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

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Abstract

We examine empirically and theoretically the relation between firms' risk and distance to consumers in a production network. We document two novel facts: firms farther away from consumers have higher risk premiums and higher exposure to aggregate productivity. We quantitatively explain these findings using a general equilibrium model featuring a multilayer production process. The economic force is "vertical creative destruction," that is, positive productivity shocks to suppliers devalue customers' assets-in-place, thereby lowering the cyclicality of downstream firms' values. We show that vertical creative destruction varies with competition and firm characteristics and generates sizable cross-sectional differences in risk premiums. (*JEL* G12, L14, L23, O33)

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

Intuitively, not all firms along the production chain benefit equally from technological progress. Innovations improving the production of new capital by suppliers can devalue existing capital of customers. This yields differential exposures of firms along the chain to productivity shocks. These exposures are also affected by the competition faced by suppliers, as monopolistic power rations new capital's production. We develop this intuition in this paper and confirm it empirically.

The main empirical challenge to address the aforementioned questions is the availability of comprehensive data that allows measuring a firm's granular position in the network over time. To overcome this challenge, we use a novel firm-level database of supplier-customer relationships, which allows to compute firms' upstreamness dynamically. 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 which it belongs.

Our first contribution is to empirically document two novel stylized facts that highlight a monotonic relation between a firm's vertical position in the network and their riskiness. First, we show that the farther away a firm is from final consumers (i.e., the higher its vertical position is), the higher its average stock return. An investment strategy that longs (shorts) firms with the longest (shortest) distance to consumers generates a return of 105 basis points per month. We refer to this spread as TMB (top-minus-bottom). Second, we show that a firm's exposure (beta) to aggregate

[1]The term "upstreamness" in this paper refers to the distance of a firm to final consumers.

productivity increases monotonically with its vertical position.

Our second contribution is to propose and test a quantitative theory which jointly accounts for these facts. Our explanation is based on a new form of creative destruction that arises in a multilayer supply chain economy. We develop a general equilibrium model with multiple layers of production. 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.

A positive aggregate 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. This *demand effect*, which appreciates all firms' valuation, exists also in a single sector setup. However, a separate effect exists, which is novel to our multilayer environment. The same positive shock increases the productivity of the firm's direct and indirect suppliers. As they all become more productive, the supply curve of the firm's input shifts to the right. This *supply effect* puts a downward pressure on the valuation of firms' assets-in-place: installed capital or inventory. Technological improvements make the production of firms' capital input cheaper. In a competitive environment, this erodes the marginal value of firms' installed capital. We refer to this supply effect as vertical creative destruction.[2]

The strength of the supply effect is heterogeneous across layers. A bottom-layer firm experiences the greatest impact of the supply effect. Its existing capital is built using the goods produced by all the layers above it. As each intermediate capital good becomes cheaper to produce, the supply effect cascades downwards cumulatively, and the assets-in-place value of the bottom-layer experiences the greatest downward pressure, as its replacement cost becomes relatively the cheapest. By contrast, a top-layer firm is not subject to vertical creative destruction force, as it has no suppliers. Firms in the middle layers experience some amount of this cumulative supply effect, but not as strongly as the bottom layer, because they have fewer indirect suppliers. Vertical creative destruction acts as a hedge by making the productivity exposure of a firm less positive, as the negative supply effect partially offsets the positive demand effect. This logic explains both the TMB spread as well as

[2] One typically thinks of creative destruction as value destroyed by competition or by new entrants into the market, as in the spirit of Schumpeter (1942). Another term for this is 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.

why the productivity beta monotonically increases with the vertical position.

We formalize this intuition in closed form using a simplified model and examine its quantitative power in a calibrated full DSGE model. 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.

To tighten the connection between the model and the data, and we perform several tests for the mechanism. First, the model predicts that Tobin's q, input prices and investment rates are more cyclical for top-layer firms. We confirm this using the Compustat data and the BLS intermediate-demand price indices. Second, an augmented model with monopolistic power predicts that the TMB spread is smaller when firms have greater monopolistic power. When productivity rises monopolistic suppliers do not increase supply as much as competitive suppliers. Hence, the creative destruction on customers' assets-in-place diminishes. Consistent with this prediction, the TMB is smaller for a subsample of firms that operate under lower competition in the data. The augmented model's logic also has a novel implication. It predicts a negative relation between firms' cost of capital and competitiveness of their upstream suppliers. Consistently, we find that consumption-goods producers whose direct or indirect suppliers have more competitors earn higher expected returns. Third, we confirm the model's 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 organization capital, and firms with more inventory. For these firms, a larger fraction of firm value stems from assets-in-place, which is the component subject to vertical creative destruction.

We confirm the robustness of our empirical findings. The TMB remains significant when we (a) use input-output tables from the U.S. Bureau of Economic Analysis (BEA) to compute an inter-industry TMB spread from 1973 to 2017; (b) use the Compustat Segment database to construct a sample from 1985 to 2017, accounting for the strength of each supplier-customer relationship; and (c) use different rebalancing or methodologies to compute vertical positions.

The paper contributes to three strands of literature: creative destruction, production networks, and production-based asset pricing. Schumpeter's idea of creative destruction has influenced economic research in many areas.[3] Recently, it also spurs research in finance. Several papers use the fact that not all firms benefit equally from innovations to derive cross-sectional risk premiums implications. For example, Gârleanu, Kogan, and Panageas (2012), Loualiche (2016), Barrot, Loualiche, and Sauvagnat (2019), and Kogan, Papanikolaou, and Stoffman (2020) study displacement risk, in which innovations benefit new firms at the expense of incumbents.[4] In these papers, creative destruction works horizontally: it is induced by firms' competitors. Our contribution to this literature is to introduce vertical creative destruction: suppliers' innovations devalue customer firms. Our model reveals a seemingly counterintuitive result: this creative destruction provides a hedge for the customer firm and lowers its 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 stock return predictability via supplier-customer links. In contrast, we study contemporaneous cross-sectional return implications across different layers. Ahern (2013) finds that industries with a higher network centrality have higher returns. We verify that the TMB spread is not explained by centrality. Ozdagli and Weber (2018) find sizable network effects in the propagation of monetary shocks. Our paper focuses on the network effects from common productivity shocks.[5] Herskovic (2018) derives two risk factors based on the changes in network concentration and sparsity. By contrast, we focus on the vertical dimension of production by modeling a supply chain. We find that TMB increases with the chain's length. This is not a result of sparsity or connectivity, but of a larger cumulative supply effect.[6]

More broadly, our paper is related to studies that connect investment to asset prices.[7] The novelty of our model is to account for a multilayer production process instead of assuming a single sec-

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

[4] Opp (2019) extends the quality ladder model of Schumpeterian growth (Grossman and Helpman (1991)) to study the impact of venture capital financing on the macroeconomy.

[5] A nascent literature considers the propagation of shocks in a production network. Shock types include idiosyncratic productivity shocks (Acemoglu et al. (2012); Atalay (2017)), liquidity shocks (Bigio and La'O (2017)), and natural disaster shocks (Barrot and Sauvagnat (2016); Carvalho et al. (2016)).

[6] Other asset pricing implications of production networks have been studied by Buraschi and Porchia (2012); Aobdia, Caskey, and Ozel (2014); Branger et al. (2018); Rapach et al. (2015); Herskovic et al. (2019), Richmond (2015), and Ready, Roussanov, and Ward (2017). None of these studies have examined the effect of creative destruction on stock returns or the relation between stock returns and firms' vertical position.

[7] See, for example, Berk, Green, and Naik (1999), Boldrin, Christiano, and Fisher (2001), Gomes, Kogan, and Zhang (2003), Carlson, Fisher, and Giammarino (2004), Jermann (2010), Van Binsbergen et al. (2012), Ai, Croce, and Li (2013), Belo, Lin, and Bazdresch (2014), and Drechsler, Savov, and Schnabl (2018).

tor. Several studies examine asset pricing implications in two-sector economies. Gomes, Kogan, and Yogo (2009) document higher expected returns of durable goods producers relative to nondurables. The TMB spread is independent from this result. Yang (2013), Papanikolaou (2011), and Garlappi and Song (2017a,b) examine the premium difference between the consumption 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. The majority of the TMB spread stems from *within* the investment sector, not from the return differentials of consumption versus investment firms.

1 Data and Measure of Vertical Position

1.1 Data

The main databases used in our empirical analysis are the CRSP stock database (for stock returns), the Compustat North America database (for accounting data), and the FactSet Revere relationships database (for information about suppliers, customers, and competitors).

The FactSet Revere database provides arguably the most comprehensive coverage of firm-level supplier-customer relationships that is currently available. It includes relationships disclosed by either suppliers or customers (or by both), with the start and end dates for each relationship. FactSet's analysts monitor the relationships data on a regular basis. They collect information from firms' annual reports, which by regulation should include names of customers that generate above 10% of sales, as well as information from other sources, including press releases and announcements, investor presentations, and firms' websites.[8] The comprehensive supplier-customer data allows us to measure firms' upstreamness over time. The database also provides information about firms competitors, which is useful for some of our tests.

Our sample period is from April 2003, when the database started, to September 2013, when we purchased it from Revere. To allow for a sufficient time for the analysts to fully update the supplier-customer relationships, we use only relationships that were present up to December 2012. Over this period, the FactSet Revere database includes 433,271 supplier-customer relationships

[8]This database is now available from Wharton Research Data Services (WRDS). A number of recent papers that study short-selling behavior (Dai, Ng, and Zaiats (2017)), network centrality (Wu (2015)), and credit risk propagation (Agca et al. (2017)) also have used this database.

between 193,851 pairs of firms, covering a total of 43,656 firms (many of which are private firms and international 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 firms). We also combine multiple relationships between the same pair of firms over different time periods into one continuous relationship if the time gap between two consecutive relationships is not longer than 6 months. There are 206,264 supplier-customer relationships after these steps.

We merge the FactSet Revere database with the Compustat North America and the CRSP databases (using CUSIP and the CRSP-Compustat linking table). We exclude financial firms (GICS code 40), industrial conglomerates (GICS 201050, whose vertical positions in the production network are not precisely measured), as well as penny stocks (i.e., stocks with a price of less than $1 in the previous month). Our matched sample has a total of 5,926 common stocks (with the CRSP share code 10, 11, or 12). Over the sample period, the total number of nonpenny, nonfinancial, and nonconglomerate common stocks in the CRSP-Compustat merged database is 6,437. Our matched sample thus encompasses a majority (92%) of these stocks.

1.2 The vertical position measure

We now describe our measure of the main production-based characteristic of interest: a firm's vertical position (i.e., its upstreamness). Production networks can be split into tranches, with firms in the same tranche having a similar distance from final consumers. 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. 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 in layers below to $i-1$.

Our methodology of computing vertical positions is based on Gofman (2013). 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 network in month t, and m_t is the number of consumption-good 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 consumption-good producer j. Given the matrix D_t, the vertical position of firm i is defined as the minimum number of supplier-customer relationships to any consumption-good producer:[9]

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

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. The number of layers of production in each month is endogenous and depends on the observed supplier-customer relationships. Given that the vertical position of firms can change over time, we compute our vertical position measures on a monthly base to reflect the latest information.

We apply the above methodology to our Revere-Compustat-matched sample. 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 of the parties are from this sample.[10] We require a relationship to last at least 6 months before it is used to compute the vertical position. As a result, we obtain a comprehensive firm-level panel of vertical positions starting in September 2003. To the best of our knowledge, ours is the first paper to measure upstreamness *dynamically* for a large cross-section of U.S. firms.

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

We form portfolios by sorting firms according to their vertical positions. To ensure that public information about supplier-customer relationships are known to investors, we sort firms at the beginning of month t using vertical positions computed at the end of month $t-2$ (Section 7.2 shows similar results under alternative sorting schemes). Accordingly, our portfolio holding period starts in November 2003. The number of production layers and the distribution of firms across these layers are endogenous, so firms need not be allocated equally across different layers. In fact, as we discuss in detail in Section 8, upper layers of production (layers of high vertical positions)

[9]This measure does not account for the strength of the supplier-customer link, as information about sale volumes is unavailable for the majority of links. In Section 7.1, we consider a different measure of the vertical position using two alternative databases that account for the strength of each link. In Section 7.2, we also conduct a robustness check using the median distance to the bottom layer as a measure of vertical position.

[10]To maximize the number of firms available for constructing the production network, in this step we do not require a firm to have a match in the CRSP database. Nor do we require both parties in a supplier-customer relationship to be in the Revere-Compustat-matched sample, which contains a total of 10,957 nonfinancial, nonconglomerate firms. Thus, our measure also accounts for supplier-customer relationships between public and private firms.

include fewer firms. To reduce the amount of noise due to the smaller number of firms at the top layers, we combine all firms with a vertical position five or above into a single portfolio, while keeping firms in each of the layers below five in separate portfolios. In all, we obtain six portfolios, representing six production layers.

2.1 Stylized fact 1: Layer portfolio returns and the TMB spread

Table 1 presents the first main stylized fact that we uncover from the sorted portfolios: a monotonic relation between vertical position and average stock returns, as well as a sizable return spread between the top and bottom layers of production (the TMB spread). Both the value-weighted and equal-weighted average returns increase monotonically from the bottom to the top layer. The TMB spread is 105 (108) basis points per month when the portfolios are value-weighted (equal-weighted). Both are economically and statistically significant. Table 1 also implies that the Sharpe ratios rise with the vertical position. The annualized Sharpe ratio of the value-weighted (equal-weighted) TMB portfolio is 0.68 (0.82). In contrast, 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.

Table 1: **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
TMB (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). Layer 0 represents the consumption-good producers, and layer 5 refers to firms in the top vertical position. Returns are computed from November 2003 to February 2013. ** indicates the statistical significance at the 5% level.

The TMB spread is not specific to the FactSet Revere database. Section 7 uses the less detailed BEA input-output tables and the Compustat Segment database to show that the spread also exists in much longer sample periods. Online Appendix Section OA.8 also shows that the TMB spread is largely independent from known production-related and cross-industry spreads, including the spread between durables and nondurables, the spread between investment and consumption firms, and the book-to-market premium, among others.

2.2 Stylized fact 2: Exposure of layer portfolios to productivity shocks

Related to the monotonic relation between vertical position and average returns reported above, we examine in this section whether this relation is a result of exposure to fundamental macroeconomic risks. 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 use two proxies for aggregate productivity. The first is quarterly labor productivity data published by the U.S. Bureau of Labor Statistics (BLS). Measuring aggregate productivity using labor productivity is presumably less noisy as it is based on easily observed variables, namely, value added and hours. The second proxy is a Hicks-neutral productivity shock, which we term Solow residual. This proxy is directly computed from the TFP data published by the San-Francisco Federal Reserve Bank (see Basu, Fernald, and Kimball (2006) and Fernald (2014)). To make sure that the Hicks-neutral shock parallels to our theoretical analysis, we follow Croce (2014), and adjust the TFP growth measure so that it accounts for physical nonresidential capital (equipment and land), and not for other forms of capital not transmitted as inputs in the supply chain, such as artistic or residential capital.[11] The correlation between the constructed Solow residual and the utilization-adjusted TFP of Fernald (2012) is 0.97.

Panel A of Table 2 reports the regression coefficients (betas) of each layer and of the TMB portfolio with respect to the aggregate productivity, obtained from a projection of quarterly portfolio returns on annualized growth of the productivity measures. By and large, the productivity beta increases with the vertical position. Using both productivity proxies, the beta is about 1.2 for the bottom layer, whereas it is over 2.5 for the top layer.

[11] The Solow residual is computed similar to the method used in Fernald (2014). Our specific computation is as follows:

$$\Delta Solow_t = \Delta Y_t - \alpha_t \Delta K_t - (1-\alpha_t)\Delta L_t - \Delta u_t,$$

where ΔY_t is the log-growth in business output, ΔL is the log growth of labor inputs (adjusted by productivity), α is capital's share of output, u is utilization rate, and ΔK is the growth of capital stock. The growth of capital ΔK is a weighted average of the growth of physical capital (investment) and the growth of land value. This computation is identical to that used by Fernald (2014) for TFP, with the exception that we exclude from ΔK forms of capital that relate more to organization capital (e.g., artistic, R&D). We exclude these other intangible capital forms, because they do not have a matching equivalent in our model. All data used in the calculation come from the San Francisco Fed.

Table 2: **Vertical position and exposures to aggregate productivity shocks**

	TMB	Layer 0	Layer 1	Layer 2	Layer 3	Layer 4	Layer 5
A. $R^e_{i,t} = const + \beta_1 \Delta Prod_t + error$							
$Prod$ = *BLS labor productivity:*							
β_{prod}	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)
$Prod$ = *Solow residual:*							
β_{prod}	1.332	1.245	1.193	1.409	1.491	1.414	2.578
	(1.87)	(2.37)	(2.14)	(2.32)	(2.80)	(2.08)	(3.54)
B. $R^e_{i,t} = const + \beta_1 \Delta Prod_t + \beta_2 \Delta Prod^2_t + error$							
$Prod$ = *BLS labor productivity:*							
β_{prod}	3.254	1.530	2.006	2.882	4.308	4.175	4.784
	(2.76)	(1.14)	(1.42)	(1.73)	(2.29)	(2.22)	(4.77)
$Prod$ = *Solow residual:*							
β_{prod}	1.937	0.599	0.583	0.909	1.171	0.942	2.536
	(2.32)	(1.07)	(0.86)	(1.02)	(1.17)	(0.95)	(2.45)

The table shows the sensitivities of layer portfolio returns to percentage changes in productivity for different layers of production using quarterly data. Layer 0 represents the consumption-good producers, and layer 5 refers to firms in the top vertical position. We use both labor productivity and Solow residual as productivity measures. In panel A, β_{prod} is defined as β_1. In panel B, we combined the linear sensitivity β_1 and the quadratic sensitivity β_2 to form β_{prod}. t-statistics for β_{prod} in the nonlinear model are obtained using the delta method.

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. This is the case in the model used to explain our findings in Section 3. Therefore, in panel B of Table 2, we change the projection specification to include a quadratic term of productivity. We combine the slope coefficients on the linear and quadratic terms to form productivity betas. Specifically:

$$\beta_{prod} = E[\frac{\partial R^e_i}{\partial \Delta Prod}] = \beta_1 + 2\beta_2 E[\Delta Prod], \tag{2}$$

where β_{prod} is the productivity beta, R^e_i is the excess return of layer i, $Prod$ is either labor productivity or Solow residual, and β_1 (β_2) is the slope coefficient on the linear (quadratic) term of $\Delta Prod$. Accounting for model nonlinearities, the exposure pattern becomes more pronounced, both economically and statistically. By and large, β_{prod} still increases monotonically with the vertical position. The TMB productivity beta, accounting for nonlinearity, is 3.3 using labor productivity, and 1.9 using Solow residual, both significant at 5%.[12]

Why are firms with higher vertical position more exposed to aggregate productivity? In the next section, we present a DSGE model to explain stylized facts 1 and 2 jointly. The challenge lies

[12]For brevity, for the quadratic projection, we only report in Table 2 the combination of the slope coefficients of the linear term (β_1) and the quadratic term (β_2), as in Equation (2), but do not show each slope coefficient separately. Table OA.12 The coefficient of the TMB spread on the linear term is positive and statistically significant. The coefficient of the TMB spread on the quadratic term is negative and significant, consistent with nonlinearity.

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.

3 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, which operates under perfect competition. 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 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 layer-j's productivity shock $Z_{j,t}$:

$$Y_{j,t} = Z_{j,t} k_{j,t}^{\alpha} n_{j,t}^{1-\alpha}, \quad j \in \{0, 1, .., N\}, \tag{3}$$

where α is the capital share of output. Because 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 Online Appendix Section OA.5.3. The capital for firms in layer $j \in \{0, .., N-1\}$ depreciates at rate δ according to

$$k_{j,t+1} = (1 - \delta + i_{j,t}) k_{j,t}, \tag{4}$$

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 directly purchase $\Phi(i_{j,t}) k_{j,t}$ units of its layer-specific capital goods 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

$$\Phi(i) = \frac{1}{\phi}(1+i)^{\phi} - \frac{1}{\phi}, \tag{5}$$

where $\phi \geq 1$. The dividend of firm $j \in \{0, .., N-1\}$ in period t, $d_{j,t}$, is given by

$$d_{j,t} = P_{j,t} Y_{j,t} - W_t n_{j,t} - P_{j+1,t} \Phi(i_{j,t}) k_{j,t}, \tag{6}$$

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:

$$V_{j,t} = \max_{\{n_{j,s}\ k_{j,s+1}\}} \quad E_t \sum_{s=t}^{\infty} M_{t,s} d_{j,s} \qquad \text{subject to (4) for } j \in \{0, ..., N-1\}. \tag{7}$$

3.2 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:

$$U_t = \left[(1-\beta) C_t^{\frac{1-\gamma}{\theta}} + \beta (E_t U_{t+1}^{1-\gamma})^{\frac{1}{\theta}} \right]^{\frac{\theta}{1-\gamma}}, \tag{8}$$

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 power utility. 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 $N + 1$ firms. The household chooses the layer-specific labor supply and consumption to maximize its lifetime utility, subject to the budget constraint:

$$\max_{C_s, \{n_{j,s}, \omega_{j,s+1}\}_{j \in \{1..N\}}} U_t, \quad s.t. \quad P_{0,t} C_t + \sum_{j=0}^{N} \omega_{j,t+1} V_{j,t}^X = W_t \sum_{j=0}^{N} n_{j,t} + \sum_{j=0}^{N} \omega_{j,t} V_{j,t}, \tag{9}$$

where $\omega_{j,t}$ is the share of the household in the ownership of the layer j firm, and $V_{j,t}^X$ is the ex-dividend firm value. The stochastic discount factor (SDF) used to discount the dividends of firms in all layers is given by

$$M_{t,t+1} = \beta \left(\frac{C_{t+1}}{C_t} \right)^{\frac{-1}{\psi}} \left(\frac{U_{t+1}}{\left[E_t U_{t+1}^{1-\gamma} \right]^{\frac{1}{1-\gamma}}} \right)^{\frac{1}{\psi} - \gamma}. \tag{10}$$

3.3 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: $\sum_{j=0}^{N} n_{j,t} = 1,$ (11)
- Differentiated capital goods market clearing: $\Phi(i_{j-1,t}) k_{j-1,t} = Y_{j,t}, \quad \forall j \in \{1, ..., N\},$ (12)
- Consumption goods market clearing: $C_t = Y_{0,t},$ (13)
- Firm ownership market clearing: $\omega_{j,t} = 1, \quad \forall j \in \{0, ..., N\}.$ (14)

An equilibrium consists of prices $\{W_t, \{P_{j,t}\}_{j\in 0..N}\}_{t=0}^{\infty}$, labor allocations $\{n_{j,t}\}_{t=0}^{\infty}$ for $j \in \{0..N\}$, and capital allocations $\{k_{j,t}\}_{t=0}^{\infty}$ for $j \in \{0..N-1\}$ s.t. (a) taking prices and wages as given, the household's allocation solves (9), and firms' allocations solve (7), and (b) all markets clear.

Section OA.5 of Online Appendix provides a discussion of our modeling assumptions, including the nature of goods transmitted along the supply chain, the ex ante heterogeneity across layers, the linear network structure, and the time-invariant vertical positions of firms. We show that our results are robust to various extensions along these lines.

4 Closed-Form Qualitative Results

The general equilibrium model outlined in Section 3 (henceforth, the full DSGE model) does not admit a closed-form solution and has to be solved numerically. In this section we formulate a variation of the full DSGE model that is tractable. The purpose of this section is to formalize the intuition behind the quantitative results of the calibrated full DSGE model given in Section 5. To obtain a closed-form solution, we make a few simplifying assumptions:

Assumption 1. *No adjustment costs.* We assume no capital installation frictions (i.e., $\phi = 1$).

Assumption 2. *Independent and standard random walks.* The productivity growth of layer j is given by $\Delta z_{j,t+1} \equiv log(Z_{j,t+1}) - log(Z_{j,t}) = \varepsilon_{j,t+1}$, where $\text{Corr}(\varepsilon_{k,t+1}, \varepsilon_{j,t+1}) = \rho_z$, with $\rho_z = 0$ $\forall j \neq k \in \{0,..,N\}$.

Assumptions 1 and 2 simplify the setup for tractability. Assuming that all productivity shocks are orthogonal ($\rho_z = 0$) is made for the transparency of the economic mechanism. It allows to isolate the effect of innovations of layer j on layer k's valuation. In the full DSGE model, ρ_z is set to 1 for the simplicity of the calibration, and we will impose this assumption later in this section (referred to as **Assumption 2'**).[13]

Assumption 3. *Capital quality shocks.* The capital of each layer is subject to a zero-mean quality shock χ_j that realizes in time $t+1$. Specifically, the capital accumulation dynamics in Equation (4) are altered to

$$k_{j,t+1} = ((1-\delta)k_{j,t} + I_{j,t})\, e^{\chi_{j,t+1}},$$

where $I_{j,t} \equiv i_{j,t}k_{j,t}$ is the amount of investment, $\chi_{j,t}$ is independent across time, and $E_t[\chi_{j,t+1}] = 0$. Assumption 3 is used only to obtain a closed-form solution. In the standard RBC model, as well as in the full DSGE model, there are no capital quality shocks ($\chi_{j,t+1} = 0$). Productivity changes in the

[13]Section 5.2.3 offers a quantitative examination of the full DSGE model with layer-specific and orthogonal shocks.

economy lead to transition period(s), as the economy readjusts the capital of each layer to the new optimum. These transitions make a closed-form solution infeasible. Quality shocks χ_j can eliminate these transition periods, because the capital of each layer instantaneously adjusts by the "correct" amount by time $t+1$ to restore the steady state. In our setup, quality shocks χ_j can immediately restore the steady state in each layer j by assuming that $\chi_{j,t+1} = \sum_{\ell=j+1}^{N} \alpha^{\ell-j-1}\varepsilon_{\ell,t+1}, \quad \forall j \in \{0,..,N-1\}$. The assumption implies that firms' problems are homogeneous in the underlying productivity shocks, which simplifies the solution (see, e.g., Gabaix (2011) and Gourio (2012), who utilize a similar technique).[14]

Assumption 4. *Existence of capital stock.* The depreciation rate is not full, $\delta < 1$.

Assumption 4 guarantees that some portion of firms' stock of installed capital in period t remains positive in the next period $t+1$. As a result, the shadow price of the capital stock can be used to price the (ex-dividend) firm value. We discuss depreciation more formally in Online Appendix Section OA.1, and show that when depreciation is full ($\delta = 1$), there is no dispersion in the riskiness of firms' assets-in-place.

Under Assumptions 1–4, we can solve for the dynamics of the model in closed form. The appendix gives all proofs. A.1

Theorem 1. Equilibrium. *The equilibrium policies and prices are given by*

$$n_{j,t} = \overline{n}_j, \tag{15}$$

$$k_{j,t} = \left(\prod_{\ell=j+1}^{N} Z_{\ell,t}^{\alpha^{\ell-j-1}}\right)\overline{k}_j, \tag{16}$$

$$I_{j,t} = \left(\prod_{\ell=j+1}^{N} Z_{\ell,t}^{\alpha^{\ell-j-1}}\right)\overline{I}_j, \tag{17}$$

$$P_{j,t} = D_t \cdot S_{j,t}^{-1} \cdot \overline{P}_j, \tag{18}$$

where $D_t = \prod_{\ell=0}^{N} Z_{\ell,t}^{\alpha^{\ell}}, \quad S_{j,t} = \prod_{\ell=j}^{N} Z_{\ell,t}^{\alpha^{\ell-j}}$*, and* $\left\{\overline{n}_{j\in\{0..N\}}, \overline{k}_{j\in\{0..N-1\}}, \overline{I}_{j\in\{0..N-1\}}, \overline{P}_{j\in\{1..N\}}\right\}$ *are time-invariant scalars.*

In expressions (16)–(18), the terms that premultiply $\overline{k}_j$, $\overline{I}_j$, and $\overline{P}_j$ capture the stochastic components of the allocations and prices. These stochastic components are the key for the theorems that follow. Importantly, they do not depend on the capital quality shocks χ_j. In the full DSGE model, in which χ_j is absent, the same stochastic components of Equations (16)–(18) comprise the

[14] Beyond its technical need, Assumption 3 embodies an economic rationale. The shocks χ_j affect the efficiency of new capital vintages. Because the quality of capital can change through technological innovations from capital producers, quality shocks are typically associated with technological shocks of upstream layers (e.g., investment technology shocks as in Papanikolaou 2011). This implies that conceptually, $\text{corr}(\chi_j, Z_{j+\ell}) > 0, \forall \ell > 0$, and this is captured by our assumption on χ_j's. However, not all upstream layers should equally affect the quality of firm j's capital. Our assumption on χ_j assumes that the farther the supplier is from firm j, the weaker its impact on j's capacity. The rate of decay is α, the capital share of output.

stochastic trends of the respective variables, as shown in Appendix A.2. The layer specific terms $\overline{n}_j, \overline{k}_j$, $\overline{I}_j$, and $\overline{P}_j$ are constants because of the elimination of transition periods.

In expression (18) the term D_t is a stochastic component capturing aggregate demand. It stems from the household and amounts to the aggregate growth of the household's consumption, which in equilibrium depends on all layers' productivity shocks. The term $S_{j,t}$ is capturing a supply effect operating on layer j, and therefore depends on productivity shocks of layers that are upstream in relation to j. Expression (18) shows that D_t ($S_{j,t}$) increases (drops) the equilibrium price P_j, as we clarify later in this section.

When examining firms' valuations under a constant return to scale, we are interested in Tobin's q. Given Theorem 1, we are able to derive Tobin's q in the next theorem:

Theorem 2. Valuation ratios. *Define Tobin's q of firm $j \in \{0, .., N-1\}$ as the ex-divided valuation divided by capital:*

$$Q_{j,t} = \frac{V_{j,t} - d_{j,t}}{k_{j,t}}, \tag{19}$$

and let $q_{j,t} \equiv \log(Q_{j,t})$.[15] *For layer $j \in \{0, .., N-1\}$, we have*

$$q_{j,t} = \left(\sum_{\ell=0}^{N} \alpha^{\ell} z_{\ell,t} - \sum_{\ell=j+1}^{N} \alpha^{\ell-j-1} z_{\ell,t} \right) + \log(\overline{P}_{j+1}). \tag{20}$$

The intuition for Theorem 2 lies in the relation between the shadow price of installed capital of layer j, and its relative input prices P_{j+1}. P_{j+1} represents the cost of an additional new unit of layer j's capital input. An optimality condition of the full DSGE model stipulates that the shadow cost of capital amounts to $P_{j+1} \cdot \Phi'(i_j)$. Intuitively, the cost of replacing an installed capital unit in layer j equals to the cost of purchasing a new capital good times the installation cost Φ'. Under Assumption 1, there are no installation costs. Therefore, the ratio in Equation (19) is equal to the input price of capital: $Q_j = P_{j+1}$. Thus, the last term in Equation (20) is obtained from the equilibrium price $\overline{P}_{j+1}$.[16] The term in the parentheses has two components. The first stems from

[15] Tobin's q is usually defined as $\frac{V_{j,t}-d_{j,t}}{k_{j,t+1}}$. However, because of the existence of capital quality shocks, $k_{j,t+1}$ is unknown at time t. This leads us to divide the ex-dividend valuation by $k_{j,t}$. The results that follow are unchanged if instead we define Tobin's q as $\frac{V_{j,t}-d_{j,t}}{E_t[k_{j,t+1}]}$. To see this, notice that, under the alternative definition, Tobin's q can be expressed as $\frac{V_{j,t}-d_{j,t}}{k_{j,t}E_t[k_{j,t+1}/k_{j,t}]}$. In our economy, $k_{j,t+1}/k_{j,t} = \prod_{\ell=j+1}^{N} \left(Z_{\ell,t+1}/Z_{\ell,t}\right)^{\alpha^{\ell-j-1}}$. As all Z_ℓs are random walks, capital growth is i.i.d., and its expectation is a constant.

[16] Note that $\overline{P}_{j+1}$ depends on the model parameters and, in particular, on δ. Equation (20) implies that $\overline{P}_{j+1}$ is a multiplicative constant for $Q_{j,t}$, suggesting that $Q_{j,t}$ implicitly depends on δ. Similarly, $q_{j,t} \equiv \log(Q_{j,t})$ also depends on δ via the term $\log(\overline{P}_{j+1})$. Because $\log(\overline{P}_{j+1})$ is an additive constant for $q_{j,t}$, the derivative of $q_{j,t}$ with respect to log-productivity does not depend on δ, as shown next in Corollary 1.

D_t, whereas the second negative term stems from $S_{j,t}$. Importantly, because there are no capital adjustment costs, there are no rents associated with (dis)investment, and no growth option value. In the simplified model, firm valuations reflect only the value of assets-in-place. This observation, along with Theorem 2, yields the following corollary:

Corollary 1. *The log-valuation (shadow price) of assets-in-place of firms in layer j, as measured by q_{jt}, increases (decreases) with productivity shocks of layers below (above) it:*

$$\beta_{j,\ell}^{AP} \equiv \frac{\partial q_{j,t}}{\partial z_{\ell,t}} = \begin{cases} \alpha^{\ell} & > 0, \qquad if \quad \ell \leq j, \qquad (21) \\ \alpha^{\ell} - \alpha^{\ell-j-1} & < 0, \qquad if \quad \ell > j. \qquad (22) \end{cases}$$

We separate the analysis into several cases. The first case ($\ell \leq j$) suggests that if two layers, j and k, have higher vertical positions than layer ℓ (i.e., $j, k \geq l$), then layer ℓ's productivity increases the valuation of assets-in-place for both j and k. This is consistent with layer ℓ being a direct or an indirect customer of both. Therefore, an increase in layer ℓ's productivity increases the demand for the capital products of both. Importantly, the downstream productivity shock ℓ increases the valuation of j and k by the same amount (notice that in Equation (21) the exposure is independent of j, and $\beta_{j,\ell}^{AP} = \beta_{k,\ell}^{AP}$ is the same for all $j, k > \ell$). There is no heterogeneity between layers in the risk exposures to shocks that only shift demand. To understand why, suppose the productivity of layer ℓ rises. The firm in layer ℓ desires to increase its investment because of higher marginal productivity. However, Equation (15) shows that in equilibrium the labor of layer $\ell + 1$ is fixed over time. Coupled with the fact that the capital of layer $\ell + 1$ is predetermined, layer $\ell + 1$ cannot produce more capital goods for ℓ's investment. As a result, the price of ℓ's capital input, $P_{\ell+1}$, must increase exactly by the same proportion as the increase in ℓ's productivity, in order to suppress ℓ from investing more. Next, consider the effect of a higher $P_{\ell+1}$ on layer $\ell + 1$. A rise in its output price increases $\ell + 1$'s marginal revenue, just as a rise in its productivity would. Because of higher marginal revenue of capital it desires to invest more. By a similar logic, layer $\ell + 2$ cannot supply more capital goods, and hence, the price $P_{\ell+2}$ must rise by the same proportion as the increase in $P_{\ell+1}$. This argument can be repeated upstream recursively. Because all relative prices increase by the same proportion, and these prices are equal to the Q of the layer below, the exposure of assets-in-place to a shock that affects firms' demand is identical across different firms. By balanced growth, the exposure is equal to the elasticity of consumption growth to ℓ's shock.

To explain the TMB spread, we are interested in differential exposures to shocks. Such differences can account for heterogeneity in risk premiums between any two layers j and k. From the discussion above, such differences in premiums are not explained by exposures to (relative) downstream shocks, which purely induce a demand effect for firms j and k. As a result, for the remainder of the section we focus the discussion on firms' asset exposures to (relative) upstream shocks that act as supply shocks for the firm, and on cumulative differential supply effects.

The second case ($\ell > j$) of Corollary 1 suggests that if layer j has a lower vertical position than ℓ, then ℓ's productivity drops the valuation of installed capital for j.[17] To understand the intuition, we start with the case that ℓ is a direct supplier of j ($\ell = j + 1$). When the productivity of layer $j + 1$ rises, the supply curve of j's capital input shifts to the right. It puts a downward pressure on the valuation of j's installed capital. This is because technological advancements in $j+1$ makes the production of j's capital input easier and cheaper, and drops its replacement cost of capital. Under perfect competition, this erodes the marginal value of j's assets-in-place. We term the negative (supply) effect of a positive productivity innovation on the valuation of downstream layer's assets-in-place as *vertical creative destruction.*

Vertical creative destruction still applies, albeit with a different magnitude, when ℓ is an indirect supplier of j. Assume that $\ell > j + 1$. When ℓ's productivity improves, it is cheaper to replace not only the capital of its direct customers but also the capital of its customers of customers, third-order customers, and so on. As in the direct case, a drop in the replacement cost induces a negative impact on installed capital. However, this vertical creative destruction is not homogeneous for all (relative) downstream layers. Rather, the propagation decays at rate α, capital's share of output. To see this, notice that the ratio between the negative term in Equation (22) for layers j and $j - 1$ is given by $\frac{\alpha^{\ell-j-1}}{\alpha^{\ell-j-2}} = \alpha$. This is because to replace of a unit of capital for a customer of a customer, only α of expenditures are paid for capital inputs, and the rest is paid for labor expenditures. While the former is cheaper when ℓ innovates, the latter is unaffected (by Equation (15)).

Importantly, while the exposures $\beta_{j,\ell}^{AP}$ are fixed over time under Assumptions 1–3, they are time varying in the full-scale DSGE model. It happens as $\overline{I}_j$ is no longer a constant, along with the presence of adjustment costs. We discuss this later in Section 5.2.3.

[17] More precisely, by comparing Equation (22) to (21), it becomes clear that the first term α^{ℓ} captures a demand effect stemming from D_t. As previously discussed, this demand effect is homogeneous across all layers, and in equilibrium, equals to the elasticity consumption growth to ℓ's shock. This term cannot explain differences in risk premiums between layers. However, the second term $-\alpha^{\ell-j-1}$ is negative, is larger in absolute value, and depends on j. This term captures the direct or indirect supply effect and induces dispersion in exposures.

To assess the cumulative vertical creative destruction effect, which stems from direct suppliers as well as indirect suppliers, we need to take a stand on the relative magnitude of productivity shocks. For simplicity, the theorems below are derived under Assumption 2', that is, a perfect correlation between the productivity of different layers ($Z_{j,t} = Z_t, \quad \forall j$).

Theorem 3. Monotonicity. *If $\rho_z = 1$, then $\beta_j^{AP} \equiv \frac{\partial q_{j,t}}{\partial z_t}$ is monotonically increasing in j.*

Because the supply effect (vertical creative destruction) propagates downwards from layer ℓ to all bottom layers $j < \ell$ at rate α, and because a firm in layer $j < k$ has more direct and indirect suppliers, the *cumulative* vertical creative destruction from a positive common innovation is larger for j than for k. Focusing on the extremes, a firm at the bottom of the production chain is subject the most to the vertical creative destruction force. 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 very top of the production chain has no suppliers and is not subject to this creative destruction force.

An equivalent interpretation of Theorem 3 is that vertical creative destruction acts as a hedge. It makes a firm's installed capital less sensitive to productivity shocks by attenuating the positive and homogeneous demand effect. The cumulative supply effect is larger at the bottom, so a positive productivity shock appreciates the value of installed assets for top-layer firms more than for bottom-layer firms. The asset valuation of top-layer firms is more cyclical, and hence, riskier. As Theorem 3 shows, the riskiness monotonically increases as the vertical position increases.

Theorem 4 shows that the degree of vertical creative destruction depends not only on the relative position of a firm in the production chain, but also on the chain's length.

Theorem 4. Chain length and risk. *Under the assumption $\rho_z = 1$, we have*

(i) **Risk exposures.** *Denote by $\Delta\beta^{AP} \equiv \beta_{N-1}^{AP} - \beta_0^{AP}$ the difference between the maximum and minimum risk exposures in $\{\beta_j^{AP}\}_{j\in\{0..N-1\}}$. The longer the production chain, the greater the dispersion in risk exposures, that is, $\Delta\beta^{AP}$ increases with N.*

(ii) **SDF.** *The equilibrium log stochastic discount factor used to price dividend claims is given by*

$$m_{t,t+1} = \log(\beta) + \frac{\gamma - \frac{1}{\psi}}{1-\gamma}\overline{E} - \lambda(N)\varepsilon_{t+1},$$

where $\overline{E}$ is a positive scalar, $\lambda(N)$ is the price of risk of productivity, and ε_{t+1} is the common productivity shock. The price of risk $\lambda(N)$ increases with the chain length N, and is given by

$$\lambda(N) = \gamma \frac{1-\alpha^{N+1}}{1-\alpha}.$$

Theorem 4 suggests that the difference between top layer's and bottom layer's productivity beta rises with chain length. The market price of risk for productivity is positive and increases with the chain length. Combining a positive difference in the productivity beta between the top and the bottom (part i), along with a positive price of risk (part ii), the TMB spread should be positive, and larger in a network that involves more layers of production, all else equal.

4.1 Approximating risk premiums for the full DSGE model

For tractability, we have assumed in the closed-form model that firms are subject to quality shocks after their investment decisions are made. This is different from the setup for the full DSGE model, in which firms are not subject to quality shocks. Nevertheless, the closed-form SDF derived in Theorem 4 provides a close approximation for the SDF in the full model.[18] Using this SDF, we can analytically price a claim to a dividend stream that is not subject to the quality shock, which is closer to the dividend stream of a firm in the full DSGE model. Define the growth of this dividend stream by $\Delta\tilde{d}_{j,t+1} = \Delta d_{j,t+1} e^{-\chi_{j,t+1}}$, where $\Delta x_{t+1} \equiv x_{t+1}/x_t$, and $d_{j,t}$ is the period-t dividend of the layer-j firm in the closed-form model. Note that because $\Delta d_{j,t+1}$ (and $k_{j,t+1}$) is a function of $e^{\chi_{j,t+1}}$, the multiplication by $e^{-\chi_{j,t+1}}$ neutralizes capital from the impact of this quality shock. The expected return of a firm that pays $\tilde{d}_{j,t}$ in every period is given in Theorem 5:

Theorem 5. Expected returns of dividend claims. *Let $E[\tilde{R}_{j,t+1}]$ be the expected return of a firm that pays dividend $\tilde{d}_{j,t}$ every period. Assume ε_t is standard Gaussian. Given $M_{t,t+1}$ in Theorem 4., $E[\tilde{R}_{j,t+1}]$ increases with j.*

Theorem 5 shows that the expected returns are increasing with the vertical position. This is qualitatively consistent with stylized fact 1. In the next section, we calibrate the full DSGE model to examine the quantitative power of vertical creative destruction for explaining this fact.

[18] Under Epstein-Zin preferences, the SDF has two components: one related to consumption growth and the other to continuation utility. In the closed-form model, the continuation utility component is constant. Therefore, marginal utility drops in response to a positive productivity shock only because of increased consumption (see Equation (A.12) in Appendix A.1). In the full DSGE model, the marginal utility also drops with aggregate productivity because of an increase in the continuation utility (under early resolution of uncertainty). Thus, the price of the productivity risk in the full DSGE model is also positive and is larger in magnitude.

5 Quantitative Results

5.1 Calibration

Table 3 shows the parameter choice of the full DSGE model, calibrated at an 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 autocorrelation 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.

Technology: To reduce the dimensionality of the exogenous model parameters, we assume that all productivity shocks are perfectly correlated (i.e., $\rho_z = 1$). This implies that $Z_{j,t} \equiv Z_t, \forall j$, where Z_t is the aggregate (common) productivity. Following Croce (2014), the dynamics of the log-growth of aggregate productivity, Δz_{t+1}, feature a persistent component:

$$\Delta z_{t+1} = \mu_z + x_t + \sigma_z \varepsilon_{z,t+1}, \tag{23}$$

$$x_{t+1} = \rho_x x_t + \phi_x \sigma_z \varepsilon_{x,t+1}, \tag{24}$$

where $\varepsilon_{z,t+1}$ and $\varepsilon_{x,t+1}$ are the short- and long-run aggregate productivity shocks, respectively, and their contemporaneous correlation is ρ_{xz}. For simplicity, we set ρ_{xz} to 1. This reduces the number of shocks in the model to only one standard Gaussian shock. In the specification above, x refers to the long-run risk component in productivity growth. This component is important quantitatively, but not qualitatively, for obtaining a high equity-premium.

The aggregate productivity log-growth μ_z is set such that the average 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 autocorrelation of consumption growth to the data (about 0.5).

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, Kiku, and Yaron (2012); Colacito and Croce (2011)). The IES is important only because of the 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.

5.2 Model results

The calibrated model is solved using a third-order perturbation method. Appendix A.2 shows the first-order conditions and the required detrending. We now present the implications of the calibrated model for aggregate macroeconomic and asset pricing moments, and for the layer portfolios. We also inspect the mechanism of the model, vis-à-vis the closed-form results.

Table 3: **Calibrated parameter values for the full DSGE model**

Symbol	Value	Parameter	Symbol	Value	Parameter
A. Production			*C. Preferences*		
N	5	Number of layers	β	0.98	Subjective discount factor
α	0.33	Share of capital in output	γ	10	Relative-risk aversion
ϕ	25	Investment adjustment cost	ψ	2	Intertemporal elasticity of substitution
δ	0.1	Depreciation rate			
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			

5.2.1 Aggregate macro and pricing moments

Table 4 compares aggregate macroeconomic and return moments 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 volatility.[19] 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

[19]In the period of 1930–2012, the volatility of consumption growth is 2.11%.

Table 4: **Aggregate moments: Model versus empirical equivalents**

Statistic	Model	Data		Statistic	Model	Data	
A. Macroeconomic variables				*B. Return variables*			
Consumption growth:				*Excess market portfolio return:*			
Mean	1.94	1.97	[1.58, 2.35]	Mean	4.13	4.89	[-0.20, 9.97]
Standard deviation	1.75	1.33	[1.11, 1.67]	Standard deviation	5.10	17.70	[14.76, 22.11]
Autocorrelation	0.45	0.52	[0.29, 0.75]	Autocorrelation	-0.01	-0.04	[-0.29,0.21]
Output growth:				*Risk-free rate:*			
Mean	1.94	2.11	[1.60, 2.61]	Mean	1.02	1.04	[0.51, 1.57]
Standard deviation	2.13	1.74	[1.45, 2.18]	Standard deviation	0.90	1.84	[1.54, 2.30]
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]				

The table shows annual moments from simulated model data against their empirical counterparts. Panel A presents moments related to macroeconomic variables, and panel B presents moments 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. (2018)). Consumption, output, and investment growth rates are real and per capita. The real risk-free rate corresponds to a 3-month Treasury-bill rate net of expected inflation. All numbers are expressed as percentages. Values in brackets are empirical 95% confidence intervals.

point estimate. This low volatility does not stem from the capital adjustment costs, but rather from the value-weighted aggregation method. The 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, the output of layer 0 is used for consumption only in our model. Keeping consumption volatility low restricts the sales and investment variability of layer 0. 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.[20] 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. Investment's autocorrelation 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 data is the volatility of the market excess return. It is difficult

[20]The volatility of investment growth for layers 3, 4, and 5 is 5.39%, 6.10% and 6.43%, respectively. These model-implied estimates are close to the empirical counterpart(s). The upper layers have relatively small weights in the economy (consistent with the data), so the value-weighted aggregation scheme attenuates investment volatility.

to generate a high equity premium and a high volatility of stock returns in a general equilibrium production model (see related discussion in Gomes, Kogan, and Zhang (2003)). The nontrivial equity premium is generated through a considerable risk aversion of 10, along with a persistent productivity growth 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 IES intensifies the volatility of stock returns, while keeping low volatility for the risk-free rate.

5.2.2 Vertical position and cross-sectional return implications

Stylized fact 1: Model versus data. Our first stylized fact states that the excess return spread between the top (layer 5) and bottom layers (layer 0) is about 105 bps per month, or 11.27% p.a. (continuously compounded). Our model successfully replicates this sizable spread, consistent with the logic and implications of Theorem 5. Table 5 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, which 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 fall inside the 95% confidence interval of the data for all layers. The model generates excess returns for layers 1, 4, and 5 that are strikingly similar to the data.

Table 5: **Vertical position and expected return: Model versus data**

	Model	Data	
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]
TMB (5-0)	12.49	11.27	[6.94, 15.60]

The table presents the mean excess returns by layer and the TMB spread in the model, against their empirical counterparts. Layer 0 consists of firms producing final consumption goods, and layer 5 refers to firms in the top vertical position. The model excess returns are obtained from a simulated path of 100,000 years. The empirical excess returns are based on a monthly sample during November 2003–February 2013, aggregated over a 12-month rolling window to form continuously compounded annual return observations. Values in brackets are 95% empirical confidence intervals.

Stylized fact 2: Model versus data. Our second stylized fact is that the exposures of layer portfolios to aggregate productivity increase monotonically with the vertical position, and that the

TMB spread loads positively on aggregate productivity. We obtain model-implied productivity betas from a projection of portfolios' excess returns on both a linear and quadratic terms of productivity, as we do with empirical data (panel B of Table 2). As in our empirical analysis, we use two measures for aggregate productivity. The first is Hicks-neutral productivity (Solow residual), given by Z_t. The underlying TFP may not be observed, so we also compute within the model a measure that is equivalent to labor productivity. This is done by dividing each layer's sales by its labor and averaging across the layers. We report the model-implied TMB productivity beta against its empirical counterpart in Table 6. Table OA.12 of Online Appendix shows a breakdown of the TMB beta into each layer's productivity exposure.

Table 6: **TMB's exposure to aggregate productivity: Model versus data**

	β_1		β_2		$\hat{\beta}_{Prod} = E[\frac{\partial TMB}{\partial \Delta Prod}] = \beta_1 + 2\beta_2 E[\Delta Prod]$	
	Data	Model	Data	Model	Data	Model
$Prod = Solow$	2.863	2.182	-0.362	-1.134	1.937	2.168
$Prod = LaborProd$	8.044	1.874	-1.354	-1.397	3.254	1.845

The table shows the results of the regression: $TMB_t = const + \beta_1 \Delta Prod_t + \beta_2 \Delta Prod^2 + error$, where TMB is the return spread between layer 5 and layer 0, and $Prod_t$ is an aggregate productivity measure. $Prod$ is either Solow residual or labor productivity. The model population moments are based on a simulated path of length 100,000 for layers' excess returns and for aggregate productivity. The overall exposure β_{Prod} of TMB to aggregate productivity $Prod$ combines the linear term β_1 and the quadratic term β_2. The empirical point estimates are taken from Table 2.

The model-implied betas exhibit several patterns consistent with the data. First, quantitatively, the model-implied TMB betas are of a similar magnitude. For example, the TMB beta to Solow residual (equal to the difference in betas between layer 5 and layer 0) is 1.93 in the data versus 2.16 in the model. Second, the coefficient on the quadratic productivity term is nonzero in both the model and the data. Within the model, the relation between returns and productivity is nonlinear because of time-varying exposures. We further explain this in the next subsection. Third, the breakdown of the TMB beta, shown in Table OA.12, suggests that the model-implied productivity betas increase monotonically from layer zero to five, consistent with the data.

5.2.3 Inspecting the mechanism

Differential exposures of Tobin's q. Theorem 3 states that the productivity shock affects the Tobin's q of the top layers more strongly than that of bottom layers. This is also true in the full DSGE model, as we illustrate in Table 7, which reports the productivity elasticities of firms in layers 0 to 4 in the calibrated model. Consistent with the theorem, the sensitivity of Tobin's q to productivity shocks increases monotonically as the vertical position increases.

Table 7: **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 100,000 periods.

We can decompose the elasticities of Tobin's q into two components. The 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 into 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, whereas the latter is related to firms' rents and growth options.

Table 7 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. This is consistent with Equation (18), and results from a stronger vertical creative destruction on bottom layers' assets-in-place.

In Section 4, the simplifying Assumptions 1 and 3 imply that firms' investment rates (I_{jt}/k_{jt}) are fixed, and there are no adjustment costs. This results in two outcomes. First, there is no growth option value ($\Phi' = 1$) for firms in the closed-form equilibrium of Section 4. Second, the exposure of firms to aggregate productivity is fixed (see Equations (21) and (21)).

The full DSGE model deviates from these outcomes. In the full DSGE model investment is still given by Equation (17), however, the ratio $\overline{I}_j/\overline{k}_j$ is not a constant. As shown in the last column of Table 7, productivity shocks induce firms in the top layers to invest more compared to bottom-layer firms.[21] This is because the substitution effect induces the household to save more and resources

[21] In Section 4, capital quality shocks χ_j restore the steady state in time $t + 1$. Thus, no adjustment is needed by firms in the form of investment. In the absence of these shocks, the investment rate varies over time.

are shifted to upstream layers. Thus, firms at the top of the production chain face a greater increase in capital installation costs (Φ'). This channel increases their Tobin's q as well. Consistently, each layer's exposure to aggregate productivity becomes time varying. The exposure depends not only on the stochastic trend but also on the nonlinear degree of $\Phi'(i_{j,t})$, which varies cyclically, and depends on the realization on the productivity shock. It suggests that the relation between returns and productivity is nonlinear, as demonstrated in Table OA.12 of Online Appendix.

Numerical illustration of the mechanism via layer-specific shocks. For parsimony, our baseline model features a single shock. The existence of the TMB does not hinge on assuming a single shock. To show this, and to further illustrate the mechanism of vertical creative destruction described in Corollary 1, we now adopt Assumption 2 of Section 4: each layer is subject to a layer-specific shock Z_j (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). 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 a model-implied TMB spread that is still positive and sizable, 4.37% per annum. This spread can be boosted by raising only the volatility of shocks to upper layers (consistent with the data), while keeping consumption's volatility low. Table 8 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 8: **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 that we shut 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 (i.e., $\beta_{j,k}$, $j, k \in \{0..N\}$). The last column reports the summation all layer-specific shock betas for each layer ($\sum_{k=0}^{5} \beta_{j,k}$).

Consistent with Equation (21), $\beta_{j,k} < 0$ iff $j < k$. If the shock originates from a direct or an indirect supplier, the firm has a *negative* exposure to it, consistent with vertical creative destruction. By contrast, $\beta_{j,k} > 0$ iff $j \geq k$, consistent with Equation (22). It stems from an increased demand effect coming from a direct or an indirect customer of the firm. Although the signs are consistent, the magnitudes of the exposures deviate from expressions (21) and (22) because of time-varying investment rates and adjustment costs, which are absent in Section 4. Consistent with Equation (22), the supply effect is stronger when the shock originates from a firm's direct supplier, diminishes when it originates from a firm's supplier of supplier, and diminishes even further for higher-order suppliers. To illustrate the cumulative effect of all shocks, the last column in Table 8 sums the exposures of each layer to all layer-specific technology shocks. If one assumes the correlation between the layer-specific shocks is one, as in Theorem 3, this summation captures (in a comparative static manner) the exposure of the firm to aggregate productivity. Consistent the benchmark model, the implied aggregate productivity betas increase with the vertical position.

CAPM α. In the calibrated model all layers are affected by a common productivity shock. Nevertheless, the unconditional capital asset pricing model (CAPM) does not hold in the model because valuations are nonlinear in the underlying shock. As previously discussed, the nonlinearity is explained by the fact that the beta of firms to aggregate productivity is time varying. We find that the levered CAPM α in the model is 6.7% per year, which is about 52% of the spread. The CAPM alpha as a percentage of the overall model-implied spread can be further boosted when the model features layer-specific shocks. In that model extension, which is outlined above, the ratio between the CAPM alpha and the model-implied TMB is about 70%. With layer-specific shocks even the conditional CAPM fails to explain the spread, as each layer's productivity is priced in the cross-section.

Sensitivity analysis. In Online Appendix Section OA.1, we perform sensitivity analysis of the model's results to key parameters. We demonstrate that the only parameter that is qualitatively important for the sign of the TMB spread is the elasticity of intertemporal substitution, which governs the strength of the substitution effect and/or the sign of the market price or risk. 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.

6 Testing the Mechanism: Model Predictions and Implications

We perform several tests for the vertical creative destruction mechanism. First, we compare the cyclicality of capital investment, input prices, and Tobin's q across layers between the model and the data. Second, we examine the impact of market power on the TMB spread and on the returns of bottom-layer firms. Third, we examine the TMB spread in subsamples and demonstrate that the spread is larger for firms whose assets-in-place represent a larger fraction of their value.

6.1 Testing the model predictions for capital and price dynamics

6.1.1 Cyclicality of capital investment and sales

We illustrate that the model-implied cyclicality for sales and capital investment are consistent with the data. Let $y_{j,t}$ be a variable of interest for layer j at time t. Denote by $Prod_t$ the time series of aggregate productivity at time t. Construct a vector $Y_t = [\Delta Prod_t, y_{4,t}, y_{3,t}, y_{2,t}, y_{1,t}, y_{0,t}]$. The first variable in the vector is productivity, and the y variables, which include investment rate and sales (scaled by assets), are ordered by decreasing vertical position.[22] We estimate a VAR(k) model for the vector Y_t, where the lag k is 1 year ($k = 1$ for simulated model path at the annual frequency, and $k = 4$ for empirical data at the quarterly frequency). All variables normalized by their standard deviation prior to their inclusion in the vector Y.

In the model, we set $\Delta Prod_t$ to the aggregate productivity growth ΔZ_t. In the data, we use the Solow residual described in Section 2.2, which is the closest empirical counterpart. To assess cyclicality patterns, we are interested in how a 1-standard-deviation Cholesky shock to $\Delta Prod$ affects $y_{0,t}$ versus $y_{4,t}$. The impulse response function (IRF) uncovers whether y is more cyclical at the top or the bottom of the chain. We report IRFs for the most downstream layer (layer 0, referred to as "Bottom"), the most upstream layer in vector Y (layer 4, referred to as "Top"), and the middle layer (layer 2, referred to as "Mid") in Table OA.13 in Online Appendix.

In both the model and the data, a 1-standard-deviation shock to productivity increases the

[22] The vector Y_t does not include a time series of y variable for layer 5, because all of the y variables considered are related to capital, and the capital of layer 5 is assumed to be fixed in the model.

1-year-ahead investment rate more for the top than the bottom firms. The magnitudes are similar. A standardized shock increases the model-implied top's (bottom's) investment rate by 0.21 (0.09) standard deviations. In the data, the figures are 0.24 and 0.11, respectively. Following a positive productivity shock, the household desires to save more as the substitution effect dominates ($\psi > 1$). As a result, resources are allocated more to upstream layers, and the investment rate of the top layer rises more. This model feature is consistent with the last column of Table 7. The fact that the data exhibits a similar pattern provides real-side support for our model.

A similar pattern arises in the impulse-responses of sales across layers. A positive productivity shock has a larger impact on the sales of top-layer firms. The IRFs' magnitudes, in both the model and the data, are quite similar to investment rate's IRFs. The logic is similar. Because of a stronger substitution effect, positive productivity shocks shift labor to upstream layers. Given that capital is predetermined, the sales of the top layer rise more than those of the bottom.

Table 9: **Vertical position and exposures of q to aggregate productivity shocks**

	TMB	Layer 0	Layer 1	Layer 2	Layer 3	Layer 4	Layer 5
A. $\Delta log(Q_{i,t}) = const + \beta_1 \Delta Prod_t + error$							
$Prod$ = *BLS labor productivity:*							
β_{prod}	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)
$Prod$ = *Solow residual:*							
β_{prod}	1.034	0.643	0.584	0.839	0.819	1.114	1.677
	(2.15)	(2.34)	(1.67)	(2.10)	(1.68)	(1.90)	(3.14)
B. $\Delta log(Q_{i,t}) = const + \beta_1 \Delta Prod_t + \beta_2 \Delta Prod_t^2 + error$							
$Prod$ = *BLS labor productivity:*							
β_{prod}	2.310	0.373	0.523	1.309	1.733	1.798	2.683
	(5.11)	(0.72)	(0.92)	(1.86)	(2.30)	(2.57)	(3.47)
$Prod$ = *Solow residual:*							
β_{prod}	1.367	0.456	0.456	0.771	0.819	0.917	1.822
	(3.04)	(1.25)	(0.97)	(1.38)	(1.59)	(1.50)	(2.69)

The table shows the sensitivities of quarterly changes in $\log(q)$ to percentage changes in productivity for different layers of production in both a linear model (panel A) and a nonlinear (panel B) model. We use both labor productivity and Solow residual as productivity measures. The variables are measured quarterly over the benchmark sample period. In panel A, β_prod is defined as β_1. In panel B, we combine the linear sensitivity β_1 and the quadratic sensitivity β_2 to form β_{prod}. t-statistics for β_{prod} in panel B are obtained using the delta method.

6.1.2 Cyclicality of Tobin's q and input prices

Table 7 shows that the Tobin's q and input prices of upstream firms are more procyclical than that of downstream firms in our model. To test this prediction, we regress the quarterly change of

Tobin's q in each layer on changes of aggregate productivity.[23] Table 2 shows the exposure of each layer in a linear model (panel A), and in a model with both linear and nonlinear terms (panel B). In both panels, we use two alternative productivity proxies, the labor productivity and the Solow residual. The results strongly support the model prediction: the sensitivity of Tobin's q increases almost monotonically from layer 0 to layer 5 for both models, regardless of which productivity proxy is used, and the difference between the top and the bottom layers is statistically significant.

The model-implied cyclicality pattern for input prices is consistent with Kogan, Li, and Zhang (2018), who argue that input prices are more procyclical, and more sensitive to aggregate shocks than shipped goods prices (which affect primarily downstream firms and consumers). In Online Appendix Section OA.4, we show higher cyclicality for upstream input prices at the industry-level using input-price indexes of intermediate demand produced by BLS.

6.2 The effect of monopolistic competition on vertical creative destruction

Our benchmark model features perfect competition. Vertical creative destruction stems from competitors' ability to replace assets-in-place at a lower cost, so this effect is likely to be strongest in an environment with perfect competition. In this section, we study how firms' market power affects the TMB spread, both empirically and theoretically.

6.2.1 TMB spread: High competition versus low competition

To conduct our test, we first develop a new measure of supply chain competition. The FactSet Revere relationships data set allows us to identify each firm's competitors reported either by the firm itself or by its competitors. We use these 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.[24] Online Appendix Section OA.3 gives further details for the construction of this measure. We use the supply chain competition measure to 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. We compute

[23] We estimate Tobin's q for each firm using the quarterly Compustat database and measure the change in Tobin's q 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).

[24] 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. We set λ to 0.9 in the benchmark case.

the TMB spreads for each subsample.

To compare this empirical split to the model, we augment the benchmark model to feature monopolistic competition. Online Appendix Section OA.2. In the augmented model, the parameter μ characterizes the degree of competition. We consider two choices for μ: (1) a high competition case: $\mu = 100$, implying a markup of 1%, and (2) a low competition case: $\mu = 3$, implying a markup of 33%. These numbers are consistent with the empirical estimates of markups (see, e.g., Bilbiie, Ghironi, and Melitz (2012)). Table 10 provides the results.

The TMB spread drops when firms have more market power both in the model and in the data. The empirical spread for the high (low) competition subsample is 9.97% (4.63%) p.a.[25] The model-implied spread for these subsamples is qualitatively and quantitatively similar to the data. For the high (low) competition calibration, the model-implied TMB is 12.15% (7.9%). Model-implied excess returns fall inside the empirical 95% confidence interval for all the layers in the high competition subsample and in all, but one, layers in the low competition subsample.

Table 10: **TMB spread and competition: Augmented model versus data**

	High competition			Low competition		
	Model	Data		Model	Data	
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]
B. Spreads						
Spread (5-0)	12.15	9.97	[5.30, 14.64]	7.90	4.63	[-2.08, 11.34]

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 spread between layers 5 and 0. In the model the high competition results are based on a calibration in which $\mu = 100$, whereas the low competition results are based on a calibration in which $\mu = 3$. 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 November 2003–February 2013, aggregated to form annual observations over rolling windows of 12 months. Values in brackets are 95% confidence intervals for the data moments.

The results show that the TMB spread declines when the firm and its suppliers have greater market power. Two forces drive this result. First, keeping the market power of a firm's suppliers

[25] In untabulated results, we 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, whereas for the low competition group, it is merely 5.9%.

constant, vertical creative destruction weakens as the firm's own monopolistic power increases. Under perfect competition, firms' valuations are determined by the cost of replacing their capital stock. Under monopolistic competition, valuations also depend on monopolistic rents. The benefits arising from technological improvements are not eroded as much by competition. For downstream firms a technological improvement decreases the cost of investment and increases their rents. This cash-flow effect operates against the negative effect on assets-in-place.

Second, keeping a firm's market power constant, vertical creative destruction is weakened when its suppliers' market power increases. When suppliers have a higher degree of monopolistic power, it has a rationing effect on their production. 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.

Table 11: **Bottom-layer returns 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 into five groups based on the average number of competitors of a firm's direct and indirect suppliers. Group 1 (5) represents firms with the most (least) competitive supply chain. We report the annualized continuously compounded excess returns. The results are based on a monthly sample from November 2003–February 2013, 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. * $p < .10$; ** $p < .05$; *** $p < .01$.

6.2.2 Competitiveness of suppliers and bottom-layer returns

As discussed above, greater market power of suppliers makes downstream firms more exposed to 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. Firms with a more competitive supply chain are subject to stronger vertical creative destruction, and therefore, should be less exposed to productivity and earn lower returns. To test this novel prediction of our augmented model, we split the bottom-layer firms, which belong to consumer staples and consumer discretionary sectors, and which are subject are most affected by vertical creative destruction according to the model, into five groups based on the average number of competitors of their direct and indirect suppliers.[26] Group 1 represents firms with the most competitive suppliers, while group 5 represents firms with

[26]This measure is the same as the measure in footnote 24, but without a firm's own number of competitors. Formally, $\hat{\mathbf{C}}_t^S = \sum_{j=1}^{J} \lambda^j \bar{\mathbf{S}}_t^j \mathbf{C}_t$.

Table 12: **TMB spreads in subsamples**

	Value-weighted		Equal-weighted		Value-weighted		Equal-weighted	
	A. Book-to-market split				*B. Depreciation split*			
	Low	High	Low	High	Low	High	Low	High
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)
	C. organization capital split				*D. Inventory split*			
	Low	High	Low	High	Low	High	Low	High
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 TMB spreads 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), ratio of organization capital to total assets (panel C), or ratio of inventory to firm value (panel D). All ratios are computed using the annual Compustat database. The results are based on a monthly sample from November 2003–February 2013, aggregated over a rolling window of 12 months to form annualized returns. Newey-West t-statistics for the TMB portfolio are in parentheses. * $p < .10$; ** $p < .05$; *** $p < .01$.

the least competitive suppliers. Consistent our prediction, Table 11 shows that the value-weighted return of bottom-layer firms increases from group 1 to 5. The spread between these two groups is 4.37% p.a. and statistically significant. This finding is consistent with our mechanism, and suggests that firms whose suppliers face more (less) competition have significantly lower (higher) returns.

6.3 The importance of assets-in-place for vertical creative destruction

Vertical creative destruction affects the value of assets-in-place, so its effect should be stronger when assets-in-place account for a larger fraction of firm value. This implies a larger TMB spread among such firms. This intuition is demonstrated using model comparative statics in Online Appendix Section OA.1. Table OA.1 shows that the TMB is larger than in the benchmark case when we lower the depreciation rate or adjustment costs. These results imply that when firms derive a larger fraction of their valuation from assets-in-place, the spread is magnified.[27] We confirm this empirically below.

Book-to-market ratio and depreciation: Two measures of the weight of assets-in-place in firm value are the book-to-market ratio and the capital depreciation rate. Higher book-to-market

[27]Define the value of a firm's assets-in-place as the value of all future dividends resulting from the existing capital stock, which depreciates over time as $V_{j,AIP,t} = \max_{n_{j,t}} \quad P_{j,t} Z_t k_{j,t}^{\alpha} n_{j,t}^{1-\alpha} - w_t n_{j,t} + (1-\delta) E[M_{t,t+1} V_{j,AIP,t+1}] \quad \forall j \in \{0..N\}$. The ratio between $V_{i,AIP,t}$ and total firm value $V_{i,t}$ clearly increases as the depreciation rate δ decreases. We also confirm that this ratio increases as the adjustment cost parameter ϕ drops. In the extreme case of zero adjustment costs, firms derive their entire valuation from assets-in-place. Column 6 of Table OA.1 shows that in this case, the spread is 17.69%, substantially higher than in the benchmark case (12.49%).

ratio or lower depreciation rate implies a higher weight of assets-in-place and therefore, a larger TMB spread. To test this prediction, we split firms in each layer into two subsamples of equal size based on these ratios and report the TMB spread in each subsample in Table 12. The results are consistent with our hypothesis. Panel A of the table shows that the value-weighted and equal-weighted TMB spreads for value firms are 11.9% and 16.0%, respectively, while the same spreads are only 8.2% and 3.1%, respectively, for growth firms. Panel B shows that the value-weighted TMB spread in the low depreciation sample exceeds the spread in the high depreciation sample by 8% (14.0% vs. 6.0%), although the difference in the equal-weighted TMB spread is small.

Organization capital: Eisfeldt and Papanikolaou (2013) distinguish between two types of capital: physical capital and *organization capital* coming from key talent. organization capital is associated with specialized labor input and is not provided by suppliers along the supply chain, so suppliers' innovation should have no effect on its valuation. Put differently, it is not subject to vertical creative destruction. Thus, the TMB spread should be lower for firms that are more heavily endowed with organization capital. Panel C of Table 12 shows results in support of this hypothesis. For the low organization capital sample, the TMB spread is large and statistically significant (9.3% value-weighted), while for the high organization capital sample, it is close to zero.[28]

Inventory: Similar to the stock of physical capital, the stock of inventory is also subject to vertical creative destruction. Therefore, our model implies that the TMB spread should be greater among firms that carry more inventory. Results in panel D of Table 12 confirm this 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 OA.14 in Online Appendix shows that for both value-weighted and equal-weighted portfolios, monotonicity is strong in the high book-to-market ratio, low depreciation, low organization capital, and high inventory subsamples, in which vertical creative destruction is strong. However, it is much weaker in the subsamples with opposite firm characteristics. This provides further support for vertical creative destruction being the driving force of the return spread across vertical positions.

[28]We follow the method of Eisfeldt and Papanikolaou (2013) to construct a measure of organization capital using the Compustat database. Specifically, we use SG&A (selling, general, and administrative) expenses to measure flows to organization capital and estimate the stock of organization capital recursively using the perpetual inventory method. The initial stock of organization capital is estimated for the year 2000 using equation (36) in their paper.

7 Empirical Robustness

7.1 TMB using alternative databases

Our benchmark results are based on the FactSet Revere database. The database provides the most comprehensive coverage of supplier-customer/competitor relationships at the firm level, which allows us to measure upstreamness accurately at the firm level. However, it covers a relatively short time period and it does not allow us to construct a measure of vertical position accounting for the strength of each supplier-customer relationship. In this section we demonstrate the robustness of the TMB spread using alternative databases that allow us to overcome these two limitations.

7.1.1 Interindustry results using the input-output tables

The BEA periodically publishes Input-Output accounts, which provide snapshots of interindustry relations of the economy. Each snapshot is comprised of two tables. The "Make" table shows the production of commodities by industry in dollars. The "Use" table shows the use of each commodity by each industry, also in dollar value. We use the combination of Use and Make tables at each point in time to compute industry-level vertical positions. We follow the methodology used by Antràs et al. (2012) to compute the vertical position of each industry. This methodology accounts for the strength of each link between industries. Online Appendix Section OA.6 explains the details about the construction of the upstreamness measures.

Because the detailed I-O tables are only available once every 5 years, we use the industry vertical position computed for year t to determine firms' vertical positions from year $t-4$ to year t based on their industry affiliations. We start our sample in January 1974 as the number of firms in our CRSP database drops significantly prior to this year. The last year for which detailed I-O tables are available is 2012. To extend the industry-based result until 2017, we assign the vertical position score of a firm that belongs to industry i for the years 2013 to 2017 to be the most updated vertical position computed in 2012.

We sort firms into portfolios in each month t based on their vertical positions at the end of month $t-1$. To parallel with our baseline results, the break points are equidistant on the $[0,5]$ segment.[29] Panel A of Table 13 reports the results. The value-weighted interindustry TMB spread

[29] In other words, we use vertical positions $\{1,2,3,4\}$ as break points to form five portfolios. The layer $i \in \{0,1,...,4\}$ portfolio includes all firms with a vertical position between i and $i+1$. Unlike our main analysis, which uses the

based is about 63 basis points per month, and significant at the 5% level. Under equal weighting the spread is of almost identical magnitude, and significant at the 10% level. The average returns increase monotonically with the vertical position, with the exception of layer 0 in the value-weighted scheme.

Table 13: **TMB using alternative databases**

	A. Results using BEA I/O tables				B. Results using Compustat segment			
	Value-weighted		Equal-weighted		Value-weighted		Equal-weighted	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Layer 4	1.64	6.94	1.76	8.08	-	-	-	-
Layer 3	1.03	7.88	1.45	8.74	2.24	12.37	2.32	12.57
Layer 2	1.01	6.53	1.36	6.88	1.73	11.32	2.45	11.54
Layer 1	0.82	5.53	1.26	6.83	1.12	7.03	1.23	9.12
Layer 0	1.01	4.28	1.24	5.99	1.05	4.33	1.12	5.65
TMB	0.63**	5.76	0.52*	6.38	1.19**	11.46	1.20**	10.93
t-stat	(2.51)		(1.86)		(2.03)		(2.16)	

The table shows statistics for layer portfolio returns, constructed using alternative sources of data. Panel A reports results based on the BEA input-output tables. The sample period is from January 1974 to December 2017. Panel B reports results based on the Compustat Segment database. The sample period is from January 1986 to December 2017. In panel A (B), TMB is the return spread between layer 4 (3) and layer 0. * $p < .10$; ** $p < .05$; *** $p < .01$.

The TMB spread based on I-O data does not capture spreads that exist between firms with different vertical positions that belong to the same industry. Such within-industry spreads can be substantial, and partly account for the lower TMB in panel A of Table 13. To illustrate this, we confirm that the TMB spread exists within the three largest nonconsumption sectors in our sample: Industrials (GICS=20), Health Care (GICS=35), and Information Technology (GICS=45). For each sector, we restrict the sample only to firms that belong to the sector and examine the within sector TMB. In untabulated resulted, we find that the TMB spread in each of these sectors is over 90 bps per month. This stresses the importance of the intraindustry component of the benchmark TMB spread.

7.1.2 Results using the Compustat Segment database

Another source for supplier-customer linkages at the firm-level is the Compustat Segment database. It reports only critical customers because suppliers are only required to report customers that account for 10% or more of their total sales. We confirm a monotonic relation between firms'

Factset database, here we do not construct six portfolios, because the BEA data are less granular (i.e., only at the industry level), and, consequently, the implied supply chains are shorter on average.

vertical positions and their risk premiums, as well as a sizable TMB spread, using this database.

Our analysis covers the years 1985 to 2017 (with the holding period starting in 1986). Prior to 1985, the number of firms for which critical customers data are available is too small for supply chain construction. Our methodology for the vertical position computation is similar to the methodology used for the BEA input/output analysis. Section OA.7 of Online Appendix provides a detailed description of the methodology.

We sort firms into portfolios in December of each year t based on their vertical positions and hold the portfolios from January to December of the year $t+1$. As with the BEA analysis, we normalize the vertical positions to be on the [0, 5] segment and use $\{1, 2, 3, 4\}$ as break points. However, because of missing links in the Segment data, observed supply chains are significantly shorter and the number of firms that fall into layer 4 is too sparse. Therefore, we combine firms in layers 3 and 4 into a single top layer and form four portfolios. Panel B of Table 13 reports the portfolios' monthly returns. The results confirm our benchmark analysis. Remarkably, the value-weighted and equal-weighted TMB spreads are similar in magnitude to the spread implied by the FactSet data, about 1.2% per month, and significant at 5%. The value-weighted returns increase monotonically from layer 0 to layer 3.

7.2 Robustness to portfolio formation methods

We confirm that the TMB spread is robust to alternative methods of forming portfolios and computing vertical position. Online Appendix Table OA.16 reports the results. In Columns 1 and 2, we sort firms into portfolio using their vertical positions once a quarter or a year, respectively. The TMB spread is still positive and significant. To permit more time for the relationship information to be absorbed in stock prices, 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. The results are materially unchanged.

In the benchmark case, we define a firm's vertical position as the minimum distance between the firm and the bottom layer. In Column 4 of Table OA.16, we compute vertical positions using the median distance to the bottom. Under this alternative the TMB is 77 bps, significant at 10% level. The spread between the top layer and layer one is 92 bps, significant at the 5% level.[30] In Column 5 of Table OA.16, we reduce the number of layers from six to five. All firms with a vertical

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

position of four or above are assigned to the top layer. The TMB spread is smaller, but still positive and statistically significant at the 10% level.[31]

In Table OA.18 of Online Appendix, we assign firms into layers only once, based on firms' first vertical position observations, 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 bps per month, but statistically insignificant. The vertical position is largely a persistent measure, yet its time variation warrants a dynamic sorting. We also verify in untabulated results that the spread exists when we exclude the energy and materials sectors or when we use only durable goods producers as the bottom layer.

8 Discussion and Alternative Explanations

In this section, we consider several additional features of our model and the data, and discuss alternative explanations for the TMB spread.

Pyramid shape of firm distribution across layers: Table 14 shows the characteristics of firms in each layer. A pronounced feature is that the number of firms in layer j generally falls as the vertical position j rises. As a result, the top layer is thinly populated compared to layer 0. While this endogenous pyramid shape may capture the real structure of a multilayer production economy, it raises a concern that the TMB spread arises mechanically because of the uneven number of firms between the top and bottom layers. We rule out this explanation using a Monte-Carlo experiment in Online Appendix Section OA.9. If we keep the number of firms in each production layer equal to that in the data, but assign vertical positions to firms randomly, the implied TMB spread is indistinguishable from zero.[32]

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 14 reports that the centrality of layer 0 is an order of magnitude higher than the centrality of the top layer. Therefore, we cannot attribute the TMB spread to centrality.

[31] The spread between layer 5 and layer 1 is statistically significant at the 5% level, stressing that the TMB spread is mainly a spread *within* the investment sector.

[32] One also may be concerned about our results being potentially driven by a smaller number of firms at the top layer. However, as we show in Section 7.2, the main empirical results are qualitatively robust when we combine the top two layers and form five portfolios instead of six. In addition, we document a monotonic relation between vertical positions and stock returns (and productivity betas). This monotonicity depends on the returns and exposures across all layers, not just the top or the bottom layer.

Financial and operating leverage: Higher returns for firms with higher vertical position may be caused by higher leverage. Table 14 shows no significant difference in financial leverage between the top and bottom layers. Furthermore, top-layer firms actually have significantly lower operating leverage than do bottom-layer firms.

Table 14: **Firm characteristics 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	1,067	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	0.050***	-0.469***	0.044***	0.010	-0.004	-0.064***	-0.648***
t-stat			(-0.45)	(-5.00)	(-1.60)	(2.83)	(-17.64)	(7.06)	(0.70)	(-0.83)	(-3.09)	(-16.54)

This table presents firm characteristics by production layer. *N* is the number of firms in each layer, averaged 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); 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. *Network centrality* is eigenvector centrality. The vertical position and the network centrality are calculated using the FactSet Revere database. Institutional ownership is calculated using the Thomson Reuters Institutional (13f) Holdings database. All accounting data are from 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 parentheses. *** p<.01.

Profitability and asset growth: Recent studies established that expected returns are positively related to profitability and negatively related to asset growth rate (see, e.g., Novy-Marx (2013); Belo, Lin, and Bazdresch (2014); Hou, Xue, and Zhang (2015)). Table 14 shows that top-layer firms have lower profitability and higher asset growth. Therefore, the TMB cannot be explained by the q-factor model designed to capture risks associated with these firm characteristics.

Familiarity hypothesis: Upstream firms could be less familiar to investors and have more information asymmetry and illiquidity. However, Table 14 shows no significant difference in the bid-ask spread or the dispersion of earnings forecasts across layers, suggesting that top-layer firms are not more opaque. Furthermore, institutional ownership is lower in upper layers than in lower layers, suggesting that retail investors do not shy away from upstream firms due to lower familiarity.

In Online Appendix Section OA.10, we consider and rule out two additional alternative explanations for the TMB spread: (1) a lower persistence of vertical positions in upper layers and (2) a "bullwhip effect" (Lee, Padmanabhan, and Whang (1997)) associated with larger demand forecasting errors for upper-layer firms.

9 Conclusion

We use the novel FactSet Revere database to measure firms' vertical position in the production network, and document two stylized facts. Firms at higher vertical position have (1) higher stock returns; and (2) greater exposure to aggregate productivity. The spread between the top and the bottom layer is 105 bps per month. In a longer sample that starts in 1980s constructed using the Compustat Segment database, the spread is of almost identical magnitude. The interindustry TMB spread, measured from 1970s based on the BEA input-output tables, is 63 bps per month.

We provide a risk-based explanation of these new findings using both a closed-form model as well as a quantitative general equilibrium model. 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, which we term as vertical creative destruction. Bottom layer firms are most affected by the supply pressure because it cascades cumulatively downstream. As a result, bottom layer firms have endogenously smaller exposure to aggregate productivity.

We provide several empirical tests of the theory. The cyclicality pattern of Tobin's q, investment, and input prices across the layers aligns with the model. Our model is also supported by the interaction between our mechanism and the degree of supply chain competition. Two empirical patterns 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-good producers whose direct and indirect suppliers have more market power earn higher stock returns. We also show that the TMB spread is greater for firms that derive a larger fraction of their value from assets-in-place (e.g., value firms), as this is the component subject to vertical creative destruction.

Overall, we document several novel facts that connect firms' upstreamness and competitiveness to their risk. Vertical creative destruction can explain these facts quantitatively, suggesting its importance for explaining differences in cross-sectional risk premiums.

A Appendix

A.1 Proofs for Section 4

Proof of Theorem 1. The first-order conditions of the firms' maximization programs are given by

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

$$E_t\left[M_{t,t+1}\left\{\alpha P_{j,t+1}\frac{Y_{j,t+1}}{k_{j,t+1}} + (1-\delta)P_{j+1,t+1}\right\}\frac{e^{\chi_{j,t+1}}}{P_{j+1,t}}\right] = 1 \quad \forall j \in \{0, ..., N-1\}. \tag{A.2}$$

We conjecture and verify an equilibrium. Conjecture that

$$n_{j,t} = \overline{n}_j, \tag{A.3}$$

$$k_{j,t} = \left(\prod_{\ell=j+1}^{N} Z_{\ell,t}^{\alpha^{\ell-j-1}}\right)\overline{k}_j, \tag{A.4}$$

$$I_{j,t} = \left(\prod_{\ell=j+1}^{N} Z_{\ell,t}^{\alpha^{\ell-j-1}}\right)\overline{I}_j, \tag{A.5}$$

$$P_{j,t} = \underbrace{\left(\prod_{\ell=0}^{N} Z_{\ell,t}^{\alpha^{\ell}}\right)}_{D_t}\cdot\underbrace{\left(\prod_{\ell=j}^{N} Z_{\ell,t}^{-\alpha^{\ell-j}}\right)}_{S_t^{-1}}\overline{P}_j, \tag{A.6}$$

$$Y_{j,t} = \left(\prod_{\ell=j}^{N} Z_{\ell,t}^{\alpha^{\ell-j}}\right)\overline{Y}_j \tag{A.7}$$

$$C_t = \left(\prod_{\ell=0}^{N} Z_{\ell,t}^{\alpha^{\ell}}\right)\overline{C} \tag{A.8}$$

$$W_t = \left(\prod_{\ell=0}^{N} Z_{\ell,t}^{\alpha^{\ell}}\right)\overline{W}. \tag{A.9}$$

$$\tag{A.10}$$

The conjecture involves $5N+4$ unknowns:

$$\Theta = \{\overline{n}_0, ..., \overline{n}_N, \overline{Y}_0, ..., \overline{Y}_N, \overline{k}_0, ..., \overline{k}_{N-1}, \overline{I}_0, ..., \overline{I}_{N-1}, \overline{P}_1, ..., \overline{P}_N, \overline{C}, \overline{W}\}.$$

We use the first-order conditions, along with the market clearing conditions to provide $5N+4$ equations that give the solution to Θ. We verify that after plugging in the conjectured quantities and prices, each equation involves only deterministic model primitives and Θ terms, while all stochastic terms are eliminated.

Before laying out the equilibrium equations for Θ, it is constructive to derive the stochastic discount factor. Consumption growth is given by

$$\frac{C_{t+1}}{C_t} = \frac{\left(\prod_{\ell=0}^{N} Z_{\ell,t+1}^{\alpha^\ell}\right)\overline{C}}{\left(\prod_{\ell=0}^{N} Z_{\ell,t}^{\alpha^\ell}\right)\overline{C}} = \left(\prod_{\ell=0}^{N} \frac{Z_{\ell,t+1}}{Z_{\ell,t}}^{\alpha^\ell}\right) = e^{\sum_{\ell=0}^{N}\alpha^\ell \varepsilon_{\ell,t+1}}.$$

The stochastic trend of U_t is identical to that of C_t (it is easily verifiable that $U_t = \left(\prod_{\ell=0}^{N} Z_{\ell,t}^{\alpha^\ell}\right)\overline{U}$). As an immediate result, $U_{t+1}/U_t = e^{\sum_{\ell=0}^{N}\alpha^\ell \varepsilon_{\ell,t+1}}$. Hence:

$$E_t\left[\left(\frac{U_{t+1}}{U_t}\right)^{1-\gamma}\right] = E_t\left[e^{\sum_{\ell=0}^{N}(1-\gamma)\alpha^\ell \varepsilon_{\ell,t+1}}\right] \equiv \overline{E}. \tag{A.11}$$

The expectation in the last equation is time invariant, because all ε_ℓs are i.i.d. Therefore, we denote it by a constant $\overline{E}$. We obtain

$$\begin{aligned} M_{t,t+1} &= \beta\left(\frac{C_{t+1}}{C_t}\right)^{-\frac{1}{\psi}}\left(\frac{U_{t+1}}{\left[E_t U_{t+1}^{1-\gamma}\right]^{\frac{1}{1-\gamma}}}\right)^{\frac{1}{\psi}-\gamma} \qquad \text{(A.12)} \\ &= \beta\left(\frac{C_{t+1}}{C_t}\right)^{-\frac{1}{\psi}}\left(\frac{U_{t+1}/U_t}{[E_t(U_{t+1}/U_t)^{1-\gamma}]^{\frac{1}{1-\gamma}}}\right)^{\frac{1}{\psi}-\gamma} \\ &= \beta\left(e^{\sum_{\ell=0}^{N}\alpha^\ell \varepsilon_{\ell,t+1}}\right)^{-\frac{1}{\psi}+\frac{1}{\psi}-\gamma}\overline{E}^{\frac{\gamma-\frac{1}{\psi}}{1-\gamma}} \\ &= \beta\overline{E}^{\frac{\gamma-\frac{1}{\psi}}{1-\gamma}} exp\left(\sum_{\ell=0}^{N} -\gamma\alpha^\ell \varepsilon_{\ell,t+1}\right). \end{aligned}$$

Notice that $M_{t,t+1}$ is i.i.d. The equilibrium equations are written as

(1) (one equation): $\sum_{\ell=0}^{N} \overline{n}_j = 1$

(2) (one equation): $\overline{C} = \overline{Y}_0$

(3) (N equations, for $j \in \{0, 1, ..., N-1\}$):

$$\begin{gathered} I_{j,t} = Y_{j+1,t} \quad \Rightarrow \\ \left(\prod_{\ell=j+1}^{N} Z_{\ell,t}^{\alpha^{\ell-j-1}}\right)\overline{I}_j = \left(\prod_{\ell=j+1}^{N} Z_{\ell,t}^{\alpha^{\ell-j-1}}\right)\overline{Y}_j \quad \Rightarrow \\ \overline{I}_j = \overline{Y}_{j+1} \end{gathered}$$

(4) (one equation):

$$\begin{gathered} Y_{N,t} = Z_{N,t} n_{N,t}^{1-\alpha} \quad \Rightarrow \\ \left(\prod_{\ell=N}^{N} Z_{\ell,t}^{\alpha^{\ell-N}}\right)\overline{Y}_N = Z_{N,t}\overline{n}_N^{1-\alpha} \quad \Rightarrow \end{gathered}$$

$$Z_{N,t}\overline{Y}_N = Z_{N,t}\overline{n}_N^{1-\alpha} \quad \Rightarrow$$
$$\overline{Y}_N = \overline{n}_N^{1-\alpha}$$

(5) (N equation, for $j \in \{0, 1, ..., N-1\}$):

$$Y_{j,t} = Z_{j,t}k_{j,t}^{\alpha}n_{j,t}^{1-\alpha} \quad \Rightarrow$$
$$\left(\prod_{\ell=j}^{N} Z_{\ell,t}^{\alpha^{\ell-j}}\right)\overline{Y}_j = Z_{j,t}\left(\left(\prod_{\ell=j+1}^{N} Z_{\ell,t}^{\alpha^{\ell-j-1}}\right)\overline{k}_j\right)^{\alpha}\overline{n}_j^{1-\alpha} \quad \Rightarrow$$
$$\left(\prod_{\ell=j}^{N} Z_{\ell,t}^{\alpha^{\ell-j}}\right)\overline{Y}_j = Z_{j,t}\left(\prod_{\ell=j+1}^{N} Z_{\ell,t}^{\alpha^{\ell-j}}\right)\overline{k}_j^{\alpha}\overline{n}_j^{1-\alpha} \quad \Rightarrow$$
$$\left(\prod_{\ell=j}^{N} Z_{\ell,t}^{\alpha^{\ell-j}}\right)\overline{Y}_j = \left(\prod_{\ell=j}^{N} Z_{\ell,t}^{\alpha^{\ell-j}}\right)\overline{k}_j^{\alpha}\overline{n}_j^{1-\alpha} \quad \Rightarrow$$
$$\overline{Y}_j = \overline{k}_j^{\alpha}\overline{n}_j^{1-\alpha}$$

(6) ($N+1$ equation, for $j \in \{0..N\}$):

$$(1-\alpha)P_{j,t}Y_{j,t} = n_{j,t}W_t \quad \Rightarrow$$
$$(1-\alpha)\left(\prod_{\ell=0}^{N} Z_{\ell,t}^{\alpha^{\ell}}\right)\cdot\left(\prod_{\ell=j}^{N} Z_{\ell,t}^{-\alpha^{\ell-j}}\right)\left(\prod_{\ell=j}^{N} Z_{\ell,t}^{\alpha^{\ell-j}}\right)\overline{P}_j\overline{Y}_j = \left(\prod_{\ell=0}^{N} Z_{\ell,t}^{\alpha^{\ell}}\right)\overline{W}\overline{n}_j \quad \Rightarrow$$
$$(1-\alpha)\overline{P}_j\overline{Y}_j = \overline{W}\overline{n}_j$$

(7) (N equation, for $j \in \{0..N-1\}$):

$$k_{j,t+1} = \left((1-\delta)k_{j,t} + I_{j,t}\right)e^{\chi_{j,t+1}} \quad \Rightarrow$$
$$\left(\prod_{\ell=j+1}^{N} Z_{\ell,t+1}^{\alpha^{\ell-j-1}}\right)\overline{k}_j = \left(\prod_{\ell=j+1}^{N} Z_{\ell,t}^{\alpha^{\ell-j-1}}\right)\left((1-\delta)\overline{k}_j + \overline{I}_j\right)e^{\sum_{\ell=j+1}^{N}\alpha^{\ell-j-1}\varepsilon_{\ell,t+1}} \quad \Rightarrow$$
$$\left(\prod_{\ell=j+1}^{N}\left(\frac{Z_{\ell,t+1}}{Z_{\ell,t}}\right)^{\alpha^{\ell-j-1}}\right)\overline{k}_j = \left((1-\delta)\overline{k}_j + \overline{I}_j\right)e^{\sum_{\ell=j+1}^{N}\alpha^{\ell-j-1}\varepsilon_{\ell,t+1}} \quad \Rightarrow$$
$$e^{\sum_{\ell=j+1}^{N}\alpha^{\ell-j-1}\varepsilon_{\ell,t+1}}\overline{k}_j = \left((1-\delta)\overline{k}_j + \overline{I}_j\right)e^{\sum_{\ell=j+1}^{N}\alpha^{\ell-j-1}\varepsilon_{\ell,t+1}} \quad \Rightarrow$$
$$\overline{k}_j = \left((1-\delta)\overline{k}_j + \overline{I}_j\right) \quad \Rightarrow$$
$$\overline{I}_j = \delta\overline{k}_j$$

(8) (N equation, for $j \in \{0, 1, ..., N-1\}$): it is constructive to derive the Euler equations in stages:

$$\begin{aligned}
\frac{P_{j,t+1}Y_{j,t+1}e^{\chi_{j,t+1}}}{P_{j+1,t}k_{j,t+1}} &= \frac{\left(\prod_{\ell=0}^{N} Z_{\ell,t+1}^{\alpha^\ell}\right)\cdot\left(\prod_{\ell=j}^{N} Z_{\ell,t+1}^{-\alpha^{\ell-j}}\right)\left(\prod_{\ell=j}^{N} Z_{\ell,t+1}^{\alpha^{\ell-j}}\right)e^{\sum_{\ell=j+1}^{N}\alpha^{\ell-j-1}\varepsilon_{\ell,t+1}}}{\left(\prod_{\ell=0}^{N} Z_{\ell,t}^{\alpha^\ell}\right)\cdot\left(\prod_{\ell=j+1}^{N} Z_{\ell,t}^{-\alpha^{\ell-j-1}}\right)\left(\prod_{\ell=j+1}^{N} Z_{\ell,t+1}^{\alpha^{\ell-j-1}}\right)}\cdot\frac{\overline{P}_j\overline{Y}_j}{\overline{P}_{j+1}\overline{k}_j}\\
&= \left(\prod_{\ell=0}^{N}\left(\frac{Z_{\ell,t+1}}{Z_{\ell,t}}\right)^{\alpha^\ell}\right)\left(\prod_{\ell=j+1}^{N}\left(\frac{Z_{\ell,t+1}}{Z_{\ell,t}}\right)^{-\alpha^{\ell-j-1}}\right)e^{\sum_{\ell=j+1}^{N}\alpha^{\ell-j-1}\varepsilon_{\ell,t+1}}\cdot\frac{\overline{P}_j\overline{Y}_j}{\overline{P}_{j+1}\overline{k}_j}\\
&= e^{\sum_{\ell=0}^{N}\alpha^\ell\varepsilon_{\ell,t+1}}e^{\sum_{\ell=j+1}^{N}-\alpha^{\ell-j-1}\varepsilon_{\ell,t+1}}e^{\sum_{\ell=j+1}^{N}\alpha^{\ell-j-1}\varepsilon_{\ell,t+1}}\cdot\frac{\overline{P}_j\overline{Y}_j}{\overline{P}_{j+1}\overline{k}_j}\\
&= e^{\sum_{\ell=0}^{N}\alpha^\ell\varepsilon_{\ell,t+1}}\cdot\frac{\overline{P}_j\overline{Y}_j}{\overline{P}_{j+1}\overline{k}_j}
\end{aligned}$$

In addition:

$$\begin{aligned}
\frac{P_{j+1,t+1}e^{\chi_{j,t+1}}}{P_{j+1,t}} &= \left(\prod_{\ell=0}^{N}\left(\frac{Z_{\ell,t+1}}{Z_{\ell,t}}\right)^{\alpha^\ell}\right)\left(\prod_{\ell=j+1}^{N}\left(\frac{Z_{\ell,t+1}}{Z_{\ell,t}}\right)^{-\alpha^{\ell-j-1}}\right)e^{\sum_{\ell=j+1}^{N}\alpha^{\ell-j-1}\varepsilon_{\ell,t+1}}\\
&= e^{\sum_{\ell=0}^{N}\alpha^\ell\varepsilon_{\ell,t+1}}e^{\sum_{\ell=j+1}^{N}-\alpha^{\ell-j-1}\varepsilon_{\ell,t+1}}e^{\sum_{\ell=j+1}^{N}\alpha^{\ell-j-1}\varepsilon_{\ell,t+1}}\\
&= e^{\sum_{\ell=0}^{N}\alpha^\ell\varepsilon_{\ell,t+1}}
\end{aligned}$$

Using the expression for the SDF, define:

$$\begin{aligned}
\beta^* &\equiv E_t\left[M_{t,t+1}e^{\sum_{\ell=0}^{N}\alpha^\ell\varepsilon_{\ell,t+1}}\right]\\
&= E_t\left[\beta\overline{E}^{\frac{\gamma-\frac{1}{\psi}}{1-\gamma}}\exp\left(\sum_{\ell=0}^{N}(1-\gamma)\alpha^\ell\varepsilon_{\ell,t+1}\right)\right]\\
&= \beta\overline{E}^{\frac{\gamma-\frac{1}{\psi}}{1-\gamma}}\overline{E}^1\\
&= \beta\overline{E}^{\frac{1}{\theta}}
\end{aligned}$$

The expectation above is a time-invariant constant, because all ε_ℓ are i.i.d.

Plugging all expressions above into Equation (A.2), we obtain the following Euler equation:

$$\begin{aligned}
E_t\left[M_{t,t+1}\left\{\alpha e^{\sum_{\ell=0}^{N}\alpha^\ell\varepsilon_{\ell,t+1}}\cdot\frac{\overline{P}_j\overline{Y}_j}{\overline{P}_{j+1}\overline{k}_j}+(1-\delta)e^{\sum_{\ell=0}^{N}\alpha^\ell\varepsilon_{\ell,t+1}}\right\}\right] = 1 \quad &\Rightarrow\\
E_t\left[M_{t,t+1}e^{\sum_{\ell=0}^{N}\alpha^\ell\varepsilon_{\ell,t+1}}\left\{\alpha\frac{\overline{P}_j\overline{Y}_j}{\overline{P}_{j+1}\overline{k}_j}+(1-\delta)\right\}\right] = 1 \quad &\Rightarrow\\
\beta^*\left(\alpha\frac{\overline{P}_j\overline{Y}_j}{\overline{P}_{j+1}\overline{k}_j}+(1-\delta)\right) = 1
\end{aligned}$$

Bullet points (1)–(8) above characterize $5N+4$ equations for Θ. A solution for the system of equations exists. We illustrate this by solving for the labor allocations and describing the solution method for other constants recursively given labor.

Combining bullet points (5) and (6) for layers j and $j+1$, one obtains after simplification:

$$\left(\frac{\overline{n}_j}{\overline{n}_{j+1}}\right)^{\alpha} = \frac{\overline{P}_j \overline{k}_j^{\alpha}}{\overline{P}_{j+1}\overline{k}_{j+1}^{\alpha}} \tag{A.13}$$

Combining bullet points (3), (5) and (7) yields:

$$\overline{k}_j = \frac{1}{\delta}\overline{k}_{j+1}^{\alpha}\overline{n}_{j+1}^{1-\alpha} \tag{A.14}$$

Combining bullet points (3) and (8) provides after simplification:

$$\frac{\overline{P}_j}{\overline{P}_{j+1}}\overline{k}_j^{\alpha} = \frac{\overline{k}_j}{\overline{n}_j^{1-\alpha}}\frac{1}{\alpha}\left(\frac{1}{\beta^*}+\delta-1\right) \tag{A.15}$$

Substituting for $\overline{k}_j$ in the right hand side using Eq (A.14) yields after rearranging:

$$\frac{\overline{P}_j \overline{k}_j^{\alpha}}{\overline{P}_{j+1}\overline{k}_{j+1}^{\alpha}} = \left(\frac{\overline{n}_{j+1}}{\overline{n}_j}\right)^{1-\alpha}\frac{1}{\alpha\delta}\left(\frac{1}{\beta^*}+\delta-1\right) \tag{A.16}$$

Substituting the left hand side using Eq (A.13) and rearranging yields:

$$\frac{\overline{n}_j}{\overline{n}_{j+1}} = \frac{\frac{1}{\beta^*}+\delta-1}{\alpha\delta} \equiv \xi \tag{A.17}$$

Using bullet point (1) in conjunction with the last equation:

$$\overline{n}_j = \xi^{N-j}\cdot[1+\xi+...+\xi^{N-1}]^{-1}. \tag{A.18}$$

Equipped with labor allocations the other quantities can be solved recursively. Plugging $\overline{n}_N$ in bullet point (4) yields $\overline{Y}_N$, which yields $\overline{i}_{N-1}$ using bullet (3), and then $\overline{k}_{N-1}$ using bullet (7). Knowing $\overline{k}_{j+1}$ and $\overline{n}_{j+1}$ the process can be repeated to recover labor and capital allocations for j, until $j=0$. Combining these allocations with Eq (A.13) gives the relative prices. $\square$

Proof of Theorem 2. Let $j \in \{0,..,N-1\}$. We start by computing several useful ratios.

$$\frac{P_{j,t}Y_{j,t}}{P_{j+1,t}k_{j,t}} = \frac{\left(\prod_{\ell=0}^{N} Z_{\ell,t}^{\alpha^\ell}\right)\cdot\left(\prod_{\ell=j}^{N} Z_{\ell,t}^{-\alpha^{\ell-j}}\right)\left(\prod_{\ell=j}^{N} Z_{\ell,t}^{\alpha^{\ell-j}}\right)}{\left(\prod_{\ell=0}^{N} Z_{\ell,t}^{\alpha^\ell}\right)\cdot\left(\prod_{\ell=j+1}^{N} Z_{\ell,t}^{-\alpha^{\ell-j-1}}\right)\left(\prod_{\ell=j+1}^{N} Z_{\ell,t}^{\alpha^{\ell-j-1}}\right)}\cdot\frac{\overline{P}_j\overline{Y}_j}{\overline{P}_{j+1}\overline{k}_j} = \frac{\overline{P}_j\overline{Y}_j}{\overline{P}_{j+1}\overline{k}_j}. \tag{A.19}$$

From bullet (8), the Euler equation:

$$\frac{\overline{P}_j\overline{Y}_j}{\overline{P}_{j+1}\overline{k}_j} = \frac{1}{\alpha}\left(\frac{1}{\beta^*}+\delta+1\right)$$

From bullet (7):

$$\frac{P_{j+1,t}I_{j,t}}{P_{j+1,t}k_{j,t}} = \frac{\overline{I}_j}{\overline{k}_j} = \delta$$

From bullet (6):

$$\frac{W_t n_{j,t}}{P_{j+1,t}k_{j,t}} = \frac{\left(\prod_{\ell=0}^{N} Z_{\ell,t}^{\alpha^\ell}\right)}{\left(\prod_{\ell=0}^{N} Z_{\ell,t}^{\alpha^\ell}\right)\cdot\left(\prod_{\ell=j+1}^{N} Z_{\ell,t}^{-\alpha^{\ell-j-1}}\right)\left(\prod_{\ell=j+1}^{N} Z_{\ell,t}^{\alpha^{\ell-j-1}}\right)}\frac{\overline{W}\overline{n}_j}{\overline{P}_{j+1}\overline{k}_j} = \frac{\overline{W}\overline{n}_j}{\overline{P}_{j+1}\overline{k}_j} = \frac{(1-\alpha)\overline{P}_j\overline{Y}_j}{\overline{P}_{j+1}\overline{k}_j}$$

Combining the above:

$$\frac{d_{j,t}}{P_{j+1,t}k_{j,t}} = \frac{P_{j,t}Y_{j,t} - W_t n_{j,t} - P_{j+1,t}I_{j,t}}{P_{j+1,t}k_{j,t}} = \frac{1}{\alpha}(1-(1-\alpha))(\frac{1}{\beta^*}+\delta-1)-\delta = \frac{1-\beta^*}{\beta^*},$$

which implies:

$$d_{j,t} = \left(\prod_{\ell=0}^{N} Z_{\ell,t}^{\alpha^\ell}\right)\overline{P}_{j+1}\overline{k}_j\frac{1-\beta^*}{\beta^*}.$$

Next, conjecture that $V_{j,t} = \left(\prod_{\ell=0}^{N} Z_{\ell,t}^{\alpha^\ell}\right)\overline{V}_j$. Solve and verify:

$$\begin{aligned}
V_{j,t} &= d_{j,t} + E_t[M_{t,t+1}V_{j,t+1}] \quad \Rightarrow \\
\left(\prod_{\ell=0}^{N} Z_{\ell,t}^{\alpha^\ell}\right)\overline{V}_j &= \left(\prod_{\ell=0}^{N} Z_{\ell,t}^{\alpha^\ell}\right)\overline{P}_{j+1}\overline{k}_j\frac{1-\beta^*}{\beta^*} + E_t\left[M_{t,t+1}\left(\prod_{\ell=0}^{N} Z_{\ell,t+1}^{\alpha^\ell}\right)\right]\overline{V}_j \quad \Rightarrow \\
\overline{V}_j &= \overline{P}_{j+1}\overline{k}_j\left(\frac{1-\beta^*}{\beta^*}\right) + E_t\left[M_{t,t+1}e^{\sum_{\ell=0}^{N}\alpha^\ell\varepsilon_{\ell,t+1}}\right]\overline{V}_j \quad \Rightarrow \\
(1-\beta^*)\overline{V}_j &= \overline{P}_{j+1}\overline{k}_j\left(\frac{1-\beta^*}{\beta^*}\right) \quad \Rightarrow \\
\overline{V}_j &= \frac{1}{\beta^*}\overline{P}_{j+1}\overline{k}_j
\end{aligned}$$

The last equality suggests that $V_{j,t} = \frac{1}{1-\beta^*}d_{j,t}$. Compute Tobin's q given the above ratios:

$$\begin{aligned}
Q_{j,t} = \frac{V_{j,t}-d_{j,t}}{k_{j,t}} &= \frac{\left(\frac{1}{1-\beta^*}-1\right)d_{j,t}}{k_{j,t}} \\
&= \frac{\frac{\beta^*}{1-\beta^*}\left(\prod_{\ell=0}^{N} Z_{\ell,t}^{\alpha^\ell}\right)\overline{P}_{j+1}\overline{k}_j\frac{1-\beta^*}{\beta^*}}{\left(\prod_{\ell=j+1}^{N} Z_{\ell,t}^{\alpha^{\ell-j-1}}\right)\overline{k}_j} \\
&= \left(\prod_{\ell=0}^{N} Z_{\ell,t}^{\alpha^\ell}\right)\left(\prod_{\ell=j+1}^{N} Z_{\ell,t}^{-\alpha^{\ell-j-1}}\right)\overline{P}_{j+1}
\end{aligned}$$

Applying log to the last expression yields Eq (20) in Theorem 2. Corollary 1 is obtained immediately by taking the derivatives with respect to $z_{j,t} \equiv \log(Z_{j,t})$ from Eq (20). □

Proof of Theorem 3. Assume $Z_{j,t} = Z_t \quad \forall j$. Then:

$$\begin{aligned}
\log(Q_{j,t}) &= \left(\sum_{\ell=0}^{N}\alpha^\ell - \sum_{\ell=j+1}^{N}\alpha^{\ell-j-1}\right)z_j + log(\overline{P}_{j+1}) \\
&= \left(\sum_{\ell=0}^{N}\alpha^{N-\ell} - \sum_{\ell=j+1}^{N}\alpha^{\ell-j-1}\right)z_j + log(\overline{P}_{j+1}) \\
&= \left(\sum_{\ell=0}^{j}\alpha^{N-\ell} + \sum_{\ell=j+1}^{N}\alpha^{N-\ell} - \sum_{\ell=j+1}^{N}\alpha^{\ell-j-1}\right)z_j + log(\overline{P}_{j+1})
\end{aligned}$$

$$= \left(\sum_{\ell=0}^{j} \alpha^{N-\ell} + (1 + ... + \alpha^{N-j-1}) - (\alpha^{N-j-1} + ... + 1) \right) z_j + log(\overline{P}_{j+1})$$

$$= \left(\sum_{\ell=0}^{j} \alpha^{N-\ell} \right) z_j + log(\overline{P}_{j+1})$$

Therefore $\beta_j^{AP} = \sum_{\ell=0}^{j} \alpha^{N-\ell}$, and:

$$\partial\beta_j^{AP}/\partial j \equiv \sum_{\ell=0}^{j} \alpha^{N-\ell} - \sum_{\ell=0}^{j-1} \alpha^{N-\ell} = \alpha^{N-j} > 0$$

□

Proof of Theorem 4. To prove part (i), we wish to compute $\Delta\beta^{AP} = \beta_{N-1}^{AP} - \beta_0^{AP}$. This yields:

$$\Delta\beta = (\alpha + ... + \alpha^N) - \alpha^N = \alpha + ... + \alpha^{N-1} = \alpha \left(\frac{1-\alpha^{N-1}}{1-\alpha} \right).$$

Because $\alpha < 1$, α^{N-1} decreases as N increases, thereby increasing $\Delta\beta$

To prove part (ii), simply take the expression for $M_{t,t+1}$ derived in the proof of Theorem 1, and apply $\sum_{\ell=0}^{N} \alpha^\ell = \frac{1-\alpha^{N+1}}{1-\alpha}$, along with $\varepsilon_{\ell,t+1} = \varepsilon_{t+1}, \quad \forall \ell \in \{0, .., N\}$. □

Proof of Theorem 5. We first derive dividend growth of $\tilde{d}$. Theorem 1 shows that it is possible to express $d_{j,t}$ as $\left(\prod_{\ell=0}^{N} Z_{\ell,t}^{\alpha^\ell} \right) \overline{d}_j$, where $\overline{d}_j$ is a layer-specific scalar. Therefore:

$$\begin{aligned}
\Delta\tilde{d}_{j,t+1} &= \frac{d_{j,t+1}}{d_{j,t}} \cdot e^{-\chi_{j,t+1}} \\
&= \left(\prod_{\ell=0}^{N} \left(\frac{Z_{\ell,t+1}}{Z_{\ell,t}} \right)^{\alpha^\ell} \right) \cdot \exp(-\sum_{\ell=j+1}^{N} \alpha^{\ell-j-1}\varepsilon_{t+1}) \frac{\overline{d}_j}{\overline{d}_j} \\
&= \exp(\sum_{\ell=0}^{N} \alpha^\ell \varepsilon_{t+1}) \exp(-\sum_{\ell=j+1}^{N} \alpha^{\ell-j-1}\varepsilon_{t+1}) \\
&= \exp(\sum_{\ell=0}^{j} \alpha^{N-\ell}\varepsilon_{t+1}).
\end{aligned}$$

Note that

$$E_t \left[\Delta\tilde{d}_{j,t+1} \right] = \exp \left(\frac{1}{2} \left(\sum_{\ell=0}^{j} \alpha^{N-\ell} \right)^2 \right). \tag{A.20}$$

Next, find the ratio of ex-dividend firm value to dividend of layer j. We have:

$$\tilde{V}_{j,t}^X = E_t \left[M_{t,t+1} \left(\tilde{V}_{j,t+1}^X + \tilde{d}_{t+1} \right) \right] \quad \Rightarrow$$

$$\frac{\tilde{V}^X_{j,t}}{\tilde{d}_{j,t}} = E_t \left[M_{t,t+1} \left(\frac{\tilde{V}^X_{j,t+1}}{\tilde{d}_{j,t+1}} + 1 \right) \left(\frac{\tilde{d}_{j,t+1}}{\tilde{d}_{j,t}} \right) \right]$$

Because $\Delta \tilde{d}_j$ is i.i.d, the ratio $\tilde{V}^X_j / \tilde{d}_j$ is a constant. Denote this constant by $\overline{\upsilon}_j$. Then:

$$\overline{\upsilon}_j = (1 + \overline{\upsilon}_j) E_t \left[M_{t,t+1} \left(\frac{\tilde{d}_{j,t+1}}{\tilde{d}_{j,t}} \right) \right].$$

Define:

$$\begin{aligned}
\tilde{\beta}_j &\equiv E_t \left[M_{t,t+1} \left(\frac{\tilde{d}_{j,t+1}}{\tilde{d}_{j,t}} \right) \right] \\
&= \beta \overline{E}^{\frac{\gamma - \frac{1}{\psi}}{1-\gamma}} E_t \left[\exp \left(\left(\sum_{\ell=0}^{j} \alpha^{N-\ell} - \gamma \frac{1-\alpha^{N+1}}{1-\alpha} \right) \varepsilon_{t+1} \right) \right] \\
&= \beta \overline{E}^{\frac{\gamma - \frac{1}{\psi}}{1-\gamma}} exp \left(\frac{1}{2} \left(\sum_{\ell=0}^{j} \alpha^{N-\ell} - \gamma \frac{1-\alpha^{N+1}}{1-\alpha} \right)^2 \right). \qquad \text{(A.21)}
\end{aligned}$$

This implies that $\overline{\upsilon}_j = \frac{\tilde{\beta}_j}{1-\tilde{\beta}_j}$. Derive the expected return:

$$\begin{aligned}
E_t \left[\tilde{R}_{j,t+1} \right] &= E_t \left[\frac{\tilde{V}^X_{j,t+1} + \tilde{d}_{j,t+1}}{\tilde{V}^X_{j,t}} \right] \\
&= E_t \left[\frac{1+\overline{\upsilon}_j}{\overline{\upsilon}_j} \left(\Delta \tilde{d}_{j,t+1} \right) \right] \\
&= \frac{1}{\tilde{\beta}_j} E_t \left[\Delta \tilde{d}_{j,t+1} \right]
\end{aligned}$$

For notational ease denote $\overline{A}(j) = \sum_{\ell=0}^{j} \alpha^{N-\ell}$ and $\overline{B} = \gamma \frac{1-\alpha^{N+1}}{1-\alpha}$. Plug in Eq (A.20) and (A.21):

$$\begin{aligned}
E_t \left[\tilde{R}_{j,t+1} \right] &= \exp \left(\frac{1}{2} \left(\sum_{\ell=0}^{j} \alpha^{N-\ell} \right)^2 \right) \left(\beta \overline{E}^{\frac{\gamma - \frac{1}{\psi}}{1-\gamma}} exp \left(\frac{1}{2} \left(\sum_{\ell=0}^{j} \alpha^{N-\ell} - \gamma \frac{1-\alpha^{N+1}}{1-\alpha} \right)^2 \right) \right)^{-1} \\
&= \beta^{-1} \overline{E}^{-\frac{\gamma - \frac{1}{\psi}}{1-\gamma}} \exp \left(\overline{A}(j) \overline{B} - \frac{1}{2} \overline{B}^2 \right).
\end{aligned}$$

Because $\overline{B} > 0$ and $\partial \overline{A}(j) / \partial j > 0$, we obtain that $E_t \left[\tilde{R}_{j,t+1} \right]$ increases with j. $\square$

A.2 Detrending and Equilibrium Conditions of the Full DSGE Model

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, and write down the equilibrium conditions. In the benchmark case in which all productivity shocks are perfectly correlated, as in the calibrated full DSGE model, the equations below still hold by replacing $Z_{j,t} = Z_t \quad \forall j \in \{0..N\}$.

A.2.1 Model detrending

Define capital trends as

$$\tau_{k4,t} = Z_{5,t} \tag{A.22}$$

$$\tau_{k3,t} = Z_{4,t} Z_{5,t}^{\alpha} \tag{A.23}$$

$$\tau_{k2,t} = Z_{3,t} Z_{4,t}^{\alpha} Z_{5,t}^{\alpha^2} \tag{A.24}$$

$$\tau_{k1,t} = Z_{2,t} Z_{3,t}^{\alpha} Z_{4,t}^{\alpha^2} Z_{5,t}^{\alpha^3} \tag{A.25}$$

$$\tau_{k0,t} = Z_{1,t} Z_{2,t}^{\alpha} Z_{3,t}^{\alpha^2} Z_{4,t}^{\alpha^3} Z_{5,t}^{\alpha^4} \tag{A.26}$$

Let the price trends be:

$$\tau_{p5,t} = Z_{0,t} Z_{1,t}^{\alpha} Z_{2,t}^{\alpha^2} Z_{3,t}^{\alpha^3} Z_{4,t}^{\alpha^4} Z_{5,t}^{\alpha^5-1} \tag{A.27}$$

$$\tau_{p4,t} = Z_{0,t} Z_{1,t}^{\alpha} Z_{2,t}^{\alpha^2} Z_{3,t}^{\alpha^3} Z_{4,t}^{\alpha^4-1} Z_{5,t}^{\alpha^5-\alpha} \tag{A.28}$$

$$\tau_{p3,t} = Z_{0,t} Z_{1,t}^{\alpha} Z_{2,t}^{\alpha^2} Z_{3,t}^{\alpha^3-1} Z_{4,t}^{\alpha^4-\alpha} Z_{5,t}^{\alpha^5-\alpha^2} \tag{A.29}$$

$$\tau_{p2,t} = Z_{0,t} Z_{1,t}^{\alpha} Z_{2,t}^{\alpha^2-1} Z_{3,t}^{\alpha^3-\alpha} Z_{4,t}^{\alpha^4-\alpha^2} Z_{5,t}^{\alpha^5-\alpha^3} \tag{A.30}$$

$$\tau_{p1,t} = Z_{0,t} Z_{1,t}^{\alpha-1} Z_{2,t}^{\alpha^2-\alpha} Z_{3,t}^{\alpha^3-\alpha^2} Z_{4,t}^{\alpha^4-\alpha^3} Z_{5,t}^{\alpha^5-\alpha^4} \tag{A.31}$$

Lastly, the trend of final consumption goods is given by

$$\tau_{c,t} = Z_{0,t} Z_{1,t}^{\alpha} Z_{2,t}^{\alpha^2} Z_{3,t}^{\alpha^3} Z_{4,t}^{\alpha^4} Z_{5,t}^{\alpha^5} \tag{A.32}$$

Covariance-stationary first-order conditions can be achieved by rescaling the nonstationary 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.

A.2.2 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

$$W_t = (1-\alpha) P_{j,t} Z_{j,t} k_{j,t}^{\alpha} n_{j,t}^{-\alpha} \quad \forall j \in \{0..N\}, \tag{A.33}$$

$$Q_{j,t} = \Phi'(i_{j,t}) P_{j+1,t} \quad \forall j \in \{0..N-1\}, \tag{A.34}$$

$$Q_{j,t} = E\left[M_{t,t+1}\left(P_{j,t+1} Z_{j,t+1} \alpha k_{j,t+1}^{\alpha-1} n_{j,t+1}^{1-\alpha} - P_{j+1,t+1}\Phi(i_{j,t+1}) + (1-\delta+i_{j,t+1}) Q_{j,t+1}\right)\right] \tag{A.35}$$

$$\forall j \in \{0..N-1\},$$

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 $5N+4$ model equations: the above first-order conditions, along with $N+1$ labor market clearing Equation (11), N capital markets clearing equations given by (12), consumption good clearing (13), N capital law of motions (4), and the household SDF (A.12). We normalize $P_{0,t}=1$ as a numeraire.

In the deterministic steady state, one can show using the trend expressions in Section A.2.1 that the growth in Tobin's q, $\Delta Q_j \equiv Q_{j,t+1}/Q_{j,t}$, is given by

$$\Delta Q_0 = \Delta Z_0 \Delta Z_1^{\alpha-1} \Delta Z_2^{\alpha^2-\alpha} \Delta Z_3^{\alpha^3-\alpha^2} \Delta Z_4^{\alpha^4-\alpha^3} \Delta Z_5^{\alpha^5-\alpha^4} \tag{A.36}$$

$$\Delta Q_1 = \Delta Z_0 \Delta Z_1^{\alpha} \Delta Z_2^{\alpha^2-1} \Delta Z_3^{\alpha^3-\alpha} \Delta Z_4^{\alpha^4-\alpha^2} \Delta Z_5^{\alpha^5-\alpha^3} \tag{A.37}$$

$$\Delta Q_2 = \Delta Z_0 \Delta Z_1^{\alpha} \Delta Z_2^{\alpha^2} \Delta Z_3^{\alpha^3-1} \Delta Z_4^{\alpha^4-\alpha} \Delta Z_5^{\alpha^5-\alpha^2} \tag{A.38}$$

$$\Delta Q_3 = \Delta Z_0 \Delta Z_1^{\alpha} \Delta Z_2^{\alpha^2} Z_3^{\alpha^3} \Delta Z_4^{\alpha^4-1} \Delta Z_5^{\alpha^5-\alpha} \tag{A.39}$$

$$\Delta Q_4 = \Delta Z_0 \Delta Z_1^{\alpha} \Delta Z_2^{\alpha^2} \Delta Z_3^{\alpha^3} \Delta Z_4^{\alpha^4} \Delta Z_5^{\alpha^5-1} \tag{A.40}$$

Equations (A.37)–(A.40) are the deterministic versions of the (log) stochastic trend for Q presented in Equation (20). The equations above show that 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 $k > \ell$ ($\leq \ell$), consistent with Corollary 1. This conclusion holds in the full DSGE model, without reliance on capital quality shocks. Moreover, 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, again consistent with Corollary 1.

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