The Changing Nature of Sectoral Comovement*

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February 12, 2018

Preliminary and Incomplete

Abstract

The correlation of output and employment across sectors in the economy – comovement – is the defining feature of the business cycle. In this paper, we study how industry comovement patterns in US business cycles have changed over time. We first show that the correlation of output across sectors has fallen since the 1980s, but the correlation of employment across sectors has not. We then build a model featuring input-output linkages in production in both final goods and investment goods which is consistent with these facts. Finally, we use the model to explore the link between changes in comovement patterns across sectors and changes in aggregate dynamics. We find a significant role for comovement in both the decline of GDP volatility and the rise in the volatility of employment relative to output since the 1980s.

Keywords: Business Cycle Fluctuations, Employment, Industry Comovement, Input-Output Linkages, Investment Linkages, Great Moderation
JEL codes: E32, E24, E22, C67

*We are grateful for comments received from participants in seminars at the Fall 2016 Utah Macro Workshop, the 2016 Southern Economic Association Meetings, the 2017 North American Summer Meetings of the Econometric Society, and the 2017 International Conference in Computing in Economics and Finance. This paper was previously presented under the title "Industry Comovement, Sectoral Linkages, and the Great Moderation." A small fraction of the material in this paper was previously published in the 3rd chapter of vom Lehn's dissertation completed at Princeton University.

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1 Introduction

The comovement of output and employment across sectors in the economy is a key feature of the business cycle; in fact, the NBER defines a recession as a "period of decline in total output, income, employment, and trade... *marked by widespread contraction in many sectors of the economy*" (emphasis added). While a simple explanation for this comovement would be that business cycles are driven by common aggregate shocks, a long line of work in macroeconomics finds that a single aggregate shock in simple frictionless models is not enough to generate realistic patterns of comovement, especially in employment.[1] Hence, the positive comovement of output and employment across sectors is an important source of discipline on relevant frictions and propagation channels in quantitative business cycle models. Our goal in this paper is to confront these models with the changing nature of US business cycles since the 1980s.

We make three main contributions in this paper. First, we show empirically that the comovement patterns of output and employment have diverged since the 1980s: the correlation of output across sectors has fallen while that of employment has remained stable. Second, we build a multi-sector model with input-output networks which can explain these facts. Quantitatively modeling the input-output network of investment goods is central to this result; without it, employment comovement would counterfactually fall along with output. Finally, we use the model to assess how these changing comovement patterns across sectors are linked to changes in the behavior of aggregate output and employment in the time series. The calibrated model is consistent with the decline in aggregate output volatility and implies that most of the decline is due to productivity shocks becoming less correlated across sectors. However, the model overpredicts the decline in the volatility of aggregate employment, despite matching the correlation of employment across sectors. The model's failure is limited to overpredicting a decline in employment volatility within a few particular sectors, absent which the model would account for the change in employment volatility.

While it is well-known that the correlation of output across sectors has fallen since the Great Moderation, our finding that the correlation of employment has not fallen is new. We compute these correlations across a partition of eighteen private non-farm business sectors from 1948-2015. The average pairwise correlation of output falls from roughly 0.4 prior to 1984 to nearly 0.2 afterwards; in contrast, the correlation of employment is nearly 0.6 in both periods.

To speak to these data, we develop a multi-sector real business cycle model with input-output networks in both final- and investment-good production. Building on Foerster et al. (2011), sectors

[1]Much of this literature has focused on the standard RBC model. See Lucas (1977) for the most famous example of arguing that aggregate shocks can generate sectoral comovement. However, work by Benhabib et al. (1991), Christiano and Fitzgerald (1998), Huffman and Wynne (1999), and others, has shown that a simple aggregate shock in a two sector model with consumption and investment sectors implies a strong reallocation motive across sectors in response to a productivity shock, generating negative comovement across sectoral inputs.

in our model produce goods that can be used for consumption or as intermediate inputs in the production of other sectors. Each of these sectors is subject to a productivity shock. These sectors' shocks propagate to other sectors in the economy through the input-output networks, generating endogeneous comovement in the model. We calibrate the input-output networks using input-output and capital flows data from the BEA's Industry database.

Quantitatively, the calibrated model matches both the fall in output comovement and the stability of employment comovement post-1980s that we computed in the data. We simulate the change in business cycles across periods by feeding in two processes for sector-level TFP: a process calibrated using 1951-1983 data and another using 1984-2012 data. TFP is less correlated in the 1984-2012 period, generating the decline in output correlations. However, employment correlations are stable because they are determined mainly by the input-output network, not the structure of TFP shocks. We also show that the model is able to account for roughly half the cross-sectional variation in pairwise changes in the difference between employment and output comovements.

The input-output network in investment good production is critical to generating stable employment comovement; without these investment linkages, employment comovement would counterfactually fall by as much as output comovement. At the other extreme, employment can be perfectly correlated across sectors for any sectoral TFP process if the investment good production network is identical across sectors. We show that the empirical investment network closely resembles this second benchmark, generating the relative stability of employment comovement as TFP shocks become less correlated. In addition, under our estimated investment linkages, investment comovement is also stable post-1980s, consistent with prelminary empirical results.[2]

Our model suggests that these changes in comovement patterns are tightly linked to the behavior of aggregate output and employment since the 1980s. First, the calibration of the TFP process shows that the decline in aggregate output volatility is largely driven by sectoral TFP shocks becoming less correlated across sectors.[3] We show that both in model and data decompositions, approximately 60% of the decline in GDP volatility is occurring because of changes in comovement. Second, while the model is consistent with the stability in the correlation of employment across sectors, it nevertheless predicts a counterfactually large decline in the volatility of aggregate employment. We show that this is driven by a counterfactually large decline in the volatility of employment within a few sectors of the economy and suggests further work should focus on understanding the changes occurring within these sectors.

[2]Existing multi-sector models with investment linkages use sectoral partitions of the economy that imply linearized model dynamics do not exist. Our eighten-sector partition of the economy is not subject to this limitation, and we show that this is important for generating stable behavior in investment comovement.

[3]We calibrate the change in the TFP process to match the change in output comovement following the 1980s, implying the model closely matches the decline in aggregate output volatility by construction.

Related Literature Our work relates to several large literatures studying business cycle fluctuations. The first is obviously the lengthy literature on sectoral comovement, including work by Benhabib et al. (1991), Boldrin et al. (2001), Veldkamp and Wolfers (2007) and more recently, Jaimovich and Rebelo (2009), Yedid-Levi (2012), and Dvorkin (2014).[4] In this sizable literature, we are also not the first paper to study the role of sectoral networks in generating comovement patterns. Hornstein and Praschnik (1997) study a two sector model with a single intermediate production good and argue that the presence of this intermediate input channel can account for the comovement of employment and output between investment and consumption producing sectors. Relative to their work, we study a model with 18 sectors and include investment networks, which are essential for understanding the changes in comovement patterns. We further find that these investment linkages improve the model's performance in generating investment comovement, which the model of Hornstein and Praschnik is unable to reconcile.

Kim and Kim (2006) and Dvorkin (2014) also study the role of sectoral networks in generating comovement. In studying the relative importance of sectoral and aggregate shocks over the business cycle, Dvorkin (2014) compares the relative importance of input-output linkages in generating sectoral comovement to reallocation frictions and finds the former to be more important. However, he abstracts from capital, and thus investment linkages are not included in the analysis. Kim and Kim (2006) do include investment linkages, however, they do not discuss the role these play in their analysis and primarily focus on the importance of the specification of labor disutility for comovement patterns. Their findings for the importance of sectoral linkages are mixed, and they also find that the model struggles to generate adequate comovement in sectoral investment. While they find that a divisible labor specification requires significant frictions in labor adjustment to be consistent with employment comovement, we show that the lack of change in employment comovement is not sensitive to the parametrization of the Frisch elasticity for a reasonable range of parameters.

Our paper also relates to the expanding literature studying the role of sectoral networks in generating business cycle fluctuations.[5] More recently, this literature has been revived in work revisiting the question of how much idiosyncratic shocks can propagate through sectoral networks to generate aggregate fluctuations. Most of this work focuses on fluctuations in output and aggregate volatility; examples include Carvalho (2008), Foerster et al. (2011), Acemoglu et al. (2012), Carvalho and Gabaix (2013), Atalay (2014), and Acemoglu et al. (2015). Of these papers, we have the most in common with Foerster et al. (2011), who find that the importance of aggregate shocks relative to sectoral shocks has declined post-1984, which can account for the decline in aggregate volatility in the post-1980s period. Relative to their work, our focus is on comovement, not vola-

[4]For additional references in this literature, see the papers listed in Footnote 1.

[5]Early work in this literature includes Long Jr and Plosser (1983), Dupor (1999), Horvath (2000), and Shea (2002).

tility, and on inputs, not outputs, and we model the entire economy, instead of just the industrial production sector. However, we do confirm their findings that comovement changes are of first order importance for understanding the decline in GDP volatiltiy.

Finally, our paper also relates to the literature on the changing nature of business cycles since the 1980s, particularly changes observed in labor markets. The most comonly identified change in business cycle patterns has been the "Great Moderation" in GDP volatility.[6] A common finding in this literature has been that this decline in GDP volatility has been driven by a decline in comovement across sectors - see Stiroh (2009) and Foerster et al. (2011).[7] We confirm this finding in our data and model results.

More recent work has focused on changes in labor market, particularly the falling correlation between output and productivity and the increase in employment volatility relative to output.[8] Our study of these changes focuses on changes occurring at the industry level, particularly regarding how comovements between industries have changed, as well as employment volatility in individual industries. Most papers have proposed aggregate theories to explain these changes, something we find is at odds with the industry evidence. A handful of other papers in this literature have also focused on changes at the industry level - Wang (2014), Garın et al. (2013), and Fernald and Wang (2015). Both Wang (2014) and Fernald and Wang (2015) consider empirical decompositions of the declining productivity correlation at the industry level using utilization-adjusted TFP and discuss potential theories that could account for the evidence they find. We decompose the increasing volatility of employment at the industry level, and view out work and decompositions in both the model and the data as complementary to theirs. Garın et al. (2013) are similar to our paper in that they consider the impact of the declining importance of aggregate shocks for the changes in productivity correlations and employment volatility. In contrast, they focus on the role of reallocation frictions, and study a two sector model with costly reallocation of labor.

2 Facts About Industry Comovement

We use data from the BEA's Industry database which covers annual value added and employment for 18 private non-farm sectors from 1948-2015. While there are other potential sources of data available which cover slightly more sectors, the BEA data has the most years of data while still having a sizable number of sectors. A greater discussion of the data used, including the full list

[6]For an early overview of the Great Moderation literature focusing on the decline in GDP volatility, see Stock and Watson (2003).

[7]Note that Carvalho and Gabaix (2013) argue the opposite hypothesis - that comovements are not quantitatively important for the fall in GDP volatility, but changes in sectoral composition drive this result.

[8]See Stiroh (2009),Galí and Gambetti (2009), Barnichon (2010), Garın et al. (2013),Galí and Van Rens (2014) and Fernald and Wang (2015).

of sectors, as well as the trade-offs with using alternative sources is contained in Appendix A. To compute fluctuations over the business cycle, the data is logged and detrended using an HP filter with parameter 6.25.[9] However, all results are robust to measuring fluctuations in growth rates or a band pass filter. Aggregate employment is defined as the sum of total employment in each industry, and aggregate real output and investment are defined as Tornqvist indices of sectoral real value added and investment.

We use several measures to compute the degree of cyclical industry comovement in the data. First, we compute the pairwise correlation of value added or employment for each pair of sectors and then take a weighted average of these pairwise correlations to obtain an aggregate average measure of comovement. For sectors $i = 1, ..., N$, variable e (employment), and time period t, this can be written as:

$$\bar{\rho}_{e,t} = \frac{\sum_{i=1}^{N}\sum_{j=i+1}^{N}\mu_{it}^{e}\mu_{jt}^{e}\rho_{i,j,t}^{e}}{\sum_{i=1}^{N}\sum_{j=i+1}^{N}\mu_{it}^{e}\mu_{jt}^{e}}$$

where $\rho_{i,j,t}^{e}$ is the correlation coefficient for employment in sectors i and j in time period t and μ_{it} is the weight placed on sector i.

The second way we measure average comovement is to compute the average correlation of each sector's value added or employment with either aggregate value added or employment, as in Christiano and Fitzgerald (1998). We denote this measure of correlation by $\bar{\rho}_{e,t}^{a}$, the a denoting that the underlying correlations are not pairwise correlations, but correlations with the aggregate. This correlation can be written similarly as in the pairwise case:

$$\bar{\rho}_{e,t}^{a} = \frac{\sum_{i=1}^{N}\mu_{it}^{e}\rho_{i,t}^{e}}{\sum_{i=1}^{N}\mu_{it}^{e}}$$

where $\rho_{i,t}^{e}$ is the correlation coefficient between aggregate fluctuations in employment and sector i's fluctuations in employment, and μ_{it}^{e} is the weight placed on that correlation.

We weight employment correlations by the average share of total employment in each sector in time period t, i.e. $\mu_{it}^{e} = \frac{\bar{E}_{it}}{E_t}$. Value added correlations are similarly weighted by the share of nominal value added in each sector. To ensure measured changes in correlation are not driven by long run trends in sectoral composition, we use the average value of the weights over time, $\mu_{ij}^{y} = \bar{\mu}_{ijt}^{y}$ and $\mu_{i}^{y} = \bar{\mu}_{it}^{y}$. We show in Appendix A that our results regarding aggregate average correlations are robust to allowing these weights to change over time, as well as using either no weights ($\mu_{it}^{y} = 1$) or weights that are the product of each sector's relative size and each sector's relative standard deviation compared to the aggregate ($\mu_{it}^{e} = \frac{\bar{E}_{it}}{E_t}\frac{\bar{\sigma}_{it}^{e}}{\sigma_{t}^{e}}$).

Table 1 reports the average comovement for employment and for value added for the entire sample, as well as over time. We follow the commonly used break point of 1984 for simultaneous

[9] See Ravn and Uhlig (2002) for justification for this parameter choice.

changes in GDP volatility, and compare measures of comovement across the time periods 1951-1983 and 1984-2012.[10] Following the recommendation of Baxter and King (1999), we omit the first and last three years of data to avoid any endpoint bias from filtering.

We emphasize two key results in this table. The first is the fact that industry comovement is more correlated over the business cycle than industry output. For example, the average pairwise employment comovement over the business cycle for the whole sample is 0.57, whereas it is 0.33 for output. The aggregate average comovement shows similar results, with an average employment comovement of 0.77 and output comovement of 0.62. The second key result is that this gap between output and employment comovement has widened post-1984. By both measures of comovement, employment has remained just as correlated across the business cycle in the 1984-2012 period as before. However, the correlation in output has declined, which has widened the gap between these two measures of comovement.

We also show how these average levels of comovement have evolved over time. Figures 1 and 2 plot the average comovement of employment and output over 10 year rolling windows. Right after the 1980s recession, comovement in output drops sharply, consistent with the sharp decline in GDP volatility in the Great Moderation period. A similarly sharp decline is not observed in employment, and there is a significant increase in employment comovement in the 2000s.[11] Again, we conclude that average employment comovement has not declined (and may have risen), whereas comovement in output appears to have fallen significantly.

We conclude this section by presenting additional evidence on levels and changes in average comovement for real investment. We use BEA data on private investment in fixed assets by industry, which cover the same partition of industries over the same time period as our data for value added and employment. Table 2 reports these statistics for investment. While investment is not as correlated across industries as employment, it similarly has not seen a decline in average comovement post-1984. Relative to employment, this finding is more sensitive to the choice of weighting scheme, and we discuss robustness of these results in Appendix A. In general, however, we find that investment comovement has also remained stable throughout time, similar to employment.

[10] See McConnell and Perez-Quiros (2000) and Stock and Watson (2003) for early discussions regarding this break point.

[11] The evidence in Figures 1 and 2 suggest that employment comovement was actually trending downward prior to its sharp rise in the 2000s. Some of this stark reversal may be simply driven by the change over in industry codes from SIC to NAICS in 1998, as the BEA series for employment is not adjusted as thoroughly for these coding changes as is the series for output - see Appendix A for further discussion. Thus, it is difficult to confidently assert that the increase in employment comovement is not simply a data artifact of these coding changes.

3 Model

To understand these facts about industry comovement, we use a multi-sector model with industry linkages in both production and investment, similar to the models used in Kim and Kim (2006) and Foerster, Sarte, and Watson (2011). The model is in discrete time, with a period representing one year. There are N sectors in the economy, where sectors are indexed by $j = 1, ..., N$.

3.1 Environment

Final Good Production The final good in sector j is produced according to the gross output production technology:

$$Y_{jt} = A_{jt}(K_{jt}^{\alpha_j} L_{jt}^{1-\alpha_j})^{\theta_j} X_{jt}^{1-\theta_j}$$

where A_{jt} is TFP in sector j, K_{jt} is capital in sector j, L_{jt} is employment in sector j, and X_{jt} is a composite of intermediate goods used by sector j. Capital, labor and value added shares are determined by the parameters α_j and θ_j, which are industry specific. Note that industry value added, V_{jt}, is given by:

$$V_{jt} = A_{jt}^{\frac{1}{\theta_j}} K_{jt}^{\alpha_j} L_{jt}^{1-\alpha_j}$$

The composite of intermediate goods used by sector j, X_{jt}, is given by:

$$X_{jt} = \prod_{i=1}^{N} M_{jit}^{\gamma_{ij}}$$

where M_{jit} is the amount of the final good produced by sector i used in sector j's production. The relative importance of each intermediate good for sector j production is determined by the parameters γ_{ij}, and the production of the composite intermediate good is constant returns to scale, i.e. $\sum_{i=1}^{N} \gamma_{ij} = 1 \quad \forall j$. These parameters collectively constitute the input-output matrix for the economy, which is an NxN matrix Γ, with γ_{ij} as the element on the ith row and jth column.

TFP in each sector, A_{jt}, evolves as a log AR(1) process, where:

$$ln(A_{jt}) = \rho_j ln(A_{jt-1}) + \varepsilon_{jt}$$

We assume that $\varepsilon_t = [\varepsilon_{1t}, \varepsilon_{2t}, ..., \varepsilon_{Nt}]$is normally distributed with mean 0 and covariance matrix Σ, $\varepsilon_t \sim N(0, \Sigma)$. We explicitly assume that Σ is non-diagonal, implying correlation in TFP shocks across sectors. We assume ε_t is i.i.d. over time.

Capital Evolution and Investment Production Capital is sector-specific and evolves according to the following accumulation equation:

$$K_{jt+1} = (1-\delta)K_{jt} + Z_{jt}$$

where Z_{jt} is investment by sector j and δ is the depreciation rate. Investment in capital is also produced from an aggregate of intermediate investment goods, given by:

$$Z_{jt} = \prod_{i=1}^{N} I_{jit}^{\lambda_{ij}}$$

where I_{jit} is the use of the final good as an investment intermediate in sector j and $0 < \lambda_{ij} < 1$ governs the importance of each sectors' final good for investment production in sector j . Production of the investment good in sector j is constant returns to scale, i.e. $\sum_{i=1}^{N} \lambda_{ij} = 1$. The investment matrix for the economy is given by an NxN matrix Λ, with λ_{ij} as the element on the ith row and jth column.

Household There exists a representative household with lifetime utility given by

$$U = \sum_{t=0}^{\infty} \beta^t \mathbb{E}_t \left[ln(C_t) - \psi \frac{1}{1+\varepsilon} L_t^{1+\varepsilon} \right]$$

where C_t is a consumption aggregate and L_t is household employment, with $L_t = \sum_{j=1}^{N} L_{jt}$. The aggregate consumption bundle is given by $\prod_{j=1}^{N} C_{jt}^{\xi_j}$, where ξ_j determines the relative importance of each industry's final good in the consumption bundle.

Resource Constraint Finally, to close the model, we assume that the following resource constraint holds for each sector:

$$Y_{jt} = C_{jt} + \sum_i M_{ijt} + \sum_i I_{ijt}$$

implying that gross output in each sector is used either as consumption by the household or as an intermediate in producing final goods or investment goods in each sector.

3.2 Channels of Endogenous Comovement

We study equilibrium outcomes from this economy by solving the social planner's problem; a full list of equilibrium conditions is available in Appendix B. Ultimately, we study quantitative patterns of comovement from the log-linearized dynamics of the model system. However, before we study the quantitative properties of comovement in a calibrated version of this model, we first present some theoretical results that further intuition regarding how the inclusion of production and investment linkages generates endogenous comovement.

3.2.1 Input Output Linkages

We first present a lemma that describes the endogenous comovement generated by the input-output structure of final good production.

Lemma Using the first order conditions of the planner's problem, gross output in sector j can be rewritten in value added form, with endogenous TFP $\tilde{A}_{jt}$:

$$Y_{jt} = \left(A_{jt}\tilde{A}_{jt}\right)^{1/\theta_j} K_{jt}^{\alpha_j} L_{jt}^{1-\alpha_j}$$
$$Y_{jt} = \tilde{A}_{jt}^{1/\theta_j} V_{jt}$$

where $\tilde{A}_{jt} = (1-\theta_j)^{1-\theta_j} \Pi_{i=1}^{N} \left(\gamma_{ij}\frac{\mu_{jt}}{\mu_{it}}\right)^{\gamma_{ij}(1-\theta_j)}$ and μ_{jt} is the shadow value of the final good in sector i.

Proof See Appendix B.

The implications of this lemma for comovement are fairly simple. Suppose the price of input i falls more than the price of the final good in sector j, such as in the case of an uncorrelated sector-specific TFP shock hitting sector i. This leads to an increase in $\tilde{A}_{jt}$ without any increase in the exogenous TFP in sector j, A_{jt}. Thus, a simple way of thinking about the impact of input-output linkages in production is to think of sectoral TFP depending on the prices of final goods of the sectors that serve as inputs. Upstream impacts of input-output linkages can also be observed from this formulation. Suppose that sector j provides an input to production in sector i. The uncorrelated technology shock to sector i will increase demand for sector j as an input, and increase the shadow value of the final good in sector j, causing $\tilde{A}_{jt}$ to increase. Thus, the presence of input output linkages will endogenously generate additional comovement the exogenous correlation in TFP shocks.

We make two further observations about comovement and input-output linkages. First, note that value added does not include the endogenous component $\tilde{A}_{jt}$, as valued added excludes intermediates. Thus, additional comovement in value added across industries will only occur indirectly through the additional comovement in employment and capital. This suggests that inputs to production will tend to be more correlated across sectors than value added. Second, note that even if input-output linkages are perfectly identical, if there are no further linkages, a decline in exogenous comovement in TFP shocks will cause declines in employment and investment comovement across sectors, as the total TFP includes the purely exogenous sector-specific shock. Thus, while input-output linkages likely contribute importantly to the overall level of comovement, it seems less likely that they can generate stable comovement patterns in the face of declining comovement in exogenous shocks to TFP.

3.2.2 Investment Linkages

With regard to the investment linkages, it's helpful to draw on intuition regarding employment fluctuations from the one sector neoclassical growth model. In that model, if there is no capital or full depreciation, employment is constant in response to a TFP shock, as income and substitution effects exactly offset. [12] However, with capital that doesn't fully depreciate, labor increases in response to a productivity shock to produce more investment given the household's intertemporal smoothing motive.

In our model with investment linkages, when a productivity shock hits sector i, this similarly increases demand for investment, however, increases in employment will be concentrated in the sectors that produce intermediate investment goods. For example, consider an example where the final good in sector i is only used for consumption purposes; that is, it is not an input to final good or investment good production anywhere else in the economy. In the case where labor is indivisible ($\varepsilon = 0$), employment in that sector will be constant, like in the benchmark one-sector growth model without capital.[13] However, employment in sectors producing intermediates to that investment good *will* increase, as investment increases to smooth the benefits of the productivity increase. Thus, the exact form of the investment linkages will determine the employment response to productivity shocks.

The intuition for downstream impacts of productivity shocks via investment linkages is also straightforward. It is not difficult to show that the Euler Equation for sector j can be written as:

$$\prod_{i=1}^{N}\left(\frac{\mu_{it}}{\lambda_{ij}}\right)^{\lambda_{ij}} = \beta\mathbb{E}\left[(1-\delta)\prod_{i=1}^{N}\left(\frac{\mu_{it+1}}{\lambda_{ij}}\right)^{\lambda_{ij}} + \mu_{jt+1}\theta_j\alpha_j\frac{Y_{jt+1}}{K_{jt+1}}\right]$$

Productivity shocks to sectors that produce intermediate investment goods for sector j decrease the cost of those goods, pushing down μ_{it}. In this sense, a productivity shock in an intermediate investment sector shows up in the Euler Equation in the same way as a shock to the price of investment in sector j. The cyclical properties of investment price or investment specific technology shocks have been studied extensively - for example, see Greenwood et al. (2000) and Justiniano et al. (2011).

[12] Depending on the specification of preferences over labor supply, a similar results obtains in multi-sector growth models without capital - see, for example, Long Jr and Plosser (1983) and Shea (2002).

[13] If labor is divisible (i.e. $\varepsilon > 0$), then the productivity shock will decrease employment in sector i, reallocating employment to the sectors where investment is being produced.

However, similar to the intuition given for the upstream effects of productivity shocks, a shock to the price of investment in sector i will only increase employment in sector i if the final good from that sector is used as either an intermediate investment good to or as intermediate production good for a sector which produces an intermediate investment good. In the latter case, where sector i is not an investment intermediate for its own investment good, but a production intermediate for some sector which does produce an investment intermediate, the employment response will be comparatively smaller.

The above intuition emphasizes that the exact form investment linkages take is important for understanding comovement in employment. The following proof establishes that in a special case of investment linkages, employment can be perfectly correlated across sectors independent of the covariance matrix of TFP shocks.

Theorem If the production technology for investment is identical across sectors ($\lambda_{ij} = \lambda_i$), then consumption to output ratios in each sector will be perfectly correlated as long as they are not constant. This implies that employment will perfectly correlated across all sectors without constant consumption to output ratios if the following condition holds in each sector:

$$\frac{\theta_j(1-\alpha_j)b_j}{\sum\theta_i(1-\alpha_i)b_i} > \frac{\varepsilon}{1+\varepsilon}\frac{L_{jt}}{L_t}$$

where b_j is a function of model parameters governing the responsiveness of the consumption to output ratio to changes in the value of investment, the jth element of the vector $\vec{b} = (I-\Phi)^{-1}\lambda$, where $\lambda = [\lambda_1, \lambda_2, ...\lambda_N]$, and $(I-\Phi)^{-1}$ is the Leontief matrix for this economy, where Φ is a matrix with typical element $\phi_{ij} = (1-\theta_j)\gamma_{ij}$.

Proof See Appendix B.

The key intuition of this theorem is as follows. If investment production technology is identical across sectors, this means that the value of investment will be the same across sectors, and thus employment in each sector will fluctuate based on fluctuations in a single variable, the total value of investment in the economy. In the case of indivisible labor ($\varepsilon = 0$), it is obvious that an increased value of investment will lead to increased employment in every sector. However, with divisible labor ($\varepsilon > 0$), the incentive to increase employment in all sectors competes with the incentive to reallocate labor across sectors to equate marginal products of labor. Provided that the reallocation motive is not too strong, i.e. ε is not too big, and that the input-output structure of the economy is sufficiently dense, employment across all sectors will still be perfectly correlated. We have quantitatively evaluated a range of values for ε given our calibration and have found that for typical macro values of ε (i.e. $\varepsilon < 1$), this result still holds.

In general, the results of this theorem suggest that a very homogeneous investment matrix has the potential to generate stable comovements in employment, even as comovement in exogenous shocks declines, consistent with the patterns we have observed in the data.

4 Calibration

4.1 Parameters Calibrated Outside the Model

While our model has a large number of parameters, many of them can be calibrated in a straightforward fashion without actually solving the model. We use standard values for the discount factor and depreciation rate, $\beta = 0.96$ and $\delta = 0.1$. As an initial placeholder, we set $\psi = 0.55$, although the value of ψ is irrelevant for the outcomes we study.[14] For labor disutility, we consider a benchmark of $\varepsilon = 0$, implying an infinite Frisch elasticity, consistent with indivisible labor. We view this as consistent with our emphasis on employment comovement, and not hours comovement. This also brings the model closer to being consistent to matching employment volatility in the data, an outcome relevant for what we study. Further, the assumption of indivisible labor greatly weakens incentives to reallocate labor across sectors, limiting the scope of that channel. We find this appealing as labor reallocation is likely subject to significant barriers and frictions which we do not model here. However, we report robustness to using alternative values of ε in Appendix C, and while higher values of ε lead to greater labor reallocation and thus attenuated levels of average comovement, we find that our results regarding the change in comovements over time are very similar to the benchmark with $\varepsilon = 0$.

To calibrate the production parameters and the parameters governing the consumption aggregate, we use data from the BEA Input-Output Database. Average cost shares in intermediate goods from 1947-2015 are used to calibrate the input-output parameters, γ_{ij}, and average value added cost shares from 1947-2015 are used to calibrate the value added parameters, θ_j. Average consumption cost shares from 1947-2015 are computed from the final uses component of the Input-Output tables and are used to calibrate the Cobb-Douglas parameters in the consumption aggregate, ξ_j. To calibrate the capital shares, we similarly use data from the Input-Output tables to compute the cost share of compensation, however, this data is only available from 1987-2015. Finally, we calibrate the investment linkages matrix parameters, λ_{ij}, using cost shares from the Capital Flows Data published in 1997.[15] A more detailed description of how we measure these parameter values

[14]Allowing for heterogeneity and changes over time in depreciation rates and the scale parameter is disutility parameters is part of ongoing work on this project.

[15]Capital Flows data have only been produced in a series of isolated years throughout time, often using different industry coding definitions. The 1997 data is also the only data to at least partially allow for the updated BEA definitions of investment, which include intellectual property products, such as software.

is available in Appendix A.

We are not the first paper to use data on investment linkages from the Capital Flows data; Foerster et al. (2011) and Atalay (2014) use this data as well. However, as pointed out in both these papers, there are some potential shortcomings to using the Capital Flows data. The first is that this data only captures new investment, and does not represent either investment with used goods or maintenance and repair investment, the latter of which may be quite significant - see McGrattan and Schmitz Jr (1999). A second and more structural issue is that with the partition of sectors used in Foerster et al. (2011) and Atalay (2014), using the data directly from the Capital Flows table generates a parametrization of the model for non-invertibility arises in the log-linearized dynamics. As a result, both Foerster et al. (2011) and Atalay (2014) make a correction to the investment matrix to account for maintenance investment, assuming that maintenance investment in sector j is accomplished using only the final good produced by sector j. This results in a correction to the investment matrix that amounts to adding a fixed amount to the diagonal. We follow this procedure as well, however, given the set of sectors used in our analysis, this modification is not required. We examine the consequences of this modification in Section 5.

Figures 3 and 4 plot heat maps of both the input output matrix, Γ and the investment linkages matrix, Λ. Columns of these matrices represent the industries receiving the intermediate goods and services from other sectors and rows represent the industries providing the goods and services. The input-output matrix map shows that there are significant linkages and heterogeneity in those linkages throughout the economy. While some sectors are more prominent producers of intermediate goods, such as durable manufacturing and professional/business services, the intensity with which these are used across sectors varies. For example, intermediates in durable manufacturing comprise less than 5% of intermediate costs for the finance and insurance sector and nearly 50% in the construction sector. In contrast, the investment matrix shows much less heterogeneity. About half of the sectors we consider do not provide intermediates in investment to any sector but their own, and there is much less variation in the intensity of intermediate usage from sectors like durable manufacturing or construction. The strong diagonal component of the matrix is driven by the adjustment described above; absent this, investment production technology across sectors seems remarkably homogeneous.

4.2 Parameters Calibrated by Solving the Model

The remaining parameters of the model are obtained by solving the log-linearized system of model equations and then calibrating them to match data moments. The remaining parameters all pertain to the stochastic processes for industry TFP - the persistence parameter, ρ_j, and the covariance matrix, Σ. As our primary exercise is to evaluate how comovement changes in response to changes in the covariance matrix of TFP, we calibrate Σ for both the pre-1984 and post-1984 periods.

We calibrate the TFP parameters to match data on fluctuations in industry value added. To calibrate the persistence parameters, we remove a linear trend from the log of value added in each sector, and then estimate an AR(1) on the detrended log value added. To calibrate the covariance matrix, we match the theoretical log HP-filtered covariance matrix of industry value added in the model to the covariance matrix for value added in the data. The covariance matrix of the filtered data is computed for the period 1951-1983 and 1984-2012 to calibrate the covariance matrix in both time periods. As a benchmark, we do not consider changes in the persistence parameter, ρ_j, and simply use the estimate obtained from the whole sample, 1951-2012.

We focus on calibrating the TFP to match moments of value added data for several reasons. First, while the BEA publishes detailed data on fixed assets and investment by industry over time, there is much less reliable data on factor shares. With more reliable factor share data, we could in principle construct TFP by industry from 1948 to the present and bypass this step. While this is something for ongoing revisions, we do not consider this for our results presented here. Second, while we could match moments of something else which might have a closer relation to TFP, such as output per worker, we prefer matching value added moments, as this means we are not explicitly targeting anything with employment. Output per worker data implicitly depends on the dynamics of employment, and it is known that the dynamics of both have changed significantly post-1980s, potentially in ways difficult to account for in our framework.

As our calibration strategy matches the comovement patterns for value added, our results focus on model generated patterns in employment and how those have changed over time.

5 Results

We solve the log linear approximation of the model and report results from this solution. For model results pertaining to variance and correlations, we compute the theoretical HP moments from the model solution. All other results are generated by simulation as follows. First, we simulate the model for 2000 periods using the TFP covariance matrix calibrated to fit data from the pre-1984 period. Simulated outcomes from the first 200 periods are discarded and the remaining data is logged and HP filtered and the first three and last years of data are excluded, consistent with the data facts we compare to. Second, we simulate the model again for 2000 periods, however, we use the TFP covariance matrix calibrated to fit data from the post-1984 period. All other parameters are identical across the two simulations. Again, we discard the first 200 periods and log and filter the remaining data. For estimates of moments corresponding to the entire sample period (1951-2012), we compute these by taking either the average of the theoretical moments, or by pooling data from both simulations.

5.1 Calibration Fit and Validation

Before presenting the results of our quantitative exercise, we report the fit of the calibration on targeted moments, as well as the model's fit on several other untargeted moments. Figures 5, 6, and 7 show both model and data moments for the the autocorrelation of geometrically detrended value added, the variance of log HP-filtered value added, and all sectoral value added correlations, respectively. The calibration matches well the targeted moments, with perhaps the slight exception of the autocorrelations, however, this is likely due to this stage of the calibration being preliminary.

In addition to these targeted moments, we also present the model's performance on two non-targeted moments - the shares of nominal value added in each sector and the ratio of employment and value added variances in each sector. Figure 8 reports the average shares of nominal value added for each sector across the entire sample period in the model and in the data. Though untargeted, these match very closely, suggesting that our use of consumption, investment and input-output cost shares generates a model economy that is representative of the distribution of industrial activity in the actual economy. The second validation moment we present is the ratio of log HP-filtered variances of employment and value added in each sector for the entire sample period, shown in Figure 9. We are not surprised that simply accounting for industry linkages fails explain all the variation in this ratio, not to mention the average level. However, we take comfort from the observation that the model matches reasonably well the employment variance in sectors that are prominent producers of investment intermediates, such as construction, durable manufacturing and professional/business services. We view this as evidence that investment linkages are an important propagation channel for business cycle fluctuations in employment.

5.2 Results for Average Employment Comovement

Table 3 reports the average pairwise industry comovement for the entire sample as well as before and after 1984 for both the model and the data, weighted by average total shares of employment and output. The model captures well the level of employment comovement as well as its change over time. The model slightly overstates the degree of employment comovement while slightly understating the degree of output comovement, but the levels are very similar.[16] Further, the model is able to replicate the stability of employment comovements pre- and post-1984, all while value added comovement dropped significantly.

Table 4 reports the model findings for average industry comovement computed as the average of industry outcomes with the aggregate, and finds very similar results. Again average employment comovement in the model is slightly higher than in the data, and the model reproduces the stability

[16]Although we target the comovement of value added between individual industries, the value added and employment shares are not exactly targeted, thus, the fit on weighted average output comovements is not exact.

of employment comovement in the face of declining output comovement. Given the high degree of similarity in these results, we focus on pairwise outcomes for the remainder of the paper.

Similar to our empirical findings, we show in Appendix C that these results for employment comovement are robust to alternative weighting schemes. We also show robustness to alternative parametrizations of the Frisch elasticity parameter, ε. In general, we conclude that the sectoral linkages channel is critical for understanding employment comovement, particularly how it has remained stable over time.

We also consider how the model does at explaining individual changes in comovement for each sector pair. Given that the model is calibrated to match exactly comovement in value added across sectors, we report the difference in the comovement between employment and output for each sector pair. Figure 10 shows a scatter plot of these comovement differences for each pair of sectors opposite the data for the pre-1984 and post-1984 periods. We also plot the difference in these differences in Figure 10. The model is able to account for a meaningful fraction of the variation in the difference in employment and output comovements for each time period, but performs especially well in accounting for the difference in these differences, with an R^2 of 0.52.[17] We view this as strong evidence regarding the role of sectoral linkages in generating these changes in comovement patterns.

5.3 The Role of Sectoral Linkages in Comovement

To better understand the comovement results obtained from the model, we consider several counterfactual exercises where we adjust the exact nature of input-output and investment linkages.

First, we consider how the results vary when there are only investment linkages and when there are only input-output linkages. In shutting off input-output linkages, we continue to assume that there are intermediates in production, however, they only come from the same sector - i.e. the input output matrix, Γ, is the identity matrix.[18] In shutting off investment linkages, we assume that investment in each sector is produced solely using the final good of that sector. Using the same calibration as above, we compare how these counterfactual parametrizations impact the average level of employment comovement and how it changes over time.

Table 5 shows the results for average pairwise employment and output correlations with these alternative calibrations. When we turn off investment linkages, employment is still more strongly correlated than output, however average employment comovements decline as much as output

[17]We find similar results when instead of merely differencing out output comovements, we instead project employment comovement on output comovement and compare the model's performance on the residuals of this regression.

[18]The motivation for not shutting off intermediates altogether is that this would fundamentally alter the impact of TFP shocks on value added. Recall that value added is given by $V_{jt} = A_{jt}^{1/\theta_j} K_{jt}^{\alpha_j} L_{jt}^{1-\alpha_j}$, and thus assuming $\theta_j = 1$ would further distance these counterfactual exercises from the calibrated TFP covariance matrix. However, our results are similar when we do shut off intermediates altogether.

comovements pre- and post-1984. Thus, while input-output linkages may be important for the level of employment comovement, they are not the reason why employment comovements have remained stable. On the other hand, turning off input-output linkages and only leaving investment linkages, we see that the average level of employment comovement drops significantly, however, it remains stable even as there is a sizable drop in output comovements. Thus, investment linkages are the primary reason why employment has remained correlated at a high level even in the post-1984 period.

These results are consistent with the theory described prior. In a world with identical investment production technologies across sectors, the similarity of investment linkages means that the value of investment is identical across sectors, and thus employment is perfectly correlated, independent of the covariance structure of TFP. We argue that the investment matrix in the real world is very close to this case. With the exception of the diagonal component added to the investment matrix, investment intermediates are provided very homogeneously from a small set of sectors, meaning that the value of investment across sectors will be very highly correlated.

This can be further seen by considering how the model results look when we use the investment matrix directly from the data, without adding an additional diagonal component. We use our existing calibration to preserve greater comparability with our baseline results. The final column of table 5 shows the results when we use this alternative investment matrix instead. What we see is that employment comovement is very close to one and similarly, barely changes in response to a decline in TFP comovements. Thus, without this additional diagonal adjustment, the investment matrix from the data closely approximates the world where investment linkages are identical. Notably, the input-output matrix is still important for this result. Because so few sectors produce investment intermediates, the only reason why consumption to output ratios in non-investment producing sectors change over the business cycle, and thus the only reason why employment in these sectors changes, is because they provide inputs to investment producing sectors. Absent input-output linkages, the average comovement across all sectors, would be much lower, similar to what we see above.

5.4 Results for Average Investment Comovement

We also consider how the model does at generating stable patterns in investment comovements. Table 6 reports the results from our baseline simulations, as well as our simulations where the investment matrix is taken directly from the data, without adding an additional diagonal component. In general, the model generates slightly less comovement in investment than the data. Further, the model struggles to capture the stability of investment comovement in the baseline case, as correlations of investment drop significantly However, it appears that one reason the model fails to account for investment comovement is the artificial addition of diagonal elements on the investment matrix. When these diagonal elements are removed, investment comovement declines by much less. Thus, we find that these linkages also appear capable of reconciling stable comovement patterns in investment.[19]

5.5 Changing Linkages Over Time

Our exercises thus far have only considered changes in the structure of TFP. However, there have also been significant structural changes in both sectoral networks and production parameters that may be also relevant to consider. Thus, we also consider the effects of simultaneously varying industry labor shares, industry value added shares of gross output, final consumption shares, the input-output matrix, and the investment linkages matrix.

For all parameters except for the industry labor shares and the investment linkages matrix, we have data directly on how these parameters have changed over time and can calibrate the same way as in the baseline, albeit for the two different time periods. For industry labor share parameters and the investment linkages matrix, we require drawing on data from additional sources and some imputation. In the case of industry labor shares, while the BEA does not have data on these prior to 1987, the World KLEMS dataset compiles estimates of these back to 1948, albeit for a different sectoral partition of the economy. Using crosswalks between the ISIC classifications of the World KLEMS data and BEA data, we take changes in labor shares across pre- and post-1984, and add them to the BEA estimates of labor shares to obtain values for both the pre- and post-1984 period.

Obtaining time-varying investment matrices is significantly more involved and requires significantly more imputation. Capital Flows data has been published only intermittently over time, and the 1997 flows table is the only version that includes at least partial estimates for intellectual property investment, which was included with investment with the 2013 revision of BEA data. While detailed annual capital flows tables are not available over time, we do have a time series of the total amounts of each sector's production whose final use was for investment purposes. We use this data to impute how the investment matrix has evolved over time - detail regarding this imputation is available in Appendix A.1. The key thing we emphasize is that the results obtained from our exercises in this section are sensitive to this imputation procedure, and thus we report them merely as robustness checks to our primary exercises.

Table 7 reports our results when we allow these parameters to change over time. We find that employment comovements decline slightly, but that the model is still able to reproduce 2/3 of the increasing gap between employment and output comovements in the baseline, and thus in the data. Again, we emphasize that this number is certainly sensitive to assumptions regarding imputation

[19]Further iterations of this work plan on using heterogeneity in depreciation rates and the inclusion of durable goods, both of which may have significant implications for these results.

of how the investment matrix has evolved over time. However, we argue that given how much the model is still able to reproduce of the widening gap in comovements, this suggests the investment linkages channel is still of primary importance in explaining this facet of industry comovement.

5.6 The Role of TFP Comovement Heterogeneity

We have shown that investment linkages play an important role for generating stable comovement in employment across sectors even as TFP comovement declines. Another potential reason for our results is heterogeneity in where TFP comovement has declined. Investment linkages are able to generate stable comovement patterns because the sparseness of the investment linkages means that the set of shocks that are relevant for employment fluctuations becomes much more heavily weighted towards shocks to sectors producing investment goods. Thus, the comovement between investment producing sectors is much more important for employment comovement than comovement between other sectors.

We first show how our results compare when there is no heterogeneity in TFP comovement. We assume that the correlation between any two sectors is identical, and that the decline in this correlation has been identical across sectors.[20] We then recalibrate this average level of correlation to match the average correlation in value added fluctuations in both the pre and post-1984 periods. As seen in Table 8, we find that our results do change when we remove heterogeneity in TFP fluctuations. Absent this heterogeneity, employment comovement declines more than in our baseline case, though still not as much as the decline in output comovement. We find that without heterogeneity in TFP comovement, we still obtain nearly 50% of the increasing gap between employment and output comovement, suggesting that about half of the baseline result comes from this heterogeneity.

As further evidence of the importance of this heterogeneity, we report how comovement in our calibrated TFP matrix has changed among the most prominent investment producers, between investment producers and less prominent or non-producers, and among the less prominent and non-producing investment sectors. We define a prominent investment producing sector as one that comprises at least 10% of investment costs in at least one sector outside their own. With this definition, there are three prominent investment sectors - construction, durable manufacturing and professional/technical services. These three sectors on average account for 85% of off-diagonal investment in each sector.

Table 9 presents the average pairwise correlations amongst these three groups of sector in

[20] We could alternatively assume that the correlation across sectors is heterogeneous, and that only the declines in comovements are identical. While this exercise generates similar results, we report these results instead, as this alternative approach requires making ad hoc adjustments to the covariance matrix to ensure that it remains positive-definite.

the calibrated TFP matrix pre- and post-1984. Notably, the average comovement in TFP is quite small, smaller than either employment or output. Further, we see that TFP comovement has, on average, fallen for each of the three sector groupings we consider. However, it is fallen less among investment producing sectors. It is precisely this heterogeneity in the changes in TFP comovements that contributes to the stable comovements in employment observed in our baseline results.

While heterogeneity in the sectors where TFP comovement has declined is important for keeping employment comovement unchanged pre- and post-1984, we argue that this effect only obtains because of the investment production network. Investment linkages change the set of shocks that are relevant for employment fluctuations, and we show that those comovement in those shocks that are relevant for employment has not declined as much as between other shocks in the economy. However, absent these investment linkages, as seen in Table 5, the model generates no difference in the changes in employment and output correlations.

6 Implications for Aggregate Volatility

Comovement patterns in employment and output were not the only changes observed in business cycles after 1984, and so in this section we ask what sectoral networks and comovement changes can tell us about these other changes. We focus on two other changes occurring in business cycles over this time period - the decline in GDP volatility and the comparatively smaller decline in aggregate employment volatility.

6.1 The Role of Comovement Changes for Declining GDP Volatility

We first ask the following question - how much have changes in output contributed to the fall in GDP volatility? As shown in Stiroh (2009), in the data, comovement terms appear to be more important than changes occurring within sectors. Recent work by Foerster et al. (2011) confirms this finding, arguing that a decline in aggregate shocks (or implicitly, comovement) has been particularly important the observed fall in volatility. However, Carvalho and Gabaix (2013) argues to the contrary that comovement is quantitatively unimportant, and that the primary changes are occurring at the individual sector level.

To answer this question, we decompose the role of comovement and within sector changes using the following industry decomposition of GDP volatility:

$$\sigma_{yt}^2 = \sum w_{yit}^2 \sigma_{yit}^2 + 2\sum_{i<j} w_{yit} w_{yjt} \sigma_{yit} \sigma_{yjt} \rho_{yijt}$$

where σ^2_{yt} is the variance of fluctuations in aggregate GDP for time period t , σ^2_{yit} is the output variance for industry i at time t, w_{yit} is the share of aggregate nominal output in industry i at time t and ρ_{yijt} represents the correlation between output in industry i and industry j at time t. This is an approximate decomposition, and we provide a derivation in Appendix B.[21] We express the traditional covariance term as the product of industry standard deviations and the correlation between industries to relate our findings on comovement to the change in output volatility.

With this decomposition, we hold sector shares fixed, and then alternatively vary within sector variances, σ_{yit} and between sector comovements, ρ_{yijt}, while holding the other fixed.[22] Table 10 reports the results of this decomposition and shows that roughly 60% of the decline in output volatility is attributable to comovement changes in the data.

A natural concern with this result is that changes in comovement may simply reflect changes in the variance of industry-specific shocks interacted with sectoral networks. Thus, we do a similar decomposition in our model, alternatively holding fixed parameters governing within sector TFP variance and parameters governing between sector TFP correlations. We also do this decomposition for the model results where other model parameters are allowed to change over time.

Table 10 shows the results for the model decompositions, and finds nearly the same contribution of comovement to changes in GDP volatility. Thus, we argue that changes in the comovement patterns of TFP are of first order importance in accounting for the decline in aggregate GDP volatility.

6.2 Comovement and the Relative Increase in Employment Volatility

6.2.1 Increasing Employment Volatility and Declining Procyclicality of Productivity

Another business cycle change observed post-1980s has been the rise of employment volatility relative to GDP volatility. While the variance of both employment and GDP fluctuations has fallen over this period, the variance of employment fluctuations fell by less. This observation is closely linked to another stylized fact about business cycles in this time period - the declining correlation between aggregate output and labor productivity. These changes have been documented and discussed extensively - see Stiroh (2009), Galí and Gambetti (2009), Barnichon (2010), Garın et al. (2013), Galí and Van Rens (2014) and Fernald and Wang (2015). We establish this connection between these changes in the following lemma.

[21] Stiroh (2009) considers an exact decomposition of GDP volatility across sectors to assess changes occurring in the Great Moderation. The problem with the exact decomposition in his work is that it does not allow one to relate aggregate changes to changes in employment and output at the sectoral level. Aggregates are instead decomposed into the product of growth in sectoral quantities multiplied by the sectoral share of the total aggregate. While this allows for greater precision, we find it difficult to economically interpret results from such a decomposition.

[22] For this, we run two decompositions, one where variances or comovements are fixed at their pre-1984 level and one where they are fixed at their post-1984 level and take the average of the two simulations.

Lemma The correlation of any variable x with logged output per worker, $\rho_{x,y-e}$, can be written as $\rho_{x,y-e} \equiv f\left(\rho_{x,e}, \rho_{x,y}, \rho_{y,e}, \frac{\sigma_e}{\sigma_y}\right)$, where $\frac{\sigma_e}{\sigma_y}$ is the relative standard deviation of employment and output, and $\rho_{a,b}$ is the correlation between variables a and b. In the case where x is output, this reduces to $g\left(\rho_{y,e}, \frac{\sigma_e}{\sigma_y}\right) = f\left(\rho_{y,e}, 1, \rho_{y,e}, \frac{\sigma_e}{\sigma_y}\right)$. Further, $\rho_{y,y-e}$ is weakly decreasing in $\frac{\sigma_e}{\sigma_y}$.

Proof

See Appendix B.

The takeaway from this lemma is that the correlation between output and productivity is simply a function of the relative standard deviations of employment and output and the correlation between employment and output. The intuition for this is fairly simple. If employment and output are highly correlated, then the cyclicality of fluctuations in log productivity, or output minus employment, will simply depend on the magnitude, or volatility of those fluctuations.

We report how all of these have changed over time in the BEA data in Table 11.[23] What we observe is that the correlation of employment and output pre- and post-1984 has not changed across time, while employment has become relatively more volatile than GDP. This leads to the decline in the correlation between productivity and output.[24] Figure 11 shows these patterns across 10 year rolling windows, and it is clear that the changes occur starkly in the early 1980s, similar to the patterns we have shown in comovement. Given this close connection, we focus on the rise in employment volailtiy relative to GDP volatility, as it is more straightforward to decompose at the industry level.

6.2.2 Decomposing Increasing Employment Volatility

We use a similar decomposition as in the prior section to decompose the ratio of employment and output variances into industry variances and correlations:

$$
\begin{aligned}
\frac{\sigma_{et}^2}{\sigma_{yt}^2} &= \frac{\sum w_{eit}^2 \sigma_{eit}^2 + 2\sum_{i<j} w_{eit} w_{ejt} \sigma_{eit} \sigma_{ejt} \rho_{eijt}}{\sum w_{yit}^2 \sigma_{yit}^2 + 2\sum_{i<j} w_{yit} w_{yjt} \sigma_{yit} \sigma_{yjt} \rho_{yijt}} \\
&= \underbrace{\left(\frac{\sum w_{yit}^2 \sigma_{yit}^2}{\sigma_{yt}^2}\right)}_{\text{Within Wgt.}} \underbrace{\frac{\sum w_{eit}^2 \sigma_{eit}^2}{\sum w_{yit}^2 \sigma_{yit}^2}}_{\text{Within Sector Rel. Var.}} + \underbrace{\left(1 - \frac{\sum w_{yit}^2 \sigma_{yit}^2}{\sigma_{yt}^2}\right)}_{\text{Covariance Wgt}} \underbrace{\frac{\sum_{i<j} w_{eit} w_{ejt} \sigma_{eit} \sigma_{ejt} \rho_{eijt}}{\sum_{i<j} w_{yit} w_{yjt} \sigma_{yit} \sigma_{yjt} \rho_{yijt}}}_{\text{Relative Covariance}}
\end{aligned}
$$

[23] For these statistics, a slight adjustment has been made to account for employment discontinuities; details are available in Appendix A. These adjustments have not been made to the reported data figures regarding comovement, and the results in prior sections are nearly identical when this correction is made.

[24] There has been some debate regarding whether or not these facts are consistent across alternative filters, such as growth rates, or across alternative data sources. However, as discussed in Galí and Van Rens (2014) and Fernald and Wang (2015), these findings are quite robust.

where σ^2_{Xt} is the aggregate variance for time period t in variable X, σ^2_{Xit} is the variance of X in industry i at time t, w_{Xit} is the aggregate share of industry i in X at time t and ρ_{Xijt} represents the correlation between Xs in industry i and industry j at time t. This decomposition thus expresses the relative volatility of employment to output as a weighted average of the relative volatility within sectors and the relative covariance across sectors.

We report the results of this decomposition in Table 12, and find that according to this simple decomposition, it is changes in covariances that drive the majority of increase in relative employment volatility. We also report this decomposition holding employment and output shares fixed and reach the same conclusion. Thus, a simple reading of the data suggests a central role for changes in the comovement patterns in employment and output for explaining the aggregate change in employment volatility.

6.2.3 Understanding Model Results for Employment Volatility

What does the model generate in terms of employment volatility? Table 13 shows the employment volatility decomposition for the baseline results. The model generates a slight increase in aggregate employment volatility relative to output volatility, but no more than a quarter of what is observed in the data for the fixed sector shares case. Qualitatively, however, the model generates the same patterns in the decomposition, with what increase there is driven by an increase in relative covariances.

Some of this may simply be the well known failing of the standard growth model to generate sufficient employment volatility in general. Thus, we consider an ad hoc scaling of employment variance to match the data and see how that impacts the results. This is also reported in Table 13, and we find that this does improve the model results slightly, generating closer to a third of the increase in employment volatility in the data. This is effectively the same result as comparing the percent change in the employment to output volatility ratio from the baseline case, instead of the level difference. But this still suggests there is potentially something missing beyond simply the level of variances. While not reported, we also find that allowing for sector-specific scaling to match the levels of employment volatility in the data in the pre-1984 period generates the same result.[25] Thus, we focus on how within sector employment variance has changed in the model relative to what is observed in the data.

The third column in Table 13 reports the model results where employment variance in each sector for the post-1984 period is replaced by an employment variance that generates the same percent change in the employment to output variance in the data. Allowing for heterogeneous changes in sector-specific employment volatility actually does bring the model much closer to

[25] We have also explored replacing model values for sector shares with those from the data and found that this has negligible effect.

what is observed in the data for aggregate changes in employment volatility. And when the same scaling factor is applied additionally, as seen in the last column of the table, the model output very closely resembles the data in each aspect of the decomposition. Thus, what we conclude is that the reason the model is unable to account for these changes in employment volatility stems from counterfactual changes in employment volatility within sectors.

To conclude, we assess which sectors' changing employment volatilities are most important for explaining this result to provide focus for future research. Computing the counterfactual exercise where only sector's employment volatility is replaced by the data counterfactual, we find that of the 18 sectors we study, only seven deviate from the data in an economically significant way. Those seven sectors are: mining, construction, non-durable manufacturing, wholesale trade, information, professional, scientific and technical services, and administrative and waste management services. These sectors comprise approximately one-third of aggregate employment on average between 1951 and 2012, both in the model and in the data. Table 14 reports the average ratio of employment and output variances for this group of sectors and the remaining 11 sectors. We see that for these these remaining 11 sectors, the model predicts a slight decline in the ratio of employment to output variance, similar to what is seen in the data. However, for the seven sectors listed, while the data shows an increase in employment volatility, the model counterfactually predicts a substantial *decline*. Thus, we argue that further work should particularly focus on understanding why employment variance has risen in these sectors.

7 Conclusion

In this paper, we have studied the extent to which sectoral networks in production and investment can account for both the levels and patterns of industry comovement observed in employment and investment. We have documented that while output comovements have fallen post-1984, employment and investment comovements have not. We further show that a model with these sectoral networks can reproduce this behavior in average comovement of inputs, and emphasize that the important channel for this is the presence of investment linkages.

In conclusion, we observe that this comovement channel may also be important for explaining other changes in business cycles that have occurred since the 1980s, including the decline in GDP volatility and the rising relative volatility of employment. Our model implies a significant contribution of comovement changes for the decline in GDP volatility, and we show empirical evidence suggesting these changes are also important for the increase in employment volatility. While our model as presently constructed cannot replicate this increase in employment volatility, we show where the model differs from the data and use this as a guide for understanding what the model is missing. In particular, we see that the model misses on the increase in employment volatility for a subset of the economy, totaling one-third of final employment. Absent this discrepancy, the model is consistent with the data on other dimensions. Thus, future research on these changes should not merely focus on aggregate explanations for what has changed, but rather changes in these particular sectors. As limited research has been done thus far with such an industry-specific perspective, we believe this to be a fruitful area for future study.

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Table 1: Cyclical Industry Comovement in Employment and Value Added

	Average Pairwise Comovement, $\bar{\rho}_{y,t}$			Average Aggregate Comovement, $\bar{\rho}^{a}_{y,t}$		
	Employment	Value Added	**Difference**	Employment	Value Added	**Difference**
1951-2012	0.57	0.33	**-0.24****	0.77	0.62	**-0.15****
1951-1983	0.58	0.41	**-0.17****	0.78	0.67	**-0.11****
1984-2012	0.57	0.22	**-0.35****	0.77	0.53	**-0.24****
Difference	**-0.01**	**-0.19****	**-0.18****	**-0.01**	**-0.14****	**-0.13****

** indicates significance at the 5% level. Statistical significance is determined by confidence intervals computed via block bootstrapping. Significance is robust to varying the size of the window in the block bootstrap.

Table 2: Cyclical Industry Comovement in Investment

	Average Pairwise Comovement, $\bar{\rho}_{y,t}$	Average Aggregate Comovement, $\bar{\rho}^{a}_{y,t}$
1951-2012	0.31	0.60
1951-1983	0.33	0.62
1984-2012	0.34	0.63
Difference	**0.01**	**0.01**

** indicates significance at the 5% level. Statistical significance is determined by confidence intervals computed via block bootstrapping. Significance is robust to varying the size of the window in the block bootstrap.

Table 3: Average Pairwise Industry Comovement, Model vs. Data

	Data			Model		
	Employment	Output	**Difference**	Employment	Output	**Difference**
1951-2012	0.57	0.33	**-0.24**	0.68	0.29	**-0.39**
1951-1983	0.58	0.41	**-0.17**	0.69	0.39	**-0.30**
1984-2012	0.57	0.22	**-0.35**	0.66	0.19	**-0.47**
Difference	**-0.01**	**-0.19**	**-0.18**	**-0.03**	**-0.20**	**-0.17**

Employment and output correlations in the model and in the data are both weighted by average sector shares of employment and output, respectively. The underlying data has been logged and filtered with an HP filter with parameter 6.25.

Table 4: Average Industry Comovement with Aggregates, Model vs. Data

	Data			Model		
	Employment	Output	**Difference**	Employment	Output	**Difference**
1951-2012	0.77	0.62	**-0.15**	0.83	0.58	**-0.25**
1951-1983	0.78	0.67	**-0.11**	0.83	0.66	**-0.17**
1984-2012	0.77	0.53	**-0.24**	0.82	0.50	**-0.32**
Difference	**-0.01**	**-0.14**	**-0.13**	**-0.01**	**-0.16**	**-0.15**

Employment and output correlations in the model and in the data are both weighted by average sector shares of employment and output, respectively. The underlying data has been logged and filtered with an HP filter with parameter 6.25.

Table 5: Average Employment Comovement in Model with Counterfactual Linkages

	Model (Baseline)			Model (No Inv. Links)			Model (No IO Links)			Model (No Inv Adj)		
	Emp.	Output	**Diff.**	Emp.	Output	**Diff.**	Emp.	Output	**Diff.**	Emp.	Output	**Diff.**
1951-1983	0.69	0.39	**-0.30**	0.50	0.30	**-0.20**	0.22	0.33	**0.11**	0.96	0.41	**-0.55**
1984-2012	0.66	0.19	**-0.47**	0.31	0.11	**-0.20**	0.19	0.17	**-0.02**	0.95	0.21	**-0.74**
Difference	**-0.03**	**-0.20**	**-0.17**	**-0.19**	**-0.19**	**0.00**	**-0.03**	**-0.16**	**-0.13**	**-0.01**	**-0.20**	**-0.19**

Table 6: Average Pairwise Investment Comovement, Model vs. Data

	Data	Model	Model (No Inv Adj)
1951-2012	0.31	0.23	0.22
1951-1983	0.33	0.30	0.25
1984-2012	0.34	0.17	0.19
Difference	**0.01**	**-0.13**	**-0.06**

Investment correlations in the model and in the data are weighted by average nominal shares of investment in each sector. The underlying data has been logged and filtered with an HP filter with parameter 6.25.

Table 7: Average Employment Comovement in Model, Changing Linkages Over Time

	Model (Baseline)			Model (Changing Parm.)		
	Emp.	Output	**Diff.**	Emp.	Output	**Diff.**
1951-1983	0.69	0.39	**-0.30**	0.62	0.37	**-0.25**
1984-2012	0.66	0.19	**-0.47**	0.56	0.19	**-0.37**
Difference	**-0.03**	**-0.20**	**-0.17**	**-0.06**	**-0.18**	**-0.12**

Table 8: Average Employment Comovement in Model, With and Without Heterogeneity in TFP Comovement

	Model (Baseline)			Model (No TFP Het.)		
	Emp.	Output	**Diff.**	Emp.	Output	**Diff.**
1951-1983	0.69	0.39	**-0.30**	0.66	0.36	**-0.30**
1984-2012	0.66	0.19	**-0.47**	0.57	0.19	**-0.38**
Difference	**-0.03**	**-0.20**	**-0.17**	**-0.09**	**-0.17**	**-0.08**

Table 9: Average TFP Comovement Changes for Investment Producing Sectors and All Other Sectors

	Among Inv. Producers	Betw. Inv. Producers and Oth.	Among Oth.
1951-1983	0.14	0.32	0.28
1984-2012	0.04	0.15	0.13
Difference	**-0.10**	**-0.17**	**-0.15**

Average TFP comovement is weighted by average sector shares of aggregate nominal value added for the entire sample period, 1951-2012. Results are robust to alternative weighting schemes.

Table 10: Decomposition of Aggregate GDP volatility into Comovement and Within Sector Terms

	Data			Model			Model (Chang. Parm)		
	Pre-1984	Post-1984	**Diff**	Pre-1984	Post-1984	**Diff**	Pre-1984	Post-1984	**Diff**
Agg. Variance	0.42	0.23	**-0.19**	0.44	0.21	**-0.23**	0.36	0.18	**-0.18**
Within Sector Only	0.35	0.27	**-0.08**	0.35	0.27	**-0.08**	0.30	0.23	**-0.07**
Comovement Only	0.37	0.26	**-0.11**	0.39	0.23	**-0.16**	0.32	0.21	**-0.11**

Actual variances are figures in table multiplied by 10^{-3}. For all results, shares of industry output in the aggregate are held fixed at their average levels. Levels of within and comovement contributions to variance are less than the actual levels because they are constructed via the average of counterfactual exercises. Totals may not sum exactly due to rounding.

Table 11: Labor Market Correlations and Relative Variances, Pre- and Post- 1984

	Output, Lab. Prod. Corr.	Var. of Emp. / Var. of Output	Output, Emp. Corr.
1951-1983	0.64	0.59	0.81
1984-2012	0.27	1.03	0.83

Data is from BEA Industry Database. Labor productivity is defined as output divided by employment. All series have been logged and detrended using an HP filter with parameter 6.25. Employment data has been adjusted for discontinuities betweeen 1997-1998. See Appendix A for details.

Table 12: Decomposition of Ratio of Variances in Employment and Output into Within Sector and Covariance Terms

	Baseline Decomposition		Fixed Sector Shares	
	1951-1983	1984-2012	1951-1983	1984-2012
$\sigma^2_{et}/\sigma^2_{yt}$	0.57	1.01	0.60	0.93
Within Sector	0.50	0.45	0.48	0.45
Relative Covariance	0.60	1.25	0.64	1.14
Within Wgt.	0.25	0.29	0.22	0.31

Data is from BEA Industry Database. Labor productivity is defined as output divided by employment. All series have been logged and detrended using an HP filter with parameter 6.25. Employment data has been adjusted for discontinuities between 1997-1998. See Appendix A for details.

Table 13: Decomposition of Model Results on Employment Volatility

	Baseline		Scaled Emp. Var.		Heterog. Change		Heterog. Change and Scaling	
	1951-1983	1984-2012	1951-1983	1984-2012	1951-1983	1984-2012	1951-1983	1984-2012
$\sigma^2_{et}/\sigma^2_{yt}$	0.40	0.48	0.60	0.71	0.40	0.64	0.60	0.97
Within Sector	0.34	0.28	0.50	0.42	0.34	0.32	0.50	0.48
Relative Cov.	0.42	0.58	0.63	0.87	0.42	0.82	0.63	1.23
Within Wgt.	0.23	0.35	0.23	0.35	0.23	0.35	0.23	0.35

Table 14: Ratio of Employment to Output Variances for Selected Sector Groups, Model and Data

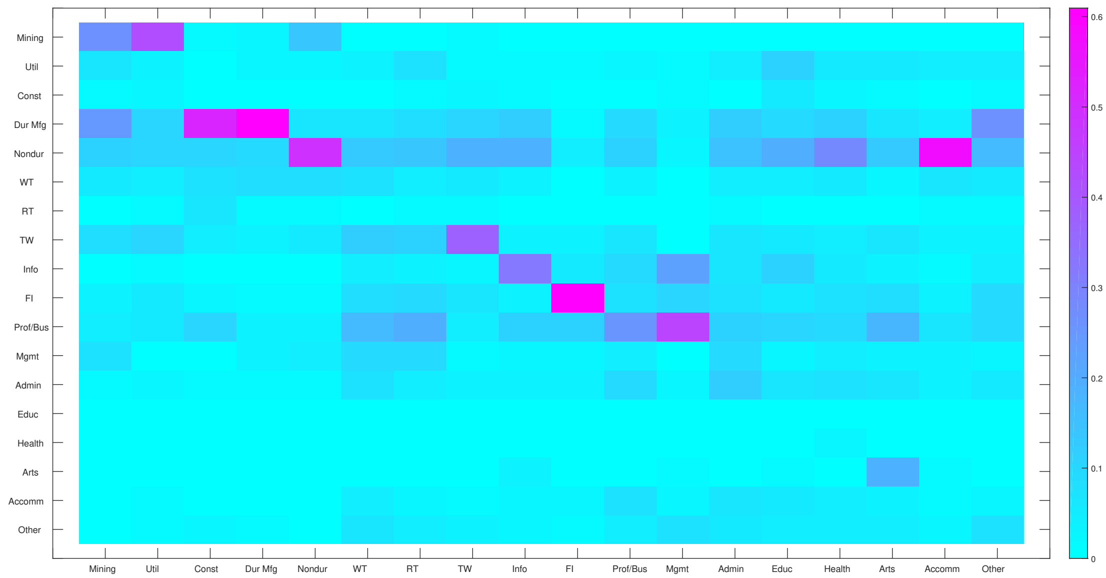
	Mining, Const., Non-dur Mfg, WT, Info, Prof/Sci, Adm/Waste		Remaining Sectors	
	1951-1983	1984-2012	1951-1983	1984-2012
Model $\sigma^2_{et}/\sigma^2_{yt}$	0.56	0.36	0.11	0.09
Data $\sigma^2_{et}/\sigma^2_{yt}$	0.72	0.92	0.34	0.30

Results are reported holding sector shares of aggregates fixed for consistency with model results. However, the same patterns are observed when sector shares are allowed to change.

Figure 1: Average Pairwise Industry Comovement over Time, 10 Year Rolling Windows

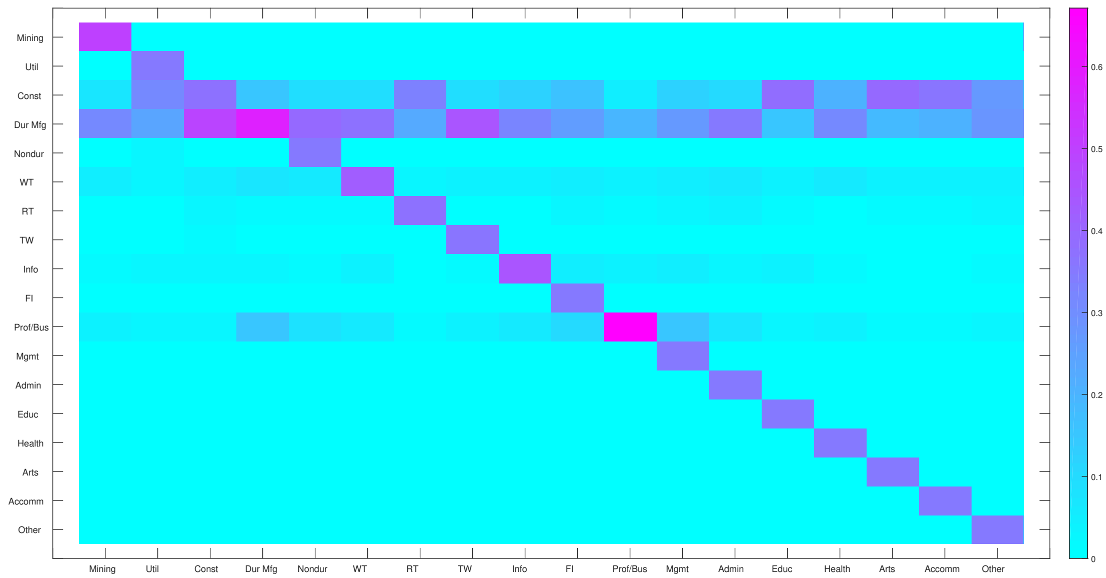
Figure 2: Average Aggregate Industry Comovement over Time, 10 Year Rolling Windows

Figure 3: Heat Map of Input-Output Matrix



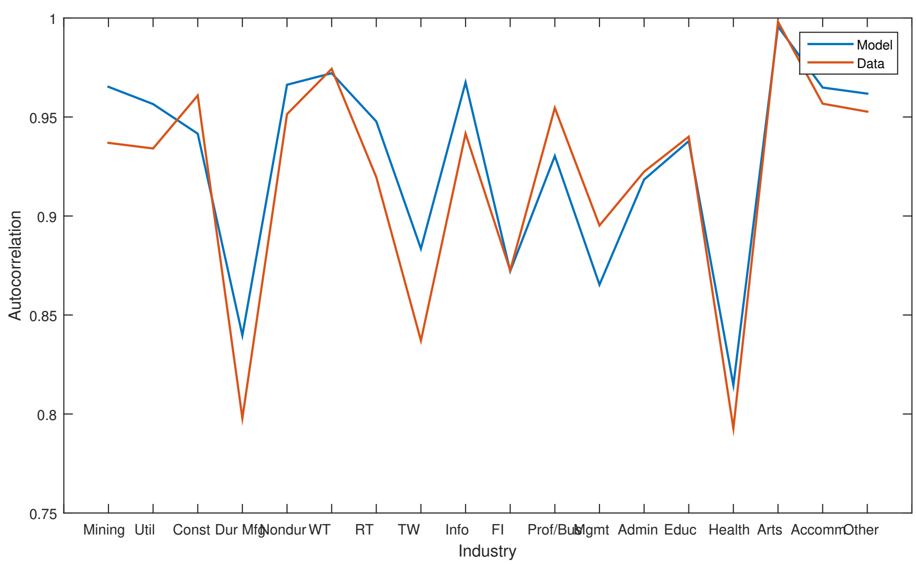
The input-output matrix Γ is computed from BEA data on Input-Output tables spanning back to 1948. Rows in the matrix represents industries providing intermediates; columns represent industries receiving those products. Each entry in the table is the total payments made by the receiving industry on final products from the delivering industry divided by the total intermediates expenditures of the receiving industry. Each column sums to 1.

Figure 4: Heat Map of Investment Linkages Matrix



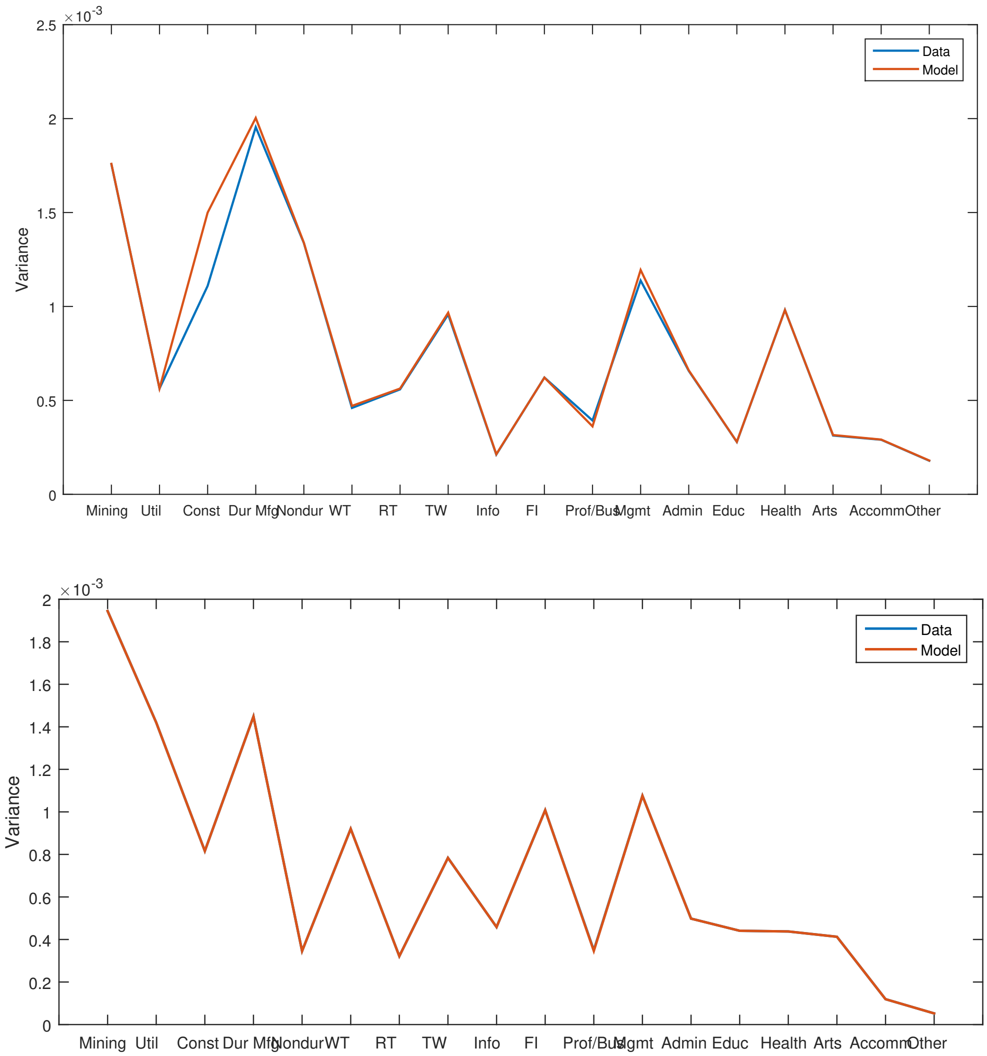
The investment linkages matrix Λ is computed from BEA data on capital flows in 1997. Rows in the matrix represents industries providing intermediates; columns represent industries receiving those products. Each entry in the table is the total capital payments made by the receiving industry on final products from the delivering industry divided by the total capital expenditures of the receiving industry. Each column sums to 1. An adjustment to the diagonal is made to be consistent with the existing literature - see discussion in the text.

Figure 5: First-Order Autocorrelation of Geometrically De-trended Value Added, Model vs. Data



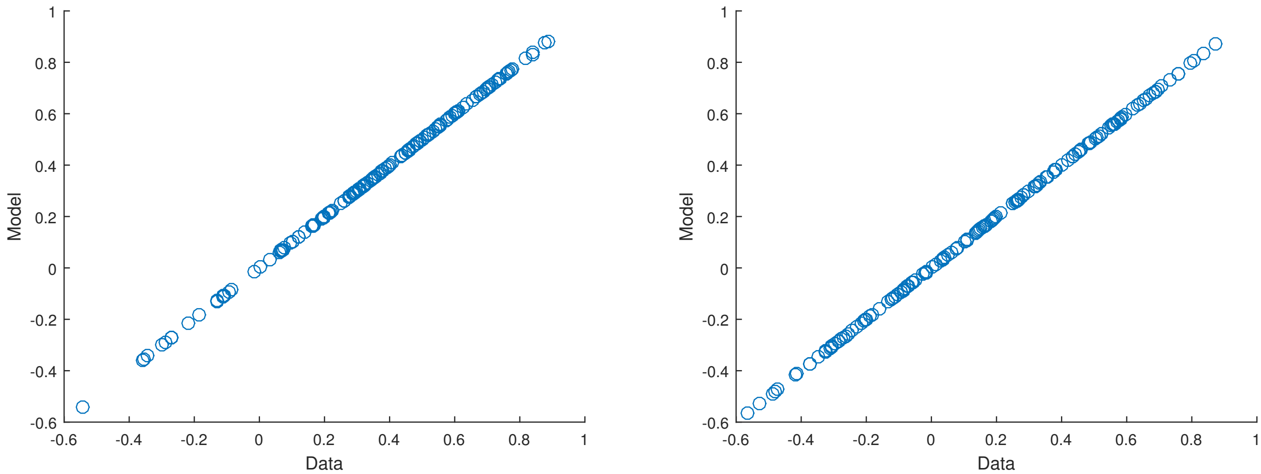
Autocorrelation coefficients are computed by removing a linear trend from the the log of value added and then estimating an AR(1) process via OLS. For both model and data, the estimate of autcorrelation is computed using all data in the sample.

Figure 6: Variance of Filtered Value Added Data Pre- and Post-1984, Model vs. Data



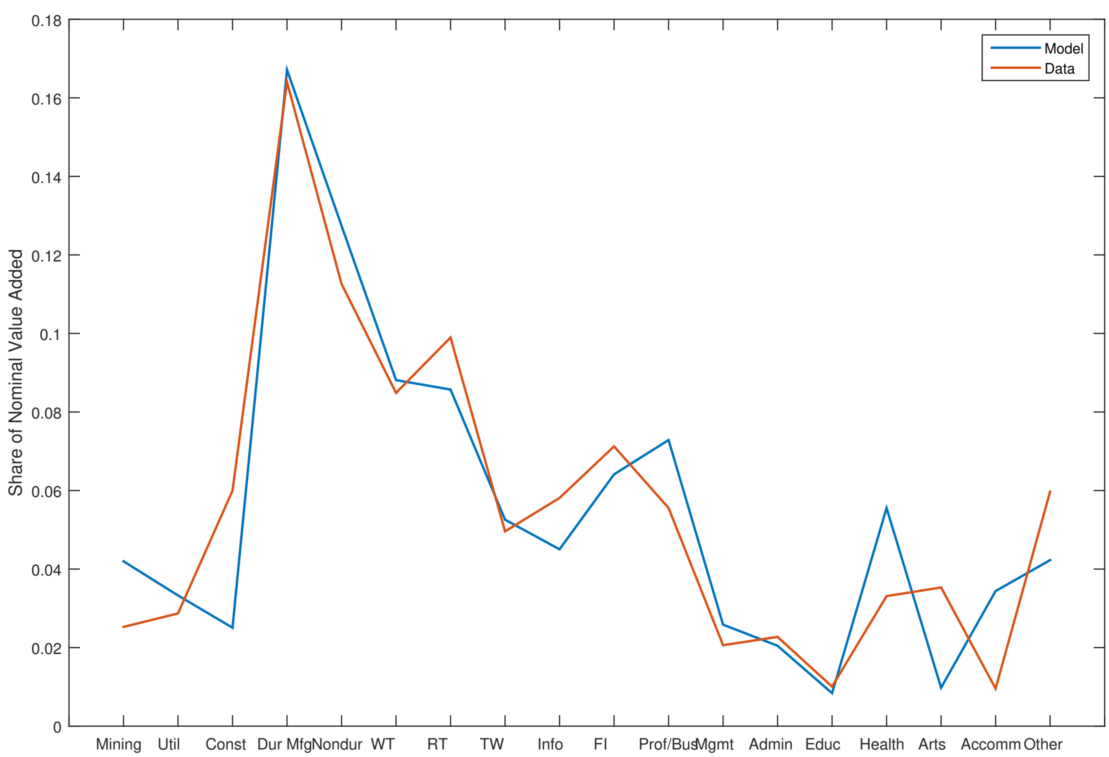
Value added data has been logged and detrended using an HP filter with parameter 6.25. The upper panel reports the variance of filtered value added data in each sector for the period 1948-1983. The lower panel reports the same moments for the period 1984-2012.

Figure 7: Sectoral Correlations in Value Added, Pre- and Post-1984, Model vs. Data



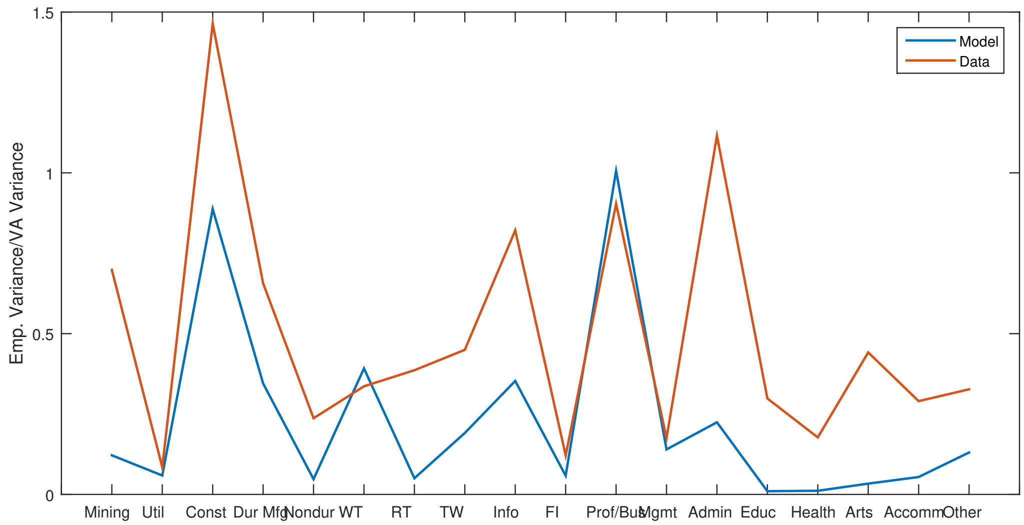
The above is a scatter plot of all pairwise value-added correlations in the model and in the data for 1948-1983 (left panel) and 1984-2012 (right panel). The closeness of fit of the model moments can be assessed by the extent to which all points lie on the 45 degree line.

Figure 8: Nominal Value Added Shares, Model vs. Data



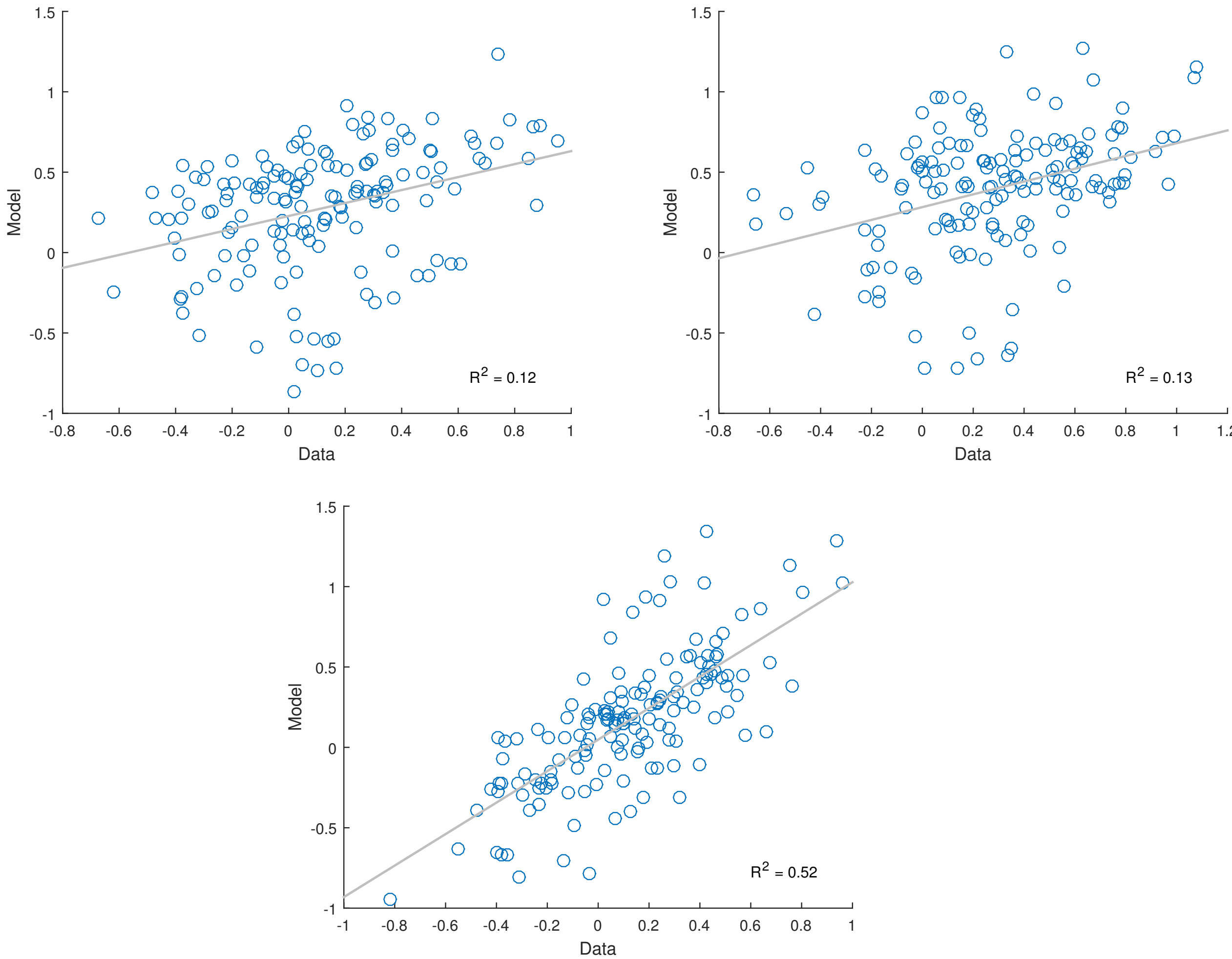
Nominal value added shares are computed for the entire sample, 1948-2012.

Figure 9: Ratio of Employment Variance to Value Added Variance, Model vs. Data



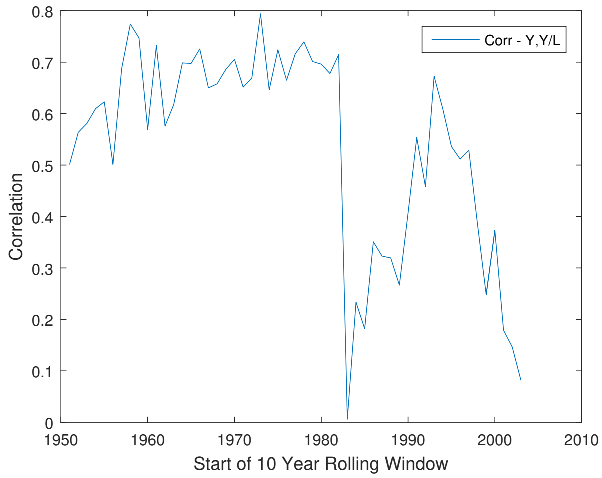
Value added and employment in the model and the data have been logged and detrended using an HP filter with parameter 6.25. The variance of employment and value added in each sector is computed for the entire sample period, 1948-2012.

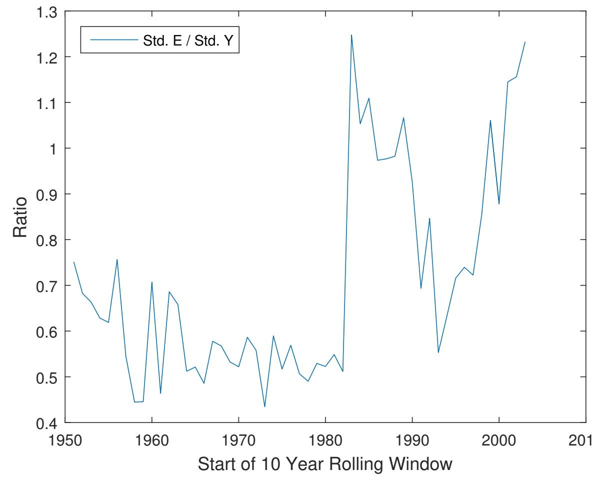
Figure 10: Pairwise Differences in Employment and Value Added Comovements, Pre-1984 and Post-1984, Model vs. Data



The above is a scatter plot of all pairwise employment correlations minus value-added correlations in the model and in the data for 1948-1983 (left panel), 1984-2012 (right panel), and then the difference in the two (bottom panel).

Figure 11: Labor Market Volatilities and Correlations Over Time, 10 Year Rolling Windows





The left panel shows the correlation coefficient between output and output per worker; the right panel shows the standard deviation of employment divided by the standard deviation of output. Data is from BEA Industry Database. Labor productivity is defined as output divided by employment. All series have been logged and detrended using an HP filter with parameter 6.25.

A Data, Measurement and Robustness of Comovement Statistics

A.1 Data and Measurement

A.1.1 Employment, Output and Investment Data

The industry data we use comes from the BEA's Industry Database, which has annual data on real and nominal value added by industry from 1947-2015 for 45 sectors and annual data on full-time and part-time employment by industry from 1948-2015 for 22 sectors. Data on value added has been published with consistent industry codes and is current with the latest revisions of the national accounts. On the other hand, employment data is compiled from a historical conversion of SIC data to NAICS data from 1947-1997, and then from the national accounts from 1998 to the present. As a result, there is the potential for a slight discontinuity in 1998, as the historical conversion file is only consistent with BEA revisions through 2006, and there is the possibility of slight differences in the coding definitions used to convert historical data and those used presently. For our results regarding employment volatility beginning in Section 6, especially heterogeneity in employment volatility, we make a correction for this discontinuity by assuming that the growth rate of employment in all sectors is identical to the aggregate growth rate between 1997 and 1998. This adjustment has virtually no impact on any aggregate statistics (including those on comovement), but is important for individual sectors.

As we only have data on 22 sectors for employment, we restrict our attention to these sectors. Once we remove government sectors, agriculture and real estate (because of the large owner-occupied housing component), this leaves 18 non-farm sectors. The list of these 18 sectors is given in Table A.1. An obvious downside with the BEA data as constructed here is the limited coverage of manufacturing sectors, with only two manufacturing sectors. That said, the lengthy time series on such a large number of services sectors is uncommon in industry data and a virtue of this particular dataset.

Table A.1: List of Sectors Studied in BEA Industry Data

Number	Sector
1	Mining
2	Utilities
3	Construction
4	Durable Manufacturing
5	Non-Durable Manufacturing
6	Wholesale Trade
7	Retail Trade
8	Transportation and Warehousing
9	Information
10	Finance and Insurance
11	Professional, Scientific and Technical Services
12	Management of Companies and Enterprises
13	Administrative and Waste Management Services
14	Educational Services
15	Health Care and Social Assistance
16	Arts, Entertainment and Recreation Services
17	Accommodation and Food Services
18	Other Services

In terms of other datasets with total economy coverage for sufficient time series length to study industry level business cycle fluctuations before and after the 1980s, there are only two other viable options - the 10 sector database published by the GGDC, and the World KLEMS dataset published by the World KLEMS initiative. As the 10 sector database offers strictly fewer sectors and no additional time periods, the BEA data is strictly preferable to this option. On the other hand, the World KLEMS data offers greater sector coverage (27 non-farm sectors), particularly for the manufacturing sector, though with significantly less detail in services sectors and with data only through the year 2010. The World KLEMS database also has consistent data on capital, and thus TFP by industry dating back to 1948. Despite these virtues, we prefer the BEA data for several reasons. The first is simply the time coverage. Significant revisions have been made to the national accounts since 2010, primarily to output and value added, and thus the additional 5 years of data provided in the BEA is of great value. Second, the sector definitions in World KLEMS follow ISIC codes, which do not allow for as clear a distinction between private and public sectors. For example, sizable components of the utilities, health services, education services, and post/telecommunications services sectors in World KLEMS include public provision of these services. The use of ISIC codes also requires additional care, as some industry data used to calibrate the model is coded according to NAICS codes, and thus there is a risk of inconsistency in the calibration and results for industries. Finally, preliminary analysis of World KLEMS data at business cycle frequencies has highlighted some idiosyncrasies that complicate business cycle analysis. Thus, we find the BEA data preferable for this study.

Investment data comes from the BEA Fixed Assets tables by industry, and comprises real and nominal investment by industry in private fixed assets. A further advantage of using BEA data is the direct compatibility with this investment data, as the World KLEMS database only has estimates of capital services and not actual investment.

A.1.2 Input-Output and Capital Flows Data

To calibrate the model, we draw from the Use Table from the BEA's Input-Output Database from 1948-2014 as well as the BEA's Capital Flows table for the year 1997. We compute input output matrices for each year of the data by dividing entries in the Use Table of that year by the sum of each column, converting dollar payments from one sector to another into cost shares. Similarly, we use the final uses column on private consumption, divided by its column sum in each year to compute cost shares for consumption.[26] Value added shares are computed for each industry in each year by dividing value added by gross output for each industry. Beginning in 1987, the Input Output tables also publish components of value added. We compute labor shares from this as the ratio of compensation to employees and total value added in each industry.

For our calibration, we also draw on the data from the BEA's Capital Flows Table for the year 1997. For our baseline, we compute the investment linkages as the entries of the capital flows table divided by column sums to generate investment cost shares. As an extension of our baseline results, we construct imputed investment linkage tables for the years 1948 to 2014 using the final use data in the annual Input-Output tables. In each of the annual Input-Output tables there is data on how the final goods produced in each industry are used, whether as intermediates, consumption goods, or investment goods. Using the data on investment final uses, we can observe how the share of total investment production across industries has varied over time and use this to impute changes in the investment matrix over time. The approximate relationship between the share of total investment produced and the investment linkage tables can be written as follows:

$$\frac{I^P_{jt}}{I_t} = \sum_{i=1}^{N} \frac{I^U_{it}}{I_t} \frac{I^U_{jit}}{I^U_{it}} = \sum_{i=1}^{N} \frac{I^U_{it}}{I_t} \theta_{ijt}$$

where I^P_{jt} is the nominal value of the investment good produced by industry j in year t, I_t is the total nominal value of investment in year t, I^U_{it} is the total nominal value of investment goods received by industry i at time t, I^U_{jit} is the total nominal value of investment goods received by industry i from industry j at time t, and θ_{ijt} is the typical entry of the investment matrix Θ at time t. This

[26] In future revisions, we plan on adding in residential investment expenditures to these cost shares.

relationship is only approximate because the total investment accounted for in the input-output table includes some investment that is not counted in the capital flows data. For example, brokers' commissions on real estate sales are not counted in the capital flows data, but are counted in the input-output table investment final uses. For a greater discussion of these small differences, see Meade et al. (2003).

To obtain imputations of the entries of the capital matrix at each date t, θ_{ijt}, requires an expansion of the above decomposition and several assumptions. We expand the above decomposition as follows:

$$\frac{I_{jt}^P}{I_t} = \sum_{i=1}^{N} \frac{V_t}{I_t} \frac{V_{it}}{V_t} \frac{I_{it}^U}{V_{it}} \theta_{ijt}$$

where V_{it} is nominal value added in sector i at time t, and V_t is aggregate value added at time t. We use annual data on the total shares of investment produced, $\frac{I_{jt}^P}{I_t}$, and the shares of nominal value added, $\frac{V_{it}}{V_t}$, and assume that the ratio of value added shares and investment used shares, $\frac{I_{it}^U}{I_t} / \frac{V_{it}}{V_t}$ is constant over time, and use data from the 1997 capital flows data for this value. The final assumption we make is that the entries in the investment matrix each year can be written as:

$$\theta_{ijt} = \frac{\omega_{jt}\theta_{ij,1997}}{\sum_{k=1}^{N} \omega_{kt}\theta_{ik,1997}}$$

Thus, to solve for the investment matrix entries of each year amounts to solving for a set of scaling factors, ω_{jt}. This implicitly assumes that changes in the investment matrix are roughly proportional to the matrix observed in 1997, and rules out new adoption of investment products from other sectors.[27] We solve for these entries to generate a time series of entries on the investment matrix θ_{ijt}.

A.2 Robustness of Comovement Statistics

As discussed in Section 2, there are a number of possible ways to weight individual correlations between sectors or with the aggregate to obtain an average measure of comovement. In Table 1, we presented average comovement statistics for employment and output where correlations were weighted by sector size, i.e. for employment, $\mu_{it}^e = \frac{\bar{E}_{it}}{E_t}$. In this section, we show that the patterns of higher average comovement in employment and greater declines in comovement in output are also visible when we compute an unweighted average of correlations ($\mu_{it}^y = 1$) as well as a weighted average using both sector sizes and sector volatilities ($\mu_{it}^e = \frac{\bar{E}_{it}}{E_t} \frac{\sigma_{it}^e}{\sigma_t^e}$). The latter weighting scheme allows for a closer connection to a decomposition of aggregate volatility, which will depend on

[27]The scaling is only roughly proportional, since the scaling factors are normalized by the sum of the product of the scale factors and the investment matrix entries.

both the correlation between sectors, as well as their volatility.[28] We also report the comovement statistics for our baseline weighting scheme where we allow the weights to change over time.

Tables A.2, A.3 and A.4 report the unweighted average, weighted by size and volatility average, and the time-varying size weighted average of both pairwise and aggregate correlations in employment and output. We observe that while the actual levels of comovement vary mildly based on the weighting scheme and the time-varying nature of the weights, our observations in the body of the paper are robust to these alternate weights - employment comovement is bigger than output comovement and has not declined nearly as much as output comovement.

Table A.2: Cyclical Industry Comovement in Employment and Output, Unweighted

	Average Pairwise Comovement, $\bar{\rho}_{y,t}$			Average Aggregate Comovement, $\bar{\rho}^a_{y,t}$		
	Employment	Output	**Difference**	Employment	Output	**Difference**
1951-2012	0.44	0.28	**-0.16****	0.67	0.54	**-0.13****
1951-1983	0.46	0.35	**-0.11***	0.68	0.60	**-0.08***
1984-2012	0.45	0.17	**-0.29****	0.67	0.45	**-0.22****
Difference	**-0.01**	**-0.18****	**-0.17***	**-0.01**	**-0.15****	**-0.14****

** indicates significance at the 5% level, * indicates significance at the 10% level. Statistical significance is determined by confidence intervals computed via block bootstrapping. Significance is robust to varying the size of the window in the block bootstrap.

Table A.3: Cyclical Industry Comovement in Employment and Output, Share and Standard Deviation Weighted

	Average Pairwise Comovement, $\bar{\rho}_{y,t}$			Average Aggregate Comovement, $\bar{\rho}^a_{y,t}$		
	Employment	Output	**Difference**	Employment	Output	**Difference**
1951-2012	0.65	0.37	**-0.28****	0.87	0.69	**-0.18****
1951-1983	0.66	0.43	**-0.23****	0.87	0.73	**-0.14****
1984-2012	0.67	0.26	**-0.41****	0.89	0.61	**-0.28****
Difference	**0.01**	**-0.17****	**-0.18****	**0.02**	**-0.12****	**-0.14****

** indicates significance at the 5% level. Statistical significance is determined by confidence intervals computed via block bootstrapping. Significance is robust to varying the size of the window in the block bootstrap.

[28]Were we to allow weights on the averages to change over time, using standard deviation weights and sector size weights would be effectively constructing an average scaled covariance in employment and output.

Table A.4: Cyclical Industry Comovement in Employment and Output, Time-Varying Share Weights

	Average Pairwise Comovement, $\bar{\rho}_{y,t}$			Average Aggregate Comovement, $\bar{\rho}^{a}_{y,t}$		
	Employment	Output	**Difference**	Employment	Output	**Difference**
1951-2012	0.57	0.33	**-0.24****	0.77	0.62	**-0.15****
1951-1983	0.61	0.45	**-0.16****	0.80	0.71	**-0.09****
1984-2012	0.52	0.18	**-0.34****	0.74	0.48	**-0.28****
Difference	**-0.09**	**-0.27****	**-0.18****	**-0.06**	**-0.23****	**-0.17****

** indicates significance at the 5% level, * indicates significance at the 10% level. Statistical significance is determined by confidence intervals computed via block bootstrapping. Significance is robust to varying the size of the window in the block bootstrap.

Table A.5 also reports how the investment comovement statistics vary when we use time-varying weights, no weights or weights of sector shares multiplied by standard deviations. We see investment comovements generally don't decline in each of these alternative weighting schemes, however the unweighted averages of investment comovement do decline somewhat significantly. As they do not decline as much as declines in output comovements, we still find that investment comovement has become greater relative to output comovement over time, however the effect is weaker in this one case.

Table A.5: Cyclical Industry Comovement in Investment, Alternative Weights

	Average Pairwise Comovement, $\bar{\rho}_{y,t}$			Average Aggregate Comovement, $\bar{\rho}^{a}_{y,t}$		
	No Wgt	Share/Std. Dev	Varying Shares	No Wgt	Share/Std. Dev	Varying Shares
1951-2012	0.29	0.33	0.31	0.53	0.62	0.60
1951-1983	0.35	0.35	0.35	0.57	0.64	0.64
1984-2012	0.25	0.36	0.33	0.52	0.65	0.62
Difference	**-0.10**	**0.01**	**-0.02**	**-0.05**	**0.01**	**-0.02**

** indicates significance at the 5% level, * indicates significance at the 10% level. Statistical significance is determined by confidence intervals computed via block bootstrapping. Significance is robust to varying the size of the window in the block bootstrap.

B Equilibrium Conditions, Proofs and Derivations

B.1 Equilibrium Conditions for Social Planner Solution

The social planner's problem for this economy is given by

$$max_{C_{jt},L_{jt},M_{ijt},I_{ijt},K_{jt+1}} \sum_{t=0}^{\infty} \beta^t \mathbb{E}_t \left[ln(\prod_{j=1}^{N} C_{jt}^{\xi_j}) - \psi \frac{1}{1+\varepsilon} \left(\sum_{j=1}^{N} L_{jt} \right)^{1+\varepsilon} \right]$$

subject to

$$\begin{aligned} Y_{jt} &= C_{jt} + \sum_{i=1}^{N} M_{ijt} + \sum_{i=1}^{N} I_{ijt} \\ Y_{jt} &= A_{jt} \left(K_{jt}^{\alpha_j} L_{jt}^{1-\alpha_j} \right)^{\theta_j} \left(\prod_{i=1}^{N} M_{jit}^{\gamma_{ij}} \right)^{1-\theta_j} \\ K_{jt+1} &= (1-\delta) K_{jt} + \prod_{i=1}^{N} I_{jit}^{\lambda_{ij}} \\ Z_{jt} &= \prod_{i=1}^{N} I_{jit}^{\lambda_{ij}} \end{aligned}$$

Let μ_{jt} represent the multiplier associated with the resource constraint and ζ_{jt} represent the multiplier associated with the capital accumulation equation in sector j. This yields the following set of first order conditions from the planner's problem, which combined with the above constraints, constitute the set of equilibrium equations for this economy.

$$\begin{aligned} \mu_{jt} \theta_j (1-\alpha_j) \frac{Y_{jt}}{L_{jt}} &= \psi \left(\sum_{j=1}^{N} L_{jt} \right)^{\varepsilon} \\ \mu_{jt} &= \frac{\xi_j}{C_{jt}} \\ \zeta_{jt} \lambda_{ij} \frac{Z_{jt}}{I_{jit}} &= \mu_{it} \\ \mu_{it} &= \mu_{jt} \gamma_{ij} (1-\theta_j) \frac{Y_{jt}}{M_{jit}} \\ \zeta_{jt} &= \beta \mathbb{E} \left[\zeta_{jt+1}(1-\delta) + \mu_{jt+1} \theta_j \alpha_j \frac{Y_{jt+1}}{K_{jt+1}} \right] \end{aligned}$$

B.2 Proof of Production Linkages Comovement Lemma

Lemma Using the first order conditions of the planner's problem, gross output in sector j can be rewritten in value added form, with endogenous TFP $\tilde{A}_{jt}$:

$$Y_{jt} = \tilde{A}_{jt} K_{jt}^{\alpha_j} L_{jt}^{1-\alpha_j}$$

where $\tilde{A}_{jt} = \left(A_{jt}(1-\theta_j)^{1-\theta_j} \Pi_{i=1}^{N} \left(\gamma_{ij} \frac{\mu_{jt}}{\mu_{it}} \right)^{\gamma_{ij}(1-\theta_j)} \right)^{1/\theta_j}$ and μ_{jt} is the shadow value of the final good in sector i.

Proof Using the first order conditions for intermediates in production, we have that $M_{jit} = \frac{\mu_{jt}}{\mu_{it}} \gamma_{ij}(1-\theta_j) Y_{jt}$. Plugging this into the production function yields:

$$\begin{aligned}
Y_{jt} &= A_{jt} \left(K_{jt}^{\alpha_j} L_{jt}^{1-\alpha_j} \right)^{\theta_j} \left(\prod_{i=1}^{N} \left(\frac{\mu_{jt}}{\mu_{it}} \gamma_{ij}(1-\theta_j) Y_{jt} \right)^{\gamma_{ij}} \right)^{1-\theta_j} \\
Y_{jt} &= A_{jt} \left(K_{jt}^{\alpha_j} L_{jt}^{1-\alpha_j} \right)^{\theta_j} \left((1-\theta_j) \prod_{i=1}^{N} \left(\frac{\mu_{jt}}{\mu_{it}} \gamma_{ij} \right)^{\gamma_{ij}} \right)^{1-\theta_j} \left(Y_{jt} \right)^{1-\theta_j} \\
Y_{jt}^{\theta_j} &= A_{jt} \left((1-\theta_j) \prod_{i=1}^{N} \left(\frac{\mu_{jt}}{\mu_{it}} \gamma_{ij} \right)^{\gamma_{ij}} \right)^{1-\theta_j} \left(K_{jt}^{\alpha_j} L_{jt}^{1-\alpha_j} \right)^{\theta_j} \\
Y_{jt} &= \tilde{A}_{jt} K_{jt}^{\alpha_j} L_{jt}^{1-\alpha_j}
\end{aligned}$$

where $\tilde{A}_{jt} = \left(A_{jt}(1-\theta_j)^{1-\theta_j} \Pi_{i=1}^{N} \left(\gamma_{ij} \frac{\mu_{jt}}{\mu_{it}} \right)^{\gamma_{ij}(1-\theta_j)} \right)^{1/\theta_j}$

B.3 Proof of Investment Linkages Comovement Theorem

Theorem If the production technology for investment is identical across sectors ($\lambda_{ij} = \lambda_i$), then consumption to output ratios in each sector will be perfectly correlated as long as they are not constant. This implies that employment will perfectly correlated across all sectors without constant consumption to output ratios if the following condition holds in each sector:

$$\frac{\theta_j(1-\alpha_j)b_j}{\sum \theta_i(1-\alpha_i)b_i} > \frac{\varepsilon}{1+\varepsilon} \frac{L_{jt}}{L_t}$$

where b_j is a function of model parameters governing the responsiveness of the consumption to output ratio to changes in the value of investment, the jth element of the vector $\vec{b} = (I-\Phi)^{-1}\lambda$, where $\lambda = [\lambda_1, \lambda_2, \ldots \lambda_N]$, and $(I-\Phi)^{-1}$ is the Leontief matrix for this economy, where Φ is a matrix with typical element $\phi_{ij} = (1-\theta_j)\gamma_{ij}$.

Proof We can rearrange the first order condition for investment to be:

$$I_{jit} = \frac{\zeta_{jt}\lambda_{ij}Z_{jt}}{\mu_{it}}$$

Plugging this back in to the definition of Z_{jt}, we get:

$$\begin{aligned}
Z_{jt} &= \prod_{i=1}^{N}\left(\frac{\zeta_{jt}\lambda_{ij}Z_{jt}}{\mu_{it}}\right)^{\lambda_{ij}} \\
Z_{jt} &= (\zeta_{jt}Z_{jt})\prod_{i=1}^{N}\left(\frac{\lambda_{ij}}{\mu_{it}}\right)^{\lambda_{ij}} \\
\zeta_{jt} &= \prod_{i=1}^{N}\left(\frac{\mu_{it}}{\lambda_{ij}}\right)^{\lambda_{ij}}
\end{aligned}$$

If $\lambda_{ij} = \lambda_i$, that is, the investment linkages technology is identical across all sectors, then $\zeta_{jt} = \zeta_t$, meaning the shadow value of capital will be equated across all sectors.

Using the first order conditions for intermediates, and the first order condition for consumption, you can rewrite the resource constraint as:

$$\begin{aligned}
Y_{jt} &= C_{jt} + \sum_{i=1}^{N}\left(\frac{\phi^M_{ji}\mu_{it}Y_{it}}{\mu_{jt}}\right) + \sum_{i=1}^{N}\left(\frac{\zeta_{it}\lambda_{ji}Z_{it}}{\mu_{jt}}\right) \\
Y_{jt} &= \frac{\xi_j}{\mu_{jt}} + \frac{1}{\mu_{jt}}\sum_{i=1}^{N}\left(\phi^M_{ji}\mu_{it}Y_{it}\right) + \frac{1}{\mu_{jt}}\sum_{i=1}^{N}\left(\zeta_{it}\lambda_{ji}Z_{it}\right)
\end{aligned}$$

where $\phi^M_{ji} = (1-\theta_i)\gamma_{ji}$. If $\lambda_{ji} = \lambda_i$, then this reduces to:

$$\begin{aligned}
Y_{jt} &= \frac{\xi_j}{\mu_{jt}} + \frac{1}{\mu_{jt}}\sum_{i=1}^{N}\left(\phi^M_{ji}\mu_{it}Y_{it}\right) + \frac{1}{\mu_{jt}}\zeta_t\lambda_j\sum_{i=1}^{N}(Z_{it}) \\
\mu_{jt}Y_{jt} &= \xi_j + \sum_{i=1}^{N}\left(\phi^M_{ji}\mu_{it}Y_{it}\right) + \zeta_t\lambda_j\sum_{i=1}^{N}(Z_{it})
\end{aligned}$$

Stacking these equations and rewriting in matrix form, you get

$$\vec{\mu_t Y_t} = \underbrace{\begin{bmatrix} \xi_1 \\ \xi_2 \\ \vdots \\ \vdots \\ \xi_3 \end{bmatrix}}_{\xi} + \underbrace{\begin{bmatrix} \phi_{11}^M & \phi_{12}^M & \cdots & \phi_{1N}^M \\ \phi_{21}^M & \phi_{22}^M & & \vdots \\ \vdots & & \ddots & \vdots \\ \phi_{N1}^M & \cdots & \cdots & \phi_{NN}^M \end{bmatrix}}_{\Phi} \vec{\mu_t Y_t} + \zeta_t \sum_{i=1}^{N} Z_{it} \underbrace{\begin{bmatrix} \lambda_1 \\ \lambda_2 \\ \vdots \\ \vdots \\ \lambda_N \end{bmatrix}}_{\lambda}$$

$$\vec{\mu_t Y_t} = \xi + \Phi \vec{\mu_t Y_t} + \lambda \zeta_t \sum_{i=1}^{N} Z_{it}$$

$$\vec{\mu_t Y_t} = (I - \Phi)^{-1}(\xi + \lambda \zeta_t \sum_{i=1}^{N} Z_{it})$$

Thus, $\mu_{jt} Y_{jt}$ in each sector is a linear transformation of the sole stochastic term, $\tilde{Z}_t = \zeta_t \sum_{i=1}^{N} Z_{it}$. We can write this as $\mu_{jt} Y_{jt} = a_j + b_j \tilde{Z}_t$, where $\vec{a} = [a_1, a_2, ..., a_N] = (I - \Phi)^{-1}\xi$ and $\vec{b} = [b_1, b_2, ..., b_N] = (I - \Phi)^{-1}\lambda$. Because the Leontief Matrix, $(I - \Phi)^{-1}$, is an M-matrix, and all other constants are known to be non-negative, this implies that $a_j \geq 0$ and $b_j \geq 0$. Given that μ_{jt} is proportional to $1/C_{jt}$, this implies that the consumption to output ratio in each sector will be perfectly correlated provided that $b_j > 0$, or in other words, provided that the consumption to output ratio is not constant.

Turning to the first order conditions for employment, we have:

$$\mu_{jt} \theta_j (1 - \alpha_j) \frac{Y_{jt}}{L_{jt}} = \psi \left(\sum_{j=1}^{N} L_{jt} \right)^{\varepsilon}$$

If $\varepsilon = 0$, then $L_{jt} = \theta_j (1 - \alpha_j)(a_j + b_j \tilde{Z}_t)$. Thus, provided $b_j > 0$, all employment is a function of the single variable $\tilde{Z}_t$ and thus perfectly correlated. Otherwise, employment is a constant, and has zero correlation with employment in all other sectors.

If $\varepsilon > 0$, then all employment will be perfectly correlated for a subset of parameter values. Given the presence of only one stochastic driving force for employment, a sufficient condition for employment to be correlated is that the derivative of employment in each sector, L_{jt}, with respect to fluctuations in $\tilde{Z}_t$ is the same in each sector. In particular, we derive the condition necessary for this derivative to be positive.

Rearranging the first order condition for labor above, we get

$$\theta_j (1 - \alpha_j)(a_j + b_j \tilde{Z}_t) = \psi L_{jt} \left(\sum_{i=1}^{N} L_{jt} \right)^{\varepsilon}.$$

Given that marginal products of labor will be equated across sectors, we know that employment in sector i can be as a function of employment in sector j and $\tilde{Z}_t$ as follows:

$$L_{it} = \frac{\theta_i(1-\alpha_i)(a_i+b_i\tilde{Z}_t)}{\theta_j(1-\alpha_j)(a_j+b_j\tilde{Z}_t)}L_{jt}$$

Using this to solve for $\sum_{i=1}^N L_{jt}$, the first order condition for employment in sector j becomes:

$$\begin{aligned}
\theta_j(1-\alpha_j)(a_j+b_j\tilde{Z}_t) &= \psi L_{jt}\left(\sum_{i=1}^N \frac{\theta_i(1-\alpha_i)(a_i+b_i\tilde{Z}_t)}{\theta_j(1-\alpha_j)(a_j+b_j\tilde{Z}_t)}L_{jt}\right)^{\varepsilon} \\
\left[\theta_j(1-\alpha_j)(a_j+b_j\tilde{Z}_t)\right]^{1+\varepsilon} &= \psi L_{jt}^{1+\varepsilon}\left(\sum_{i=1}^N \theta_i(1-\alpha_i)(a_i+b_i\tilde{Z}_t)\right)^{\varepsilon} \\
L_{jt} &= \frac{\theta_j(1-\alpha_j)(a_j+b_j\tilde{Z}_t)}{\psi^{\frac{1}{1+\varepsilon}}\left[\sum_{i=1}^N \theta_i(1-\alpha_i)(a_i+b_i\tilde{Z}_t)\right]^{\frac{\varepsilon}{1+\varepsilon}}}
\end{aligned}$$

With this expression, we can solve for the derivative of L_{jt} with respect to $\tilde{Z}_t$ and get:

$$\begin{aligned}
\frac{dL_{jt}}{d\tilde{Z}_t} &= \frac{\theta_j(1-\alpha_j)b_j}{\psi^{\frac{1}{1+\varepsilon}}\left[\sum_{i=1}^N \theta_i(1-\alpha_i)(a_i+b_i\tilde{Z}_t)\right]^{\frac{\varepsilon}{1+\varepsilon}}} - \frac{\varepsilon}{1+\varepsilon}\frac{\theta_j(1-\alpha_j)(a_j+b_j\tilde{Z}_t)\sum_{i=1}^N \theta_i(1-\alpha_i)b_i}{\psi^{\frac{1}{1+\varepsilon}}\left[\sum_{i=1}^N \theta_i(1-\alpha_i)(a_i+b_i\tilde{Z}_t)\right]^{\frac{\varepsilon}{1+\varepsilon}+1}} \\
&= \frac{\theta_j(1-\alpha_j)}{\psi^{\frac{1}{1+\varepsilon}}\left[\sum_{i=1}^N \theta_i(1-\alpha_i)(a_i+b_i\tilde{Z}_t)\right]}\left[b_j - \frac{\varepsilon}{1+\varepsilon}\frac{(a_j+b_j\tilde{Z}_t)\sum_{i=1}^N \theta_i(1-\alpha_i)b_i}{\left[\sum_{i=1}^N \theta_i(1-\alpha_i)(a_i+b_i\tilde{Z}_t)\right]}\right]
\end{aligned}$$

Given that all parameters are positive here and $a_i+b_i\tilde{Z}_t > 0$ (by feasibility), this means that employment in each sector will increase in response to an increase in $\tilde{Z}_t$ if and only if

$$b_j > \frac{\varepsilon}{1+\varepsilon}\frac{(a_j+b_j\tilde{Z}_t)\sum_{i=1}^N \theta_i(1-\alpha_i)b_i}{\left[\sum_{i=1}^N \theta_i(1-\alpha_i)(a_i+b_i\tilde{Z}_t)\right]}$$

We arrange this condition to obtain

$$\begin{aligned}
b_j &> \frac{\varepsilon}{1+\varepsilon}\frac{\frac{\psi}{\theta_j(1-\alpha_i)}L_{jt}L_t^{\varepsilon}\sum_{i=1}^N \theta_i(1-\alpha_i)b_i}{\psi L_t^{1+\varepsilon}} \\
\frac{\theta_j(1-\alpha_i)b_j}{\sum_{i=1}^N \theta_i(1-\alpha_i)b_i} &> \frac{\varepsilon}{1+\varepsilon}\frac{L_{jt}}{L_t}
\end{aligned}$$

If this condition holds in every sector, then employment will be perfectly correlated. The left hand side effectively represents a notion of how responsive movements in labor in each sector should be in response to a change in the value of investment in the economy relative to the responsiveness of total employment, whereas the right hand side represents the share of total employment in each sector multiplied by $\frac{\varepsilon}{1+\varepsilon}$, which governs the strength of the reallocation motive from curvature in the disutility of labor. As long as this condition holds, it is optimal to increase employment in this sector when $\tilde{Z}_t$ increases instead of reallocating it to another sector where the returns might be higher.

B.4 Proof of Lemma Stating Output-Productivity Correlation as a Function of Relative Employment Volatility

Begin with the definition of correlation between some random variable x and logged labor productivity, where σ_z denotes the standard deviation of variable z:

$$\rho_{x,y-e} \equiv \frac{COV(x,y-e)}{\sigma_y \sigma_{y-e}}$$

Using the linearity properties of covariance and rearranging terms, we can write:

$$\begin{aligned} \frac{COV(x,y-e)}{\sigma_y \sigma_{y-e}} &= \frac{COV(x,y)-COV(x,e)}{\sigma_y \sigma_{y-e}} = \frac{COV(x,y)}{\sigma_y \sigma_{y-e}} - \frac{COV(x,e)}{\sigma_y \sigma_{y-e}} = \\ & \frac{\sigma_y}{\sigma_{y-e}}\rho_{x,y} - \frac{\sigma_e}{\sigma_{y-e}}\rho_{x,h} = \frac{\sigma_y}{\sigma_{y-e}}\left(\rho_{x,y} - \frac{\sigma_e}{\sigma_y}\rho_{x,e}\right) \end{aligned}$$

Then, given the linear properties of variance, we know that we can write σ_{y-h} as:

$$\sigma_{y-e} = \sqrt{\sigma_y^2 + \sigma_e^2 - 2COV(y,e)} = \sqrt{\sigma_y^2 + \sigma_e^2 - 2\sigma_y\sigma_e\rho_{y,e}} = \sigma_y\sqrt{1+\left(\frac{\sigma_e}{\sigma_y}\right)^2 - 2\left(\frac{\sigma_e}{\sigma_y}\right)\rho_{y,e}}$$

Combining this with the above expression, we get that:

$$\frac{\sigma_y}{\sigma_{y-e}}\left(\rho_{x,y} - \frac{\sigma_e}{\sigma_y}\rho_{x,he}\right) = \frac{\rho_{x,y} - \frac{\sigma_e}{\sigma_y}\rho_{x,e}}{\sqrt{1+\left(\frac{\sigma_e}{\sigma_y}\right)^2 - 2\left(\frac{\sigma_e}{\sigma_y}\right)\rho_{y,e}}} \equiv \rho_{x,y-e} \equiv f\left(\rho_{x,e}, \rho_{x,y}, \rho_{y,e}, \frac{\sigma_e}{\sigma_y}\right)$$

In the case where $x = y$, then this expression simplifies to

$$f\left(\rho_{y,e}, \rho_{y,y}, \rho_{y,e}, \frac{\sigma_e}{\sigma_y}\right) = g\left(\rho_{y,e}, \frac{\sigma_e}{\sigma_y}\right) = \frac{1 - \frac{\sigma_e}{\sigma_y}\rho_{y,e}}{\sqrt{1+\left(\frac{\sigma_e}{\sigma_y}\right)^2 - 2\left(\frac{\sigma_e}{\sigma_y}\right)\rho_{y,e}}}$$

Showing that g is weakly decreasing in $\frac{\sigma_e}{\sigma_y}$ is straightforward. Taking the partial derivative with respect to $\frac{\sigma_e}{\sigma_y}$, we get the following expressions:

$$
\begin{aligned}
\frac{\partial g\left(\rho_{y,e}, \frac{\sigma_e}{\sigma_y}\right)}{\partial \frac{\sigma_e}{\sigma_y}} &= -\frac{\rho_{y,e}}{\sqrt{1+\left(\frac{\sigma_e}{\sigma_y}\right)^2-2\left(\frac{\sigma_e}{\sigma_y}\right)\rho_{y,e}}}+\frac{\left(1-\frac{\sigma_e}{\sigma_y}\rho_{y,e}\right)\left(\rho_{y,e}-\frac{\sigma_e}{\sigma_y}\right)}{\left(1+\left(\frac{\sigma_e}{\sigma_y}\right)^2-2\left(\frac{\sigma_e}{\sigma_y}\right)\rho_{y,e}\right)^{3/2}} \\
&= \frac{-\rho_{y,e}\left(1+\left(\frac{\sigma_e}{\sigma_y}\right)^2-2\left(\frac{\sigma_e}{\sigma_y}\right)\rho_{y,e}\right)+\left(1-\frac{\sigma_e}{\sigma_y}\rho_{y,e}\right)\left(\rho_{y,e}-\frac{\sigma_e}{\sigma_y}\right)}{\left(1+\left(\frac{\sigma_e}{\sigma_y}\right)^2-2\left(\frac{\sigma_e}{\sigma_y}\right)\rho_{y,e}\right)^{3/2}} \\
&= \frac{\frac{\sigma_e}{\sigma_y}\left(\rho_{y,e}^2-1\right)}{\left(1+\left(\frac{\sigma_e}{\sigma_y}\right)^2-2\left(\frac{\sigma_e}{\sigma_y}\right)\rho_{y,h}\right)^{3/2}} = \frac{\frac{\sigma_e}{\sigma_y}\left(\rho_{y,e}^2-1\right)}{\sigma_{y-e}^3}
\end{aligned}
$$

Given that the denominator is positive by definition of the standard deviation, as is the relative volatility in the numerator, since $\mid \rho_{y,h} \mid \leq 1$ by definition of the correlation coefficient, f is weakly decreasing in $\frac{\sigma_h}{\sigma_y}$.

B.5 Derivation of Decomposition Methodology

In deriving this decomposition, we rely on the fact that aggregate output is derived via a Tornqvist index such that $\Delta ln(Y_t) = \sum_i \bar{w}_{it}\Delta ln(Y_{it})$, where Y_{it} is industry level output, and $\bar{w}_{it}$ is the two period average of the share of industry level output in nominal aggregate output. This contrasts with employment, whose aggregation is simply linear, $E_t = \sum_i E_{it}$.

The decomposition is an approximate decomposition, where the approximation comes from the assumption that $\bar{w}_{it} \approx w_i$ over the relevant time period. With this assumption, growth in aggregate output becomes $\Delta ln(Y_t) = \sum_i \bar{w}_i \Delta ln(y_{it})$, and aggregate output can thus be written as:

$$ln(Y_t) \approx \sum_i \bar{w}_i ln(Y_{it}) + C$$

Applying a linear filter like the HP filter removes the constant and gives the relationship between aggregate output and industry output in log deviations as follows (deviations denoted with a tilde):

$$ln(\tilde{Y}_t) \approx \sum_i \bar{w}_i ln(\tilde{Y}_{it})$$

Thus, using standard properties of variance, the variance of aggregate output can be written as:

$$\begin{aligned} Var(ln(\tilde{Y}_t)) &\approx \sum_i \bar{w}_i^2 Var(ln(\tilde{Y}_{it})) + 2\sum_{i<j} \bar{w}_i \bar{w}_j Cov(ln(\tilde{Y}_{it}), ln(\tilde{Y}_{jt})) \\ \sigma_{Yt} &\approx \sum_i w_{Yit}^2 \sigma_{Yit}^2 + 2\sum_{i<j} w_{Yit} w_{Yjt} \sigma_{Yit} \sigma_{Yjt} \rho_{Yijt} \end{aligned}$$

where the last step expresses the covariance as the product of standard deviations (σ_{Yit}) and the correlation between sectors i and j (ρ_{Yijt}) .

The derivation of the variance of aggregate employment follows similarly. Since employment aggregates linearly, however, to generate an additive decomposition in log deviations requires either an approximation of log deviations with percent deviations from trend, or a Taylor approximation of log aggregate employment. The latter approach yields the relationship, $ln(E_t) \approx ln(\bar{E}) + \sum \left(\frac{\bar{E}_i}{\bar{E}}\right)(ln(E_{it}) - ln(\bar{E}_i))$, where $\frac{\bar{E}_i}{\bar{E}}$ is the share of industry employment at the linearization point. When a linear filter is applied, again, the constant terms drop out, and we are left with

$$ln(\tilde{E}_t) \approx \sum \bar{w}_{ei} ln(\tilde{E}_{it})$$

where $\bar{w}_{ei} = \frac{\bar{E}_i}{\bar{E}}$. The variance of log deviations from aggregate employment is similarly:

$$\begin{aligned} Var(ln(\tilde{E}_t)) &\approx \sum_i \bar{w}_{ei}^2 Var(ln(\tilde{e}_{it})) + 2\sum_{i<j} Cov(ln(\tilde{e}_{it}), ln(\tilde{e}_{jt})) \\ \sigma_{Et} &\approx \sum_i w_{Eit}^2 \sigma_{Eit}^2 + 2\sum_{i<j} w_{Eit} w_{Ejt} \sigma_{Eit} \sigma_{Ejt} \rho_{Eijt} \end{aligned}$$

This decomposition assumes that the shares of employment and output are held constant over only the relevant window for which the variance is computed. Thus, if we compute the variance of output for the periods 1951-1983 and 1984-2012, the shares used are the average shares for 1951-1983 and 1984-2012, respectively. Similarly, for ten year rolling windows, the value of the shares for each window is the average over the shares during that 10 year span.

C Robustness Checks on Model Simulations

C.1 Robustness of Average Comovement Results to Alternative Weighting Schemes

Here we report our model results on comovement using alternative weighting schemes, where we weight either by both standard deviations and sector shares or do not weight comovements at all. Table C.1 shows the results when no weights are used and Table C.2 shows results when both sector shares and standard deviation weights are used. In both cases, the model is able to account for 75% of the widening gap between employment and output comovements, which is not quite the 100% of our baseline, but still quite large nonetheless.

Table C.1: Baseline Pairwise Comovement Results, Unweighted

	Data			Model		
	Employment	Output	**Difference**	Employment	Output	**Difference**
1951-2012	0.44	0.28	**-0.16**	0.59	0.26	**-0.33**
1951-1983	0.46	0.35	**-0.11**	0.62	0.35	**-0.27**
1984-2012	0.45	0.17	**-0.29**	0.56	0.17	**-0.39**
Difference	**-0.01**	**-0.18**	**-0.17**	**-0.06**	**-0.18**	**-0.12**

Table C.2: Baseline Pairwise Comovement Results, Weighted by Sector Sizes and Standard Deviations

	Data			Model		
	Employment	Output	**Difference**	Employment	Output	**Difference**
1951-2012	0.65	0.37	**-0.28**	0.82	0.32	**-0.50**
1951-1983	0.66	0.43	**-0.23**	0.85	0.42	**-0.43**
1984-2012	0.67	0.26	**-0.41**	0.80	0.22	**-0.58**
Difference	**0.01**	**-0.17**	**-0.18**	**-0.05**	**-0.20**	**-0.15**

C.2 Robustness of Average Comovement Results to Alternative Values of ε

Here we report our model results on comovement using $\varepsilon = 0.25$ and $\varepsilon = 0.5$, implying Frisch elasticities of 2 and 4. Table C.3 shows that while higher values of ε (and thus lower values of the Frisch elasticity) significantly dampen the overall levels of employment comovement, they do not significantly impact the change in those comovements over time. The reason for the lower level of comovement is that the higher value of ε generates incentives to reallocate labor across sectors, and given that we do not model the sizable frictions associated with such reallocation, we prefer our benchmark results with $\varepsilon = 0$. We have also considered $\varepsilon = 4$ and found similar results.

Table C.3: Model Results on Average Employment Comovement, $\varepsilon = 0.25$ and $\varepsilon = 0.5$

	Model (Baseline)			Model ($\varepsilon = 0.25$)			Model ($\varepsilon = 0.5$)		
	Emp.	Output	**Diff.**	Emp.	Output	**Diff.**	Emp.	Output	**Diff.**
1951-1983	0.66	0.38	**-0.28**	0.36	0.37	**0.01**	0.17	0.38	**0.21**
1984-2012	0.65	0.19	**-0.46**	0.30	0.19	**-0.11**	0.12	0.19	**0.07**
Difference	**-0.01**	**-0.19**	**-0.18**	**-0.06**	**-0.18**	**-0.12**	**-0.05**	**-0.19**	**-0.14**