section, we present a model of vertical creative destruction in a production chain, and use it to examine the risk profiles of firms in different vertical positions.

3.1 The Model

There are $N+1$ layers of production in the economy, indexed by $j \in \{0, 1, ..., N\}$. Each production layer is captured by a single representative firm. The firms that operate in layers $\{1, .., N\}$ produce differentiated (intermediate) capital goods. A firm that operates in layer $j \in \{1, .., N\}$ supplies capital to the firm operating in the layer vertically below it, $j-1$. The firm in the bottom layer ($j = 0$) produces final consumption goods, sold to the household for consumption.

3.1.1 Aggregate Productivity

Aggregate productivity is denoted by Z_t, and its lower case denotes log-units. The log-growth of aggregate productivity features a persistent component as in Croce (2014):

$$\Delta z_{t+1} = \mu_z + x_t + \sigma_z \varepsilon_{z,t+1}, \tag{2}$$

$$x_{t+1} = \rho_x x_t + \phi_x \sigma_z \varepsilon_{x,t+1}, \tag{3}$$

where $\varepsilon_{z,t+1}$ and $\varepsilon_{x,t+1}$ are standard Gaussian shocks with contemporaneous correlation ρ_{xz}. In the specification above, x refers to the long-run risk component in productivity growth. The long-run risk component is only important quantitatively, but not qualitatively.

3.1.2 Firms

A firm in layer $j \in \{0, 1, ..., N\}$ hires labor $n_{j,t}$ from the household and owns capital stock $k_{j,t}$, which is layer-specific. The firms produce their output using constant returns to scale Cobb-Douglas production function over capital and labor, subject to aggregate productivity shock Z_t:

$$Y_{j,t} = Z_t k_{j,t}^{\alpha} n_{j,t}^{1-\alpha}, \quad j \in \{0, 1, .., N\}, \tag{4}$$

where α is the capital share of output for all firms. Since there are no capital suppliers for the top layer (layer N), its capital stock is assumed to be fixed over time ($k_{N,t} = k_{N,0}$). We relax this assumption in Section OA.6.2. The capital stock for firms in layer $j \in \{0, .., N-1\}$ depreciates at rate δ, and evolves according to:

$$k_{j,t+1} = (1 - \delta + i_{j,t})k_{j,t}, \tag{5}$$

where $i_{j,t}$ denotes the investment-rate of firm j. Each firm in layer $0 \geq j \geq N-1$ that wishes to invest amount $i_{j,t}k_{j,t}$, must purchase $\Phi(i_{j,t})k_{j,t}$ units of its layer-specific capital goods directly from the layer above it. Purchasing these layer-j capital goods is done under the equilibrium output price of layer $j+1$, P_{j+1}. The convex adjustment cost function $\Phi(i)$ is given by:

$$\Phi(i) = \frac{1}{\phi}(1 + i)^{\phi} - \frac{1}{\phi}. \tag{6}$$

In all, the period dividend of firm $j \in \{0, .., N-1\}$, $d_{j,t}$, is given by:

$$d_{j,t} = P_{j,t}Y_{j,t} - W_t n_{j,t} - P_{j+1,t}\Phi(i_{j,t})k_{j,t}, \tag{7}$$

where W_t denotes the real wage per unit of labor. Given that the top-layer firm's capital is fixed, the dividend of the top-layer firm is similarly given by $d_{N,t} = P_{N,t}Y_{N,t} - W_t n_{N,t}$.

Each firm chooses optimal investment (except for the top firm) and optimal hiring to maximize its market value, taking as given wages W_t, output prices $P_{j,t}, \quad j \in \{0, .., N\}$, and the stochastic discount factor of the household $M_{t,t+1}$. Specifically, the layer-j representative firm maximizes:

$$V_{j,t} = \max_{\{n_{j,s}\ k_{j,s+1}\}} \quad E_t \sum_{s=t}^{\infty} M_{t,s} d_{j,s}, \tag{8}$$

subject to (5) if $j \in \{0, ..., N-1\}$.

3.1.3 Household

The economy is populated by a representative household. The household derives utility from an Epstein and Zin (1989) and Weil (1989) utility over a stream of consumption C_t:

$$U_t = \left[(1 - \beta)C_t^{\frac{1-\gamma}{\theta}} + \beta(E_t U_{t+1}^{1-\gamma})^{\frac{1}{\theta}}\right]^{\frac{\theta}{1-\gamma}}, \tag{9}$$

where β is the subjective discount factor, γ is the risk aversion coefficient, and ψ is the elasticity of the intertemporal substitution (IES). For ease of notation, the parameter θ is defined as $\theta \equiv \frac{1-\gamma}{1-\frac{1}{\psi}}$. Note that when $\theta = 1$, that is, $\gamma = 1/\psi$, the recursive preferences collapse to the standard case of expected power utility, in which case the agent is indifferent to the timing of the resolution of the uncertainty of the consumption path. When risk aversion exceeds the reciprocal of IES ($\gamma > 1/\psi$), the agent prefers an early resolution of the uncertainty of consumption path; otherwise, the agent has a preference for a late resolution of the uncertainty.

The household supplies labor to all firms inelastically. It derives income from labor, as well as from the dividends of all $N+1$ production firms. The household chooses the layer-specific labor supply and consumption to maximize its lifetime utility, subject to the following budget constraint:

$$\max_{C_s, \{n_{j,s}, \omega_{j,s+1}\}_{j\in\{1..N\}}} U_t, \quad s.t. \quad P_{0,t}C_t + \sum_{j=0}^{N} \omega_{j,t+1} V^{ex}_{j,t} = W_t \sum_{j=0}^{N} n_{j,t} + \sum_{j=0}^{N} \omega_{j,t} V_{j,t}, \tag{10}$$

where $\omega_{j,t}$ is the share of the household in the ownership of the layer j firm, and $V^{ex}_{j,t}$ is the ex-dividend firm value. It is straightforward to show that the SDF used to discount the dividends of firms in all layers is given by:

$$M_{t,t+1} = \beta \left(\frac{C_{t+1}}{C_t}\right)^{\frac{-1}{\psi}} \left(\frac{U_{t+1}}{\left[E_t U_{t+1}^{1-\gamma}\right]^{\frac{1}{1-\gamma}}}\right)^{\frac{1}{\psi}-\gamma}. \tag{11}$$

3.1.4 Equilibrium

In equilibrium, wage W_t, and output prices $\{P_{j,t}\}_{j\in\{0,..,N\}}$, are set to clear all markets:

- Labor market clearing:

$$\sum_{j=0}^{N} n_{j,t} = 1. \tag{12}$$

- Differentiated capital-goods market clearing:

$$\Phi(i_{j-1,t})k_{j-1,t} = Y_{j,t}, \quad \forall j \in \{1, ..., N\}. \tag{13}$$

- Consumption-good market clearing:

$$C_t = Y_{0,t}. \tag{14}$$

- Firm-ownership market clearing:

$$\omega_{j,t} = 1, \quad \forall j \in \{0, ..., N\}. \tag{15}$$

An equilibrium consists of prices, labor, and capital allocations such that (i) taking prices and wages as given, the household's allocation solves (10), and firms' allocations solve (8); (ii) all markets clear.

3.2 Discussion of the Main Modeling Assumptions and Extensions

Goods transmitted in supply-chains. In the model, we assume that suppliers sell capital goods to customer firms. Our interpretation of capital in this economy is loose: it is possible to interpret capital goods as machines or as intermediate inputs.[20] One can view intermediate inputs as a form of "capital" that depreciates faster (see e.g. Belo and Lin (2011); Jones and Tuzel (2013)). For parsimony, we refrain from introducing to the model two types of capital goods (fixed capital and inventory). Instead, we model production using one form of capital, but we verify that the conditions needed for the mechanism to be applied for inventory inputs are held. There are two crucial ingredients for vertical creative destruction to apply for a given input: (1) the depreciation rate for the good transmitted is less than one, and (2) the good is stored in a stock by the firm (either physically or through a forward contract). These conditions naturally apply for fixed assets. We also confirm that they apply for intermediate inputs. First, we verify in Section OA.3 that if we assume that only intermediate inputs are transmitted, and consequently, alter the calibrated depreciation rate to match inventory carrying costs (i.e., inventory's depreciation as in Jones and Tuzel (2013)), then the quantitative effect on our results is minor (the TMB spread is 12% per annum under a higher depreciation versus 12.5% under the benchmark calibration). Second, we confirm in the data that on average all layers have positive inventories, and that the ratio of inventory to firm value is the largest for bottom-layer firms. Consistent with the fact that the mechanism can be equally applied to stocks of inventories, we show in Section 4.2 that

[20] For example, magnets producer purchases a large stock of rare earths and uses them in production of magnets over a period of one year or more. From our mechanism's perspective, it is not conceptually different from purchasing a grinding machine, which is used to smooth magnets. Both rare earths and grinding equipment are held in stocks, and depreciate gradually over time.

the TMB spread is larger for firms that carry a higher amount of inventory.

Layer Heterogeneity. In the model, we deliberately introduce (almost) no heterogeneity between the layers in terms of the production technology, adjustment costs, or depreciation rates. The goal of this assumption is to show that the differences in returns across the layers are driven by network effects, and not by ex-ante heterogeneity in production technology. In Section OA.6.1 of the Online Appendix, we introduce ex-ante parameter heterogeneity between the layers. We allow firms with higher vertical position to have lower depreciation rate, or higher adjustment costs. The quantitative contributions to the model-implied TMB spread from these ex-ante heterogeneities are marginal. In Section 3.4.4 we consider another form of heterogeneity: layer-specific technology shocks. Our model results still hold under that modeling extension.

Network Structure. To focus on the vertical dimension of the production network and to keep the model parsimonious, we use a perfectly vertical supply chain.[21] In Section OA.6.2, we consider alternative network specifications: a pyramidal network, and a chain which includes a loop at the top (i.e., the capital of the top layer is not fixed). When the elasticity of substitution between the consumption good is close to unity, the pyramidal structure yields a results which are quantitatively close to the benchmark chain model. We also confirm that a positive and sizable model-implied TMB spread exists when the chain has a loop at the top (that is, the top layer firm sells capital to itself, and to the layer below it, making the capital of the top layer time-varying).

3.3 Calibration

Table 6 shows the parameter choice of the model in the benchmark case. The model is calibrated at an annual frequency. There are two sets of parameters: production parameters and preference parameters.

[21] Our decision to have a perfectly vertical supply chain, where the capital of the top layer is fixed, stems from two reasons. First, this assumption allows us to capture a salient feature of the data, in which the spread between the average return of layer five and four is relatively large. As the top layer cannot reduce the cyclicality of its dividends via investment, it bears an extra premium for that. Second, this modeling assumption is also consistent with empirical evidence that the labor share of output is higher for investment good producers (see e.g. Basu et al. (2012)).

Table 6: **Model Calibration**

Symbol	Value	Parameter
Panel A: Production		
N	5	Number of layers
α	0.33	Share of capital in output
ϕ	25	Investment adjustment cost
δ	0.1	Depreciation rate
Panel B: Technology Shock		
μ_z	0.013	Productivity growth rate
σ_z	0.017	Short-run productivity shock volatility
ϕ_x	0.085	Ratio of Long-to-Short-run productivity volatility
ρ_x	0.98	Persistent of long-run productivity
ρ_{xz}	1	Correlation between short and long run productivity shocks
Panel C: Preferences		
β	0.98	Subjective discount factor
γ	10	Relative risk aversion
ψ	2	Intertemporal elasticity of substitution

The table shows the parameter values used in the benchmark model calibration. The model is calibrated at the annual frequency.

Production parameters. We set N to 5, implying 6 production layers, similarly to the benchmark empirical results. We set $\alpha = 0.33$, so that the labor share of output across different layers is 2/3. The annual depreciation rate is 10%. The capital adjustment cost parameter ϕ helps to match the auto-correlation of output growth to the data, and boost the volatility of the equity premium. To target these moments, we set the adjustment cost to 25. While it is a relatively high parameter value, it is important to stress that we demonstrate in the sensitivity analysis that the spread does not depend quantitatively or qualitatively on the existence of these adjustment costs. The aggregate productivity log-growth μ_z is set such that the steady state growth rate of consumption is about 2%, similarly to the data. We set σ_z to 1.7%, to obtain an annual volatility of consumption growth slightly below 2%, consistent with a long-run sample equivalent. To keep the long-run component of consumption small, we impose ϕ_x to be 0.085. This is a conservative value. Croce (2014) shows that in the sample of 1930-2008, the ratio of the long-run risk volatility to the short-run risk volatility is roughly 10%. We set the persistence of the long-run component ρ_x to

0.98. This value is set to match the annual autocorrelation of consumption growth to the data (about 0.5). For simplicity, we set ρ_{xz} to 1. This reduces the number of shocks in the model to only one.

Preference parameters. We set the relative risk aversion and the intertemporal elasticity of substitution (IES) to 10 and 2, respectively. We utilize an IES which is greater than unity, consistent with recent empirical estimates (see e.g. Bansal et al. (2012), and Colacito and Croce (2011)). However, the IES parameter is important only because of the existence of a long-run risk component in productivity growth. We set the subjective time discount factor to 0.98, to target the level of the real risk free rate.

3.4 Model Results

We first present the implications of the calibrated multi-layer production model for aggregate macroeconomic and asset-pricing moments. In Subsection 3.4.2 we show the implications of the model for the cross-section of layers, and the TMB spread. We inspect the mechanism of the model and perform sensitivity analysis in Subsection 3.4.3. Lastly, to further illustrate the mechanism, we present the results of an extended model that features layer-specific technology shocks in Subsection 3.4.4.

3.4.1 Aggregate Macro and Pricing Moments

The calibrated model is solved using a third-order perturbation method. The first order conditions, and the required detrending are shown in the Appendix.

Table 7 compares aggregate moments of macroeconomic and return variables implied by the model with their empirical counterparts. The model-implied moments are computed from a simulated population path. Panel A reports summary statistics for consumption, output, and investment growth rates.

The growth rate of all macro quantities is roughly 2% per annum, consistent with the data. The volatility of consumption growth is 1.75% in the model versus 1.33% in the data. While the model-implied consumption volatility is somewhat larger than the data, it is still conservatively low, and consistent with a long-run sample estimate of consumption growth

Table 7: **Aggregate Moments: Model versus Empirical Equivalents**

Variable and Statistic	Model	Data	
	Panel A. Macroeconomic Variables		
Consumption growth:			
Mean (%)	1.94	1.97	[1.58, 2.35]
Standard deviation (%)	1.75	1.33	[1.11, 1.67]
Autocorrelation	0.45	0.52	[0.29, 0.75]
Output growth:			
Mean (%)	1.94	2.11	[1.60, 2.61]
Standard deviation (%)	2.13	1.74	[1.45, 2.18]
Autocorrelation	0.30	0.28	[-0.04, 0.60]
Investment growth:			
Mean (%)	1.94	1.74	[-0.22, 3.70]
Standard deviation (%)	3.26	6.83	[5.69, 8.53]
Autocorrelation	0.13	0.32	[0.13, 0.52]
	Panel B. Return Variables		
Excess Market portfolio Return:			
Mean (%)	4.13	4.89	[-0.20, 9.97]
Standard deviation (%)	5.10	17.70	[14.76, 22.11]
Autocorrelation	-0.01	-0.04	[-0.29,0.21]
Risk-free rate:			
Mean (%)	1.02	1.04	[0.51, 1.57]
Standard deviation (%)	0.90	1.84	[1.54, 2.30]

The table shows annual moments from simulated model data against their empirical counterparts. Panel A presents moments related to macroeconomic variables, and Panel B related to aggregate asset-prices. The model implied moments are obtained from a simulated population path of length 100,000. The empirical moments are based on annual data of a modern sample, 1964-2012 (we adopt the term "modern" from Campbell et al. (2017)). Consumption, output and investment growth rates are real and per-capita. The market portfolio is measured using CRSP value weighted returns. The real risk free rate corresponds to a three month T-bill rate net of expected inflation. Brackets represent empirical 95% confidence-intervals.

volatility.[22] The model implied volatility of output, 2.11%, falls inside the empirical 95% confidence interval.

Investment's volatility is larger than the volatility of consumption or output, in-line with the data, yet smaller than the data point estimate.[23] This low volatility does not stem from the capital adjustment costs, but rather from the value-weighted aggregation method. The

[22] In the period of 1930-2012, the volatility of consumption growth is 2.11%

[23] The model can be augmented with capital efficiency shocks to boost the volatility of aggregate investment. For parsimony, we refrain from doing so.

aggregate investment volatility is primarily driven by the low investment volatility of the largest layer, layer 0, which equals 3.05% per annum. Unlike a one-sector economy, in which output is used for both consumption and investment, in our model, the output of layer 0 is used for consumption purposes only.

Keeping consumption volatility low restricts the cash-flow variability of layer 0 and also its investment volatility. Importantly, computing an equally-weighted average of investment growth rate across the different layers yields annual volatility of 5.05%, much closer to the data. The volatility of investment growth for layers 3, 4, and 5 are 5.39%, 6.10% and 6.43%, respectively. These model-implied estimates are very close to the empirical counterpart(s). Since the upper layers have relatively small weights in the economy (consistent with the data), the value-weighted aggregation scheme attenuates investment volatility. The autocorrelation of consumption and output are 0.45 and 0.30 in the model, respectively. These are strikingly close the empirical estimates of 0.52 and 0.28, for consumption and output growth. The autocorrelation of investment growth falls inside the empirical 95% confidence interval.

The model also generates reasonable aggregate asset pricing moments. The equity premium in the model is levered by a factor of 5/3, to account for financial leverage. The model-implied equity premium equals 4.13% per annum, close to the empirical counterpart of 4.89%. One dimension in which the model deviates from the empirical evidence is the volatility of the market excess return. It is difficult to generate a high equity premium and a high volatility of stock returns in a general equilibrium production model (see related discussion in Gomes et al. (2003)). The non-trivial equity premium is generated through a considerable risk aversion of 10, along with a persistent growth-productivity component similar to Bansal and Yaron (2004) and Croce (2014).

The risk-free rate is about 1% per annum in the model and the data, with a very conservative annual volatility of 1%. The elasticity of intertemporal substitution intensifies the volatility of stock returns, while keeping low volatility for the risk-free rate.

3.4.2 Vertical Position and Cross-Sectional Return Implications

Stylized Fact I: model versus data. Our first stylized fact is a novel spread based on vertical position. The excess return spread between the top (layer 5) and bottom layers (layer 0) is about 105 bps per month, or 11.27% per annum (continuously compounded). Our model successfully replicates this sizable spread.

Table 8: **Vertical Position and Expected Return: Model versus Data**

	Model	Data	
Panel A. Excess returns by vertical position			
Layer 5	16.07	16.49	[11.89, 21.08]
Layer 4	12.01	11.86	[7.21, 16.52]
Layer 3	9.42	7.39	[3.13, 11.64]
Layer 2	7.15	6.40	[2.57, 10.23]
Layer 1	5.23	5.27	[1.81, 8.73]
Layer 0	3.59	5.22	[1.86, 8.58]
Panel B. Spreads			
spread (5-0)	12.49	11.27	[6.94, 15.60]
spread (5-4)	4.06	4.62	[0.12, 9.13]

The table presents excess returns and spreads in the model against their data equivalents. Panel A shows mean excess returns of firms at different vertical positions (layers). Panel B shows return spreads between layers 5 and 0 and layers 5 and 4. Layer 0 refers to the firm(s) that produce final consumption goods, while layer 5 refers to the firm(s) that produce capital goods in the top vertical position. The model excess returns are obtained from a simulated model path of length 100,000 years. The empirical excess returns are based on a monthly sample from 2003/11–2013/02, aggregated over a rolling window of 12 months to form continuously-compounded annual return observations. In brackets are the 95% empirical confidence interval.

Table 8 reports the model-implied average excess return of the different layers, against the empirical estimates. The model-implied return spread between layers 5 and 0 is 12.49% per annum. The spread is impressively large and falls inside the empirical confidence interval. The model-implied mean excess returns increase monotonically from layer 0 to layer 5, and for all layers, fall inside the 95% confidence interval of the data. The model generates excess returns for layers 1, 4, and 5 that are strikingly similar to the data.

Stylized Fact II: model versus data. Our second stylized fact is that the exposures of layer portfolios to aggregate productivity increase monotonically with the vertical position. We report the model-implied productivity betas against their empirical counterparts in Table OA.6 of the Online Appendix. The model-implied betas are obtained from a projection of excess returns onto simulated productivity growth, in an identical fashion to the data (Panel

A of Table 5). The model-implied betas exhibit the same pattern as the empirical exposures, and increase monotonically from layer zero to five. Quantitatively, the model-implied betas are of similar magnitude. For example, the productivity betas of layers zero and three are 1.32 and 2.34 in the model, compared to 1.21 and 2.53 in the data, respectively. While the quantitative fit is quite similar, the model-implied betas are larger than the empirical ones, as the model-implied return volatility is too low (see discussion in Section 3.4.1).

3.4.3 Inspecting the Mechanism: The Role of Vertical Creative Destruction

The TMB Spread. A positive productivity shock increases future consumption in the model. Under the benchmark calibration, which implies a preference for an early resolution of uncertainty, this reduces the marginal utility of the consumer. As a result, the productivity shock has a positive market price of risk. At the same time, the productivity betas of all layers are positive, and increase monotonically from layer 0 to layer 5. In other words, the sensitivity of the top layer to productivity innovations is larger than that of the bottom layer. Due to their higher exposure to aggregate risk, firms in a higher vertical position are riskier, and their valuations are more cyclical. Combining the pattern of exposures with the positive market-price of risk for aggregate productivity, firms in the top command a larger risk premium compared to bottom-layer firms, which gives rise to the TMB spread. The pattern of exposures across the layers is rationalized via vertical creative destruction, as explained below.

In the model, a positive productivity shock has a simultaneously two effects on firms valuations. On one hand, the shock increases the demand for firms' output for each layer. This leads to improved growth options, and to higher future cash flows. Such *demand effect*, which appreciates a firm's valuation following a positive shock, exists also in a single sector setup. However, a separate effect exists, which is novel to our supply chain environment. The same positive shock increases the productivity of the firm's direct and indirect suppliers. As a result, the supply curve of the firm's capital input shifts to the right. This *supply effect*, which we term vertical creative destruction, puts a downward pressure on the valuation of firms' installed capital. Technological advancements make the production of firms' capital input easier and cheaper, which erodes the marginal value of their assets-in-place.

A firm at the bottom of the production chain is subject the most to this vertical creative destruction force. The reason is that its existing capital is built using the capital goods produced by all the layers above it. As each of the intermediate capital goods becomes cheaper to produce, the supply effect propagates downwards cumulatively, and the value of the assets-in-place of the bottom-layer firm experiences the greatest downward pressure. By contrast, the firm at the top of the production chain has no suppliers, and is not subject to this creative destruction force.

Vertical creative destruction acts as a hedge, as it makes the sensitivity of a firm to productivity shocks less positive (i.e., it attenuated the positive demand effect). Since top-layer firms do not experience vertical creative destruction, their exposure to productivity is larger than that of bottom-layer firms. Firms in the middle layers experience some amount of devaluation to their installed capital, but it is smaller in magnitude compared to the bottom-layer firm (the cumulative supply effect is smaller). In all, the exposure to productivity is positive for all layers (due to the demand effect), but it increases monotonically with the layer (due to cumulative supply effect).

Example of the Mechanism. To illustrate the logic above, consider the following example of Nvidia and Amazon. Nvidia supplies Graphics Processing Units (GPUs) to Amazon for its Amazon Web Services (AWS), which is a cloud services platform. AWS uses Nvidia's GPUs to accelerate artificial intelligence and high performance computing workloads. For simplicity, assume that AWS is Amazon's only business and that Nvidia and Amazon are the only two firms in the supply chain, in a perfect competition setup. An economy-wide technological improvement should appreciate the value of Nvidia more than the value of Amazon. While the technological advancement increases the dividends for both firms, it has a vertical creative destruction effect only on Amazon. The price of the existing stock of GPUs deployed in Amazon's hyperscale data center, which is Amazon's installed capital, experiences devaluation pressure. The technological improvement means that it is easier for Amazon and its competitors to replace assets-in-place because they are now cheaper to produce. However, this vertical creative destruction argument does not apply to Nvidia, as it has no capital suppliers that can erode its existing capital stock. Thus, Nvidia has a higher exposure to the productivity shock than Amazon. This logic can be extended to the economy with more than two layers.

Analytical Illustration of the Mechanism. In Appendix A.3 we provide additional analytical illustration for vertical creative destruction. We show that the steady-state growth of Tobin's Q is larger for top firms compared to bottom firms, consistent with a larger cumulative supply effect for bottom-layer firms. We also provide steady-state analytical expressions for the sensitivities of layers to aggregate productivity, showing that the sensitivity rises with the layer.

Numerical Illustration of the Mechanism. The vertical creative destruction argument can be illustrated by observing how productivity shocks affect firms' Tobin's Q. Because of the constant returns to scale and perfect competition, Tobin's Q is a sufficient statistic for the ex-dividend firm value ($V_t^{ex} = Q_t \cdot k_{t+1}$). Table 9 reports the productivity elasticities of firms in layers 0 to 4. Consistent with the logic above, the table shows that productivity shock affects the Tobin's Q of the top layers more strongly than that of bottom layers.

An optimality condition for all layers stipulates that $Q_j = P_{j+1} \cdot \Phi'(i_j) \quad \forall j \in \{0..4\}$. The condition implies that the changes in Tobin's Q can be attributed to two separate channels: a change in the price of new capital (P_{j+1}) and a change in the capital installation costs (Φ'). Loosely speaking, the former is related to the value of firms' assets-in-place, while the latter is related to firms' rents and growth options.

Table 9 shows that a positive productivity shock increases the relative price of new capital inputs for all layers. This positive sensitivity is a result of a demand effect. However, the capital input price increases less strongly for the bottom layers. Again, this is a result of a more pronounced vertical creative destruction (or equivalently, a greater supply effect). In addition, productivity shocks induce firms in the top layers to invest more compared to bottom-layer firms. This is because the expected marginal revenue of capital is higher for the

Table 9: **Model Implied Productivity Elasticities By Vertical Position**

Layer j	$dlog(Q_j)/d\varepsilon_z$	$dlog(P_{j+1})/d\varepsilon_z$	$dlog(\Phi'(i_j))/d\varepsilon_z$	$d(i_j)/d\varepsilon_z \times 10$
4	0.058	0.016	0.042	0.128
3	0.052	0.014	0.039	0.126
2	0.045	0.012	0.034	0.122
1	0.036	0.009	0.028	0.107
0	0.025	0.005	0.021	0.081

The table presents slope coefficients (b) of the following projection, using a simulated model path: $dY_{j,t} = const + b \cdot \varepsilon_t + error$, where $Y_{j,t}$ is a model-implied variable of interest of vertical layer j, and ε_t is the aggregate productivity shock. The first column shows the appropriate j layer index number. The variable $Y_{j,t}$ is either the logarithms of layer-j's (detrended) Tobin's Q, (detrended) capital input price P_{j+1}, marginal cost of new capital $\Phi'(i_j)$, or investment rate i_j. All results are based on a simulated path of length 100,000 periods.

former firms, as their output price appreciates more. Thus, firms at the top of the production chain face a greater increase in capital installation costs (Φ'). This further enhances their Tobin's Q. The pattern implied by the model for Tobin's Q sensitivity to productivity shock across layers is consistent with the empirical evidence presented in Table 5.

Input Price Cyclicality. Table 9 shows that the input prices for all layers are procyclical: they rise in response to a positive productivity shock. Importantly, even the input price of downstream firms is procyclical, though less procyclical than that of upstream firms. The procylicality pattern implied by our model is broadly consistent with empirical evidence by Kogan et al. (2018), who document that input prices are strongly procyclical, and more sensitive to aggregate shocks than shipped goods prices (which affect primarily downstream firms and consumers).

Sensitivity Analysis. In Appendix OA.3 we perform sensitivity analysis of the model's results to key parameters. We demonstrate that the only parameter which is qualitatively important for the sign of the TMB spread is the elasticity of intertemporal substitution, which needs to be greater than unity. Other parameters, such as the existence of a long-run risk in productivity, or the magnitude of adjustment costs are only important quantitatively. In particular, the TMB spread does not hinge on capital adjustment costs: the spread is larger than the benchmark in the absence of these costs. Intuitively, without adjustment cost firms derive their entire valuation from assets-in-place (the weight of growth options is zero). As assets-in-place is the firm's component that is subject to vertical creative destruction, the spread is amplified. For a similar reason, the spread is amplified when the depreciation parameter drops.

CAPM α. In the model, all layers of production are affected by a common productivity shock. Our modeling choice to rely on a single shock is for parsimony. Nevertheless, the unconditional CAPM does not hold in the model because valuations are non-linear in the underlying shock. The non-linear effect is explained by the fact that the beta of firms to aggregate productivity is time-varying.[24] We find that the levered CAPM α in the model is 6.7% percent per year, which is about 52% of the spread. This is sizable considering that our model features only a single shock, and suggests that the non-linear effects in the model are quantitatively large. The CAPM alpha as a percentage of the overall model-implied spread can be further boosted when the model features layer-specific shocks. For instance, in an extension of the model described in Section 3.4.4, each layer of production is subject to its own orthogonal productivity shock. In that model extension, and in the absence of adjustment costs, the ratio between the CAPM alpha and the model-implied TMB spread is about 70%. It is important to stress that in the presence of layer-specific shocks even the conditional CAPM fails to explain the model-implied spread.

The Value Premium. In the model, value firms, i.e., firms with a larger ratio of assets-in-place to total firm value (V_{AIP}/V), or a larger ratio of detrended capital to market value, have higher expected returns, in-line with the existence of a value premium. This happens because the steady-state detrended (stationary) Tobin's Q drops with the vertical position, and higher vertical position implies a higher risk premium. In the model, firms with higher vertical position hire less (on average), which all else equal implies a larger marginal productivity of labor. The relative output price, which is positively related to the Tobin's Q of the layer below, must fall with the vertical position to equalize the marginal revenue of

[24] To see this, note that the firm's beta is a function of the derivative of the capital adjustment costs function. Since the model features convex adjustment costs, and the investment rate varies over time, betas for each layer are not constant.

labor across the layers.

In Section 4.2, we demonstrate an interesting interaction between the TMB spread and the value premium. The TMB spread is larger for value firms. This is because for these firms a larger fraction of firm value is obtained from assets-in-place, the component subject to creative destruction. Relatedly, we document a novel stylized fact in Section 4.3: the value premium is nullified *within* in the bottom layers of production (i.e., layers zero and one). This empirical finding suggests that while value firms are generally riskier than growth firms, this is not the case for firms that operate at the bottom layers of production, where the force of vertical creative destruction is the strongest.[25]

3.4.4 Layer-Specific Shocks: Dissection of the Mechanism

For parsimony, our baseline model features a single shock. To better illustrate the mechanism, we consider a variation of the model in which the production function of each layer is driven by a layer-specific technology shock (i.e., $Y_{j,t} = Z_{j,t} k_{j,t}^{\alpha} n_{j,t}^{1-\alpha}$, for $j \in \{0..N\}$, where all Z_j shocks are orthogonal). Our purpose in this section is twofold. First, we show that the the existence of the TMB does not hinge on the existence of a single aggregate productivity shock. Second, we illustrate the vertical creative destruction mechanism through the exposure of firms to supplier- and customer- firms' innovations.

For simplicity, we calibrate the drift and the volatility of all layer-productivity Z_j shocks to the same value as that of aggregate productivity in the benchmark model. All layer-specific shocks are systematic, and carry a risk-premium in equilibrium. We obtain that the model-implied TMB spread is still positive and sizable, 4.37% per annum. This spread can be boosted by raising only the volatility of shocks to upper layers, while keeping consumption's volatility low.

The existence of the TMB spread in the layer-specific shock model stems from the same vertical creative destruction mechanism that applies to the baseline model. Importantly,

[25] Our model does not feature firm-level heterogeneity within layers. Each layer is populated by a single representative firm. As such, in the current version of the model, the value premium is well-defined across layers, but not within layers. We leave the quantitative exploration of the stylized fact presented in Section 4.3 to future research.

it does not hinge qualitatively on featuring long-run risks. To illustrate the mechanism, Table 10 reports the exposure of the firm in each layer j to the productivity shock of layer k ($\beta_{j,k} = E\left[\frac{\partial V_{j,t}}{\partial \varepsilon_{z,k,t}}\right]$ for $j, k \in \{0..N\}$, where $\varepsilon_{z,k,t}$ is the productivity shock experienced by firms in layer k at time t).

Table 10: **Exposures of Firms to Layer-Specific Technology Shocks**

Layer index (j)	$\beta_{j,5}$	$\beta_{j,4}$	$\beta_{j,3}$	$\beta_{j,2}$	$\beta_{j,1}$	$\beta_{j,0}$	$\sum_{k=0}^{5} \beta_{j,k}$
5	0.0485	0.0339	0.0420	0.0937	0.2562	1.7000	2.1743
4	-0.1242	0.1001	0.0788	0.1091	0.2599	1.7000	2.1237
3	-0.0172	-0.1102	0.1089	0.1217	0.2595	1.7000	2.0627
2	-0.0023	-0.0155	-0.1002	0.1420	0.2565	1.7000	1.9805
1	-0.0003	-0.0018	-0.0121	-0.0798	0.2474	1.7000	1.8533
0	-0.0000	-0.0003	-0.0014	-0.0069	-0.0298	1.7000	1.6616

The table reports the exposure of firms in different layers to layer-specific technology shocks. The results are based on a variation of the benchmark model in which the production function of each layer is driven by a layer-specific shock (i.e., $Y_{j,t} = Z_{j,t} k_{j,t}^{\alpha} n_{j,t}^{1-\alpha}$, for $j \in \{0..N\}$, where all Z_j shocks are orthogonal). The calibration of the layer-specific shock model is identical to that of the benchmark model, except for shutting down long run risks (i.e., $\phi_x = 0$). Row j shows the exposures of the firm in layer j to the productivity shock that originates from layer k, where k varies with the columns (that is, $\beta_{j,k}$, $j, k \in \{0..N\}$). The right-most column reports the summation all layer-specific shock betas for each layer ($\sum_{k=0}^{5} \beta_{j,k}$).

Note that $\beta_{j,k} < 0$ iff $j < k$. Put differently, if the shock originates from a direct or an indirect supplier, the firm has a *negative* exposure to it. This is consistent with the notion that an suppliers' shocks shift the supply curve of the firm's capital input to the right, which puts a downward pressure on the valuation of its installed capital. Suppliers' shocks induce vertical creative destruction as it becomes cheaper to replace the firm's assets in place. By contrast, we obtain that $\beta_{j,k} > 0$ iff $j \geq k$. This is consistent with an increased demand effect coming from a direct or an indirect customer of the firm. Notice that due to the network effect, the supply (demand) effect is stronger when the shock originates from a firm's direct supplier (customer), diminishes when it originates from a firm's supplier of supplier (customer of customers), and diminishes even further for higher-order suppliers (customers). That is, $|\beta_{j,\ell}| - |\beta_{j,k}| > 0$ if $k < \ell < j$ or if $k > \ell > j$. To illustrate the cumulative effect of all shocks, the last column in Table 10 sums up the exposures of each layer to all layer-specific technology shocks. If one assumes the correlation between the layer-specific shocks is one, this summation captures (in a comparative static manner) the exposure of the firm to aggregate productivity. Consistent with our benchmark model, the implied aggregate productivity beta, monotonically increases with the vertical position.

4 Testing the Mechanism: Model Predictions and Novel Implications

We perform several tests for the vertical creative destruction mechanism. First, we examine the impact of market power on the TMB spread and the stock return of the bottom-layer firms. Second, we split the firms in each layer into subsamples based on the book-to-market equity ratio, depreciation rate, organization capital, or stock of inventory, demonstrating that the TMB spread is larger for firms whose assets-in-place represent a larger fraction of firm value. Lastly, we study the effect of vertical creative destruction on the value premium.

4.1 The Role of Monopolistic Competition

Our benchmark model features perfect competition. Since vertical creative destruction stems from competitors' ability to replace assets-in-place at a lower cost, this effect is likely to be strongest in an environment with perfect competition. To study how firms' market power affects the TMB spread, we augment the benchmark model to account for monopolistic competition. The model is presented in Appendix (OA.4). The main prediction of the model is that the TMB spread is higher if firms or their suppliers face higher competition.

To test this prediction, we develop a new measure of supply chain competition. The FactSet Revere relationships dataset allows us to identify each firm's competitors at any point in time, reported either by the firm itself or by its competitors. We use this data to construct a novel measure of competition that takes into account not only a firm's own competition environment, proxied by the number of competitors, but also the competition faced by its direct and indirect suppliers.[26] Further details about the construction of this measure are

[26] We define our supply chain competition measure as: $\hat{\mathbf{C}}_t = \mathbf{C}_t + \sum_{j=1}^{J} \lambda^j \bar{\mathbf{S}}_t^j \mathbf{C}_t$, where $\mathbf{C}_t$ is an n by 1 column vector that measures the number of each firm's competitors in month t, $\hat{\mathbf{C}}_t$ is an n by 1 column vector that measures each firm's supply chain competition, $\bar{\mathbf{S}}_t$ is a customer-supplier adjacency matrix normalized by the number of suppliers that each customer has. The $\lambda < 1$ parameter discounts the importance of the competition faced by a firm's direct and indirect suppliers relative to the competition faced by the firm itself.

given in Online Appendix section OA.5. Using this measure of supply chain competition, we split firms in each layer into two subsamples. The high (low) competition subsample includes firms with a measure higher (lower) than the median of its layer. The comparison between these two subsamples allows us to test augmented model's main predictions.

4.1.1 TMB spread: high competition vs. low competition

We examine the TMB spreads in the high and low competition subsamples. To compare the empirical results to the model, we consider two choices for the value of μ, the parameter in our augmented model that characterizes the degree of competition: (i) a high competition calibration, $\mu = 100$, implying a markup of 1%, and (ii) a low competition calibration: $\mu = 3$, implying a markup of 33%. These numbers are consistent with the empirical estimates of markups (see, e.g., Bilbiie et al. (2012)). The results are reported in Table 11.

The TMB spread drops when firms have more market power both in the model and in the data. The empirical spread for the high competition subsample is 9.97% per annum, while for the low competition subsample it is only 4.63%.[27] The model-implied spread for these subsamples is qualitatively and quantitatively similar to the data. Specifically, for the high competition calibration, the model-implied TMB spread is 12.15%, while for the low competition calibration, the spread is 7.9%. In addition, in both the model and the data, the spread between the return of layers 5 and 4 is positive and sizable under the high competition subsample, but much smaller, and even negative, under the low competition subsample.

We set λ to 0.9 in the benchmark case.

[27] In untabulated results, we further confirm this finding using equally weighted portfolios. In fact, the difference between the high and low competition subsample TMB spreads is more pronounced using equally weighted returns. For the high competition group, the TMB spread is 15% per annum, while for the low competition group, it is merely 5.9%.

Table 11: **Vertical Position, Competition, and Expected Return: Augmented Model versus Data**

	High Competition			Low Competition		
	Model	Data		Model	Data	
Panel A. Excess returns by vertical position						
Layer 5	16.14	15.21	[10.10, 20.32]	16.26	11.10	[3.48, 18.72]
Layer 4	12.85	10.18	[5.64, 14.72]	16.13	14.10	[8.37, 19.83]
Layer 3	10.31	8.29	[4.36, 12.22]	14.86	6.44	[1.64, 11.25]
Layer 2	7.96	5.28	[1.90, 8.66]	13.03	8.65	[3.54, 13.76]
Layer 1	5.86	4.67	[1.28, 8.07]	10.80	6.18	[1.40, 10.95]
Layer 0	3.98	5.25	[2.01, 8.48]	8.37	6.47	[2.08, 10.86]
Panel B. Spreads						
spread (5-0)	12.15	9.97	[5.30, 14.64]	7.90	4.63	[-2.08, 11.34]
spread (5-4)	3.29	5.04	[1.27, 8.80]	0.13	-3.00	[-7.52, 1.51]

The table presents excess returns and spreads in the model against their data equivalents, for both high and low competition subsamples. Panel A shows mean excess returns of firms at different vertical positions (layers). Panel B shows return spreads across layers 5 and 0 and layers 5 and 4. Layer 0 refers to the firm(s) that produce final consumption goods, while layer 5 refers to the firm(s) that produce capital goods in the top vertical position. In the model the high competition results are based on a calibration in which $\mu = 100$ (implying a markup of 1%), while the low competition results are based on a calibration in which $\mu = 3$ (implying a markup of 33%). The model excess returns are obtained from a simulated model path of length 100,000 years. The empirical excess returns are based on a monthly sample from 2003/11–2013/02, aggregated to form annual observations over the past 12 months. Brackets represent 95% confidence-intervals for the data moments. The empirical measure of competition is described in Section OA.5.

Model-implied excess returns fall inside the empirical 95% confidence interval for returns of all the layers in the high competition subsample and in all, but one, layers in the low competition subsample.

The results show that the TMB spread declines when the firm and its suppliers have greater market power. There are two driving forces behind this result. First, keeping the market power of a firm's suppliers constant, vertical creative destruction weakens as the firm's own monopolistic power increases. The intuition is as follows. Under perfect competition, firms' valuations are determined by the cost of replacing their capital stock (Tobin's Q). Under monopolistic competition, however, valuations also depend on monopolistic rents. The benefits arising from technological improvements are not eroded as much by competition. For downstream firms that possess monopolistic power, a technological improvement decreases the cost of investment and increases their rents. This positive cash-flow effect operates against the negative effect on the value of assets-in-place.

Second, keeping a firm's market power constant, vertical creative destruction is weakened when its suppliers' market power increases. When suppliers of a certain firm have a higher degree of monopolistic power, it has a rationing effect on the production of these suppliers. In other words, in response to a positive productivity shock, the suppliers increase their output less than under the perfect competition case. Consequently, the supply of the firm's capital input does not rise as much, weakening the vertical creative destruction.

4.1.2 Competitiveness of Suppliers and Stock Returns

As discussed above, greater market power of suppliers makes downstream firms more exposed to the productivity shocks. Thus, we expect a positive relation between the market power of a firm's direct and indirect suppliers and its own stock return. To test this novel prediction of our augmented model, we split the bottom-layer firms, which belong to consumer staples and consumer discretionary sectors, into five groups based on the average number of competitors of their direct and indirect suppliers (up to five layers).[28] Group 1 represents firms with the most competitive suppliers, while group 5 represents firms with the least competitive suppliers.

We focus on the bottom-layer firms in this test for three reasons. First, according to the model, firms at the bottom layer are most affected by vertical creative destruction and therefore, focusing on this layer increases the power of our test. Second, this sort does not depend on the vertical position measure, as all the sorted firms belong to consumer staples and consumer discretionary sectors. Lastly, our sort generates portfolios with around 200 firms each, assuring that the test is based on a large sample.

Consistent with our model prediction, Table 12 shows that the value-weighted return of bottom-layer firms increases from group 1 to group 5. The spread between these two groups is 4.37% per annum, significant at the 5% level. This finding suggests that firms whose suppliers face more competition have excess returns significantly lower than firms whose

[28]This measure is the same as the measure in footnote 26, but without a firm's own number of competitors. Formally, $\hat{\mathbf{C}}_t^S = \sum_{j=1}^{J} \lambda^j \bar{\mathbf{S}}_t^j \mathbf{C}_t$.

suppliers face less competition. It provides support for the prediction that firms with a more competitive supply chain are subject to stronger vertical creative destruction, and therefore, are less exposed to productivity shocks and earn lower returns.

Table 12: **Bottom Layer Return and Supply Chain Competition**

	Most competitive				Least competitive		
Layer Zero Group	(1)	(2)	(3)	(4)	(5)	(5) - (1)	t[(5)-(1)]
$E(R^e)$	4.32	5.06	5.71	6.71	8.69	4.37**	(2.48)

We split the firms in the bottom layer (consumer discretionary and consumer staples sectors) into five groups based on the average number of competitors of a firm's direct and indirect suppliers (up to five layers). Group 1 (5) represents firms with the most (least) competitive supply chain. We report the annualized continuously compounded excess returns for each portfolio. The results are based on a monthly sample from 2003/11–2013/02, aggregated over a rolling window of 12 months to form annualized returns. The last column reports Newey-West t-statistic for the return spread between group 5 and group 1. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

4.2 The Importance of Assets-in-Place for Vertical Creative Destruction

In this subsection we test the mechanism by exploring the cross-sectional variation in the book-to-market equity ratio, depreciation rate, organization capital and inventory. These firm characteristics are proxies for the weight of assets-in-place in firm value, and therefore, are related to the intensity of vertical creative destruction.

Book-to-Market Ratio and Depreciation. Since vertical creative destruction affects the value of assets-in-place, its effect should be stronger when assets-in-place account for a larger fraction of firm value. This implies that the TMB spread should be larger for value firms than for growth firms, and that it should be larger for firms with a lower capital depreciation rate.

We confirm this intuition using the model in Section OA.3. Column (5) of Table OA.1 shows that the TMB is larger than in the benchmark case when we lower the depreciation rate. Column (6) of Table OA.1 shows that when adjustment costs are lowered, the spread rises. These results imply that whenever firms derive a larger fraction of their valuation from assets-in-place, the spread is magnified. Naturally, when the depreciation rate is lower, the weight of assets-in-place in firm value is higher. To see how the weight of assets-in-place is related to adjustment costs, note that capital adjustment costs prevent firms from reaching the optimal capital stock immediately, which generally leads to a higher growth option component in the firm value. We define the value of a firm's assets-in-place as the value of all future dividends resulting from the existing capital stock, which only depreciates over time: $V_{j,AIP,t} = \max_{n_{j,t}} \quad P_{j,t} Z_t k_{j,t}^{\alpha} n_{j,t}^{1-\alpha} - w_t n_{j,t} + (1-\delta) E[M_{t,t+1} V_{j,AIP,t+1}] \quad \forall j \in \{0..N\}$. We confirm that the ratio between $V_{i,AIP,t}$ and total firm value $V_{i,t}$ increases as the capital adjustment costs parameter ϕ drops. In the extreme case of zero adjustment costs, firms under perfect competition derive their entire valuation from assets-in-place. Column (6) of Table OA.1 shows that in this case, the spread is 17.69%, which is 5.2% higher than in the benchmark case (12.49%).

Table 13 presents evidence in support of these predictions. In Panel A of the table, we split firms in each layer into two subsamples of equal size based on the book-to-market equity ratio, computed using the annual Compustat database. Consistent with the model prediction, the value-weighted and equal-weighted TMB spreads for the high book-to-market sample (i.e., value firms) are 11.9% and 16.0%, respectively, while the same spreads are only 8.2% and 3.1%, respectively, for the low book-to-market sample (i.e., growth firms).

In Panel B of Table 13, we split firms in each layer into two equal-sized groups by the capital depreciation rate (defined as the ratio of annual depreciation to the sum of annual depreciation and the net PP&E (property, plant & equipment) at the fiscal year end). While the difference in the equal-weighted TMB spread is small between the low depreciation and the high depreciation samples (10.7% vs. 9.1%), the value-weighted TMB spread in the low depreciation sample exceeds the spread in the high depreciation sample by 8.0% (14.0% vs. 6.0%), consistent with the model's prediction.

Organization Capital. Eisfeldt and Papanikolaou (2013) distinguish between two types of capital: physical capital and intangible capital coming from key talent (Organization Capital). Since organization capital is associated with *highly specialized* labor input, common innovation of suppliers should have no effect on its valuation. In other words, as organization capital is not provided as an input along a supply chain, it is not subject to the vertical

Table 13: **Sample Split by Book-to-Market, Depreciation, Organization Capital, and Inventory**

	Value-weighted		**Equal-weighted**		**Value-weighted**		**Equal-weighted**	
	Panel A. Book-to-market split				Panel B. Depreciation split			
	Book-to-market		Book-to-market		Depreciation rate		Depreciation rate	
	Low	High	Low	High	Low	High	Low	High
Layer 5	13.50	15.91	5.21	19.56	18.95	10.81	13.55	12.14
Layer 4	10.05	11.39	1.49	11.37	12.65	8.90	8.65	3.96
Layer 3	4.40	9.06	0.64	9.75	7.51	4.12	8.51	1.91
Layer 2	3.97	8.86	0.46	7.93	6.63	2.57	6.47	2.02
Layer 1	4.88	5.45	3.14	4.77	5.80	3.13	4.13	3.68
Layer 0	5.32	4.03	2.14	3.51	4.94	4.79	2.87	3.06
TMB	8.18	11.87	3.07	16.05***	14.01*	6.02	10.68**	9.08**
t-stat	(1.23)	(1.59)	(0.68)	(3.08)	(1.92)	(1.27)	(2.2)	(2.07)
	Panel C. Organization capital split				Panel D. Inventory split			
	Organization capital		Organization capital		Inventory		Inventory	
	Low	High	Low	High	Low	High	Low	High
Layer 5	13.45	5.49	16.11	7.63	14.54	15.48	6.99	17.73
Layer 4	13.61	8.00	0.73	13.32	8.35	14.42	1.93	10.83
Layer 3	6.91	7.69	5.33	5.07	8.84	5.26	5.26	4.83
Layer 2	6.61	4.35	4.34	4.22	4.82	7.33	2.41	6.05
Layer 1	4.23	6.77	3.31	4.69	5.19	4.27	4.18	3.66
Layer 0	4.16	6.03	1.12	5.18	5.78	3.47	1.52	4.41
TMB	9.30**	-0.54	14.99***	2.44	8.76	12.01**	5.47	13.33**
t-stat	(2.34)	(-0.04)	(4.15)	(0.27)	(1.28)	(1.99)	(1.17)	(2.52)

This table reports the annualized continuously compounded excess returns by vertical position for different subsamples. Firms in each layer are split into two subsamples of equal size based on the book-to market equity ratio (Panel A), depreciation rate (Panel B), organization capital (Panel C), or inventory (Panel D). The results are based on a monthly sample from 2003/11–2013/02, aggregated over a rolling window of 12 months to form annualized returns. Newey-West t-statistics for the TMB portfolio are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

creative destruction. We therefore hypothesize that the TMB spread should be lower for firms that are more heavily endowed with organization capital.

To test this hypothesis, we follow the method of Eisfeldt and Papanikolaou (2013) to construct a measure of organization capital using the Compustat database.[29] We then split

[29]Specifically, we use SG&A (selling, general & administrative) expenses to measure flows to organization capital, and estimate the stock of organization capital recursively using the perpetual inventory method. We first estimate the initial stock of organization capital in year 2000 using Equation (36) in Eisfeldt and Papanikolaou (2013), and we then update it annually by cumulating the deflated value of

firms in each layer into two equal-sized portfolios based on the estimated organization capital index. The TMB spreads for these two subsamples are reported in Panel C of Table 13. Consistent with our hypothesis, for low organization capital firms, the value-weighted TMB spread is large and statistically significant (9.3%), while for high organization capital firms it is slightly negative and indistinguishable from zero (-0.54%). The equal-weighted TMB spread is also economically and statistically significant (15%) for low organization capital subsample and insignificant (2.44%) for high organization capital subsample.

Inventory. Similarly to the stock of physical capital, the stock of inventory carried by the firm is also subject to vertical creative destruction. Therefore, our model implies that the TMB spread should be greater among firms that carry more inventory. To test this prediction, we split firms in each layer into two subsamples based on the layer's median ratio of inventory to firm value. Panel D of Table 13 report the TMB spread for both subsamples. Consistent with our conjecture, the TMB spread is 12.0% (value-weighted) or 13.3% (equal-weighted) for the high inventory subsample, statistically significant at the 5% level, but it is insignificant in the low-inventory subsample.

As an additional test, we examine the monotonicity of layer returns within each subsample. Table 13 shows that for both value-weighted and equal-weighted portfolios, monotonicity is present in the high book-to-market subsample (Panel A), the low depreciation subsample (Panel B), and with one or two exceptions, the low organization capital subsample (Panel C) and the high inventory subsample (Panel D). However, monotonicity is much weaker in the low book-to-market, high depreciation, and high organization capital subsamples. Consistent with our hypothesis, the monotonic pattern of returns is much stronger in subsamples that are more exposed to vertical creative destruction.[30]

SG&A expenses and deducting depreciation, using Equation (35) in their paper. We adopt their benchmark parameter values. Furthermore, to account for the differences in accounting practices across industries, we follow their procedure to group firms into 17 industries (based on the Fama-French industry classification), and rank them on their ratio of organization capital to book assets relative to their industry peers. Each firm is then assigned an organization capital index (from 1 to 10) based on its rank within the industry.

[30]The individual layer returns also show which layers are responsible for the amplification or the attenuation of the TMB spread in each subsample. We might expect bottom layer returns to differ the most in each split because bottom-layer firms are most affected by the vertical creative destruction. However, one has to take into account that the baseline average returns are not the same across subsamples. For instance, without the

4.3 Within-Layer Value Premium

In this subsection we examine a novel implication of vertical creative destruction for a well-documented asset pricing phenomenon: the value premium. Numerous studies have found that value firms, i.e., firms with a high book-to-market equity ratio, offer higher stock returns. Consistent with the existing literature, Table 14 shows that over our sample period, the value premium for the full sample is positive and amounts to 3.7% per annum (based on value-weighting scheme). Interestingly though, when we restrict attention only to the firms that belong to the bottom layers (layers zero and one), the value premium flips signs, shrinks significantly to -2.3%, and is no longer statistically significant. By contrast, the value premium for the upper layers (layers two to five) is 10.1% per annum, and significant at the 1% level. In simple terms, we find that value premium is concentrated in upstream firms, and that for final consumption good producers and their *direct* suppliers, there is no premium associated with a high book-to-market ratio. This is a striking finding, given that layers zero and one together contain over 1,700 firms.

Table 14: **Within-Layer Value Premium: Bottom versus Upper layers**

	Value-weighted		Equal-weighted	
	HML	t-stat	HML	t-stat
Full Sample	3.72*	(1.07)	8.32**	(2.53)
Upper Layers ($vp \in \{2..5\}$)	10.07***	(2.71)	14.64***	(4.25)
Bottom Layers ($vp \in \{0..1\}$)	-2.29	(-0.61)	2.21	(0.61)

This table shows the annualized value premium for various samples: (1) the full sample, (2) a sample that includes firms that belong to the bottom two layers only, and (3) a sample that includes firms that belong to the upper most four layers. Within each sample, firms are split into five quintiles based on the book-to-market equity ratio. The value premium is estimated as the time series average of the return difference between the top quintile and the bottom quintile (HML = High book-to-market (top 20%) minus Low book-to-market (bottom 20%) within each sample of firms). Newey-West t-statistics are in parentheses.

The result of a lower value premium among firms closer to consumers is not specific to our sample period. We find a similar finding using the consumption sector (durables, nondurables and services) identified by Gomes et al. (2009), over a much longer period (from 1963/07

effect of vertical creative destruction, bottom-layer returns in the high book-to-market subsample should be higher than in the low book-to-market subsample. Once the effect of vertical creative destruction is added, the bottom-layer returns can look similar in both subsamples.

to 2013/02). In this time period, the value premium in the consumption sector is 3.49% per annum. This is significantly lower, both economically and statistically, than the value premium in all other sectors: 6.90% per annum.[31]

While we acknowledge that there are multiple factors that can contribute to this empirical pattern, this finding is consistent with the effect of vertical creative destruction. Assume that for reasons that are outside our model, assets-in-place are riskier than growth options (see e.g. Zhang (2005), Ai and Kiku (2013)). That is, for an average firm, the exposure of its assets-in-place to productivity shocks is larger than the exposure of its growth options. This assumption naturally gives rise to a value premium. However, our logic suggests that for firms that are further down in the supply chain, which are affected the most by vertical creative destruction, the exposure of assets-in-place to productivity shocks is mitigated substantially. Vertical creative destruction acts as a hedge for the assets-in-place component of firm value, and this mitigating effect is strongest for firms in the bottom layers. In principle, the effect of vertical creative destruction can be sufficiently large for those bottom-layer firms, such that the sensitivities of growth options and assets-in-place to productivity are roughly the same. As a result, the value premium shrinks (and even vanishes) within the bottom layers.

5 Discussion of Alternative Explanations

In this section, we consider several alternative explanations for the TMB spread.

Familiarity hypothesis. Firms that are further away from consumers in the production chain may be less familiar to investors and therefore, suffer from more severe information asymmetry and illiquidity. However, in Table 1, we find no significant difference in the bid-ask spread or the dispersion of earnings forecasts by financial analysts across layers,

[31] The value premium for each sector is calculated as the spread between the portfolio of firms in the top quintile of the book-to-market equity ratio and the portfolio of firms in the bottom quintile. We choose July 1963 as the starting point because there are only a small number of firms in Compustat that have book equity information prior to fiscal year 1962. We identify consumption goods producers using the SIC code-based classification developed by Gomes et al. (2009) instead of the Global Industry Classification Standard (GICS) because historical SIC codes are available from CRSP. GICS was developed in 1999, and we only have the most recent GICS code for each firm.

suggesting that top-layer firms are not more opaque than other firms. Furthermore, institutional ownership is actually lower in upper layers than in lower layers, suggesting that retail investors do not shy away from upstream firms due to lower familiarity.

Financial and Operating Leverage. Higher returns for firms with higher vertical position may be caused by higher leverage. However, Table 1 shows that there is no significant difference in financial leverage between the top and bottom layers. Furthermore, top-layer firms actually have significantly lower operating leverage than bottom-layer firms. Therefore, the TMB spread cannot be explained by financial or operating leverage.

Profitability and Asset Growth. Recent studies established that expected stock returns are positively related to profitability and negatively related to the asset growth rate (see e.g. Novy-Marx (2013), Belo et al. (2014), Hou et al. (2015)). However, Table 1 shows that top-layer firms have lower profitability and higher asset growth than bottom-layer firms. Therefore, the TMB spread cannot be explained by the q-factor model designed to capture risks associated with these firm characteristics.

Network Centrality. Firms at different vertical positions could differ in their centrality. Ahern (2013) finds that industries with higher network centrality have higher returns. However, the last column in Table 1 reports that firms in upper layers have significantly lower eigenvector centrality than those in lower layers, and that firms in layer one have the highest centrality. The centrality of layer 0 is an order of magnitude higher than the centrality of the top layer. Since the top layer has considerably lower centrality than the bottom layer, we cannot attribute the TMB spread to centrality.

The Bullwhip Effect. Due to forecasting errors that accumulate upward following a change in consumer demand, the top of the supply chain may face greater uncertainty in response to demand shocks than the bottom layer. This amplification in demand uncertainty is coined the "bullwhip effect" (Lee et al. (1997)). To the best of our knowledge, the bullwhip effect literature does not make any predictions regarding the risk premia of firms at different supply-chain positions. A potential implication of the bullwhip effect is that upstream firms should experience greater inventory turnover volatility. We therefore check empirically the relation of inventory turnover volatility to vertical positions and to risk premia. We first compute inventory turnover for each firm in our sample, defined as the ratio of sales to the average stock of inventory in the current and the previous quarters. We then use the past 12 quarters to compute firms' inventory turnover volatility. In untabulated results, we confirm that firms with higher vertical position have higher volatility of inventory turnover. This is broadly consistent with the bullwhip effect. However, greater inventory turnover volatility does not imply a higher risk premium in the data. We sort firms into five portfolios each quarter based on their lagged inventory turnover volatility, using a long sample from 1978 to 2013. The return spread between the high and low inventory turnover volatility portfolios is insignificant under the value-weighted scheme, and negative under the equal-weighted scheme. The results are the same if we use only the 2003-2013 sample period.[32]

We conclude that none of the five alternative explanations we considered is able to generate the TMB spread. While it is not possible to rule-out every potential explanation for our empirical findings, it is important to note that any alternative explanation needs to account for all of the following empirical regularities *jointly*: (1) the TMB spread; (2) the monotonic pattern in returns across vertical positions; (3) the monotonic betas with respect to the aggregate productivity; (4) higher TMB spread for high competition supply chains, for firms with higher book-to-market ratio, with lower depreciation, with lower organizational capital, and with higher inventory; (5) positive relation between downstream firms' returns and their direct and indirect suppliers' market power. The vertical creative destruction explanation is not only consistent with all these facts, but also is able to match the TMB spread quantitatively.

[32]While there may be other implications for the bullwhip effect, it is important to note that it cannot explain numerous related empirical facts that we document: for instance, that the TMB spread is higher for firms with low organizational capital, or that bottom-layer firms' return drop with the number of competitors of their direct and indirect suppliers.

6 Empirical Robustness

6.1 Robustness of the TMB Spread

We conduct several robustness checks to confirm that the TMB spread is statistically and economically robust to alternative methods of forming portfolios and computing vertical position. The results are reported in Online Appendix Table OA.8. In columns (1) and (2) we sort firms into portfolio using their vertical positions at a lower frequency than in the benchmark case (once a quarter or a year, respectively). Lower frequency sorting results in an even higher spread, and improved t-statistics. This is not surprising given the persistence of the assigned vertical positions. In column (3) we sort firms into portfolios at the beginning of every month t, based on the vertical position computed at the end of month $t-4$, as opposed to $t-2$ in the benchmark implementation. This permits more time for the relationship information to be absorbed in stock priced (although the database is updated daily). Again, the results are materially unchanged.

In the benchmark case we define a firm's vertical position as the minimum distance between the firm and firms in the bottom layer (see equation 1). In column (4) of Table OA.8, we compute vertical positions using the median distance between the firm and firms in the bottom layer. Under this alternative measure, the TMB spread is 77 basis points, significant at 10 percent level, and the spread between the top layer and layer one is 92 basis points, significant at the 5% level.[33] This suggests that the minimum-based vertical position measure is not crucial to obtain the spread. Lastly, in column (5) of Table OA.8 we reduce the number of layers from six to five. All firms with a vertical position of four or above are assigned to the top production layer. Consequently, the top layer includes more than a hundred firms. In this case, the top minus bottom spread is quantitatively smaller, but still positive and statistically significant at the 10% level. This is consistent with the model prediction that also exhibits a smaller spread when the number of layers decreases. The spread between layer 5 and layer 1 is statistically significant at the 5% level, stressing the the TMB spread is mainly a spread *within* the investment sector.

[33]The top portfolio includes all firms with a median vertical position above eight.

In the Online Appendix, Table OA.10, we assign firms into layers only once based on each firm's first observation of vertical position, and keep firms' portfolio assignment constant throughout the sample period. Qualitatively, we still obtain a monotonically increasing pattern between average returns and vertical position. The TMB spread is 41 basis point per month, yet we lose significance. This highlights that the vertical position is largely a persistent measure, yet its time-variation warrants a dynamic sorting strategy.

We also verify in untabulated results that the spread exists when we exclude the energy and materials sectors, or when we use only producers of durable goods as the bottom layer.

6.2 Relation to Other Risk Factors and Spreads

Next, we demonstrate that the TMB spread is a novel empirical finding, as it is unexplained by existing spreads/factors. We consider five well-known factor models: the classic CAPM, the Fama and French (1993) three-factor model, the Carhart (1997) four-factor model, the Hou et al. (2015) q-factor model, and the Kogan and Papanikolaou (2014) IMC factor. The results are reported in the first five columns of Table 15. The alpha of the spread is mostly not affected by controlling for the factors, and it is still positive and statistically significant at least at the 10% significance level.[34] Qualitatively, the TMB portfolio has positive betas with respect to the market excess return, and to the HML, SMB, and MOM factors. It has a significantly negative loading on the investment factor of the q-factor model (I/A). The loading on the investment-minus-consumption (IMC) factor of Kogan and Papanikolaou (2014) is significantly positive, which is to be expected because the bottom layer consists of consumption good producers. However, the alpha of the TMB portfolio is still economically and statistically significant, suggesting that the TMB spread is distinct from the IMC factor. We stress that the TMB spread is mostly within the investment sector, instead of a spread between the investment and consumption sectors. In all, the TMB spread cannot be explained by usual unconditional factor models.

[34] All alphas are significant at the 1% level if we do annual rebalancing (see Table OA.9 in the Online Appendix). If we use equal-weighted portfolios, most alphas are significant at the 1% level (see Table OA.7 in the Online Appendix).

Table 15: **Time series regressions of the TMB portfolio return**

	(1)	(2)	(3)	(4)	(5)	(6)
Rm-Rf	0.078	0.016	0.097	0.007	-0.280*	
	(0.68)	(0.11)	(0.69)	(0.05)	(-1.98)	
SMB		0.261	0.211	0.348		
		(1.02)	(0.84)	(1.37)		
HML		0.008	0.119			
		(0.03)	(0.52)			
MOM			0.227**			
			(2.04)			
I/A				-0.917**		
				(-2.56)		
ROE				-0.069		
				(-0.25)		
IMC					0.784***	
					(3.94)	
DMN						0.042
						(0.49)
Constant	1.010*	0.993*	0.952*	1.100**	1.167**	1.058**
	(1.98)	(1.93)	(1.88)	(2.15)	(2.42)	(2.08)
R^2	0.004	0.014	0.051	0.072	0.128	0.002

This table presents the results of the time series regressions of the value-weighted TMB spread on various risk factors and the durable-nondurable spread. The TMB portfolio is constructed by longing the value-weighted portfolio of companies with a vertical position of five or above, and shorting a value-weighted portfolio of companies with a vertical position of zero. The returns are computed from November 2003 to February 2013. Rm-Rf is the excess return of the market portfolio. SMB and HMB are the size (small-minus-big) and book-to-market (high-minus-low) factors in the Fama and French (1993) three-factor model, and MOM is the momentum factor in the Carhart (1997) four-factor model. I/A and ROE are the investment and profitability factors, respectively, in the q-factor model of Hou et al. (2015). IMC is the investment-minus-consumption factor in the Kogan and Papanikolaou (2014) two-factor model. DMN is the return difference between the portfolio of durable goods producers and the portfolio of nondurable goods and service producers. Both IMC and DMN are constructed based on Gomes et al. (2009). T-statistics are reported in parentheses. Significance at the 5% and 10% levels are indicated by ** and * respectively.

In addition, we examine whether our TMB spread simply reflects the durable-nondurable spread (DMN) studied by Gomes et al. (2009). The last column of Table 15 shows the result of a univariate regression, where the TMB spread is regressed on the DMN. It reveals that these two spreads are largely orthogonal to each other.[35]

[35]Both the IMC factor (Kogan and Papanikolaou (2014)) and the DMN spread (Gomes et al. (2009)) are based on industry classification derived from the benchmark Input-Output tables compiled by the Bureau of Economic Analysis. We construct sector portfolios (consumption vs. investment, durable vs. nondurable & service) using the industry classification table developed by Gomes et al. (2009), and use the value-weighted

Our risk-based explanation for the TMB spread, detailed in Section 3, relies on a single factor: aggregate productivity. Our explanation implies an important caveat for the interpretation of Table 15. We do not set out to claim that the TMB spread represents a new risk factor, nor do we intend to claim that it represents evidence for mispricing. As such, the significance of alphas is not our main interest. It is only meant to show that the TMB spread is unexplained existing spreads/factors. The TMB spread is important to the extent that it informs us about previously undocumented relation between average returns and the vertical dimension of the economy, and to the extent that its large magnitude imposes a quantitative challenge. Moreover, the evidence in Section 2.3 shows that the spread *can* be explained by exposures to aggregate productivity, which arise endogenously in our model. Existing factor models fail to fully explain the spread as they do not account for non-linearity, and they are noisy approximations for the underlying productivity shock(s).

6.3 The Importance of Intra-Sectoral TMB Spread

The TMB spread based on BEA I-O data, or based on the layer-mimicking industry portfolios, does not capture return spreads that exist between firms with different vertical positions that belong to the same industry.[36] Such return differential can be substantial, and partly account for the lower spread reported in Table 4. To illustrate this point, we check and confirm that the TMB spread exists within the three largest non-consumption sectors in our sample: Industrials (GICS=20), Health Care (GICS=35), Information Technology (GICS=45). For each sector, we restrict the sample only to firms that belong to the specific GICS code, and examine the return difference between firms with the highest vertical position (layer 5) and those with the lowest (layer 1). In untabulated resulted, we find that the TMB spread in each of these sectors is over 90 bps per month. This result qualitatively stresses

returns of these portfolios to estimate the time series of IMC and DMN. We thank Motohiro Yogo for making this table available. We also thank Ken French and Chen Xue for making their factor data available.

[36]At the end of our sample period, a median within-industry dispersion in the vertical position, defined as max(VP)-min(VP), is one at the 6-digit NAICS level (310 industries). It increases to three at the 2-digit NAICS level (22 industries). For ten percent of industries at the six (two) digits NAICS level, the dispersion is as high as three (five). Lastly, the mean standard deviation of the vertical position within the 6-digit NAICS level is half of the standard deviation across firms.

the importance of the intra-industry component of the benchmark TMB spread.

7 Conclusion

We use the novel FactSet Revere database of supplier-customer relationships to dynamically measure the vertical position of each firm in the production network. We sort firms into portfolios based on their vertical positions. Comparing the returns of these portfolios, we document two stylized facts: (1) firms at a higher vertical positions (further up from producers of consumption goods) have higher expected returns; and (2) the exposure of firms with higher vertical position to aggregate productivity is greater. The spread between the top and the bottom layer portfolios is 105 basis points per month, during the period for which FactSet Revere's data is available. In a longer sample that starts in the 70's, we confirm that the inter-industry TMB spread is sizable using BEA input-output tables. We also confirm that the TMB spread is still significant using industry-based layer-mimicking portfolios starting at 1945. The TMB spread is not explained by common risk factors and known cross-industry spreads.

We provide a risk-based explanation of this new finding using a quantitative general equilibrium model with multiple layers of production. The model suggests that firms at a lower vertical position have endogenously lower exposure to aggregate productivity shocks compared to firms at a higher vertical position. While firms at all layers of production derive a direct benefit from improved productivity, this benefit is attenuated by a downward supply pressure on the value of assets-in-place (i.e., vertical creative destruction). Following an aggregate improvement in productivity, bottom layer firms are most affected by the vertical creative destruction because their capital is produced by all the layers above them. As a result, these firms are less risky than the top layer firms because their exposure to the aggregate productivity shock is attenuated the most. This intuition is further confirmed in a model with layer-specific productivity shocks.

We provide several empirical checks to test the predictions of this theory. A strong support for our theory stems from studying the interaction between vertical creative destruction and the degree of competition in the supply chain. We document two empirical patterns that are consistent with an augmented model that features monopolistic competition. First, we empirically show that the TMB spread is smaller for the sample of firms that belong to supply chains with less competition. Second, we document a new stylized fact: consumption goods producers whose direct and indirect suppliers have more market power earn higher expected returns.

We also show that the TMB spread is greater for firms that derive a larger fraction of their value from assets-in-place, as this is the component that is subject to vertical creative destruction. Specifically, the TMB is larger for value firms, low depreciation firms, low organization capital firms, and firms with high inventory. Moreover, we find a novel and striking implication of vertical creative destruction for the value premium: the value premium is smaller within firms in the bottom of the production chain. Vertical creative destruction lowers the exposure of assets-in-place to productivity shocks, and it has the greatest quantitative effect for bottom-layer firms. Consequently, even though value firms are generally more risky than growth firms, this is not the case for bottom-layer firms.

Overall, we document a number of novel stylized facts that connect firms' supply chain characteristics, namely upstreamness and suppliers' competitiveness, to firms' risk profiles. Vertical creative destruction can explain these facts quantitatively, suggesting its economic importance for explaining differences in risk premia across the cross-section of firms.

A Appendix

A.1 Vertical Position Computation Using Input-Output Tables

We compute vertical positions from Make and Use tables using two steps, as described next. Let N_t be the number of industries considered by the BEA analysis at year t, and let C_t be the number of commodities considered. The dimension of the Make table, denoted by M_t, is $N_t \times C_t$. The dimension of the Use table, denoted by U_t, are $C_t \times (N_t + 1)$. The first N_t columns of the Use table capture the dollar flow of a commodity into each industry (as an input), whereas the last column shows the flow of the good for consumption.

The first step to compute industries' vertical position at time t, is to normalize the Use and Make tables such that the sum of elements in each row is one, as follows:

$$\tilde{M}_{j,i,t} = \frac{M_j, i, t}{\sum_{k=1}^{C_t} M_{j,k,t}}, \quad \forall i \in \{1..N_t\}, j \in \{1..C_t\},$$
$$\tilde{U}_{i,j,t} = \frac{U_i, j, t}{\sum_{k=1}^{N_t+1} U_{i,k,t}}, \quad \forall i \in \{1..N_t\}, j \in \{1..C_t\}.$$

The element (j, i) in $\tilde{M}_t$ captures the share of commodity i produced by industry j. Likewise, the element (i, j) in $\tilde{U}_t$ captures the share of commodity i used by industry j. That share takes into account that some amount of the commodity flow may also be used for final consumption. Further information about the Use and Make tables, the procedures to filter the data and to construct the share tables is detailed in Online Appendix OA.1.

Let $\tilde{U}_{C_t \times N_t}$ be the first N_t columns of $\tilde{U}$. If entire row i in this sub-matrix is zero, then commodity i is used strictly for consumption. Any industry that produces solely this commodity should have the lowest vertical position (i.e., it belongs to the bottom-most layer of production). If the sum of elements in row i in matrix $\tilde{U}_{C_t \times N_t}$ is positive, then the commodity is used for intermediate stages of production by other industries. Thus, any industry producing this commodity, perhaps along with other commodities, should have a vertical position above the lowest score.

The second step involves combining the information from the shares matrices of Make and Use to form upstreamness scores. Following Antràs et al. (2012), we compute upstreamness as follows:

$$\tilde{VP}_t^{Ind} = (I_{N_t \times N_t} - \tilde{M}_{N_t \times C_t} \cdot \tilde{U}_{C_t \times N_t})^{-1} \iota, \tag{A.1}$$

where $\tilde{VP}_t^{Ind}$ is a $N_t \times 1$ vector of industries' upstreamness scores at time t, I is the identity matrix, and ι is an $N_t \times 1$ vector of ones. The minimal value in vector $\tilde{VP}_t^{Ind}$ is 1, but the maximal value is unbounded. As we are using Make and Use tables from different years, there is a significant variation in the maximum values. For portfolio formation, and for meaningful comparison between years, it is important to keep the vertical positions score of different years on the same scale. Thus, we define industries' vertical position, VP_t^{Ind} at time t, as a linear transformation of the upstreamness score $\tilde{VP}_t^{Ind}$:

$$VP_t^{Ind} = A \cdot \frac{\tilde{VP}_t^{Ind} - min(\tilde{VP}_t^{Ind})}{max(\tilde{VP}_t^{Ind}) - min(\tilde{VP}_t^{Ind})}, \tag{A.2}$$

where VP_t^{Ind} is an $N_t \times 1$ vector of (normalized) vertical positions. The transformation ensures that the minimal vertical position score is 0 and the maximal one is a scalar $A-1$. For comparison with our baseline results we set $A = 5$ such that the maximal vertical position is four.

A.2 Equilibrium Conditions

For an economy with $N+1$ layers, there are $5N+4$ endogenous variables, denoted by: $n_{j,t} \quad (\text{for } j \in \{0..N\}), k_{j,t+1}, Q_j, i_j \quad (\text{for } j \in \{0..N-1\}), P_{j,t} \quad (\text{for } j \in \{1..N\}), W_t, C_t$, and M_t. The first-order conditions are given by:

$$W_t = (1-\alpha) P_{j,t} Z_{j,t} k_{j,t}^{\alpha} n_{j,t}^{-\alpha} \quad \forall j \in \{0..N\}, \tag{A.3}$$

$$Q_{j,t} = \Phi'(i_{j,t}) P_{j+1,t} \quad \forall j \in \{0..N-1\}, \tag{A.4}$$

$$Q_{j,t} = E\left[M_{t,t+1}\left(P_{j,t+1} Z_{j,t+1} \alpha k_{j,t+1}^{\alpha-1} n_{j,t+1}^{1-\alpha} - P_{j+1,t+1}\Phi(i_{j,t+1}) + (1-\delta+i_{j,t+1}) Q_{j,t+1}\right)\right] \quad \forall j \in \{0..N-1\}, \tag{A.5}$$

where the capital of the top layer N is fixed to unity, and $Q_{j,t}$ is the Lagrangian multiplier on the law of motion for capital of layer j for period t. In total, there are there are $5N+4$ model equations: the above first-order conditions, along with $N+1$ labor market clearing equation (12), N capital markets clearing equations given by (13), consumption good clearing (14), N capital law of motions (5), and the household SDF (11). We normalize $P_{0,t} = 1$ as a numeraire. We demonstrate how to detrend the model and obtain a stationary equilibrium in Section OA.2 of the Online Appendix.

A.3 Analytical Steady-State Analysis

In this section we assume that each layer of production $j \in \{0..N\}$ is subject to a layer-specific productivity shock denoted by $Z_{j,t}$. We set N to 5, in-line with the benchmark calibration. In the deterministic steady state, one can show using the trend expressions in

Section OA.2 that the growth in Tobin's Q, $\Delta Q_j \equiv Q_{j,t+1}/Q_{j,t}$, is given by:

$$\Delta Q_0 = \Delta Z_0 \Delta Z_1^{\alpha-1} \Delta Z_2^{\alpha^2-\alpha} \Delta Z_3^{\alpha^3-\alpha^2} \Delta Z_4^{\alpha^4-\alpha^3} \Delta Z_5^{\alpha^5-\alpha^4} \tag{A.6}$$

$$\Delta Q_1 = \Delta Z_0 \Delta Z_1^{\alpha} \Delta Z_2^{\alpha^2-1} \Delta Z_3^{\alpha^3-\alpha} \Delta Z_4^{\alpha^4-\alpha^2} \Delta Z_5^{\alpha^5-\alpha^3} \tag{A.7}$$

$$\Delta Q_2 = \Delta Z_0 \Delta Z_1^{\alpha} \Delta Z_2^{\alpha^2} \Delta Z_3^{\alpha^3-1} \Delta Z_4^{\alpha^4-\alpha} \Delta Z_5^{\alpha^5-\alpha^2} \tag{A.8}$$

$$\Delta Q_3 = \Delta Z_0 \Delta Z_1^{\alpha} \Delta Z_2^{\alpha^2} Z_3^{\alpha^3} \Delta Z_4^{\alpha^4-1} \Delta Z_5^{\alpha^5-\alpha} \tag{A.9}$$

$$\Delta Q_4 = \Delta Z_0 \Delta Z_1^{\alpha} \Delta Z_2^{\alpha^2} \Delta Z_3^{\alpha^3} \Delta Z_4^{\alpha^4} \Delta Z_5^{\alpha^5-1} \tag{A.10}$$

Equations (A.7) - (A.10) illustrate the effect of productivity shocks on the steady-state growth of the Tobin's Q for different production layers (without accounting for risk premia, of course). Notice that for these steady-state values, $\frac{\Delta Q_\ell}{\partial \Delta Z_k} < 0$ whenever $k > \ell$.

Corollary. *A positive productivity shock from layer $k \in \{0..N\}$ decreases (increases) installed capital's value growth of layer $\ell \in \{0..N-1\}$ iff $k > \ell$ ($\leq \ell$).*

The corollary above demonstrates the vertical creative destruction argument at the steady-state. When a shock originates from a production layer below a given layer, the higher demand operates to appreciate the value of installed capital. However, when a shock originates from a production layer above a given layer (i.e. a supplier, or a supplier of suppliers), it triggers vertical creative destruction which erodes the value of existing capital stock. The creative destruction of a shock originating in layer k on the value growth of layer $\ell < k$ diminishes in the absolute distance between the layers $|k - \ell|$, at a constant rate of α, the capital share of output.

We now turn to formalize the notion that production layers having higher vertical position have a greater sensitivity to aggregate productivity. Since the DSGE model does not admit a closed-form solution, we analyze the betas at the (deterministic) steady-state. We make further simplifying assumptions, only for analytical tractability.

Assumption A1. The productivity shock of all production layers are perfectly correlated, as in the benchmark model: $Z_{j,t} = Z_t \quad \forall j \in \{0..N\}$;

Assumption A2. There are no adjustment costs: $\phi = 1$;

Assumption A3. ΔZ_t is i.i.d. with steady-state value greater than one.

Proposition. *Let $j \in \{0..N-1\}$. Under assumptions A1-A3, the exposure to aggregate productivity of layer's j ex-output return, evaluated at the steady-state, $\beta^{ex}_{j,ss}$, falls with j.*

Proof. Without loss of generality we assume $N = 5$ as in the benchmark case. By constant returns to scale, one can write the value of a firm in layer $j \in \{0..N-1\}$ as: $V_{j,t} = d_{j,t} + Q_{j,t}k_{j,t+1}$. Plugging the expression for dividend, and capital's law of motion yields:

$$\begin{aligned}V_{j,t} &= Y_{j,t} - W_t n_{j,t} - i_{j,t}k_{j,t}P_{j+1,t} + Q_t((1-\delta)k_{j,t} + i_{j,t}k_{j,t}) \\ &= Y^*_{j,t} + Q_{j,t}k_{j,t}(1-\delta),\end{aligned}$$

where the second equality follows from the fact that $Q_{j,t} = P_{j+1,t}$ in the absence of adjustment costs, and $Y^*_{j,t} = \max_{n_{j,t}} Y_{j,t}(n_{j,t}) - W_t n_{j,t}$. We denote $Y^*_{j,t}$ as the net output of layer j at time t (that is, output net of wage payments). We also define $V^{ex}_{j,t} = V_{j,t} - Y^*_{j,t}$. The ex-net output return of layer j is given by:

$$R^{ex}_{j,t} = \frac{V^{ex}_{j,t}}{V_{j,t-1} - d_{j,t-1}} = \frac{Q_{j,t}k_{j,t}(1-\delta)}{Q_{j,t-1}k_{j,t}} \approx (1-\delta)\Delta Q_{j,t}.$$

Since ΔZ_t is i.i.d., it follows that $\beta^{ex}_{j,t} = \frac{\partial R^{ex}_{j,t}}{\partial \varepsilon_{z,t}} \propto \frac{\partial \Delta Q_{j,t}}{\partial \Delta Z_t}$. From equations (A.7) - (A.10), one obtains that:

$$\Delta Q_{0,ss} = \Delta Z_{ss}^{\alpha^5}, \tag{A.11}$$

$$\Delta Q_{1,ss} = \Delta Z_{ss}^{\alpha^4+\alpha^5}, \tag{A.12}$$

$$\Delta Q_{2,ss} = \Delta Z_{ss}^{\alpha^3+\alpha^4+\alpha^5}, \tag{A.13}$$

$$\Delta Q_{3,ss} = \Delta Z_{ss}^{\alpha^2+\alpha^3+\alpha^4+\alpha^5}, \tag{A.14}$$

$$\Delta Q_{4,ss} = \Delta Z_{ss}^{\alpha+\alpha^2+\alpha^3+\alpha^4+\alpha^5}. \tag{A.15}$$

Define the ex-output steady-state beta as $\beta^{ex}_{j,ss} \propto \frac{\partial \Delta Q_{j,ss}}{\partial \Delta Z_{ss}}$. Since the exponent of ΔZ_{ss} in equations (A.11) - (A.12) increases monotonically from layer 0 to layer 4, and since $\Delta Z_{ss} > 1$ it is straightforward to obtain that $\beta^{ex}_{j,ss}$ increases with j. $\square$

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Online Appendix

OA.1 Further Details on Vertical Position Computation Using Use/Make Tables

We use the Make and Use Tables for years 2007, 2002, 1997, 1992, 1987, 1982, and 1977. For each year, we remove in the Use and Make tables industries that relate to the local, state and federal Government (S001–S007), as well as Other Services (NAICS 81). The final consumption usage of each commodity (i.e., column $N_t + 1$ in the use table) is taken from Personal Consumption Expenditures column in the BEA Use files (F01000 or 910000). In case that the sum of a particular row in the use matrix U_t is zero, we use a row of zeros in the respective use share table $\tilde{U}_t$. When computing the use share table $\tilde{U}_t$, if a particular industry supplies more than 90% of its output to itself (i.e. $\tilde{U}_t(i,i) > 0.9$), we exclude it from the table. We apply this filtering, as such industries are almost completely disconnected from the rest of the economy (i.e., close to an autarky industry). Including such industries in the vertical position computation not only generates an extreme vertical position score for the industry itself, but also artificially elevates the vertical position for other industries that supply to it, directly or indirectly. As part of the vertical position scores, we multiply the the use and make share matrices (see equation A.1). Denote the $N_t \times N_t$ multiplication matrix by Δ_t (i.e. $\Delta_t = \tilde{M}_{N_t \times C_t} \cdot \tilde{U}_{C_t \times N_t}$). For each row i in this Δ_t matrix, if a certain element indexed by (i,j) is less than 1% (i.e., the amount transferred from industry i to industry j is negligible) we set it to zero, but then reallocate that small amount into all other non-zero entries of row i. This allows us to filter noise in the input/output tables and to focus the analysis on economically meaningful inter-industry flows. We use the data provided by the BEA to map between I-O codes of industries into NAICS codes (for 1997, 2002, and 2007 tables), and to map between I-O codes of industries into SIC codes (for 1977-1987 tables). For years 1997-2007, when assigning vertical positions for firms, we first try to match a firm's 6-digit NAICS code to a 6-digit NAICS industry for which vertical position is available (the success of this matching depends on the granularity of the input/output tables). If no such vertical position was found, we try to match the firm's 5-digit NAICS code to an available industry. If no match was found we turn to the 4-digit code, and so on, up to the 2-digit code. Similarly, for the years 1977-1987 we first try to match firms to 4-digit SIC code industries, and if no match was found we use the 3-digit code or the 2-digit code, in that order. We consider only stocks with share codes 10, 11 or 12.

OA.2 Model Detrending

In this section we assume that each layer of production $j \in \{0..N\}$ is subject to a layer-specific productivity shock denoted by $Z_{j,t}$. We set N to 5, in-line with the benchmark calibration. We demonstrate how to detrend the model for this general case. In the benchmark case in which all productivity shocks are perfectly correlated, as in the main text of this paper, the equations below still hold by replacing $Z_{j,t} = Z_t \quad \forall j \in \{0..N\}$.

Define capital trends as:

$$\tau_{k4,t} = Z_{5,t} \tag{OA.1}$$

$$\tau_{k3,t} = Z_{4,t} Z_{5,t}^{\alpha} \tag{OA.2}$$

$$\tau_{k2,t} = Z_{3,t} Z_{4,t}^{\alpha} Z_{5,t}^{\alpha^2} \tag{OA.3}$$

$$\tau_{k1,t} = Z_{2,t} Z_{3,t}^{\alpha} Z_{4,t}^{\alpha^2} Z_{5,t}^{\alpha^3} \tag{OA.4}$$

$$\tau_{k0,t} = Z_{1,t} Z_{2,t}^{\alpha} Z_{3,t}^{\alpha^2} Z_{4,t}^{\alpha^3} Z_{5,t}^{\alpha^4} \tag{OA.5}$$

Let the price trends be:

$$\tau_{p5,t} = Z_{0,t} Z_{1,t}^{\alpha} Z_{2,t}^{\alpha^2} Z_{3,t}^{\alpha^3} Z_{4,t}^{\alpha^4} Z_{5,t}^{\alpha^5 - 1} \tag{OA.6}$$

$$\tau_{p4,t} = Z_{0,t} Z_{1,t}^{\alpha} Z_{2,t}^{\alpha^2} Z_{3,t}^{\alpha^3} Z_{4,t}^{\alpha^4 - 1} Z_{5,t}^{\alpha^5 - \alpha} \tag{OA.7}$$

$$\tau_{p3,t} = Z_{0,t} Z_{1,t}^{\alpha} Z_{2,t}^{\alpha^2} Z_{3,t}^{\alpha^3 - 1} Z_{4,t}^{\alpha^4 - \alpha} Z_{5,t}^{\alpha^5 - \alpha^2} \tag{OA.8}$$

$$\tau_{p2,t} = Z_{0,t} Z_{1,t}^{\alpha} Z_{2,t}^{\alpha^2 - 1} Z_{3,t}^{\alpha^3 - \alpha} Z_{4,t}^{\alpha^4 - \alpha^2} Z_{5,t}^{\alpha^5 - \alpha^3} \tag{OA.9}$$

$$\tau_{p1,t} = Z_{0,t} Z_{1,t}^{\alpha - 1} Z_{2,t}^{\alpha^2 - \alpha} Z_{3,t}^{\alpha^3 - \alpha^2} Z_{4,t}^{\alpha^4 - \alpha^3} Z_{5,t}^{\alpha^5 - \alpha^4} \tag{OA.10}$$

Lastly, the trend of final consumption goods is given by:

$$\tau_{c,t} = Z_{0,t} Z_{1,t}^{\alpha} Z_{2,t}^{\alpha^2} Z_{3,t}^{\alpha^3} Z_{4,t}^{\alpha^4} Z_{5,t}^{\alpha^5} \tag{OA.11}$$

Covariance-stationary first-order conditions can be achieved by rescaling the non-stationary variables of the model as follows: (1) Divide $k_{j,t}$ by $\tau_{kj,t-1}$, for $j \in \{0..4\}$; (2) Divide $P_{j,t}$ and $Q_{j-1,t}$ by $\tau_{pj,t-1}$, for $j \in \{1..5\}$; (3) Divide C_t and W_t by $\tau_{c,t-1}$.

After plugging the rescaled variables in the first-order equations, the equilibrium conditions can be written using stationary quantities.

OA.3 Sensitivity Analysis

In this subsection we demonstrate that the TMB spread is *qualitatively* robust to most calibration parameters. We point out the quantitative importance of the parameter choices.

Table OA.1: **Sensitivity Analysis to Model Parameters**

	(1) Benchmark Calibration	(2) IES = 1.1	(3) IES = 0.9	(4) LR-Vol=0; SR-Vol=1.8%	(5) $\delta = 0.05$	(6) No Adj. Costs
Mean Excess Returns (%)						
Layer 5	16.07	3.84	1.20	0.87	17.27	19.12
Layer 4	12.01	3.43	1.34	0.86	14.52	5.71
Layer 3	9.42	3.17	1.40	0.84	10.39	4.23
Layer 2	7.15	2.91	1.50	0.82	7.32	3.52
Layer 1	5.23	2.64	1.64	0.78	5.02	2.61
Layer 0	3.59	2.36	1.86	0.72	3.29	1.43
Spread (5-0)	12.49	1.49	-0.66	0.15	13.98	17.69
Mean Returns (%)						
Market Portfolio	4.13	2.40	1.82	0.75	3.85	1.94
Risk-free rate	1.02	3.57	5.12	4.40	1.13	0.67
Consumption Growth						
Mean (%)	1.94	1.79	1.98	1.94	2.01	1.99
Standard deviation (%)	1.74	1.94	1.98	1.74	1.73	1.80

The table presents summary model results using different calibrations. The left most column shows the variable of interest. Column (1) presents results from the model under the benchmark calibration. Columns (2) - (6) present results from the model calibrated using the same parameters as in the benchmark case, other than the parameter(s) specified right below the column number. In Column (2) the IES parameter ψ is set to 1.1. In Column (3) the IES parameter is set to 0.9. In Column (4) the long-run volatility is set to zero, and the short-run volatility is raised to 1.8%. In Column (5) the capital depreciation rate δ is reduced to 5%. In Column (6) the capital adjustment cost parameter ϕ is set to 1 (no adjustment costs). All model implied moments are based on a simulated population path of length 100,000 periods.

The Role of IES. Column (1) of Table OA.1 shows the summary model statistics for a model with a similar calibration to the benchmark case, except that the IES parameter, ψ, is reduced to 1.1 (still above unity). The drop in the elasticity of intertemporal substitution parameter raises the level of the risk-free rate and drops the level of the equity premium compared to the benchmark case. Importantly, the spread in the returns between layers 5 and 0 is still positive, but diminished in magnitude to 1.49%. Intuitively, a lower IES implies that firms invest less in response to long-run productivity shocks, which attenuates their productivity betas. Column (2) of Table OA.1 shows the results when the IES parameter is dropped below the unity threshold to 0.9. In that case, the spread between the layer 5 and layer 0 excess returns turns negative. When the IES is less than unity, the income effect dominates the substitution effect. In response to a productivity news shock, the household desires to increase consumption strongly. The productivity news shock acts as a positive demand shock for the final goods, but less so for intermediary goods (that is, saving or capital goods). This positive demand shock diverts resources to firms at bottom layers. The capital installation costs become larger for these bottom layer firms, increasing their Tobin's Q and making them more sensitive to productivity shocks.

The Role of Long-Run Productivity. In Column (3) of Table OA.1 we report the results when we shut down the long-run productivity news shocks ($\phi_x = 0$). To keep consumption growth volatility constant at the benchmark case level, we simultaneously raise the short-run production volatility σ_z to 1.8%. In this case, consumption growth volatility remains 1.74% per annum. However, the equity premium is diminished to only 0.75% per annum. Similarly, the spread between layer 5 and layer 0 remains positive, but it is only 0.15%. As shown in Croce (2014), short-run productivity shocks do not induce firms to invest largely enough, which implies positive yet low productivity betas. Introducing a persistent component to the growth of aggregate productivity, as in the benchmark case, causes firms to react more strongly to technology news (so long as the substitution effect dominates), and amplified betas.

The Role of Depreciation Rate. Creative destruction in the model puts a downward pressure on the valuation of installed capital stock of customer firms. Thus, the creative destruction channel has a stronger quantitative bite when capital depreciates more slowly, and the stock of existing capital has a persistent impact on future periods. Put differently, with a lower depreciation rate the relative importance of assets-in-place out of firm value rises, which is the component that is subject to the creative destruction mechanism. In line with this intuition, column (3) of Table OA.1 shows that the spread is amplified when the depreciation rate is reduced from 10% in the benchmark case to 5%. In untabulated results we show that the reverse is also true: with higher depreciation rates, the importance of the capital stock is diminished, and the spread gets smaller. However, as long as the depreciation is not full (i.e., $\delta = 1$), creative destruction is still at work, and the TMB spread survives. This is important given the fact that in principle, some suppliers sell intermediate goods, which can be viewed as a form of capital that depreciates faster. To see how the results may change if we interpreted our capital good as an inventory, we raise the depreciation rate to 20%. This value is consistent with the findings of Richardson (1995) and Jones and Tuzel (2013) that noninterest inventory carrying costs, which are equivalent to depreciation, vary from 19% to 43% per annum. We find that the (local) sensitivity of the spread to the δ parameter is relatively small. Under a depreciation rate of 20% the spread drops by a small amount to 12.00% per annum.

The Role of Capital Adjustment Costs. Column (6) of Table OA.1 presents the results when there are no capital adjustment costs ($\phi = 1$). Without adjustment costs, the spread between layers 5 and 0 is still positive and very sizable. The creative destruction channel, which is the primary force behind our benchmark result, is amplified in the *absence* of adjustment costs. Notice that without adjustment costs, the TMB spread is higher than the benchmark calibration (17.69% versus 12.49%). The spread is now too large compared to the data. In addition, the average market excess return drops to only 1.94%, and the excess return for the firm in the bottom layers is counterfactually low (about 1.4%).

The intuition behind this result is that in the absence of adjustment costs, a larger fraction of firms' value comes from assets-in-place. Since assets-in-place is the component that is subject to the creative destruction force, the spread is amplified. To see that, note that in a prefect competition model, firms earn rents from positive productivity shocks (that is, have higher growth option component) due to the existence of capital adjustment costs.

The adjustment costs are in essence an installation costs that create a wedge between the price of new uninstalled capital goods and the marginal value of installed capital (Tobin's Q). This wedge boosts Tobin's Q and generates rents. To formalize this idea, we define the value of a firm's assets-in-place as the value of all future dividends resulting from the existing capital stock, which only depreciates over time:

$$V_{j,AIP,t} = \max_{n_{j,t}} \quad P_{j,t} Z_t k_{j,t}^{\alpha} n_{j,t}^{1-\alpha} - w_t n_{j,t} + (1-\delta) E[M_{t,t+1} V_{j,AIP,t+1}] \quad \forall j \in \{0..N\}.$$

We then define the weight of assets-in-place for a firm j as the ratio between $V_{j,AIP,t}$ and the total firm value $V_{j,t}$. In the benchmark calibration the average weight of assets-in-place is 52% across the layers. As the capital adjustment cost parameter ϕ drops to 1 in Column (6), the ratio becomes 100% in the limit. In other words, in column (6) firms look more like "value" firms compared to the benchmark case, which enhances the spread.[37]

OA.4 An Augmented Model with Monopolistic Competition

We now present an augmented model that accommodates monopolistic competition.

Aggregate productivity has the same dynamics as those described in Section 3.1.1. The household side of the economy is identical to that described in Section 3.1.3. Unlike the perfect competition model, we now assume that each production layer $j \in \{0..N\}$ is populated by a mass of differentiated intermediate good producers, indexed by $m \in [0,1]$. The output of an intermediate good producer in layer j at time t of variety m is denoted by $y_{j,t}(m)$. Its output price is $p_{j,t}(m)$.

Aggregators. In each layer j, an aggregator converts the layer's intermediate goods into a final composite layer good, $Y_{j,t}$, using a CES production function:

$$Y_{j,t} = \left[\int_0^1 y_{j,t}(m)^{\frac{\mu_j - 1}{\mu_j}} dm \right]^{\frac{\mu_j}{\mu_j - 1}}, \tag{OA.12}$$

when $\mu_j \to \infty$, the intermediate good producers of the j-th layer face perfect competition. For any finite μ_j, the intermediate good producers are not perfect substitutes, and they possess some amount of monopolistic power.

[37]The intuition for the decline in the equity premium in column (6) is straightforward. By excluding adjustment costs, productivity shocks are absorbed in how much the firms invest (that is, in quantities), as opposed to being absorbed in prices. This allows the firms to smooth their dividends more easily, making their valuations less volatile. As a result, the equity risk premium drops.

The j^{th} layer aggregator faces perfect competition in the product market. It solves:

$$\max_{\{y_{j,t}(m)\}} \quad P_{j,t}Y_{j,t} - \int_0^1 p_{j,t}(m)y_{j,t}(m)dm$$
$$\text{s.t equation (OA.12).}$$

The above implies that the price index in layer j is given by $P_{j,t} = \left[\int_0^1 p_{j,t}(m)^{1-\mu_j}dm\right]^{\frac{1}{1-\mu_j}}$. The demand schedule for each intermediate good producer in layer j of variety m is given by $\left[\frac{p_{j,t}(m)}{P_{j,t}}\right]^{-\mu_j} Y_{j,t}$.

The aggregator of layer $j \in \{1..N\}$ supplies capital to intermediate good producers in layer $j-1$. The aggregator at layer 0 sells its goods to the household for final consumption.

Intermediate good producers. The intermediate good producer in each layer j of variety m faces the same production technology and conditions as described in Section 3.1.2. It owns its capital stock, $k_{j,t}(m)$, which depreciates at rate δ, and it hires labor from the household. Now, however, it has an additional degree of freedom: the ability to optimally select its output price. Specifically, the period dividend of an intermediate good producer of variety m in layer $j \in \{0,..,N-1\}$, $d_{j,t}$, is given by:

$$d_{j,t}(m) = p_{j,t}(m)\left[\frac{p_{j,t}(m)}{P_{j,t}}\right]^{-\mu_j} Y_{j,t} - P_{j+1,t}\Phi(i_{j,t}(m))k_{j,t}(m) - W_t \cdot n_{j,t}(m), \tag{OA.13}$$

where, as before, W_t denotes the real wage per unit of labor. Given that the top layer intermediate good producer's capital is fixed as before ($k_{N,t}(m) = k_{N,0}(m)$), their dividend is similarly given by $d_{N,t} = p_{N,t}(m)\left[\frac{p_{N,t}(m)}{P_{N,t}}\right]^{-\mu_N} Y_{N,t} - W_t n_{N,t}(m)$. Each intermediate good producer chooses its output price, optimal hiring, and investment (except producers at the top firm), to maximize its market value, taking as given wages W_t, its layer price index $P_{j,t}, \quad j \in \{0,..,N\}$, and the stochastic discount factor of the household $M_{t,t+1}$. Specifically, layer-j firm maximizes:

$$V_{j,t}(m) = \max_{\{n_{j,s}(m) \text{ and } p_{j,s}(m) \text{ iff j} \in \{0,..,N\};k_{j,s+1}(m) \text{ iff j} \in \{0,..,N-1\}\}} E_t \sum_{s=t}^{\infty} M_{t,s}d_{j,s}(m); \tag{OA.14}$$

$$\text{s.t.} \tag{OA.15}$$

$$\left[\frac{p_{j,t}(m)}{P_{j,t}}\right]^{-\mu_j} Y_{j,t} \leq Z_t k_{j,t}(m)^{\alpha} n_{j,t}(m)^{1-\alpha} \tag{OA.16}$$

$$k_{j,t+1}(m) = (1-\delta+i_{j,t}(m))k_{j,t}(m) \text{ if } j \in \{0,...,N-1\}. \tag{OA.17}$$

Market clearing and equilibrium. Compared to Section 3.1.4, the market clearing conditions of the labor markets, the capital goods markets, and the consumption good market are modified as follows:

$$\Sigma_{i=0}^{N} \int_0^1 n_{j,t}(m)dm = 1,$$

$$\int_0^1 \Phi(i_{j,t}(m))k_{j,t}(m)dm = Y_{j+1,t} \quad \forall j \in \{0, ..., N-1\},$$

$$C_t = Y_{0,t}.$$

All other market clearing conditions remain the same. Equilibrium consists of prices, labor, and capital allocations such that (i) taking prices and wages as given, the household's allocation solves (10), and firms' allocations solve (OA.14); (ii) all markets clear; (iii) we are interested in a symmetric equilibrium in which $k_{j,t}(m) = k_{j,t}$, $n_{j,t}(m) = n_{j,t}$, and $p_{j,t}(m) = p_{j,t}$, for all $m \in [0, 1]$.

We calibrate the augmented model at an annual frequency using a calibration identical to that described in Section 3.3. We further impose that $\mu_j = \mu, \quad \forall j \in \{0, ..., N\}$. We are interested in varying the markup parameter μ, and considering the quantitative implications that it has on the spread.

OA.5 A Measure of Supply Chain Competition

To derive a measure of competition that captures not only a firm's own competition environment, but also the competition faced by its direct and indirect suppliers, we combine the information about the supplier-customer relations with the information about the number of competitors each firm has. The FactSet Revere relationships dataset allows us to identify each firm's competitors at any point in time, reported either by the firm itself or by its competitors. We assume that competition relationships are undirected links, meaning that it is sufficient for only one firm to report the relationship. We observe 271,586 competition links in the database. We eliminate links that last less than 90 days and combine relationships where there is a gap of less than 90 days, with a gap defined as the number of days between the end of the previous relationship and the beginning of a new relationship between the same pair of firms.

Let $\mathbf{C}_t$ be an n by 1 column vector that measures the number of each firm's competitors in month t. While it could be a measure of competition, it does not account for competition at the supply chain level. We define our supply chain competition measure as:

$$\hat{\mathbf{C}}_t = \mathbf{C}_t + \sum_{j=1}^{J} \lambda^j \bar{\mathbf{S}}_t^j \mathbf{C}_t, \tag{OA.18}$$

where $\hat{\mathbf{C}}_t$ is an n by 1 column vector that measures each firm's supply chain competition, $\bar{\mathbf{S}}_t$ is a customer-supplier adjacency matrix normalized by the number of suppliers that each customer has. In other words, if $\mathbf{S}_t$ is an adjacency matrix of zeros and ones, such that $\mathbf{S}_t(i,j) = 1$ if firm j is a supplier to firm i and $\mathbf{S}_t(i,j) = 0$ otherwise, then $\bar{\mathbf{S}}_t(i,j) = \mathbf{S}_t(i,j)/\sum_{k=1}^{n_t} \mathbf{S}_t(i,k)$. The $\lambda < 1$ parameter discounts the importance of the competition faced by a firm's direct suppliers relative to the competition faced by the firm itself, and the importance of competition faced by indirect suppliers relative to the competition faced by direct suppliers.[38]

When $J = 1$, the supply chain competition measure $\hat{\mathbf{C}}_{it}$ for a given firm i includes the firm's own number of competitors and the average number of its direct suppliers' competitors. For $J = 2$, the average number of competitors of the firm's suppliers' suppliers is also included in the measure. In our benchmark specification we use $J = 5$, accounting for the competitiveness of indirect suppliers five layers above the firm itself.

OA.6 Additional Model Extensions

OA.6.1 Ex-ante Layer Heterogeneity

In the baseline model we introduce as little heterogeneity between the layers as possible, to ensure that any differences in returns arise from network effects and not from any hardwired ex-ante heterogeneity. As previously discussed, many supply chains are very long and extend almost exclusively within sectors. Hence, the TMB spread is not driven by any specific industry. Nonetheless, top layer firms could exhibit a greater amount of durability in their capital input and/or output because of the nature of their technology. We modify the benchmark model parameters such that firms with higher vertical position have either higher

[38] We set $\lambda = 0.9$ in our calculation of the supply chain competition measure. The results are robust to altering this parametrization.

durability due to lower depreciation, or higher degree of adjustment costs. The results are reported in Table OA.2. When the depreciation rate (capital adjustment costs) of the top layer is *twice* as low (high) as that of the bottom layer, the marginal increase in the TMB spread compared to the baseline model is quantitatively very small, about 1%. Thus, we do not consider ex-ante heterogeneity as a *quantitatively* important source for the TMB spread.

Table OA.2: **TMB Spread and Ex-Ante Layer Heterogeneity**

	(1) Benchmark Calibration	(2) δ_{mid} fixed $\delta_0 > \delta_{N-1}$	(3) ϕ_{mid} fixed $\phi_0 < \phi_{N-1}$
Mean Excess Returns (%)			
Layer 5	16.07	16.83	16.41
Layer 4	12.01	11.35	13.16
Layer 3	9.42	8.97	9.78
Layer 2	7.15	6.97	6.87
Layer 1	5.23	5.23	4.69
Layer 0	3.59	3.66	2.89
Spread (5-0)	12.49	13.17	13.51

This table reports how the benchmark results would change if we allow for ex-ante heterogeneity between the layers of production. It shows the model-implied excess returns for the different production layers under three calibrations: (1) The benchmark calibration, in which the depreciation rate and adjustment costs are homogeneous for all layers (i.e., $\delta_0 = \delta_1 = \delta_2 = \delta_3 = \delta_4 = \delta$; $\phi_0 = \phi_1 = \phi_2 = \phi_3 = \phi_4 = \phi$), (2) A calibration with a mean-preserving spread of depreciation rates, in which the top layers' capital deprecaites slower (i.e., $\delta_0 = 1.5\delta, \delta_1 = 1.25\delta, \delta_2 = \delta, \delta_3 = 0.75\delta, \delta_4 = 0.5\delta$), (3) A calibration with mean-preserving spread of capital adjustment costs, in which the top layers incur larger adjustment costs (i.e., $\phi_0 = 0.5\phi, \phi_1 = 0.75\phi, \phi_2 = \phi, \phi_3 = 1.25\phi, \phi_4 = 1.5\phi$).

OA.6.2 Alternative Network Specifications

Pyramidal Structure. A salient feature of the data, demonstrated in Table 1 is that the production network features a pyramidal shape, in-line with the Hayerkian Triangle notion. More firms populate downstream layers. To capture the main economic force, and for tractability reasons, our benchmark model features a strict chain where each layer is populated by a single representative firm. In light of the empirical regularity, we wish to qualitatively assess the impact of the pyramidal structure on the TMB spread. To that end, we solve a simple model that features only two layers of production. The top layer is populated by a single firm, while the bottom layer is populated by *t*wo final consumption

Table OA.3: **TMB Spread implied From A Pyramid versus Chain Network**

ρ	σ	TMB-Pyramid	TMB-Chain
1.2	0	7.56	7.56
1.2	0.15	6.09	6.03
1.2	0.30	4.45	4.34
0.8	0	7.56	7.56
0.8	0.15	5.87	6.03
0.8	0.30	3.95	4.34

This table compares the TMB spread in a model with a production chain, like in the benchmark case, and the spread in a pyramidal model, in which a supplier has two customers. The specification of the chain model is identical to the benchmark model, with the modification of setting N to 2, and an introduction of a firm specific shock. In both the pyramidal and chain models, the production function for any firm i is given by $Y_{i,t} = Z_{i,t}k_{i,t}^{\alpha}n_{i,t}^{1-\alpha}$, where $Z_{it}/Z_{i,t-1} = \underbrace{Z_t/Z_{t-1}}_{\text{common trend}} \cdot \underbrace{exp(\sigma_{idio}\varepsilon_{i,t})}_{\text{layer-specific shock}}$, and $\varepsilon_{i,t}$ is i.i.d. standard Gaussian firm-specific shock. In the pyramidal model, the TMB spread is defined as the difference between the return of the top-layer firm and the value-weighted return of the two bottom-layer firms. The table shows the results when the CES parameter ρ takes the values $\{0.8, 1.2\}$, and the firm-specific volatility parameter σ_{idio} takes the values $\{0, 0.15, 0.3\}$.

good producers. Denote the two final consumption goods by c_1 and c_2, respectively, the period utility of the bundle (c_1, c_2) is given by the CES function:

$$\left[(1-\eta)c_{1t}^{1-\frac{1}{\rho}} + \eta c_{2t}^{1-\frac{1}{\rho}}\right]^{\frac{1}{1-\frac{1}{\rho}}},$$

where the parameter ρ captures the degree of substitutability between the consumption goods. Specifically, for $\rho = 1$ the period utility reduces to the Cobb-Douglas function. When $\rho = 0$, the function reduces to a Leontief function, and the goods are perfect complements. When ρ approaches infinity, the function becomes linear, and the goods are perfect substitutes. We set $\eta = 0.5$, so that both consumption goods receive an equal weight. The CES period utility function is nested inside an Epstein-Zin preferences over today's consumption and the continuation utility. The output of the top layer is sold to both bottom-layer firms:

$$Y_{top,t} = \Phi(i_{c1,t})k_{c1,t} + \Phi(i_{c2,t})k_{c2,t}).$$

This structure captures a very simple triangle-shaped economy.

Table OA.3 compares the TMB spread in a strict chain model with the spread in a pyramidal model. The triangle shape has an ambiguous effect on the TMB spread. In general, the higher the substitutability between the consumption goods, the higher the spread.

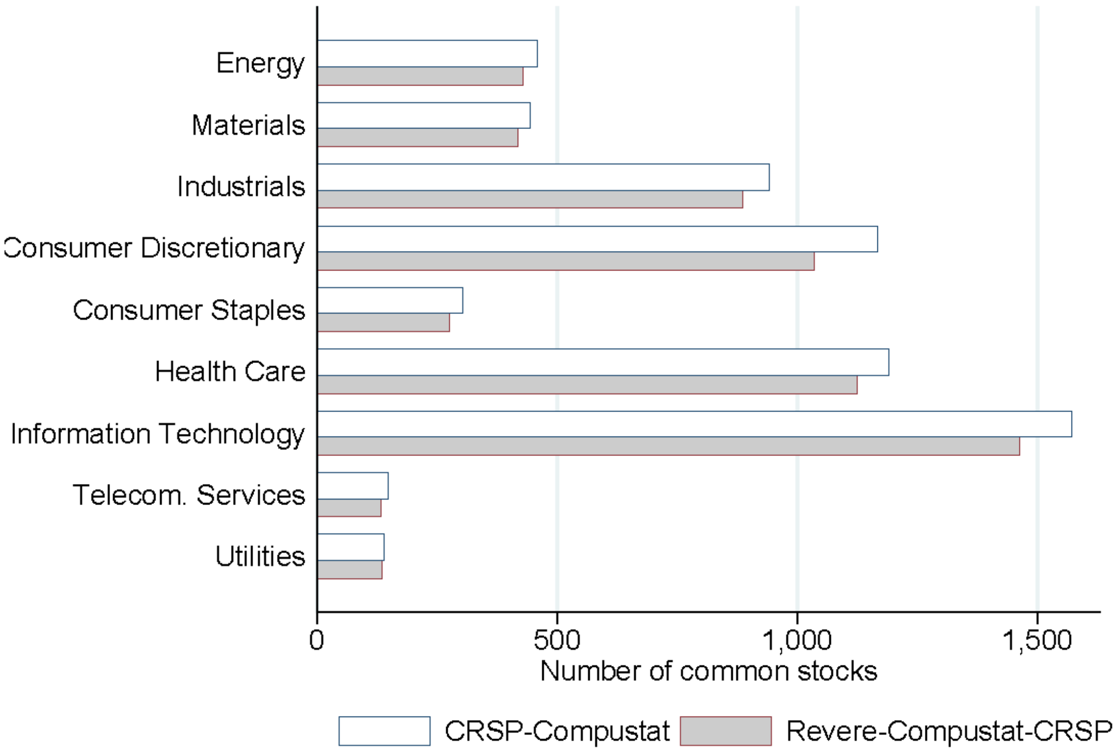
Specifically, we find that if the CES parameter is above (below) unity, the pyramidal structure boosts (shrinks) the TMB spread, relative to a chain structure. Moreover, the triangle structure has no effect on the spread if the period utility between the two consumption goods is Cobb-Dougles (CES parameter equals to one) and/or if the firm specific productivity shocks are sufficiently small. In reality, empirical estimates of the CES parameter for the bottom layer (i.e., complementarity or substitutability between durable and non-durable consumption goods) is not much different from unity (see e.g. Yang (2011)). For instance, Ogaki and Reinhart (1998) find the CES parameter to be around 1.2, whereas Yogo (2006) estimates it at around 0.8. As a result, the triangle shape should have a quantitatively small effect on the TMB spread.

Supply chain with a loop. Our benchmark model features a perfectly vertical supply chain. It also implies that the capital of the top layer is fixed over time because it does not have suppliers. This assumption helps to capture the sizable spread between layer 5 and 4, and is motivated by the fact that top-layer firms are more labor intensive. However, the TMB spread exists even when the top layer firms can purchase inputs from other top layer firms, allowing a loop within layer 5. Specifically, we solve a variation of the benchmark model in which the top layer's capital is time-varying. The output of the top layer is sold as capital input for the layer below it (layer 4), as well as to itself (layer 5, thus featuring a circle). We confirm that a positive and sizable TMB exists under this circular model.[39]

[39]The spread is attenuated to about 4.3% per annum.

OA.7 Supplemental Figures and Tables

Figure OA.1: **Sample Coverage by Industry**



The figure presents the number of common stocks in our Revere-Compustat-CRSP matched database vs. the number of common stocks in the CRSP-Compustat merged database for each industry. The industries are classified based on the Global Industry Classification Standard (GICS).

Table OA.4: **Transition Matrix of the Vertical Position**

Layer in month t	Layer in month $t+1$				
	Layer 5	Layer 4	Layer 3	Layer 2	Layer 1
Layer 5	0.83	0.07	0.06	0.04	0.01
Layer 4	0.02	0.88	0.06	0.04	0.00
Layer 3	0.00	0.02	0.92	0.05	0.01
Layer 2	0.00	0.00	0.01	0.97	0.01
Layer 1	0.00	0.00	0.00	0.01	0.98

This table presents the transition probability of a firm's vertical position from one month to another. The matrix of transition probabilities is computed using monthly data from September 2003 to December 2012. Layer zero is not a part of the transition matrix because it does not change given that it is based on the time-invariant Global Industry Classification Standard (GICS) code reported in Compustat.

Table OA.5: **Correlations of Returns across Layers**

	Layer 5	Layer 4	Layer 3	Layer 2	Layer 1	Layer 0
Layer 5	1.00					
Layer 4	0.67	1.00				
Layer 3	0.70	0.89	1.00			
Layer 2	0.68	0.87	0.90	1.00		
Layer 1	0.63	0.80	0.82	0.93	1.00	
Layer 0	0.57	0.70	0.70	0.84	0.89	1.00

This table reports the correlations between the returns of the value-weighted portfolios formed based on the vertical position measure defined in Equation (1).

Table OA.6: **Risk Exposures to Aggregate Productivity: Model versus Data**

	Data	Model
Layer 5	2.88	3.51
Layer 4	2.07	2.95
Layer 3	2.53	2.68
Layer 2	1.65	2.34
Layer 1	1.31	1.89
Layer 0	1.21	1.32
TMB	1.66	2.19

The table shows the exposures of layers portfolio returns to aggregate productivity growth. In both the model and the data, the exposures are estimated as the β coefficient in the following projection: $R^e_{i,t} = const + \beta \Delta Prod_t + error$. The data point estimates are taken from Table 5. The model population moments are based on a simulated path of length 100,000 for layers' excess returns and for aggregate productivity.

Table OA.7: **Time series regressions of the TMB portfolio return: Equal-weighted**

	(1)	(2)	(3)	(4)	(5)	(6)
Rm-Rf	-0.107	-0.057	0.027	0.031	-0.364***	
	(-1.10)	(-0.50)	(0.23)	(0.27)	(-3.00)	
SMB		-0.020	-0.071	0.135		
		(-0.09)	(-0.34)	(0.65)		
HML		-0.242	-0.127			
		(-1.28)	(-0.67)			
MOM			0.234**			
			(2.53)			
I/A				-0.784***		
				(-2.69)		
ROE				0.504**		
				(2.21)		
IMC					0.563***	
					(3.29)	
DMN						-0.112
						(-1.57)
Constant	1.129**	1.157***	1.114***	1.023**	1.242***	1.050**
	(2.62)	(2.68)	(2.64)	(2.45)	(3.00)	(2.46)
R^2	0.011	0.026	0.081	0.137	0.100	0.022

This table presents the results of the time series regressions of the equal-weighted Top-Minus-Bottom (TMB) portfolio returns on various risk factors and the durable-nondurable spread. The TMB portfolio is constructed by taking a long position in the value-weighted portfolio of companies with a vertical position of five or above, and shorting a value-weighted portfolio of companies with a vertical position of zero. The returns are computed from November 2003 to February 2013. The factor description and construction is identical to those in Table 15. T-statistics are reported in parentheses. Significance at the 1%, 5%, and 10% levels are indicated by ***, ** and * respectively.

Table OA.8: **Empirical Robustness of the Top-Minus-Bottom Spread**

	(1) Quarterly Rebalance	(2) Annually Rebalance	(3) Four-month Lag	(4) Median Distance	(5) Five Layers
Panel A. Return by vertical position					
Layer 5	1.90	1.85	1.62	1.50	-
Layer 4	1.31	1.05	1.24	1.00	1.43
Layer 3	1.00	0.95	0.98	1.04	0.99
Layer 2	0.87	0.88	0.81	0.84	0.87
Layer 1	0.73	0.72	0.68	0.58	0.73
Layer 0	0.73	0.73	0.71	0.73	0.73
Panel B. Spreads					
Top-minus-Bottom	1.17**	1.12***	0.91*	0.77*	0.70*
	(2.48)	(2.94)	(1.97)	(1.77)	(1.73)
Top-minus-Layer 1	1.17***	1.13***	0.94**	0.92**	0.70**
	(2.63)	(3.39)	(2.18)	(2.26)	(2.04)

The table presents excess returns of the different layers (Panel A) and spreads (Panel B) under multiple alternative portfolio formation methods. The portfolios are constructed in an identical manner to the benchmark case, except the following changes: (1) sorting firms into portfolios based on their vertical position only at the end of each quarter(March, June, September and December); (2) sorting firms into portfolios based on their vertical position only once a year (at the end of June); (3) sorting firms into portfolio every month t based on the vertical position computed in month $t-4$; (4) using the operator median instead of minimum in equation (1) for the vertical position assignment; and (5) grouping firms into only five layers, where the top layer includes all firms with vertical position of 4 or above. In columns (1)-(4), the top layer is layer five, and in column (5) it is layer 4. All numbers are in percentage units. T-statistics are reported in parentheses. Significance at the 1, 5, and 10 percent levels are indicated by ***, **, and *, respectively. The returns are computed from November 2003 to February 2013.

Table OA.9: **Time series regressions of the TMB portfolio return: Annual Rebalancing**

	(1)	(2)	(3)	(4)	(5)	(6)
Rm-Rf	0.017	0.105	0.229**	0.187*	-0.153	
	(0.19)	(1.04)	(2.36)	(1.79)	(-1.38)	
SMB		-0.367*	-0.443**	-0.245		
		(-1.94)	(-2.53)	(-1.33)		
HML		-0.012	0.157			
		(-0.07)	(0.99)			
MOM			0.346***			
			(4.49)			
I/A				-0.674**		
				(-2.60)		
ROE				0.318		
				(1.57)		
IMC					0.371**	
					(2.38)	
DMN						-0.167***
						(-2.71)
Constant	1.106***	1.129***	1.066***	1.076***	1.181***	1.076***
	(2.89)	(2.97)	(3.03)	(2.90)	(3.13)	(2.92)
R^2	0.000	0.034	0.187	0.129	0.050	0.062

This table presents the results of the time series regressions of the value-weighted Top-Minus-Bottom (TMB) portfolio returns on various risk factors and the durable-nondurable spread. As opposed to the benchmark case, firms are sorted into vertical position portfolios only once a year, and the end of June. The TMB portfolio is constructed by taking a long position in the value-weighted portfolio of companies with a vertical position of five or above, and shorting a value-weighted portfolio of companies with a vertical position of zero. The returns are computed from November 2003 to February 2013. The factor description and construction is identical to those in Table 15. T-statistics are reported in parentheses. Significance at the 1%, 5%, and 10% levels are indicated by ***, ** and * respectively.

Table OA.10: **Top-Minus-Bottom Spread: Constant Portfolio Assignment**

Panel A. Monthly return by vertical position	
Layer 5	1.141
Layer 4	0.969
Layer 3	0.965
Layer 2	0.855
Layer 1	0.737
Layer 0	0.731
Panel B. Spread	
Top-minus-Bottom	0.409
	(0.920)

The table presents monthly returns for 11/2003–02/2013 of different layers (Panel A) and the TMB spread (Panel B) when firms are assigned into layer portfolios by their first vertical positions observed during the sample period. After the initial assignment, a firm remains in the same layer portfolio through out the sample period. All numbers are in percentage units. T-statistics are reported in parentheses.