Pro-cyclical Aggregate R&D: Timing or Propagation?

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Abstract

The literature has taken pro-cyclical aggregate R&D as evidence against the conventional Schumpeterian view on the optimal timing of innovation. We decompose aggregate R&D and real GDP in the U.S. into those by 22 industry groups. Surprisingly, we find that only 5.67% of aggregate R&D's procyclicality reflects within-industry timing, but 94.37% arises from inter-industry R&D-output co-movement. Our estimation results suggest input-output linkage between capital-good industries and the rest of the economy contributes to such comovement, helps to account for over 50% aggregate R&D's procyclicality, and amplifies aggregate fluctuations by about 15%. We propose an economy's input-output structure as an important factor on the link between short-run cycles and long-run growth.

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1. Introduction

The literature has repeatedly documented aggregate R&D appears pro-cyclical: it co-moves positively with aggregate output over time.[1] Many researchers have taken such pro-cyclicality as evidence questioning the conventional Schumpeterian view that suggests innovative activities, including R&D, should be concentrated during downturns when their opportunity cost as forgone output is low.[2] This paper investigates whether aggregate R&D's pro-cyclicality truly reflects the timing of R&D and, more importantly, what are the causes and consequences of such pro-cyclicality.

We are motivated by the fact that the business cycle itself is a co-movement phenomenon: it is characterized by extensive co-movement of various sectors, which contributes significantly to aggregate volatility (Christiano and Fitzgerald, 1998). To investigate whether co-movement matters to aggregate R&D's pro-cyclicality, we decompose aggregate R&D and real GDP into those at the industry level and hence the covariance between aggregate R&D growth and real GDP growth into a "within-industry" and a "cross-industry" components. The former reflects how each industry's R&D co-varies with its own output, and the latter captures how R&D and output co-move across industries. Applying such decomposition exercises to the case of the U.S., we find the cross-industry component accounts for 94.37% of the covariance between aggregate R&D growth and real GDP growth. In other words, the observed pro-cyclical aggregate R&D is largely an inter-industry co-movement phenomenon, just as the business cycle itself.

[1] For example, Fatas (2000), Walde and Woitek (2004), Comin and Gertler (2006), and Barlevy (2007) show growth in aggregate R&D expenditures tracks GDP growth for the U.S. and for G7 countries.
[2] This view traces back to Schumpeter (1939) and has been revived by authors such as Hall (1991), Aghion and Saint-Paul (1998), and Davis and Haltiwanger (1999).

What drives such inter-industry co-movement of R&D and output? In exploring this question, our findings point to capital-good industries – Machinery, Electronics, and Transportation Equipment. They are major R&D performers; their R&D co-varies positively and strongly with many other industries' output, accounting for all of the observed inter-industry R&D-output co-movement. When examining the inter-industry input-output linkage as a potential factor, our findings once again highlight the role of capital-good industries: they demand large shares of output *from* as well as supply significant amount of input *for* most of other industries; moreover, the strength in their R&D's co-movement with other industries' output rises in the strength of the input-output linkage.

Based on these findings, we propose input-output linkage as a propagation mechanism causing synchronized output responses to variations in capital-good R&D, giving rise to the observed inter-industry R&D-output comovement. We estimate the strength of such input-output propagation, and apply our estimates to approximate aggregate R&D's cyclicality in the U.S. Our approximation exercises suggest the input-output propagation explains over 50% of the observed aggregate R&D's pro-cyclicality and amplifies aggregate fluctuations by about 15%.

The importance of the input-output linkage for macroeconomic outcome has long been recognized. It has been proposed by Horvath (2000) as an important factor for short-run fluctuations, and by Jones (2011) as a helpful element explaining long-run national income.[3] However, our results suggest the input-output linkage matters not only for short-run cycles and long-run growth per se, but also for the link between the two. In particular, for understanding this link the cyclicality of innovation activities by industries that serve as input-output network "hubs" should be the key. In the case of the U.S., capital-good industries are broad demanders

[3] Horvath (2000) argues input-output linkage propagates sectoral shocks throughout the economy, causing aggregate fluctuations; Jones (2011) proposes input-output linkage amplifies micro-level distortions, contributing to long-run income differences across nations.

and key suppliers for other industries, so that variations in their R&D are accompanied by synchronized fluctuations in other industries' output. As a result, lower capital-good R&D during downturns amplifies short-run fluctuations on the one hand, and hinders long-run growth of the entire economy on the other hand, both through the input-output propagation.

The rest of the paper is organized as follows. Section 2 describes the data. Section 3 carries out the decomposition exercises. Section 4 explores input-output linkage in driving inter-industry co-movement between R&D and output. Section 5 estimates the strength of input-output propagation and investigates its quantitatively significance. We conclude in Section 6.

2. Data

Two data sources are combined to construct a disaggregated industry panel of R&D and output. Data on R&D by industry is taken from the National Science Foundation (NSF) that publishes nominal R&D expenditures for 22 industry groups mostly at the level of approximately two-digit 1987 SIC.[4] The NSF publishes both company-financed and federal-financed R&D. Only data on company-financed R&D are used for the purpose of this paper. Some industry-year observations are suppressed to avoid disclosure of individual firms' operations. However, in all but three of these observations, either company-financed R&D or total R&D is suppressed, but not both. Following Shea (1998), we use growth in total R&D to interpolate gaps in the series of company-financed R&D. The three observations where company-financed R&D and total R&D are both suppressed are R&D by Textile and Apparel (SIC 22 and 23) in 1989, R&D by Rubber (SIC 30) in 1991, and R&D by Other Equipments (SIC 361-364, 369) in 1991. We interpolate

[4] Starting from 1999, R&D industries are defined according to the North American Industry Classification System (NAICS) instead of the SIC. To make the year-to-year comparison more convenient, the NSF transforms the 1997-1998 R&D-by-industry series under the SIC into those under the NAICS. Unfortunately, the concordance behind the transformation remains confidential. Moreover, it is claimed that "the estimates for 1997 and 1998 (after transformation) are not necessarily representative of the NAICS categories of industries in those years…as it may involve a large number of errors." (http://www.nsf.gov/statistics/srs01410/).

these three gaps using growth in company-financed R&D based on the original NSF publications back in 1988, 1989, 1990, and 1991.[5] Following Barlevy (2007), we convert the R&D series into 2000 dollars using the GDP deflator. Alternative deflators from the R&D Satellite account published by the Bureau of Economic Analysis (BEA) generate similar results. All details are available upon request.

Data on manufacturing output are taken from the NBER manufacturing productivity (MP) databases that provide production data for 469 four-digit manufacturing industries from 1958 to 1996, and recently extended to 2005. Our results are robust to leaving the extended part of the data out of the analysis. The MP data are aggregated to the R&D industries defined by the NSF. Output is measured as real value added, as the deflated value added using shipment-value-weighted price deflator.[6] Data on non-manufacturing output is from the series of GDP by industries published by the Bureau of Economic Analysis (BEA).

Table 1 decomposes aggregate R&D and real GDP in the U.S. from 1958 to 1998 into those by non-manufacturing sectors and by 21 manufacturing industry groups. Manufacturing industries are further divided into those of non-durable goods and of durable goods. Column 2 lists each industry's average share of aggregate R&D; Column 3 reports its average share of real GDP. According to Column 2, R&D in the U.S. is overwhelmingly dominated by the manufacturing sector that accounts for 92.19% of the observed total R&D expenditures, among which 25.65% is from non-durable manufacturing industries and 66.54% is from durable manufacturing industries. By contrast, only 20.52% of real GDP is from the manufacturing

[5] These three observations, while suppressed in the revised series, were not missing in the original publications at http://www.nsf.gov/statistics/iris/excel-files/nsf_92-307/b-2.xls, http://www.nsf.gov/statistics/iris/excel-files/nsf_94-325/a-7.xls, http://www.nsf.gov/statistics/iris/excel-files/nsf_94-325/a-7.xls.

[6] According to Bartelsman and Gray (1996), value added is adjusted for inventory changes while value of shipment is not. For our purpose of examining the correlation between R&D and production, value added is a more appropriate measure of output that includes both sold and unsold goods. Nonetheless, the results remain similar when output is measured as deflated value of shipments. Details are available upon request.

sector, among which non-durable manufacturing industries take 8.07% and durable manufacturing industries take 12.45%.

Two factors contribute to the dominance of manufacturing R&D on aggregate R&D in the U.S. reported by the NSF. First, producers of intermediate goods and capital goods are usually also active innovators. In the U.S., the manufacturing sector is an important provider of intermediate goods and capital goods for the rest of the economy. For example, Long and Plosser (1987) report that the manufacturing sector constitutes over 40% of the production cost of the construction sector. Second, the Survey of Industrial Research and Development (SIRD), on which the NSF R&D series are based, was designed in the 1950s when the U.S. economy was largely manufacturing based.[7] Hence, SIRD has most likely missed a significant amount of on-going R&D by non-manufacturing firms. Nonetheless, many researchers have documented pro-cyclical aggregate R&D for the case of the U.S. based on the NSF R&D data. Thus, we proceed to explore the causes of pro-cyclical aggregate R&D employing the NSF R&D data, and discuss in following sections the potential influence of such data limitation on our results.

3. Decomposition

Following Shea (1996) and Comin and Philippon (2005), we approximate the growth rate of aggregate R&D, denoted as R, and that of aggregate output, denoted as Y, as the weighted averages of R&D growth and output growth by N disaggregated industries:

$$\begin{aligned} R_t &\cong \sum_{i=1}^{N} S_i^R R_{it} \\ Y_t &\cong \sum_{i=1}^{N} S_i^Y Y_{it} \end{aligned} \tag{1}$$

[7] In 2008, the NSF started the new Business R&D and Innovation Survey to incorporate changes in the structure of the economy since the 1950s.

S_i^R and S_i^Y are industry *i*'s long-run shares of aggregate R&D and aggregate output. Let S^R and S^Y to be 1-by-*N* vectors whose elements are S_i^R and S_i^Y; let Ω^{RR}, Ω^{YY} and Ω^{RY} to be *N*-by-*N* variance-covariance matrixes of industry R&D, of industry output, and between industry R&D and industry output; let $Var(R_t)$ to denote the variance of aggregate R&D growth, $Var(Y_t)$ to be that of aggregate output growth, and $Cov(R_t, Y_t)$ to be the covariance between aggregate R&D growth and aggregate output growth. Then, $Var(R_t)$, $Var(Y_t)$, and $Cov(R_t, Y_t)$ are approximately:

$$
\begin{aligned}
& Var(R_t) \cong S^R \Omega^{RR} S^{R\,\prime}; \\
(2)\quad & Var(Y_t) \cong S^Y \Omega^{YY} S^{Y\,\prime}; \\
& Cov(R_t, Y_t) \cong S^R \Omega^{RY} S^{Y\,\prime}.
\end{aligned}
$$

(2) decomposes the variances of *R* and *Y* and their covariance into "within-industry" components from the diagonals of Ω's and "cross-industry" components from the off-diagonal elements of Ω's. The "within-industry" components reflect how R&D growth and output growth vary or co-vary within each industry, weighted by their R&D shares and output shares. The "cross-industry" components capture the inter-industry co-movements of R&D growth, of output growth, and between R&D growth and output growth, weighted by their R&D shares and output shares.

3.1 Decomposition Results

We apply (2) to our industry panel of R&D and output. The decomposition results are summarized in Table 2. Aggregate R&D and real GDP are decomposed into two groups in Panel A as manufacturing and non-manufacturing sectors, into three groups in Panel B as non-durable manufacturing industries, durable manufacturing industries, and non-manufacturing sectors, and into 22 groups in Panel C as 21 manufacturing industry groups and non-manufacturing sectors. Column 2 lists the observed variance and covariance; Column 3 reports the approximated variance and covariance based on (2); Columns 4 and 5 present the within-industry and cross-industry components. Column 6 summarizes the fractions of the variances and covariance attributable to the cross-industry components. Column 7 reports the averages of the pair-wise correlation coefficients between industry output growths, between industry R&D growths, or between industry R&D and output growths.

Table 2 suggests the following. First and unsurprisingly, output co-moves positively across industries. For example, according to Panel C, the pair-wise correlation coefficients of industry output growth average 0.4908; inter-industry output co-movement accounts for 64.35% of the volatility in real GDP growth. This is consistent with the existing literature that documents the business cycle as a "co-movement" phenomenon. For example, Christiano and Fitzgerald (1998) observe most sectors in the U.S. to move up and down together over the business cycle; Shea (1995) documents inter-industry employment co-movement at the three-digit SIC level accounts for about 95% of the volatility in total U.S. manufacturing employment; he also reports quantitatively similar results hold for output.

Second, R&D does *not* co-move as much across industries. The pair-wise correlation coefficients between industry R&D growths are negative both in Panel A and in Panel B. This suggests inter-industry R&D co-movement *dampens* rather than facilitates aggregate R&D volatilities. In Panel C with the decomposition conducted at approximately the two-digit SIC level, the average pair-wise correlation coefficient turns positive, but is very small quantitatively; inter-industry R&D co-movement accounts for only 13.56% of aggregate R&D volatilities.

Third, R&D and output co-move positively across industries. The pair-wise correlation coefficients between industry R&D growth and industry output growth are positive in all three panels, although relatively small quantitatively. However, such co-movement plays a dominant role in driving pro-cyclical aggregate R&D: its share of the approximated covariance between aggregate R&D growth and real GDP growth is 50.63% in Panel A, 91.25% in Panel B, and 94.37% in Panel C of Table 2. Put differently, at the approximately two-digit SIC level, inter-industry R&D-output co-movement accounts for 94.37% of the pro-cyclicality of aggregate R&D, but inter-industry output co-movement takes only 64.35% of volatilities in real GDP. This result suggests inter-industry co-movement is a key factor in explaining the pro-cyclicality of aggregate R&D, even more so than its role in accounting for aggregate output volatilities documented by Christiano and Fitzgerald (1998) and Shea (1995).

3.2 Pro-cyclical Aggregate R&D and the Schumpeterian View

The literature has taken pro-cyclical aggregate R&D as evidence against the conventional Schumpeterian view (Aghion et al., 2005; Barlevy, 2007; Francois and Lloyd-Ellis, 2009). This view argues, as long as innovation competes with production for resources, a rational entrepreneur who balances innovation and production inter-temporarily would choose to perform more R&D when the return to output, the opportunity cost of R&D, is low.[8] Under the representative-firm paradigm, this view contradicts the observed pro-cyclicality of aggregate R&D. Now consider a framework of heterogeneous firms, and let our sample industries represent firms that produce various products and engage in innovation. Then (2) suggests the average timing of R&D, as whether an industry's R&D is concentrated when its own output is low or

[8] Aghion and Saint-Paul (1998) propose, if innovation requires produced goods instead of factors of inputs, the optimal timing of innovation should be pro-cyclical. However, Griliches (1990) argues that the major input into R&D is labor, not produced goods.

high, is reflected by the "within-industry" component. But our decomposition results suggest the cross-industry component capturing inter-industry R&D-output comovement dominates the pro-cyclicality of aggregate R&D.

Hence, on whether pro-cyclical aggregate R&D contradicts the Schumpeterian view, two messages can be taken away from Table 2. First, although the within-industry component remains positive, its share in accounting for the pro-cyclicality of aggregate R&D *decreases* as the decomposition moves to a more detailed industry level. This fact suggests the positive within-industry component may still be driven by co-movement across heterogeneous producers. In other words, most likely, R&D and output by the same producer do co-vary negatively over time as the Schumpeterian view suggests at the more detailed industry level or even the firm level; but such Schumpeterian timing is masked by co-movement of R&D and output across producers, so that R&D in aggregates appears pro-cyclical.

Second, the within-industry cyclicality of R&D differs significantly across our sample industries. The last column of Table 1 reports the correlation coefficients between R&D growth and output growth for each industry category. At the most detailed decomposition level of 22 industry groups, six coefficients are negative and 16 are positive; the coefficient ranges from -0.3144 for Petroleum Refining (SIC 29) to 0.4594 for Electronics Equipments (SIC 366-367).

Based on these findings, we argue the conventional Schumpeterian view should be examined at the detailed industry level or at the firm level, to uncover how various producers choose the timing of innovation, and to shed light on when and why the Schumpeterian theory fails the data.

4. Source of Comovement

We proceed to examine the source of inter-industry R&D-output co-movement that dominates pro-cyclical aggregate R&D. Two factors have to be considered: a size effect, as bigger industries have more influence on total comovement, and a comovement effect arising from either the R&D end or the output end, as an industry's contribution to total comovement depends on how its R&D co-moves with others' output as well as on how its output co-moves with others' R&D.

Table 3 presents a simple case for the comovement effect, displaying the matrix of correlation coefficients between R&D growth and output growth under the decomposition of non-durable manufacturing, durable manufacturing, and non manufacturing sectors. The rows report, from the R&D end, the correlation coefficients between each sector's R&D growth and other's output growths; the columns report, from the output end, those between each sector's output growth with others' R&D growth. Examining across columns suggests sectors differ little on the output end: each is identical in the number of positive comovements. Examining across rows, however, shows the source of comovement on the R&D end focuses intensely on durable manufacturing. In particular, the correlation coefficients are all positive for durable manufacturing R&D, but are all negative for non-durable manufacturing R&D and non-manufacturing R&D. Put intuitively, durable manufacturing R&D co-moves with all sectors' output positively, driving aggregate R&D pro-cyclical; but non-durable manufacturing R&D and non-manufacturing R&D co-moves with all sectors' output negatively, dampening such pro-cyclicality.

We move our analysis to a more disaggregated level of 22 industry groups. Define a 22-by-22 matrix *C*, whose (*i, j*) element equals $corr(R_i, Y_j)$, the correlation coefficient between industry i's R&D growth and industry j's output growth. Define a corresponding 22-by-22 matrix D whose (i, j) element equals one if $corr(R_i, Y_j)$ is positive and zero otherwise. To focus on comovement, we set the diagonals of both D and C to zeros, while the results are robust to keeping the diagonals. Define $P_i^R = \sum_j D_{ij}$ and $P_j^Y = \sum_i D_{ij}$, as the row sum and column sum of D, and $C_i^R = \frac{1}{21}\sum_j corr\left(R_i, Y_j\right)$ and $C_j^Y = \frac{1}{21}\sum_i corr\left(R_i, Y_j\right)$ as the row mean and column mean of C. Intuitively, P_i^R and P_j^Y indicate the numbers of positive comovements for each industry from the R&D end and from the output end; C_i^R and C_j^Y capture the average comovement strengths.

Figure 1 presents the distributions of P_i^R and P_j^Y in Panel A, and those of C_i^R and C_j^Y in Panel B. P_i^R and C_i^R are plotted on the left; P_j^Y and C_j^Y are on the right. Not surprisingly, P_i^R and P_j^Y have the same mean; so do C_i^R and C_j^Y. In higher moments, however, the distributions on the R&D end differ greatly from those on the output end: in Panel A, P_i^Y is clustered around the mean; but the distribution of P_i^R is more spread out, displaying fat tails on both sides. Panel B shows similar patterns for C_i^R and C_j^Y. Figure 1 delivers a message similar to that suggested by Table 3: industries differ little in how their output co-moves with others' R&D, but differ greatly in how their R&D co-moves with others' output. This message suggests we should focus on the R&D end to explore the source of the comovement.

4.1 Capital-good R&D

We combine the size effect with the comovement effect, defining the following two variables:

$$
(3) \quad \begin{aligned} R_i - Comove &\equiv S_i^R \sum_{j \neq i} Cov(R_{it}, Y_{jt}) S_j^Y; \\ Y_i - Comove &\equiv S_i^Y \sum_{j \neq i} Cov(Y_{it}, R_{jt}) S_j^R; \end{aligned}
$$

$R_i - Comove$ is the sum of the share-weighted co-variances between industry *i*'s R&D and other industries' output. $Y_i - Comove$ is that between industry *i*'s output and other industries' R&D. $R_i - Comove$ and $Y_i - Comove$ both sum over *i* to total comovement. The distribution of $R_i - Comove$ and $Y_i - Comove$ reflect the source of the comovement from the R&D end and from the output end.

Table 4 reports, at different decomposition levels, the values of $R_i - Comove$ and $Y_i - Comove$ together with their shares in accounting for total co-movement. The results in Panel B under the decomposition of three industry groups re-enforce the impression given by Table 3: inter-industry co-movement of R&D and output is *entirely* due to durable manufacturing R&D. In particular, $R_i - Comove$ by durable manufacturing accounts for 120.95% of total inter-industry R&D-output component.

Panel C of Table 4 presents the results under the decomposition of 22 industry groups. Again, the source of comovement appears much sparser on the output end than on the R&D end. Out of 22 industries, $Y_i - Comove$ is positive for 21 but $R_i - Comove$ is positive for 14 industries. Moreover, the share of $Y_i - Comove$ in accounting for total comovement is distributed relatively evenly across industries, but those of $R_i - Comove$ are concentrated among five durable manufacturing industries that produce capital goods: Machinery (SIC 35), Electronics and Communication Equipment (SIC 366-367), Other Equipment (SIC 361-365, 369), Autos and Others (SIC 371, 373-75, 379), and Aerospace (SIC 372,376). The two-digit sectors containing these five industries, Machinery (SIC 35), Electronics (SIC 36), and Transportation Equipment (SIC 37), each contribute to over 20% of total comovement. Altogether, they account for 109.41% of total comovement. Hence, inter-industry R&D-output comovement that dominates aggregate R&D's pro-cyclicality can be viewed as entirely driven by capital-good R&D's co-moving with other industries' output.

Capital-good R&D dominates inter-industry R&D-output co-movement due to both the size effect and the comovement effect. Capital-good industries are the biggest R&D performers: according to Table 1, altogether they compose only 5.87% of real GDP but account for 50.45% of aggregate R&D. Moreover, capital-good R&D tends to co-moves positively and strongly with most other industries' output.[9] This is shown in Figure 2, which plots the matrix of correlation coefficients between industry R&D growth and output growth. Again, the diagonals are set to zeros to focus on inter-industry comovement. In Figure 2, R&D by industry is indicated by row; output by industry is by columns. A contour plot method is used, showing only those coefficients greater than -0.2, 0, 0.2, and 0.4. The patterns shown by Figure 2 are similar to those by Figure 1: the matrix is relatively sparse column-wise, but displays strong horizontal patterns. R&D by a few key industries including Machinery (SIC 35), Electronics (SIC 36), and Transportation Equipment (SIC 37) co-moves positively and relatively strongly with most industries' output. For example, the mean correlation coefficient is only 0.0507 for the entire matrix, but equals 0.0927 for Machinery, 0.1826 for Electronics, and 0.215 for Transportation Equipment.

[9]In other words, they are located on the right ends of the distributions by R&D industry in Figure 1. For example, R&D by Electronics and Communication Equipment co-moves positively with output by all other industries. R&D by Machinery co-moves positively with output by 17 out of the other 21 industries. This number is 16 for R&D by Other Equipment, 20 for R&D by Autos and Others, and 16 for R&D by Aerospace.

4.2 Input-output Matrixes

What drives inter-industry co-movement between R&D and output? The literature has provided several hypotheses on the causes for comovement, including aggregate shocks, input-output propagation, or geographical propagation (Shea, 2002). Under the aggregate-shock hypothesis, R&D and output co-move positively due to common aggregate shocks, assuming R&D and output respond in the same direction. However, Figure 1 and Figure 2 both display great cross-industry heterogeneity on the R&D end of the comovement, therefore providing little support for aggregate shocks as a key driving force.

Under the input-output propagation hypothesis, a shock to a particular industry is propagated to the rest of the economy through factor-demand linkages, so that fluctuations in aggregates are obtained as synchronized responses to shocks in certain industries that serve as broad suppliers or demanders. The input-output propagation can cause downstream R&D and upstream output to co-move positively: for example, a positive technology shock to Electronics raises Electrical R&D, as electrical companies attempt to develop such technology into further productivity gain; at the same time, such positive technology shock can generate higher demand for factor inputs, so that output by upstream industries such as Metals rises.[10] Input-output propagation can drive upstream R&D and downstream output to co-move positively: for example, a negative demand shock to Transportation Equipment reduces Transportation Equipment output as well as its demand for factor inputs such as Rubber, which tightens borrowing constraints by Rubber companies so that Rubber R&D declines.[11]

[10] See Basu et al.(2006) and Chang and Hong (2006) for discussions of technology shocks' being contractionary or expansionary.
[11] Aghion et al. (2005) and Ouyang (2010a) both propose borrowing constraints as key causes for pro-cyclical R&D at the aggregate level and at the industry level.

To examine the factor-demand linkages among our sample industries, we examine two indicators following Shea (1993): the ultimate-demand share (UDS) and the ultimate-cost share (UCS). The UDS of industry *I* for industry *J* is the share of *J*'s output ultimately embodied in the final demand for *I*. The UCS of industry *Y* for industry *X* is the production cost of *X* ultimately originating in *Y*. By definition, the UDS captures the impact of a downstream industry on an upstream industry as a demander; and the UCS reflects that of an upstream industry on an downstream industry as a supplier. We construct UDS and UCS based on the 1992 make table, use table, and capital-flow table produced by the BEA.[12] Note that the factor demand linkages can be either direct or indirect. For example, Transportation Equipment purchases goods from Rubber directly and indirectly through its purchase of Tire. Our UDS and UCS incorporate both direct and indirect linkages as well as both intermediate-good flows and capital-good flows. [13] Our results are robust to considering direct linkages only or taking off capital-good flows. Details are described in the appendix.

Figure 3 contour plots 22-by-22 matrixes of the UDS and UCS for our sample industries. Each row indicates an upstream or input industry; each column indicates a downstream or use industry. In particular, an (*i,j*) entry in the UDS matrix equals the UDS of industry *j* for industry *i*; and that in the UCS matrix is the UCS of industry *i* for industry *j*. The diagonals are set to zeros in order to focus on inter-industry linkages. Only shares greater than 2% and 4% are plotted.

[12] The input-output tables are produced every five years. 1992 was the last year that the BEA produced the SIC-based input-output tables. Starting from 1997, industries are defined according to the North American Industry Classification System (NAICS) instead of SIC.
[13] Many existing studies such as Nekarda and Ramey (2010) and Carvalho (2010) consider intermediate goods purchase only, as computing the rental cost of capital requires converting capital flow into capital stock. We incorporate data on capital flows because our results highlight capital goods industries whose output is largely utilized as capital goods. However, our results stay robust when data on capital-flow is taken off the UDS and UCS.

In Figure 3, the UDS matrix shows several vertical patterns, suggesting a few key industries demand output from most other industries in relatively large shares; these are Food (SIC 20 and 21), Textiles (SIC 22 and 23), Machinery (SIC 35), Electronics (SIC 36), and Transportation Equipment (SIC 37), Miscellaneous Manufacturing, and Non-manufacturing sectors. The UCS matrix displays several horizontal patterns, implying several key industries serve as relatively significant input provider for most other industries; these are Machinery (SIC 35), Electronics (SIC 36), Transportation Equipment (SIC 37), Miscellaneous Manufacturing, and Non-manufacturing sectors; they also include Textiles (SIC 22 and 23), certain Chemical industries (SIC 28), and Petroleum Refining (SIC 29). The three capital-good industries stand out in Figure 3 both as significant demanders and as important suppliers. In other words, they display important input-output linkage with others both from upstream and from downstream. According to the network analysis, they serve as input-output network “hubs” in our sample (Carvalho, 2010). This is consistent the strong positive co-movement between capital-good R&D and other industries’ output reported in Table 4, and suggests the possibility input-output linkage propagates capital-good R&D variations to output responses by the rest of the economy.

It is difficult to directly compare our UDS and UCS with the input-output structure the literature has documented for the U.S. economy, which are produced either at different aggregation levels, in a commodity-by-commodity format, or incorporating only direct flow of intermediate goods. Nonetheless, Shea (1993) reports, based on the 1972 input-output tables, Transportation Equipment demands large output shares from many other industries, consistent with the pattern shown by our UDS matrix. Jones (2010) shows, with a commodity-by-industry cost-share matrix, a few key inputs are used by many industries in significantly ways, consistent with the patterns displayed by our UCS matrix. Similar patterns in the UCS matrix is also documented by Carvalho (2010) with a commodity-by-commodity cost-share matrix at roughly four-digit SIC level for the U.S. economy in 1972, 1977, 1982, 1987, 1992, and 1997.

4.3 The Comovement Strength and Input-output Linkage.

To investigate the relationship between input-output linkage plotted in Figure 3 and the strength of inter-industry co-movement displayed in Figure 2, we estimate the following:

$$(4)\quad corr(R_i, Y_j) = \alpha_0 + \alpha_1 UDS_{ij} + \alpha_2 UCS_{ij} + \alpha_3 UDS_{ji} + \alpha_4 UCS_{ji} + \varepsilon_{ij}, i \neq j,$$

$corr(R_i, Y_j)$ is the correlation coefficient between R&D growth by industry *i* and output growth by industry *j*. The first letter of the subscripts of *UDS* and *UCS* denotes the upstream industry, and the second letter denotes the downstream industry. For example, UDS_{ij} is the ultimate demand share of industry *j* for industry *i*; UCS_{ij} is the ultimate cost share of industry *i* for industry *j*. Given that *R* is indexed by *i* and *Y* is indexed by *j* in (4), *UDSji* and *UCSij* reflect the influence of the R&D industry on the output industry; conversely, *UDSij and UCSji* represent that of the output industry on the R&D industry.

Table 5 summarizes the OLS results of (4). Row 2 reports those for the full sample; the sample size is 462. Neither of the estimated coefficients on *UDSij* and *UCSji* is statistically significant, but those on *UDSji* and *UCSij* are both positive and statistically significant at the 5% level or above. This suggests input-output linkage does contribute to the strength of the inter-industry co-movement between R&D and output, but the causality runs from the R&D industry to the output industry only. In particular, R&D and output co-move more strongly, when the R&D industry either constitutes, from upstream, a bigger share of the production cost of the output industry or demands, from downstream, a higher percentage of the products by the output industry.

Then we divide the full sample into two sub samples, one containing R&D by five capital-good industries, and the other including R&D by 17 non-capital goods industries. The sample size is 105 for the first sample and 357 for the second sample. The results are robust to pooling the two samples together but allowing the coefficients to differ for capital-good R&D and non-capital-good R&D. We re-run the OLS regression of (4) for each of the two sub samples. Row 3 of Table 5 reports, for the sub sample of capital-good R&D, the estimated coefficients on *UDSji* and *UCSij* are both positive and significant at the 1% level; they are also bigger in point estimates compared to those for the full sample. For the sub sample of non-capital-good R&D, however, none of the estimates are statistically significant. This suggests the relationship between input-output linkage and the strength of inter-industry co-movement comes entirely from capital-good R&D. This once again points to capital-good R&D as a key element for inter-industry R&D-output co-movement and to input-output propagation as a potential explanation.

5. Propagation

Our results in Section 4 are consistent with the input-output propagation hypothesis, under which capital-good R&D fluctuations are propagated by input-output linkage to the rest of the economy as synchronized output responses. To investigate the quantitative importance of the input-output propagation for the observed procyclicality of aggregate R&D, we estimate the following:

$$(5)\, Y_{it} = \alpha_i + \gamma_i A_t + \sigma R_{it} + \beta_1 \sum_{j \neq i} UDS_{ij} R_{jt} + \beta_2 \sum_{j \neq i} UCS_{ji} R_{jt} + \varepsilon_{it}\,,$$

α_i is an industry dummy. Y_{it} denotes the output growth of industry *i* in year *t*, and R_{jt} is the R&D growth of industry *j* in year *t*. A_t is a set of aggregate shocks. Following Basu et al. (2006), we apply three measures on aggregate shock A_t: oil prices as increases in the U.S. refiner acquisition price, growth in real government defense spending, and monetary shocks from an identified VAR. UDS_{ij} is the ultimate demand share of industry *j* for industry *i* from downstream; and UCS_{ji} is the ultimate cost share of industry *j* for industry *i* from upstream. Under this specification, the estimate on γ reflects impact of aggregate shocks on industry output and is allowed to differ by industry; the estimate on σ represents the average within-industry co-variation between R&D and output; we assume common σ in order to compare its estimate with the cyclicality of aggregate R&D. Intuitively, (5) estimates how input-output linkages propagates R&D variations to other industries' output, controlling for within-industry R&D-output co-variation and industry-specific impact of aggregate shocks. The estimates on β_1 and β_2 reflect the strength of the input-output propagation.

5.1 Input-output Propagation

The OLS estimation results of (5) are summarized in Panel A, Column 2 of Table 6. The estimate on σ is 0.0549, significant at the 1% level, suggesting a 10% increase in industry R&D growth is associated with about a 0.5% increase in industry output growth after controlling for common aggregate shocks and inter-industry input-output propagation. This estimate would be 0.0686, significant at the 5% level, if controlling for aggregate shocks only. As a comparison, regressing real GDP growth on a constant and aggregate R&D growth in the U.S. over the sample period generates an estimated coefficient of 0.2083 on aggregate R&D growth, significant at the 5% level. This suggests the pro-cyclicality of R&D is much milder at the industry level and after controlling for the input-output propagation, consistent with our decomposition results reported in Table 2.

However, Panel A, Column 2 of Table 6 reports neither of the estimates on β_1 or β_2 are statistically significant. Nonetheless, recall the estimation results of (4) suggest input-output linkage contributes to the strength of co-movement related to capital-good R&D only. Therefore, we run the OLS regression of (5) again, allowing β_1 and β_2 to differ for capital-good R&D and for non-capital-goods R&D. The results are summarized in Panel A, Columns 3 and 4, of Table 6. For capital-good R&D, the estimates on β_1 and β_2 are both positive and statistically significant at the 1% level; in particular, a 10% higher *UDS*-weighted growth in capital-good R&D is associated with 14.61% higher growth in upstream output, and a 10% higher *UCS*-weighted growth in capital-good R&D is with 24.63% higher downstream output growth. For non-capital-good R&D, however, none of the estimates on β_1 and β_2 is statistically significant. Consistent with the estimation results of (4), the results reported in Panel A of Table 6 suggest the input-output linkage propagates capital-good R&D only.

Moreover, note that aggregate shocks directly influence industry output and capital-good R&D. With input-output propagation, its impact on capital-good R&D would be propagated to other industries' output, causing further influence on industry output. We specify capital-good R&D as:

$$(6)\, R_{jt}^{k} = \alpha_{j}^{k} + \eta_{j}^{k} A_{t} + \mu_{jt}^{k}.$$

η represents the direct impact of aggregate shocks on capital-good R&D and is allowd to differ by capital-good industry; μ captures capital-good R&D variations driven by industry-specific shocks. Combining (6) with (5) gives:

$$(7)\, Y_{it} = \nu_{i} + \varphi_{i} A_{t} + \sigma R_{it} + \beta_{1} \sum_{j \neq i} UDS_{ij} u_{jt}^{k} + \beta_{2} \sum_{j \neq i} UCS_{ji} \mu_{jt}^{k} + \varepsilon_{it},$$

$$\nu_i = \alpha_i + \beta_1 \sum_{j \neq i} UDS_{ij} \alpha_j^k + \beta_2 \sum_{j \neq i} UCS_{ji} \alpha_j^k ,$$

where

$$\varphi_i = \gamma_i + \left(\beta_1 \sum_{j \neq i} UDS_{ij} + \beta_2 \sum_{j \neq i} UCS_{ji} \right) \eta_j^k$$

(7) estimates how input-output linkage propagates *industry-specific* capital-good R&D variations to other industries' output variations, controlling for the impact of aggregate shocks and the within-industry R&D-output co-variation. Again, estimates on β_1 and β_2 capture the strength of the input-output propagation. The OLS estimation results of (7) are summarized in Panel A, Column 5 of Table 7. All estimates on σ, β_1, and β_2 are positive and statistically significant at the 1% level; and the point estimates are very similar to those estimated by (5).

5.2 Robustness Check

We conduct two robustness checks on the OLS results of (5). First, our measures of *A* cannot capture all the existent aggregate shocks. For example, the arrival of a positive general-purpose technology shock raises industry output, and encourages capital-good R&D as capital-good companies attempt to embody new technology into future production; in this case, the estimates on β_1 and β_2 would be upper biased by the impact of aggregate technology shocks. In principle, an instrumental variable (IV) approach can correct for such bias. However, instruments that are sufficiently relevant to industry R&D but truly exogenous to industry output are hard to find. Nonetheless, we employ three instrument variables as a robustness check: growth in the patent examiners in the U.S. Patent and Trademark Office (USPTO), growth in patents granted to foreign companies in the related technology field, and growth in patent applications by foreign companies in the related technology field; data on all instruments are available from 1970 to 1999. The underlying assumption is that these instruments are relevant to industry R&D due to either policy influence or innovation spillover, but are relatively exogenous to industry output.

Data on patent examiners and on patent by technology field are all from the USPTO. We aggregate patents by technology filed to the R&D industries based on a concordance code produced by the USPTO relating patent fields to SIC. Unfortunately, data availability limits our estimation to 17 industries only from 1970 to 1998.[14] Our IV estimation treats three R&D variables on the right-hand side of (5) or (7) as endogenous and employs two lags, contemporaneous value, and two leads of each instrument variable. The IV estimation results are summarized in Panel B of Table 6: none of the IV estimates on σ is statistically significant. This suggests the possibility that the positive covariation between industry output and industry R&D can be caused by common shocks that influence output and R&D both, consistent with Ouyang (2010a).[15] But the IV estimates on β_1 and β_2, the coefficients either on raw capital-good R&D growth reported in Column 2 or on industry-specific capital-good R&D growth reported in Column 5, are all positive and statistically significant at the 10% level or above; they are also bigger in point estimates than the corresponding OLS estimates. While our instruments may not be truly exogenous to industry output growth, the IV estimates are qualitatively consistent with the OLS estimates.

Second, input-output linkage may not be the only propagation mechanism driving inter-industry R&D-output comovement. For example, if industry A's R&D labs happen to locate geographically close to industry B's manufacturing plants, then A's R&D and B's output can co-move positively over time due to geographical spillover effect. At the purpose of controlling for such potential mechanisms other than the input-output propagation, we take a simple approach by including $\sum_{j \neq i} \lambda_j R_{jt}$ as additional controls on the right-hand side of (5) and (7). The estimate

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[14] Five sample industries cannot be matched based on the USPTO concordance: Paper, Lumber, Other Instruments, Miscellaneous Manufacturing, and Non Manufacturing.

[15] Ouyang (2010) regress industry R&D on industry output, applying aggregate-demand and input-output demand to instrument for industry output, and report insignificant IV estimates on industry output.

on λ_i presumably captures the average strength of any mechanisms driving industry *j*'s R&D to co-move with other industries' output other than the input-output propagation. Note that, with these additional controls, we cannot apply the IV approach as the number of instruments is not enough to identify all the endogenous R&D variables.

Panel C of Table 6 reports the OLS results of (5) and (7) with $\sum_{j \neq i} \lambda_j R_{jt}$ as additional controls. All three estimates on σ are positive; two are statistically significant at the 5% level or above. The two estimates on β_1 for capital-good R&D are both positive, statistically significant at the 1% level, and close in point estimates to those reported in Panel A without controlling for $\sum_{j \neq i} \lambda_j R_{jt}$. The two estimates on β_2 for capital-good R&D are positive, statistically significant at the 10% level, but are smaller in point estimates compared to those without controlling for $\sum_{j \neq i} \lambda_j R_{jt}$. Nonetheless, the four estimates on β_1 and β_2 for capital-good R&D are all positive and statistically significant, consistent with the results summarized in Panel A, Panel B, and the input-output propagation hypothesis.

5.3 Covariance Accounting

To assess the quantitative significance of the input-output propagation to the observed pro-cyclical aggregate R&D, we calculate the following:

(8) $\hat{\mathrm{cov}}(Y_i, R_k) = S^Y \hat{\Sigma} S_k^{R}{}'$

S^Y is a 1-by-22 vector; its *i*'th element equals industry *i*'s long-run output share of real GDP. S_k^R is a one-by-five vector; its elements equal the long-run R&D shares of the five capital-good industries. Apparently, the calculated value depends crucially on $\hat{\Sigma}$, the approximated variance-covariance matrix between output by 22 industries and R&D by five capital-good industries.

We apply four approximations on $\hat{\Sigma}$ to evaluate the quantitative significance of aggregate shocks, industry-specific shocks, and input-output propagation to the pro-cyclicality of aggregate R&D. The results are summarized in Table 7. Row 3 reports the results with $\hat{\Sigma}$ approximated as $\left(\hat{\beta}_1 UDS + \hat{\beta}_2 UCS\right)\text{cov}\left(R^K\right)$: $\text{cov}\left(R^K\right)$ is a the observed five-by-five variance-covariance matrix of R&D growth by five capital-good industries; *UDS* is the 22-by-five matrix of the calculated ultimate-demand shares with capital-good industries as downstream industries; *UCS* is a 22-by-five matrix of the ultimate-cost shares with capital-good industries as upstream industries; $\hat{\beta}_1$ and $\hat{\beta}_2$ are the estimated strength of the input-output propagation. We apply the estimates with the smallest point estimates on $\hat{\beta}_1$ and $\hat{\beta}_2$ reported in the last column of Panel C, Table 7, as the OLS estimates by (5) with $\sum_{j \neq i} \lambda_j R_{jt}$ as additional controls. Intuitively, this approximation takes the observed variances and covariance of capital-good R&D as given, and calculates the cyclicality of aggregate R&D as synchronized responses in other industries' output to capital-good R&D variations propagated by input-output linkage. Row 3 of Table 7 reports that this approximation gives a covariance of 1.54×10^{-4}, accounting for 57.90% of the inter-industry co-movement between R&D and output, and 54.62% of the observed covariance between aggregate R&D growth and real GDP growth.

Row 4 reports the results with $\hat{\Sigma}$ approximated as $\hat{\gamma}\,\text{cov}\left(A\right)\hat{\eta}'$: $\text{cov}\left(A\right)$ is the observed three-by-three variance-covariance matrix of aggregate shocks *A*; $\hat{\gamma}$ is the estimate by (5) as *A*'s direct impact on industry output with $\sum_{j \neq i} \lambda_j R_{jt}$ as additional controls; $\hat{\eta}$ is the estimate by (6) as

A's impact on capital-good R&D. Intuitively, this approximation takes the aggregate shocks as given, and calculates the cyclicality of aggregate R&D as comovement between capital-good R&D and industry output attributable to common aggregate shocks. Row 4 reports it gives a covariance of 0.26×10^{-4}, taking 9.75% of the total comovement and 9.19% of the observed covariance between aggregate R&D growth and real GDP growth.

Note that, the direct impact of aggregate shocks on capital-good R&D would be propagated to other industries' output via input-output linkage, causing further comovement between capital-good R&D and other industries' output. Row 5 of Table 7 reports the cyclicality of aggregate R&D driven by this effect, with $\hat{\Sigma}$ approximated as $\left(\hat{\beta}_1 UDS + \hat{\beta}_2 UCS\right)\hat{\eta}\,\mathrm{cov}(A)\hat{\eta}'$. Again, $\hat{\eta}$ is the estimate by (6) as the direct impact of A on capital-good R&D; $\hat{\beta}_1$ and $\hat{\beta}_2$ are the OLS estimates by (5) with $\sum_{j \neq i} \lambda_j R_{jt}$ as additional controls. According to Row 5, it gives a covariance of 0.20×10^{-4}, accounting for 7.60% of the total co-movement and 7.17% of the observed covariance between aggregate R&D growth and real GDP growth.

Row 5 of Table 7 reports the value of (8) with $\hat{\Sigma}$ approximated as $\left(\hat{\beta}_1 UDS + \hat{\beta}_2 UCS\right)\mathrm{cov}(\hat{u})$: $\mathrm{cov}(\hat{u})$ is the variance-covariance matrix of the estimation residual from (6), as the industry-specific variations in capital-good R&D; $\hat{\beta}_1$ and $\hat{\beta}_2$ are the estimates from (5) with $\sum_{j \neq i} \lambda_j R_{jt}$ as additional controls. With this approximation, (7) calculates the cyclicality of aggregate R&D as synchronized responses in industry output to capital-industry specific R&D variations propagated by input-output linkage. It gives a covariance of 1.34×10^{-4}, accounting for 50.30% of the observed total co-movement and 47.45% of the observed total covariance. In sum, Table 7 suggests that the input-output propagation helps to account for

57.90% of the inter-industry R&D-output comovement, and 54.62% of the cyclicality of aggregate R&D.

Moreover, the input-output propagation of capital-good R&D can amplify the volatilities in aggregate output. Panel B of Table 7 approximates volatilities in real GDP growth as $\text{var}(Y) = S^Y \hat{\Omega} S^{Y}{'}$. S^Y is a 1-by-22 vector of output shares. Row 8 of Table 7, Panel B, approximates $\hat{\Omega}$ as $\hat{\gamma}\,\text{cov}(A)\hat{\gamma}'$: $\hat{\gamma}$ is a 22-by-3 matrix, the estimates by (5) as aggregate shocks' direct impact on industry output after controlling for $\sum_{j \neq i} \lambda_j R_{j\,t}$; *cov(A)* is the observed variance-covariance matrix of aggregate shocks. Intuitively, this approximation calculates real GDP volatilities arising from inter-industry output comovement caused by direct impact of common aggregate shocks. According to Row 8, it generates a variance in real GDP growth of 0.39×10^{-4}, accounting for 11.14% of total inter-industry output co-movement and 7.17% of real GDP growth volatilities.

Aggregate shocks can influence industry output indirectly, also propagated by input-output linkage from its impact on capital-good R&D. Row 9 of Table 7, Panel B, calculates variances in real GDP growth as $\left(\hat{\beta}_1 UDS + \hat{\beta}_2 UCS\right)\hat{\eta}\,\text{cov}(A)\hat{\eta}'\left(\hat{\beta}_1 UDS + \hat{\beta}_2 UCS\right)'$: $\hat{\eta}$ is the estimate by (6) as A's impact on capital-good R&D; $\left(\hat{\beta}_1 UDS + \hat{\beta}_2 UCS\right)$ is the estimated input-output propagation. Intuitively, this approximation calculates aggregate output volatilities as synchronized responses in industry output to capital-good R&D variations propagated by input-output linkage. Row 8 reports it gives a variance of 0.06×10^{-4}, accounting for 1.67% of total inter-industry output comovement and 1.08% of variance in real GDP growth. This suggests the input-output propagation amplifies aggregate volatilities by about 15%.[16]

5.4 Discussion: Consequences

What do our results imply on the consequences of pro-cyclical aggregate R&D? First, pro-cyclical aggregate R&D reflects an amplification effect on the short-run cycle, caused by the input-output propagation of pro-cyclical capital-good R&D; we estimate its quantitative significance to be about 15%. Second, our results imply input-output structure has significant influence on the impact of short-run cycles on long-run growth. Among our sample industries, capital-good industries serve as input-output network "hubs"; as a result, lower capital-good R&D during recessions hinder long-run growth of not only capital-good industries themselves but also other industries through the input-output propagation. In summary, input-output linkage amplifies the impact of the business cycle in the short-run and, in principle, propagates it into the long-run.

However, not all industries display pro-cyclical R&D. For example, Table 1 suggests Petroleum Refining R&D is counter-cyclical, which is also documented by Ouyang (2010a). Higher Petroleum Refining R&D during recessions can also cause synchronized output increases in its upstream and downstream industries, dampening the short-run business cycle and promoting long-run growth of itself and its related industries through the input-output propagation. Likely, the dampening effect of counter-cyclical Petroleum Refining R&D is

[16] Only contemporaneous relationship between output and R&D is estimated in this paper, because our experimentation with R&D lags suggest lagged effect of capital-good R&D on other industries' output is usually statistically insignificant. However, this does not imply capital-good R&D cannot influence other industries' output with lags: including lagged effect in an annual panel tends to reduce the sample size and the degrees of freedom of the estimation; moreover, it is hard to determine the lag length for innovative activities to have real return: some innovation project may generate prompt return, while others can take decades to have real outcome.

dominated by the amplification effect of pro-cyclical capital-good R&D, not only because the latter takes higher aggregate R&D share, but also because capital-good industries possess stronger input-output linkage with the rest of the economy. This suggests, once again, the input-output structure of an economy is an important factor for understanding the link between short-run cycles and long-run growth. What determines the cyclicality of industry R&D is beyond the scope of this paper, and has been explored by Ouyang (2010a, 2010b, and 2010c).

We should also be aware of the potential influence on our results of the sample selection bias of the NSF R&D survey. As pointed out earlier, the NSF R&D data has most likely missed a significant amount of on-going R&D by non-manufacturing industries. If those non-reported R&D is in fact counter-cyclical, then the dampening impact of counter-cyclical non-manufacturing R&D may dominate the amplification effect of pro-cyclical capital R&D because, according to Figure 3, non-manufacturing industry group also display high UDS and UCS with the rest of the economy. It is also possible that, with improved R&D data in the future, we find the amplification effect of some industries' pro-cyclical R&D and the dampening effect of other industries' counter-cyclical R&D fully cancel out, so that the net effect of short-run cycles on long-run growth through the R&D channel is in fact zero.

6. Conclusion

Pro-cyclical aggregate R&D has been taken as evidence against the conventional Schumpeterian view arguing entrepreneurs innovate more when producing less. We decompose aggregate R&D and real GDP in the U.S. into those by industries at various levels. Perhaps surprisingly, we find pro-cyclical aggregate R&D is in fact a co-movement phenomenon. For example, at the approximately two-digit SIC level, only 5.63% of the pro-cyclicality of aggregate R&D reflects within-industry R&D-output co-variation, but 94.37% is caused by inter-industry co-movement. The quantitative significance of such co-movement in driving aggregate R&D pro-cyclical is even greater than its accounting for aggregate volatilities long recognized in the literature.

When exploring driving forces for inter-industry R&D-output co-movement, our findings point to the importance of capital-good R&D, namely, R&D by Machinery (SIC 35), Electronics (SIC 36), and Transportation Equipment (SIC 37). In particular, capital-good R&D co-moves with other industries' output, causing all of the observed co-movement and driving aggregate R&D pro-cyclical. Moreover, we find input-output linkage contributes to the strength of such co-movement, and the causality runs from capital-good industries to others. We propose input-output linkage as a mechanism that propagates variations in capital-good R&D to other industries' output, and estimate the strength of this propagation. Our results suggest input-output propagation helps to account for over 50% of the pro-cyclicality of aggregate R&D, and amplifies aggregate output volatilities by about 15%. We posit an economy's input-put structure should be an important factor for the link between short-run cycles and long-run growth.

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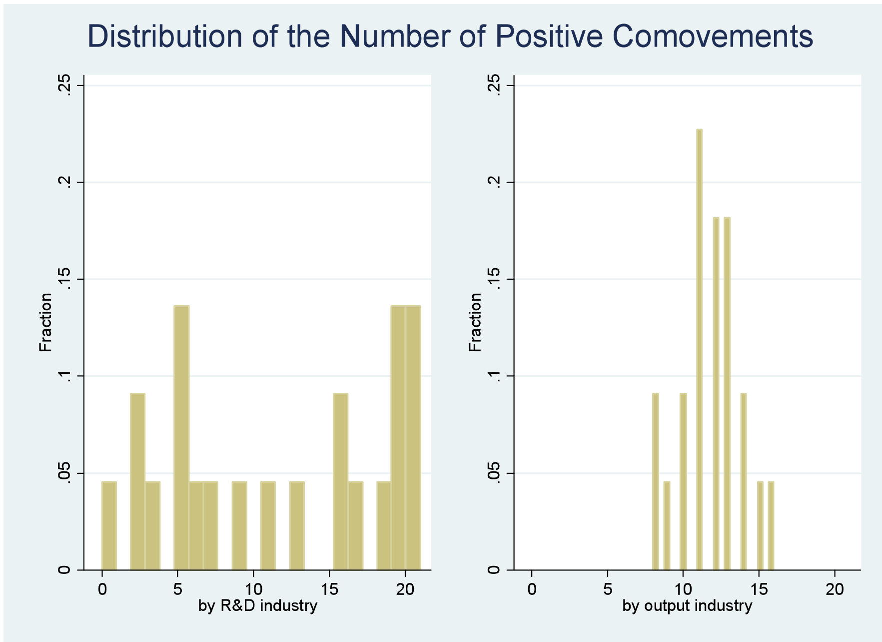
Figure 1: Source of Comovement

Panel A



Panel B

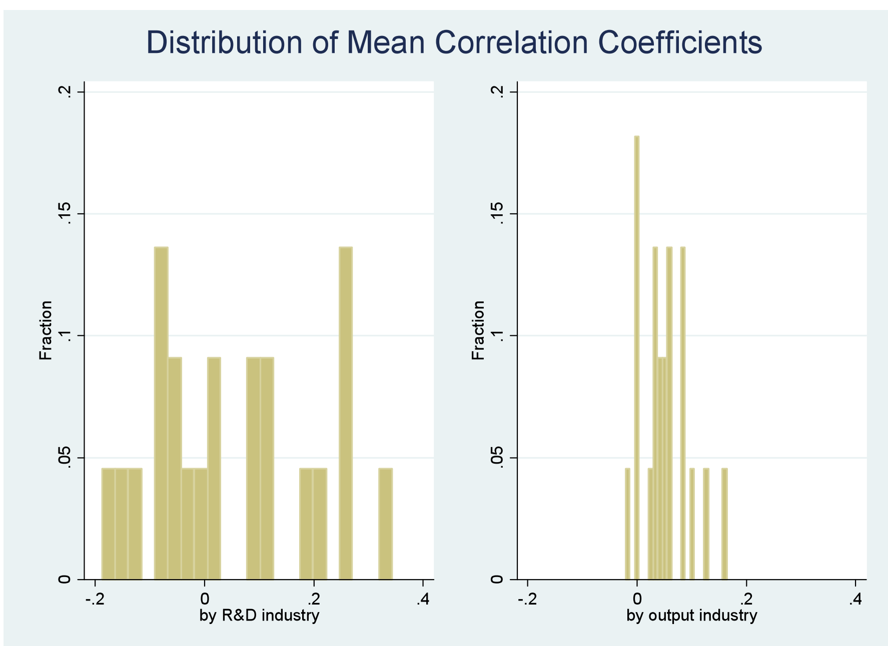
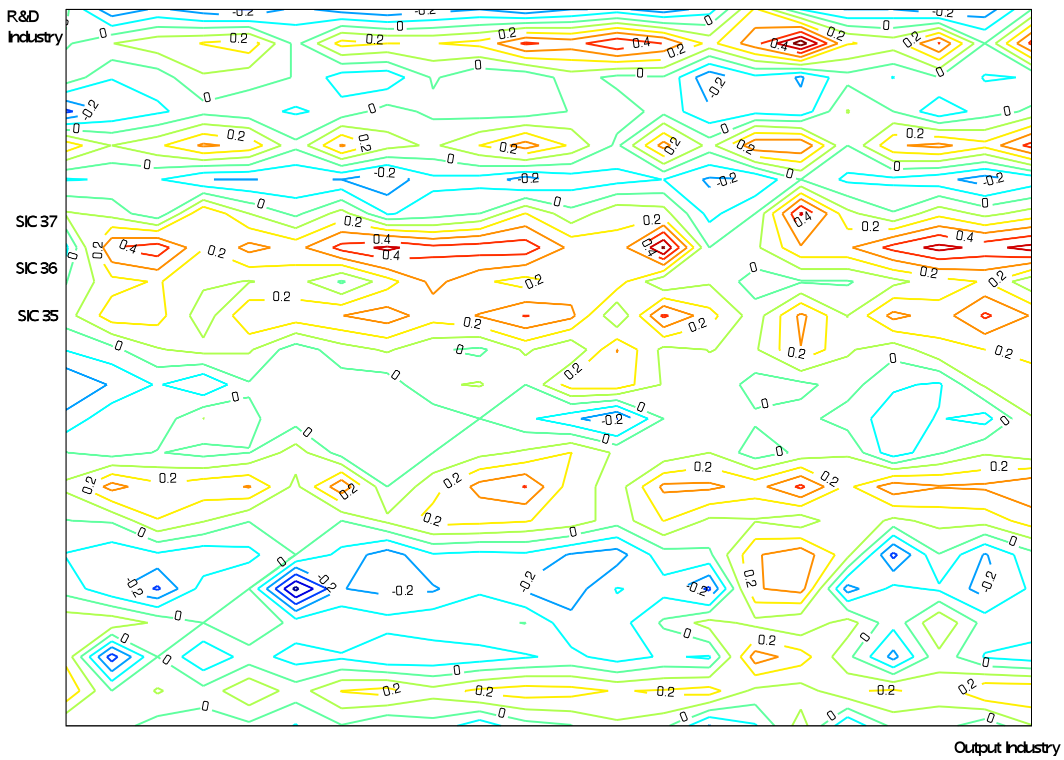


Figure 1: Source of Comovement by R&D industry and by output industry. The vertical axis in both panels denotes the fraction of industries; the horizontal axis denotes the

number of positive correlation coefficients between R&D and output in Panel A, and the mean of correlation coefficients in Panel B. The left figures plot the distributions by R&D industry; the right ones plot by output industry. Data on R&D by industry is from the NSF; data on output is from the NBER MP databases. See text for details.

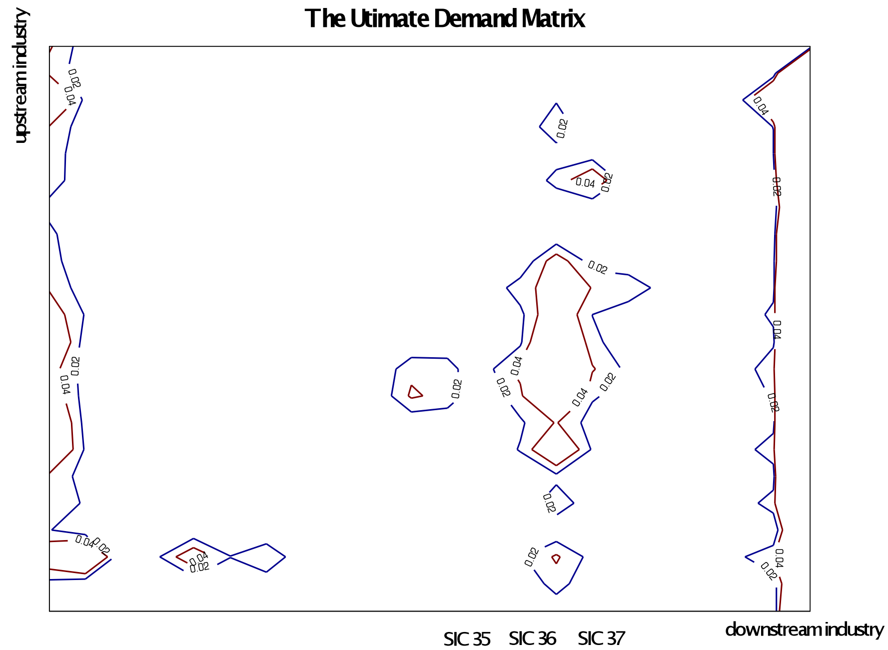
Figure 2: Correlation Coefficients between Industry R&D and Industry Output



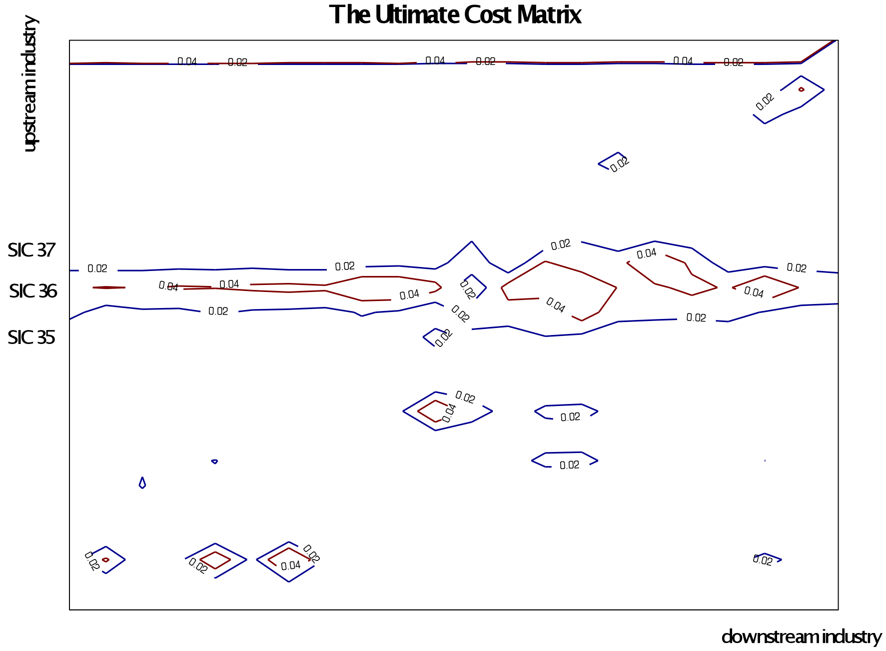
Note: Contour plots of correlation coefficients between industry R&D growth and output growth from 1958 to 1998. Each row indicates one R&D industry; and each column indicates one output industry. Data on R&D is from the NSF and data on output is from the NBER MP databases. See text for details.

Figure 3: The Matrixes of Ultimate-demand and Ultimate-cost Shares

The Utimate Demand Matrix



The Ultimate Cost Matrix



Note: the contour plots of the matrixes of the ultimate demand shares and ultimate cost shares. Each row indicates an upstream industry and each column indicates a downstream industry. The diagonals are not included. Only those above 2% and 4% are plotted. The matrixes are constructed based on the make tables, the use tables, and the capital-flow tables in 1992 published by the Bureau of Economic Analysis. See the appendix for details on the construction of the two matrixes. See text for details.

Table 1: Disaggregated Output and R&D (1958-1998)

	R-share	Y-share	Corr (R, Y)
Aggregate	100%	100%	0.3358
Non-manufacturing	7.81%	79.48%	-0.0158
Manufacturing	92.19%	20.52%	0.4078
Non-durable manufacturing	25.65%	8.07%	-0.1413
Food (SIC 20, 21)	1.98%	2.56%	0.0741
Textiles (SIC 22m23)	0.51%	1.19%	0.1255
Paper (SIC 26)	1.08%	0.80%	-0.0787
Industrial Chemicals (SIC 281-2, 286)	11.38%	0.80%	-0.1069
Drugs (SIC 283)	3.24%	0.23%	0.2243
Other chemicals (SIC 284-5, 287-9)	2.49%	0.57%	-0.1501
Petroleum (SIC 29)	6.01%	0.43%	-0.3144
Rubber (SIC 30)	1.75%	0.41%	0.2454
Durable manufacturing	66.54%	12.45%	0.2757
Lumber (SIC 24, 25)	0.31%	0.94%	0.0193
Stone (SIC 32)	1.71%	0.87%	0.3255
Furrous Metals (SIC 331-32, 3398-99)	2.00%	1.39%	0.0327
Non-ferrous metals (SIC 333-336)	1.00%	0.50%	-0.0690
Metal Prods. (SIC 34)	2.70%	1.59%	0.1050

Machinery (SIC 35)	11.26%	2.13%	0.1627
Electronics & communication Equip. (SIC 366-367)	6.50%	0.23%	0.4594
Other Equip.(SIC 361-365, 369)	9.74%	0.73%	0.0612
Autos and Others (SIC 371, 373-75, 379)	14.39%	1.26%	0.4363
Aerospace (SIC 372,376)	8.56%	1.53%	0.3736
Scientific Instrument (SIC 381,382)	1.62%	0.34%	-0.0537
Other Instrument. (SIC 384-387)	2.42%	0.19%	0.3484
Miscellaneous manufacturing	1.54%	1.85%	0.4078

Notes: R is the R&D expenditure deflated by the GDP deflator; Y is the real value added. R-share indicates the industry share in accounting for aggregate R&D; Y-share indicates that in accounting for real GDP. Corr (R, Y) refers to the within-industry correlation between real R&D growth and output growth from 1958 to 1998. Nominal R&D series are from the NSF; the manufacturing output series are compiled from the NBER MP database, measured as real value added; non-manufacturing output series are from the BEA. See text for details.

Table 2: Decomposition of Variances and Covariance
Of Aggregate R&D and Real GDP (1958-1998)

	Actual $\times 10^4$	Estimated $\times 10^4$	Within $\times 10^4$	Cross $\times 10^4$	Cross / Estimated	Average pair-wise correlation coefficients cross-industry
Panel A: Manufacturing and Non-manufacturing						
Var (Y)	4.51	5.31	3.08	2.23	42.00%	0.7317
Var (R)	11.71	12.00	12.68	-0.68	-5.67%	-0.0972
Cov (Y, R)	2.44	3.18	1.57	1.61	50.63%	0.0808
Panel B: Durable Manufacturing, Non-durable Manufacturing, and Non-Manufacturing						
Var (Y)	4.51	4.69	2.38	2.31	49.25%	0.6329
Var (R)	11.71	12.00	12.95	-0.95	-7.92%	-0.0012
Cov (Y, R)	2.44	2.86	0.25	2.61	91.25%	0.0228
Panel C: 21 Manufacturing industries and Non-manufacturing						
Var (Y)	4.51	5.47	1.94	3.52	64.35%	0.4908
Var (R)	11.71	10.45	9.03	1.42	13.56%	0.0398
Cov (Y, R)	2.44	2.82	0.16	2.66	94.37%	0.0532

Notes: R is growth in R&D expenditure deflated by the GDP deflator; Y is the real GDP growth. Var (R) is the variance in aggregate R&D growth; Var (Y) is that in real GDP growth; and Cov (Y, R) is the covariance between aggregate R&D growth and real GDP growth. The “actual” statistics are observed in the aggregate data; the “estimated” statistics are based on (2), decomposing variances and covariance into a “within-industry” component and a “cross-industry” component. Nominal R&D series are from the NSF; the manufacturing output series are compiled from the

NBER MP database, measured as real value added; non-manufacturing output series are from the BEA. See text for more details.

Table 3: Correlation Coefficients between R&D Growth and Output Growth

	Non-durable manufacturing output growth	**Durable manufacturing output growth**	**Non-manufacturing output growth**
Non-durable manufacturing R&D growth	-0.1413 (p=0.3845)	-0.1099 (p=0.4998)	-0.0908 (p=0.5775)
Durable manufacturing R&D growth	0.5068*** (p=0.0008)	0.2757* (p=0.0851)	0.4896** (p=0.0013)
Non-manufacturing R&D growth	-0.3455** (p=0.0290)	-0.3133** (p=0.0490)	-0.0912 (p=0.5757)

Notes: the correlation coefficients of real R&D growth and output growth by non-durable manufacturing industries, by durable manufacturing industries, and by non-manufacturing sectors. The P-values are in parentheses. Real R&D is measured as nominal R&D deflated by the GDP deflator. *indicates significance at the 10%, **indicates significance at the 5%, and ***indicates significance at the 1% level. Nominal R&D series are from the NSF; the manufacturing output series are compiled from the NBER MP databases, measured as real value added; non-manufacturing output series are from the BEA. See text for more details.

Table 4: Comovement

	R commoves with Y by other industries		Y commoves with R by other industries	
	$R_i - Comove$ $(\times 10^3)$	Fraction of 'cross-industry" component	$Y_i - Comove$ $(\times 10^3)$	Fraction of 'cross-industry" component
Panel A: Manufacturing and Non-manufacturing				
Non-manufacturing	-0.0315	-19.57%	0.1925	119.57%
Manufacturing	0.1925	119.57%	-0.0315	-19.57%
Panel B: Non-durable, Durable Manufacturing, and Non-manufacturing				
Non-manufacturing	-0.0161	-14.76%	0.2030	77.88%
Non-durable manufacturing	-0.0161	-6.18%	0.0793	30.41%
Durable manufacturing	0.3152	120.95%	-0.0216	-8.30%
Panel C: 21 Manufacturing Industries and Non-manufacturing				
Non-manufacturing	-0.0282	-10.59%	0.1790	67.29%
Food (SIC 20, 21)	0.0007	0.27%	-0.0007	-0.27%
Textiles (SIC 22m23)	0.0039	1.45%	0.0006	0.22%
Paper (SIC 26)	-0.0030	-1.12%	0.0049	1.85%
Industrial Chemicals (SIC 281-2, 286)	-0.0232	-8.74%	0.0051	1.92%
Drugs (SIC 283)	-0.0003	-0.12%	0.0003	0.13%
Other chemicals (SIC 284-5, 287-9)	-0.0113	-4.26%	0.0018	0.66%

Petroleum (SIC 29)	-0.0098	-3.70%	0.0003	0.12%
Rubber (SIC 30)	0.0100	3.75%	0.0013	0.49%
Lumber (SIC 24, 25)	-0.0008	-0.32%	0.0014	0.52%

Table 4 (continued): Co movement

	R commoves with Y by other industries		**Y commoves with R by other industries**	
	$R_i - Comove$ $(\times 10^3)$	**Fraction of 'cross-industry" component**	$Y_i - Comove$ $(\times 10^3)$	**Fraction of 'cross-industry" component**
Stone (SIC 32)	0.0190	7.13%	0.0015	0.57%
Furrous Metals (SIC 331-32, 3398-99)	0.0031	1.17%	0.0105	3.95%
Non-ferrous metals (SIC 333-336)	0.0002	0.08%	0.0032	1.21%
Metal Prods. (SIC 34)	0.0070	2.65%	0.0101	3.79%
Machinery (SIC 35)	0.0591	**22.21%**	0.0116	4.36%
Electronics Equip. (SIC 366-367)	0.0547	**20.56%**	0.0022	0.82%
Other Equip.(SIC 361-365, 369)	0.0356	**13.39%**	0.0050	1.87%
Autos and Others (SIC 371, 373-75, 379)	0.1168	**43.92%**	0.0001	0.04%
Aerospace (SIC 372,376)	0.0248	**9.34%**	0.0134	5.03%
Scientific Instrument (SIC 381,382)	-0.0087	-3.26%	0.0041	1.56%
Other Instrument. (SIC 384-387)	0.0112	4.23%	0.0006	0.21%
Miscellaneous manufacturing	0.0052	1.97%	0.0097	3.65%

Notes: the comovement of each industry's R&D with other industries' output or vice versa. $R_i - Comove$ reflects how industry *i*'s R&D co-moves with other industries' output, weighted by their R&D shares and output shares; $Y_i - Comove$ reflects how industry *i*'s output co-moves with other industries' R&D, weighted by their R&D shares and output shares. The fractions are those of $R_i - Comove$ or $Y_i - Comove$ in accounting for total "cross-industry" co-movement listed in Table 2. See notes to Tables 1 and 2 for data sources. See text for more details.

Table 5: Strength of Co-movement and the Input-output Linkage

$$(4)\quad corr(R_i, Y_j) = \alpha_0 + \alpha_1 UDS_{ij} + \alpha_2 UCS_{ij} + \alpha_3 UDS_{ji} + \alpha_4 UCS_{ji} + \varepsilon_{ij}$$

	UDSij	**UDSji**	**UCSij**	**UCSji**	**# of obs.**	**R^2**	**F-stat.**
Full sample	-0.1852 (0.2905)	1.9483*** (0.3321)	2.6825** (1.1530)	-0.9192 (0.8101)	462	0.1028	10.07
Capital-good R&D	-0.4866 (0.4779)	2.1431*** (0.2963)	4.7215*** (1.1735)	0.2290 (1.4901)	105	0.3683	21.82
Non-capital goods R&D	-0.3057 (0.3341)	-0.8055 (0.5056)	0.0230 (1.1100)	-1.1673 (0.7222)	357	0.0132	1.46

Notes: the OLS results of (4). *Corr (Ri, Yj)* is the time-series correlation coefficient between R&D growth by industry *i* and output growth by industry *j*. *UDSij* is the ultimate demand share of industry *j* for industry *i*, the share of *i*'s output embodied in final demand for *j*'s output; *UDSji* is that of industry *i* for industry *j*. *UCSij* is the ultimate cost share of industry *i* for industry *j*, the share of *j*'s production cost coming from *i*; *UCSji* is that of industry *j* for industry *i*. UDS and UCS are constructed using the use tables and make tables by the input-output accounts produced by the BEA. See notes to Table 1 for data sources and measurement of R&D growth and output growth. See the appendix for the construction of UDS and UCS. See text for details.

Table 6: R&D Propagation and Input-output Linkage

$$(5)\ Y_{it} = \alpha_i + \gamma_i A_t + \sigma R_{it} + \beta_1 \sum_{j \neq i} UDS_{ij} R_{jt} + \beta_2 \sum_{j \neq i} UCS_{ji} R_{jt} + \varepsilon_{it}$$

$$(7)\ Y_{it} = \nu_i + \varphi_i A_t + \sigma R_{it} + \beta_1 \sum_{j \neq i} UDS_{ij} u^k_{jt} + \beta_2 \sum_{j \neq i} UCS_{ji} u^k_{jt} + \varepsilon_{it}$$

	(5)			(7)
	Full Sample	Capital R&D	Non-capital R&D	Capital R&D Residual
Panel A: OLS				
R_{it}	0.0549* (0.0267)	0.0489* (0.0249)		0.0529*** (0.0192)
$\sum_{j \neq i} UDS_{ij} R_{jt}$	0.0308 (0.1144)	1.4612*** (0.3189)	-0.1411 (0.1735)	1.5226*** (0.4026)
$\sum_{j \neq i} UCS_{ji} R_{jt}$	-0.1722 (0.1059)	2.4630*** (0.6421)	0.0112 (0.0729)	2.6872*** (0.7734)
observations	880	880		880
R^2	0.5334	0.5651		0.5611
F-stats	19.40	24.08		23.48
Panel B: IV				
R_{it}	0.6552 (1.2673)	0.4659 (0.4454)		0.2756 (0.2343)
$\sum_{j \neq i} UDS_{ij} R_{jt}$	-0.1252 (0.9600)	3.5302* (2.0948)	-4.0378 (4.0224)	2.0383* (1.1124)
$\sum_{j \neq i} UCS_{ji} R_{jt}$	-0.0644 (0.7856)	6.7082* (3.8576)	3.3991 (3.7399)	6.6839** (2.9153)
observations	476	476		476
R^2	-	-		-
F-stats	5.86	4.07		10.50
Panel C: OLS with $\sum_{j \neq i} \lambda_j R_j$ as additional controls				
R_{it}	0.03698 (0.0191)	0.0431** (0.0189)		0.0487*** (0.0169)
$\sum_{j \neq i} UDS_{ij} R_{jt}$	-0.0089 (0.1042)	1.3564*** (0.4595)	-0.0998 (0.1039)	1.4044*** (0.4543)

$\sum_{j \neq i} UCS_{ji} R_{jt}$	-0.0814 (0.1416)	1.4536* (0.8681)	-0.0734 (0.1457)	1.4455* (0.8678)
observations	880	880		880
R^2	0.6082	0.6183		0.6174
F-stats	22.54	23.10		23.41

Note: the OLS estimation results of (5) and (7). Y_{it} and R_{it} are the output growth and R&D growth of industry *i* in year *t*. A_t is a set of aggregate shocks from Basu et al. (2006) as oil shock, government spending, and monetary shocks lagged by one year. *UDSij* is the ultimate demand share of industry *j* for industry *i*, the share of *i*'s output embodied in final demand for *j*'s output; *UCSji* is the ultimate cost share of industry *j* for industry *i*, the share of *i*'s production cost coming from *j* as intermediate goods. Column 2 presents the estimation results of (5). Columns 3 and 4 report the estimation results of (5) by allowing β_1 and β_2 to differ for capital-good R&D and non-capital-good R&D. Capital-good R&D are defined as R&D by Machinery, Electronics, and Transportation Equipments. Column 5 reports the estimation results of (7), in which μ_{jt}^k is the OLS regression residual of (6) $R_{jt}^k = \alpha_j^k + \eta_j^k A_t + \mu_{jt}^k$, where R_{jt}^k is the capital-good R&D growth. Panel A presents the OLS estimation results. Panel B presents the IV estimation results, treating the R&D terms as endogenous and employing the contemporaneous value, the two leads, and the two lags of the growth in patent examiners at the U.S. patent office, the industry growth in patent applications by foreign companies, and the industry growth in granted patents to foreign companies. Panel C presents the OLS estimation results of (5) and (7) with $\sum_{j \neq i} \lambda_j R_j$ as additional controls. Data on R&D by industry is from the NSF; data on output by industry is from the NBER MP databases; *UDS* and *UCS* are constructed based on the use table, the make table, and the capital-flow table of 1992 produced by the BEA; data on patent examiners and industry patent grants and applications by foreign corporations are from the USPTO. See text for details.

Table 7: Co-variance and Variance Decomposition

Panel A: $\hat{\mathrm{cov}} = S^{Y}\hat{\Sigma}S^{R}{}'$			
$\hat{\Sigma}$	$\hat{\mathrm{cov}}\times 10^{4}$	**Share of total comovement**	**Share of total covariance**
$\left(\hat{\beta}_1 UDS + \hat{\beta}_2 UCS\right)\mathrm{cov}\left(R^{K}\right)$	1.5402	57.90%	54.62%
$\hat{\gamma}\,\mathrm{cov}(A)\hat{\eta}'$	0.2593	9.75%	9.19%
$\left(\hat{\beta}_1 UDS + \hat{\beta}_2 UCS\right)\hat{\eta}\,\mathrm{cov}(A)\hat{\eta}'$	0.2021	7.60%	7.17%
$\left(\hat{\beta}_1 UDS + \hat{\beta}_2 UCS\right)\mathrm{cov}(\hat{u})$	1.3381	50.30%	47.45%
Panel B: $\mathrm{var}(Y) = S^{Y}\hat{\Omega}S^{Y}{}'$			
$\hat{\Omega}$	$\mathrm{var}\times 10^{4}$	**Share of total comovement**	**Share of total variance**
$\hat{\gamma}\,\mathrm{cov}(A)\hat{\gamma}'$	0.3920	11.14%	7.17%
$\left(\hat{\beta}_1 UDS + \hat{\beta}_2 UCS\right)\hat{\eta}\,\mathrm{cov}(A)\hat{\eta}'\left(\hat{\beta}_1 UDS + \hat{\beta}_2 UCS\right)'$	0.0589	1.67%	1.08%

Note: Approximated covariance, denoted as $\hat{\mathrm{cov}}$, between aggregate R&D growth and aggregate GDP growth. S^{Y} is a one-by-22 vector of industry long-run output shares; S^{R} is a one-by-five vector of long-run R&D shares of five capital-good industries. $\hat{\Omega}$ is the approximated variance-covariance matrix between capital-good R&D growth and other industries' output growth. $\hat{\beta}_1$ and $\hat{\beta}_2$ are estimates from (5) with $\sum_{j\neq i}\lambda_j R_j$ as additional controls as summarized in the last column of Panel C in Table 6; *UDS* is a 22-by-five matrix of ultimate demand shares with capital-good industries as the downstream industries; *UCS* is that of ultimate cost shares with capital-good industries as the upstream industries; $\mathrm{cov}\left(R^{K}\right)$ is the observed variance-covariance matrix of capital-good R&D growth; $\hat{\eta}$ is a five-by-three matrix as the estimated impact of *A* on capital-good R&D based on (6) $R^{k}_{jt} = \alpha_j + \eta_j A_t + \mu_{jt}$; $\hat{\gamma}$ is a 22-by-three matrix as the estimated impact of *A* on industry output growth based on (5) after controlling for $\sum_{j\neq i}\lambda_j R_j$; *cov(A)* is the observed variance-covariance matrix of three aggregate shocks: oil shock, government spending, and monetary shock; $\hat{u}$ is the estimation residuals from (6). Panel A approximates the covariance between real GDP growth and aggregate R&D growth. Panel B approximates the variance of real GDP growth. See text for details.

Data Appendix: The Construction of the Ultimate Demand Shares and the Ultimate Cost Shares

This appendix describes the construction of the ultimate demand shares and the ultimate cost shares. The base technique follows Shea (1991). Lawson (1997) provides details on the Bureau of Economic Analysis (BEA)'s 1992 input-output tables. Bonds and Aylor (1998) discuss the associated 1992 capital flow tables.

Input-Output and Capital Flow Tables

The BEA's input-output tables detail the production and consumption of goods in the U.S. economy, using data from the Census Bureau. The tables are published every five years. To construct the demand and cost matrices, we use the 1992 version of three of the BEA's tables: the make table, the use table, and the capital flow table.

The make table details the production of goods by industries. Each row of the make table shows the production of goods for a particular industry, while each column shows the distribution of production of a commodity over industries. This setup gives the make table an industry-by-commodity format, with row i, column j denoting the production of commodity j by industry i.

The use table explains the consumption of commodities by industries, by government, and by other non-producing entities. Each row of the use table gives the distribution of consumption for a particular commodity by various industries, while each column gives the consumption of various commodities by a particular industry. Therefore, row i, column j is the consumption of commodity i by industry j, giving the use table a commodity-by-industry format.

The BEA assigns each commodity to a BEA input-output commodity category, which is based on the Standard Industrial Classification (SIC) system. From there, the BEA assigns each firm to a BEA input-output industry category based on the type of commodity which composes the majority of its production. For example, a firm primarily engaged in the production of Guided Missiles and Space Vehicles, BEA commodity 130101, would be assigned to the industry Guided Missiles and Space Vehicles, BEA industry 130101. However, the firm could still be engaged in the production of other types of commodities. The industry designation indicates which commodity is the majority of the firm's output. The BEA classifies a few miscellaneous industries and commodities as final use or non-producing. In this case, no mapping to an SIC code exists.

Our first step in constructing the ultimate demand shares and ultimate cost shares for our panel of R&D expenditures and output is converting the use table and make table into a format compatible with the NSF R&D data. For the use table, we convert the commodities and industries from the BEA's classification system to the 1987 SIC system and match the aggregation level to the NSF's R&D data. For most manufacturing industries, the BEA industry classifications map into exactly one NSF R&D category. However, BEA industry 110602 is associated with two NSF R&D classifications: Non-manufacturing (various SIC codes greater than or equal to 40) and Petroleum Refining (SIC codes 13 and 29). In this case, we split the output from BEA industry 110602 evenly between Non-manufacturing and Petroleum Refining. For the BEA industries and commodities with no corresponding SIC code, we leave the industries and commodities in the BEA format. This procedure yields a 32-commodity-by-72-industry use table with row *i*, column *j* as the amount of commodity *i* consumed by industry *j*. We refer to this transformed use table as $\boldsymbol{USE^{CI}}$, with superscript CI denoting the commodity-by-industry format.

After this conversion procedure, we follow Shea (1991) by removing certain non-producing industries and miscellaneous commodities from the use table. These are BEA commodities and industries 710100, 800000, 810001, 810002, 820000, 830001, 840000, 850000, 880000, 890000, 900000, 920000, 930000, 940000, and 950000. The removal of these commodities and industries leaves a 22-commodity-by-58-industry use table, with the rightmost 36 columns being the set of non-producing entities (e.g., government).

Transformation of the make table is the same as the use table with two exceptions. First, some of the removed non-producing industries in the use table do not exist in the make table. Therefore, removal of these industries only applies to the use table. Second, we divide each column *j* of the make table by the column sum of column *j*. This procedure gives the make table a format where row *i*, column *j* is the proportion of commodity *j* produced by industry *i*. The columns each sum to one. This format contrasts with the use table where the entries are in levels instead of proportions. Again, we convert the BEA commodity and industry classifications into 1987 SIC categories conformable with the NSF R&D data. We refer to the transformed make table as $MAKE^{IC}$ with the IC superscript denoting the industry-by-commodity format. $MAKE^{IC}$ is 22-industries-by-22-commodities.

We use $MAKE^{IC}$ and USE^{CI} to create a 22-industry-by-58-industry use table, USE^{II}, following equation (A1).

$$\text{(A1) } USE^{II} = MAKE^{IC} \times USE^{CI}$$

Row *i*, column *j* of USE^{II} represents the estimated value of industry *i*'s non-capital products directly purchased as intermediate inputs by industry *j*. The II superscript refers to the industry-by-industry format.

Construction of USE^{II} uses the BEA's industry shares assumption. For example, suppose 80% of the produced value of cell phones come from the cell phone industry and the remaining 20% is produced by the computer industry. If the insurance industry buys 100 dollars worth of cell phones, then the BEA industry shares assumption assigns 80 dollars of this purchase to the cell phone industry and 20 dollars to the computer industry. USE^{II} is the basis for calculating both the ultimate demand shares and the ultimate cost shares. We first detail the construction of the ultimate demand shares followed by the ultimate cost shares.

To add detail about the flow of capital goods to USE^{II}, we turn to the BEA's capital flow table. The BEA publishes a capital flow table which captures the purchase of capital goods (structures and equipment) by industries. Row *i*, column *j* of the capital flow table represents the quantity of the capital good commodity *i* purchased by industry *j*.

The capital flow table uses a SIC based classification scheme different from the make and use tables. In particular, the BEA publishes its capital flow table at a SIC level higher than the make and use tables because the BEA considers its estimates of capital goods consumption to be too unreliable at lower SIC levels. The published capital flow table is 163-commodities-by-64-industries.

The capital flow SIC based classifications cannot be mapped precisely to the NSF's R&D categories. For example, the capital flow table aggregates all of the consumption of capital goods for Chemicals (SIC 28) to the two digit SIC level. However, the NSF R&D series for Chemicals is available at the three digit SIC level with three subcategories: Industrial Chemicals (SIC 281-282 and 286), Drugs and Medicines (SIC 283), and Other Chemicals (SIC 284-285 and 287-289). We assume the consumption of capital goods within an aggregated industry is proportional to the distribution of other value added across the NSF's disaggregated industries to make the capital flow table conformable with the make and use tables in order to maximize the available degrees of freedom from the NSF R&D panel. Other value added is available at a disaggregated level from the use table. Following Shea (1991), we remove the Real Estate industry from the capital flow table.

Following this procedure, we distribute the capital flow table data over the disaggregated NSF R&D categories. The result is a 22-commodity-by-22-industry capital flow table. As a final step, because the capital flow table only records the consumption of capital goods by producing industries (i.e., it excludes government and other non-producing entities), we append a 22-by-36 matrix of zeros to the right side of the capital flow table to give the capital flow table the same dimensions as USE^{CI} for a final size of 22-commodities-by-58-industries. We call this transformed capital flow table $CFLOW^{CI}$.

We construct the 22-industry-by-58-industry capital flow matrix, $CFLOW^{II}$, by equation (A2).

$$\text{(A2) } CFLOW^{II} = MAKE^{IC} \times CFLOW^{CI}$$

$CFLOW^{II}$ is analogous to USE^{II}, showing the estimated inter-industry flow of capital goods. Row *i*, column *j* of $CFLOW^{II}$ is the estimated amount of capital goods (equipment and structures) produced by industry *i* and purchased by industry *j*. By comparison USE^{II} shows the estimated inter-industry flow of non-capital intermediate goods between industries.

We denote the estimated total inter-industry flow of goods, including intermediate inputs and capital goods, as $FLOW^{II}$. We construct the 22-industry-by-58-industry $FLOW^{II}$ according to equation (A3).

$$\text{(A3) } FLOW^{II} = USE^{II} + CFLOW^{II}$$

Demand and Cost Shares

Our measure of the matrix of direct demand shares between industries, denoted as DDS^{II}, whose $(i,j)^{th}$ element equals the proportion of goods produced by industry i directly purchased by industry j, including both intermediate goods and capital goods, follows equation (A4).

$$\text{(A4) } DDS^{II} = FLOWROWSUM^{-1} \times FLOW^{II}$$

DDS^{II} is a 22-industry-by-58-industry matrix. $FLOWROWSUM$ is a 22-by-22 diagonal matrix whose i^{th} diagonal element equals the sum of row i of $FLOW^{II}$.

Inter-industry linkages also arise from indirect (as opposed to direct) purchases of goods. For example, the automobile manufacturing industry directly purchases tires from the tire industry. The direct demand shares of equation (A4) captures this direct inter-industry relationship. In addition, because tires are constructed with rubber, the automobile is indirectly linked to the rubber industry through the purchase of tires. The purchase of tires from the tire industry by the automobile industry reflects both the direct purchase of tires and the indirect purchase of rubber.

Following this intuition, we define the 22-industry-by-22-industry matrix of ultimate demand shares, called UDS^{II}, to incorporate both direct and indirect inter-industry linkages. To construct UDS^{II}, we proceed in two steps following Shea (1991). First we create a matrix of direct demand shares between industries, called $DDS2^{II}$, which excludes an industry's own demand by equation (A5).

$$\text{(A5) } DDS2^{II} = FLOWROWSUM2^{-1} \times (FLOW^{II} - DIAGFLOW^{II})$$

$DDS2^{II}$ is a 22-industry-by-58-industry matrix. $DIAGFLOW^{II}$ is a 22-by-58 matrix formed by appending a 22-by-36 matrix of zeros to the right side of a 22-by-22 diagonal matrix whose i^{th} diagonal element equals the i^{th} diagonal element of $FLOW^{II}$. $FLOWROWSUM2$ is a 22-by-22 diagonal matrix whose i^{th} diagonal element equals the sum of row i of $(FLOW^{II} - DIAGFLOW^{II})$. Therefore, the $(i,j)^{th}$ element of $DDS2^{II}$ is the proportion of inter-industry direct demand for industry i by industry j when $i \neq j$. Each row of $DDS2^{II}$ sums to one.

Second, we define a 22-industry-by-22-industry matrix of ultimate demand shares, UDS^{II}, by the recursive relationship in equation (A6).

$$\text{(A6) } UDS^{II} \equiv DIAGFINAL^{II} + DDS22^{II} \times UDS^{II}$$

$DDS22^{II}$ is a 22-industry-by-22-industry matrix composed of the producing industries (i.e., excluding government and other non-producing entities) of $DDS2^{II}$, and $DIAGFINAL^{II}$ is a 22-industry-by-22-industry diagonal matrix whose i^{th} element equals the sum of the inter-industry direct demand shares for industry *i* coming from non-producing entities and other final demand sources. Following the definition of equation (A6), we calculate UDS^{II} according to equation (A7), where *I* is a 22-by-22 identity matrix.

$$\text{(A7) } UDS^{II} = (I \quad - DDS22^{II})^{-1} \times DIAGFINAL^{II}$$

As noted by Shea (1991), construction of the cost shares is more complicated. The inter-industry cost linkages require the estimation of implicit rental costs of capital which, in general, is unequal to the purchase price of capital. To estimate the inter-industry cost linkages, we convert the industry-by-industry capital flow matrix, $CFLOW^{II}$, into a matrix of implicit rental costs. This estimation involves the following steps:

We re-create the capital flow matrix, $CFLOW^{II}$, at a more disaggregated level. We call this new 125-industry-by-64-industry capital flow matrix $CFLOW2^{II}$. We create $CFLOW2^{II}$ by reclassifying the commodities of the make table and the capital flow table using a more disaggregated SIC level.

Unfortunately, because the make table and the capital flow table use different classification systems for their commodities, reclassifying the output contained in both the make table and the capital flow table into a common SIC based commodity classification is difficult. In some cases, the commodities from the capital flow table correspond to multiple commodities in the make table. For example, the capital flow commodity 1510 (Residential Construction) is based on SIC codes 15, 17, and 6552. Another capital flow commodity, 1523 (New Warehouses Construction), is also based on SIC 15 and 17. The output for SIC codes 15, 17, and 6552 in make table is split over several make table industries: 110101, 110102, 110105, 110108, 110501, 110800, 110900, 120101, and 120300. Therefore, in this case because the common level of aggregation between the capital flow table and the make table is a combined commodity containing SIC codes 15, 17, and 6552, for the capital flow table we aggregate capital flow commodities 1510 and 1523 into a single commodity; for the make table we aggregate commodities 110101, 110102, 110105, 110108, 110501, 110800, 110900, 120101, and 120300 into a single commodity thereby establishing a common level of SIC aggregation between the capital flow table and the make table.

In general, we adjust the aggregation level of commodities in the capital flow table such that if multiple commodities in the capital flow table correspond to a single set of aggregated SIC industries or a single make table commodity, we aggregate the commodities of the capital flow table up to the set of aggregated SIC industries or the single make table commodity. Table A1 displays the result of this mapping procedure for commodities we apply it to.

For example, Table A1 shows the capital flow table has data for SIC codes 3491 (Industrial Valves), 3494 (Valves and Pipe Fittings, Not Elsewhere Classified), and 3498 (Fabricated Pipe and Pipe Fittings) as separate commodities. After our aggregation procedure these three commodities are combined into a single commodity.

Our aggregation procedure yields a 124-commodity-by-63-industry capital flow matrix $CFLOW2^{CI}$ after removal of the Real Estate industry. We append a row of zeros and a column of zeros to $CFLOW2^{CI}$, giving a final size of 125-commodities-by-64-industries, with the final column and final row as zeros. Again, we append the column of zeros because the capital flow table omits the capital purchases of government and other non-producing entities. We append the row of zeros because only a subset of industries produce capital goods.

Similarly, we adjust the make table to be 125-industries-by-125-commodities, as opposed to the 22-industry-by-22-commodity $MAKE^{IC}$. We call this new make table $MAKE2^{IC}$. The rules for reclassification are as follows: first, if a particular commodity in $MAKE2^{IC}$ corresponds to exactly one reclassified commodity in $CFLOW2^{CI}$, then it is assigned to that reclassified commodity of $CFLOW2^{CI}$: the majority of commodities in the make table fall into this category. For the remainder of the make table commodities, where a single make table commodity maps to multiple reclassified commodities, we split the output of the make table commodity over the reclassified commodities proportional to the categories the make table commodity corresponds to in the original capital flow table. We document these cases in Table A2. For commodities present in the make table and not present in the capital flow table, we classify them into an Other commodity.

For example, when reclassifying the output of make table commodity 420800, we assign 75% of the output to commodity 3491, 3494, and 3498 and the remaining 25% to the Other commodity.

We construct the 125-industry-by-64-industry capital flow matrix, $CFLOW2^{II}$, according to equation (A8).

$$\text{(A8)}\ CFLOW2^{II} = MAKE2^{IC} \times CFLOW2^{CI}$$

We then convert $CFLOW2^{II}$ into an industry-by-industry capital stock matrix, $CSTOCK^{II}$, following Abel and Blanchard (1986). We denote the depreciation rate of capital produced by industry *i* and used industry *j* as δ_{ij}, and the growth rate of capital goods produced by industry *i* and consumed by industry *j* as g_{ij}. Let a third subscript *t* denote time. For example, $CFLOW2^{II}_{ij,t}$ is the estimated capital goods flow from industry *i* to industry *j* at time *t*. We can then construct the 125-industry-by-64-industry matrix $CSTOCK^{II}$ following equations (A9) and (A10).

$$\text{(A9)}\ CFLOW2^{II}_{ij,t} = CSTOCK^{II}_{ij,t} - \left(1 - \delta_{ij}\right) \times CSTOCK^{II}_{ij,t-1}$$

$$\text{(A10)}\ CSTOCK^{II}_{ij,t} = \left(1 + g_{ij}\right) \times CSTOCK^{II}_{ij,t-1}$$

Equations (A9) and (A10) together imply equation (A11).

$$\text{(A11)}\ CSTOCK^{II}_{ij,t} = CFLOW2^{II}_{ij,t} \times \frac{(1+g_{ij})}{(g_{ij}+\delta_{ij})}$$

Data on the growth rate of capital for 78 selected industries comes from the BEA's National Income and Product Accounts (BEA 2010a). We calculate the real growth rate of capital as the growth rate between the end of year estimates of capital stock in 1991 and end of year estimates of capital stock in 1992. The growth rates are available separately for structures and equipment. We assign each row industry *i* of $CFLOW2^{II}$ to either structures or equipment. Next, we assign each column industry *j* to one of the 78 industries for which capital growth data is available. Therefore, the growth rate of capital of industry *i* used by industry *j*, g_{ij}, is the growth rate of capital for industry *j* for either structures or equipment, whichever type of capital industry *i* belongs to.

Estimates of capital depreciation come from the BEA's depreciation estimates (BEA 2010b). The BEA estimates depreciation rates for various types of assets. We assign each row industry *i* to one of the asset types and assume depreciation of the capital of industry *i* is independent of the using industry.

We then convert the capital stock matrix $CSTOCK^{II}$ into a matrix of implicit rental costs, $CCOST^{II}$, with the rental costs formulas provided by Hall and Jorgenson (1967). We use the tax rules for 1992. We define *u* as the marginal tax rate on corporate income, *r* as the opportunity cost of borrowing, and z_i as the present discounted value of capital consumption per dollar of invested assets for industry *i*. The rental cost of capital produced by industry *i* and used by industry *j* follows equation (A12).

$$\text{(A12)}\ CCOST^{II}_{ij} = (r + \delta_i) \times \frac{1-u\times z_i}{1-u} \times CSTOCK^{II}_{ij}$$

The matrix $CCOST^{II}$ is 125-industries-by-64-industries. Following Shea (1991), we use the top marginal tax rate of u = 0.34. We proxy the opportunity cost of borrowing by the interest rate on 10 year U.S. treasuries, as in Nadiri and Mamuneas (1994), which sets r = 0.0701. Unlike Shea (1991) and Hall and Jorgenson (1967), we ignore the investment tax credit and potential carryovers because in 1992, the only investment tax credits available were for specific assets the consumption of which we are unable to distinguish in the make table or the capital flow table. These credits were the rehabilitation credit, the energy credit, and the reforestation credit. The rehabilitation credit applies to the rehabilitation and reconstruction of certain old or historic structures. The energy credit is for generation of alternative energy. The reforestation credit is for reforestation expenses.

Calculating the present discounted value of capital consumption for each asset, z_i, depends on the tax rules. The 1992 tax rules stipulate different depreciation methods for an asset as a function of an asset's estimated service life. If an asset had an estimated service life of 3-10 years, 200% declining balance depreciation was used, switching to straight line depreciation when the value of straight line depreciation exceeded the 200% declining balance method. For assets with an estimated service life of 11-20 years, 150% declining balance depreciation was used, switching to straight line depreciation when the value of straight line depreciation exceeded the 150% declining balance method. For assets with an estimated service life of over 20 years, straight line depreciation was the only allowable method.

We obtain data on the estimated service life for capital goods for various assets from the BEA's Depreciation Estimates (BEA 2010b). Using the estimated service life for each capital good, we calculate the discounted present value of each asset according to the appropriate tax rules. We discount the tax deduction with a discrete formula once a year with a discount rate r = 0.0701.

With the estimated matrix of rental costs of capital, $CCOST^{II}$, we can compute the cost shares. Let $USE22^{II}$ be a 22-by-22 matrix composed of the producing industries of USE^{II}. Let $CCOST22^{II}$ be a 22-by-22 matrix created by recategorizing $CCOST^{II}$ to match the classification of $USE22^{II}$. We create the estimated 22-industry-by-22-industry cost flow matrix, $FLOWCOST^{II}$, using equation (A13).

$$\text{(A13)}\ FLOWCOST^{II} = CCOST22^{II} + USE22^{II}$$

$FLOWCOST^{II}$ is an estimated inter-industry flow matrix. $FLOWCOST^{II}$ is the same as $FLOW^{II}$ except it uses the estimated rental cost of capital instead of the capital flow matrix.

We compute the 22-industry-by-22-industry matrix of direct cost shares, DCS^{II}, by equation (A14).

$$\text{(A14) } DCS^{II} = FLOWCOST^{II} \times TOTCOST^{-1}$$

$TOTCOST$ is a 22-by-22 diagonal matrix whose i^{th} element is the i^{th} column sum of $FLOWCOST^{II}$ plus noncomparable imports and compensation of employees bought by industry i. Noncomparable imports and compensation of employees come from the use table. The columns of the direct cost matrix sum to between zero and one, unlike the demand matrices. Row *i*, column *j* of DCS^{II} represents the estimated share of industry *j*'s total cost coming from industry *i*.

The construction of the 22-industry-by-22-industry matrix of ultimate cost shares, UCS^{II}, follows a similar logic to the construction of the matrix of ultimate demand shares. The $(i,j)^{\text{th}}$ element of UCS^{II} is the fraction of industry *j*'s costs ultimately from labor or noncomparable imports of industry *i*. For example, suppose the cost to build semiconductors is 60% from labor and 40% from primary metals, and primary metals are constructed only from labor. Then semiconductors would have a UCS of 60% for itself, and 40% for primary metals while primary metals would have a UCS of 100% for itself. Now further suppose the cost of cell phones comes 30% from labor and 70% from semiconductors. Then cell phones would have a UCS of 30% for itself, 42% from semiconductors, and 28% from primary metals.

We create the 22-industry-by-22-industry matrix of direct cost shares excluding demand originating from demanding an industry's own goods, denoted $DCS2^{II}$, following equation (A15).

$$\text{(A15) } DCS2^{II} = (FLOWCOST^{II} - DIAGFLOWCOST^{II}) \times TOTCOST2^{-1}$$

$DIAGFLOWCOST^{II}$ is a 22-by-22 diagonal matrix with the diagonal equal to the main diagonal of $FLOWCOST^{II}$. $TOTCOST2$ is a 22-by-22 diagonal matrix whose i^{th} element equals the i^{th} column sum of $(FLOWCOST^{II} - DIAGFLOWCOST^{II})$ plus noncomparable imports and compensation of employees by industry *i*.

Let $DIAGSHARE^{II}$ be a 22-by-22 diagonal matrix whose i^{th} element equals the share of industry *i*'s costs from noncomparable imports and compensation of employees. We compute the 22-industry-by-22-industry matrix UCS^{II} with equation (A16).

$$(A16)\ UCS^{II} = DIAGSHARE^{II} \times (I - DCS2^{II})^{-1}$$

Table A1: Capital Flow Commodities	
New Commodity (Aggregated SIC Classification)	Old Commodities Defined by the Original Capital Flow Table (Disaggregated SIC Classifications)
15, 17, and 6552	1510, 1523, 1524, 1525, 1526, 1527, 1528, 1529, 1532, 1533, 1534, 1535, 1536, 1543, 1544, 1545, 1552, 1572, 1573, 1574, 1612, 1621, 1624, 1625, 1628, 1631, 1706, 1772
3491, 3494, and 3498	3491, 3494, 3498
3561 and 3563	3561, 3563
3572, 3575, and 3577	3572, 3575, 3577
3645, 3646, and 3648	3645, 3646, 3648
3663 and 3669	3663, 3669
3823, 3824, and 3829	3823, 3824, 3829
3826 and 3827	3826, 3827
4810 and 4822	4810, 4822

Table A2: Make Table Commodity Splits		
Make Table Commodity (Old Classification)	Split Fraction	New Commodity (SIC Classification)
060200	0.5	1094
	0.5	Other
110602	0.5	1381, 1382, and 1383
	0.5	Other
270100	0.5	2819
	0.5	Other
320400	0.5	3086
	0.5	Other

420800	0.75	3491, 3494, and 3498
	0.25	Other
470300	0.5	3544
	0.5	Other
500200	0.5	3594
	0.5	Other
550200	0.75	3645, 3646, and 3648
	0.25	Other
550300	0.5	3643
	0.5	Other
600200	0.5	3724
	0.5	Other
650100	0.5	40, 42, 44, and 45
	0.5	Other
660100	0.33	481 and 4822
	0.67	Other