Aggregate Shocks or Aggregate Information? Costly Information and Business Cycle Comovement

Laura Veldkamp
Justin Wolfers

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Laura Veldkamp
Stern School of Business
New York University

Justin Wolfers*
Wharton School of Business
University of Pennsylvania

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Abstract

When similar patterns of expansion and contraction are observed across sectors, we call this a business cycle. Yet explaining the similarity and synchronization of these cycles across industries remains a puzzle. Whereas output growth across industries is highly correlated, identifiable shocks, like shocks to productivity, are far less correlated. While previous work has examined complementarities in production, we propose that sectors make similar input decisions because of complementarities in information acquisition. Because information about driving forces has a high fixed cost of production and a low marginal cost of replication, it can be more efficient for firms to share the cost of discovering common shocks than to invest in uncovering detailed sectoral information. Firms basing their decisions on this common information make highly correlated production choices. This mechanism amplifies the effects of common shocks, relative to sectoral shocks.

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Business cycles involve similar and synchronized movements in output across sectors. While this comovement across industries in output is readily observed, its source is not. In canonical business cycle models, similar output across industries is the result of aggregate shocks hitting each industry. Yet the data reject this view: while output is highly correlated across industries, total factor productivity is much less so (Rebelo 2005). While alternative aggregate shocks may explain the comovement of output, Cochrane (1994) argues that they are elusive: "we haven't found large, identifiable, exogenous shocks to account for the bulk of output fluctuations" (p.296).[1] This led him to characterize business cycles as driven by shocks to *endogenous* variables. Alternatively, it could be that complementarities across industries synchronize output. Yet, the search for quantitatively important production complementarities has not produced a consensus.[2] Our paper proposes a new source of complementarity, based on efficient joint information acquisition about sectoral productivity shocks.

Complementarity in information acquisition is a natural market outcome due to the special characteristics of information. Because information has a high fixed cost of production and is non-rival in consumption (and hence has a low marginal cost of replication), competitive information producers must charge more for highly-tailored research (forecasting firm- or sector-specific shocks), to cover their high average cost. By contrast, forecasts of macroeconomic aggregates, are relevant to many producers. In equilibrium, aggregate forecasts will be purchased widely and produced at low average cost. Information markets facilitate firms sharing the expense of acquiring that information that they will find jointly useful, while there are fewer opportunities for joint consumption of sector-specific information.

In our model, firms don't necessarily want to produce more when others are producing more. They simply want to acquire the same information others acquire; similar information leads to

[1]Similarly, a 1993 AEA session including Blanchard, Hall, Hansen and Prescott, examined oil prices, monetary policy, fiscal policy, regulation, international factors, and sectoral shifts. None could explain the 1990 U.S. recession in particular, or more generally, the bulk of business cycle fluctuations.

[2]See Hornstein (2000). Various approaches have been tried, including input-output linkages (Long and Plosser (1983), Hornstein and Praschnik (1997), Horvath (1998), Dupor (1999), Horvath (2000)), consumption complementarities (Verbrugge 1997), inventory demands (Cooper and Haltiwanger 1990), strategic complementarity (Cooper and Haltiwanger 1996), spillovers (Shea 2002), external economies of scale (Baxter and King 1991), and aggregate demand spillovers (Murphy, Shleifer and Vishny 1989).

similar decisions, and this drives comovement in both inputs and outputs. The low equilibrium price of aggregate information induces some firms to use aggregate data to make inferences about their sector's productivity. When many firms' inferences are based on common information, expected productivity is more correlated than true productivity. Since production decisions depend only on variables in producers' information sets, our model predicts that production decisions are highly correlated across sectors, and hence output is more highly correlated than productivity is. While sectoral productivity shocks are the model's driving force, the information market strips out much of their sector-specific effects. The information market passes on aggregate shocks to beliefs that mimic the aggregate shocks to endogenous choice variables Cochrane (1994) observes in the data.

We begin by outlining the facts about comovement in Section 1. We show that output is much more highly correlated across industries than productivity, and characterize the key empirical puzzles. In Section 2, we illustrate our basic mechanism in the simplest possible setting: an island model of production, appended with an information sector that supplies forecasts at an endogenously determined price each period. In section 3 we calibrate and simulate the model. The results highlight our main contribution—for most industries we generate comovement in output in excess of comovement in driving forces, roughly in proportion to the facts outlined in Section 1.

A typical problem with models emphasizing information frictions is that the effect of the frictions disappears when observable market prices can efficiently aggregate information.[3] Since the real business cycles models we are building on are premised on efficient markets, this is a serious concern. Our effect does not disappear with a fully-revealing price. Comovement arises because agents have similar information; it does not require information asymmetry. Markets that efficiently aggregate information can in fact strengthen the comovement of beliefs. To illustrate this effect, Section 4 adds a market for labor that fully reveals all information through its market price and equilibrium demand for labor. Even when information is a public good for all firms, a few large firms still discover it. Their signals become common, aggregate information, which are the basis

[3]For example, herding models collapse when there are a sufficient number of informative prices. This literature includes papers such as Avery and Zemsky (1998), Banerjee (1992), Bikhchandani, Hirshleifer and Welch (1992), Caplin and Leahy (1994) and Welch (1992). The same can happen in models of global games, such as Morris and Shin (2002).

for projections by the remaining smaller firms and sectors. Thus once again uncorrelated shocks can yield strongly correlated beliefs about productivity.

However, this model does not generate comovement in output. The problem is shared by all standard business cycle models: Highly-cyclical industries demand lots more labor in booms. This demand drives up the wage. Less-cyclical industries, seeing mild cyclical increases in productivity but large wage increases, decide to hire fewer workers. Their output declines. This makes all the industries with lower-than-average cyclicality have negative output correlations with aggregate output. The average output correlation ends up near zero (Christiano and Fitzgerald 1999). Macroeconomists have discovered many mechanisms that solve this cyclical wage problem, including home production (Benhabib, Rogerson and Wright 1991), habit persistence (Boldrin, Christiano and Fisher 2001), or capital adjustment costs (Jaimovich and Rebelo 2006). But these models are based on aggregate productivity shocks. With sector-specific shocks, they generate only as much comovement in output as what there is in productivity (section 4.2).

Solving the *excess comovement puzzle* therefore requires two ingredients: a solution to the aggregate shock problem and a solution to the cyclical wage problem. Our information friction produces aggregate shocks. For less cyclical wages, section 4.3 uses home production, as in Benhabib et al. (1991). The model delivers output comovement that exceeds productivity comovement. For many industries, cross-industry output correlations in the model match or exceed those in the data. Our approach still has one important shortcoming: It does not produce positive output comovement for industries with counter-cyclical productivity. Section 4.4 shows how a change in the information cost can amplify the effect of aggregate shocks to the wage and allow any industry to exhibit positive output comovement.

The idea that common information is unduly influential also arises in models of global games. In Morris and Shin (2002), a coordination motive in actions leads firms to overweight and overvalue common information, relative to what is socially efficient. Our coordination motive in learning does not require any coordination motive in production. Instead of being more valuable, our common information is less costly. It is an efficient way to economize on the fixed cost of information discovery.

Any theory of business cycle comovement should also be able to account for its long-run changes and cross-sectional differences (section 5). As Comin and Philippon (2005) have documented, much of the long-run decline in business cycle volatility can be traced to a decline in comovement across industries. A decreasing cost of information can replicate this decline. With cheaper information, sectors purchase more sector-specific information, rely less on aggregates, and comove less with the aggregate economy. In the cross-section, we examine data on industry output and asset prices. The information contained in equity prices summarizes the information available about firms' profitability. Abundant information corresponds with lower comovement and more efficient input decisions, both in the model and the data. The industry output data shows that industries with a higher model-predicted demand for information comove less. These findings all support our main premise, that industry comovement comes from incomplete information.

1 The Facts About Comovement

We begin by outlining the basic facts about sectoral comovement. Our data—which come from Basu, Fernald and Kimball (2006)—describe the evolution within the United States of sectoral gross outputs and inputs of capital, labor, energy and materials within each of 29 private non-farm, (roughly two-digit SIC) industries from 1949-1996.[4] One of the advantages of the data provided by Basu et al. (2006) is that they have constructed a "purified" measure of sectoral total factor productivity (TFP)—a measure of the Solow residual, constructed to take account of non-constant returns to scale in industry production functions, imperfect competition, and varying utilization of labor and capital inputs.

Three facts paint a stark picture of the comovement puzzle. The average correlation of detrended sectoral output with aggregate output is 0.51, while the average correlation of detrended sectoral

[4] These data are manipulations of current and past vintages of the Jorgenson KLEM data; see (Basu et al. 2006) and appendix B for further details. We detrend these annual data using a Hodrick-Prescott filter. We set the smoothing parameter to 6, as suggested by Ravn and Uhlig (2002). Given the similarity of our approaches, it is reassuring that our description of industry comovement is largely similar to that in Christiano and Fitzgerald (1999). But there are differences in our data sources, industry categorizations, sample periods and detrending procedures, although none that lead us to expect important differences.

TFP with aggregate TFP is only 0.17. The high comovment in output comes from inputs: The average correlation of detrended sectoral inputs with aggregate inputs is 0.57. (See appendix B for sector-specific correlations.) Why are input decisions highly correlated when productivity is not?

Shea (2002) provides a simple way to account for the importance of cross-industry correlations in driving aggregate movements. He notes that the variance of aggregate output can be approximated by $\mathbf{wVw'}$, where $\mathbf{w}$ is a vector of industry shares, and $\mathbf{V}$ is the variance-covariance matrix of sectoral output. He proposes decomposing aggregate output variance into a term due to the diagonal elements of $\mathbf{V}$, and a "comovement term" due to the off-diagonal elements. Performing this exercise on our data suggests that 83% of the variance in aggregate output is due to industry comovement (and the corresponding proportion of variation in aggregate input use due to comovement is 85%). Performing the same decomposition as above, the proportion of the variation in aggregate TFP due to comovement is only 14%. It is the contrast of relatively strong comovement in output with weaker comovement in sectoral productivity that presents a challenge to existing models.

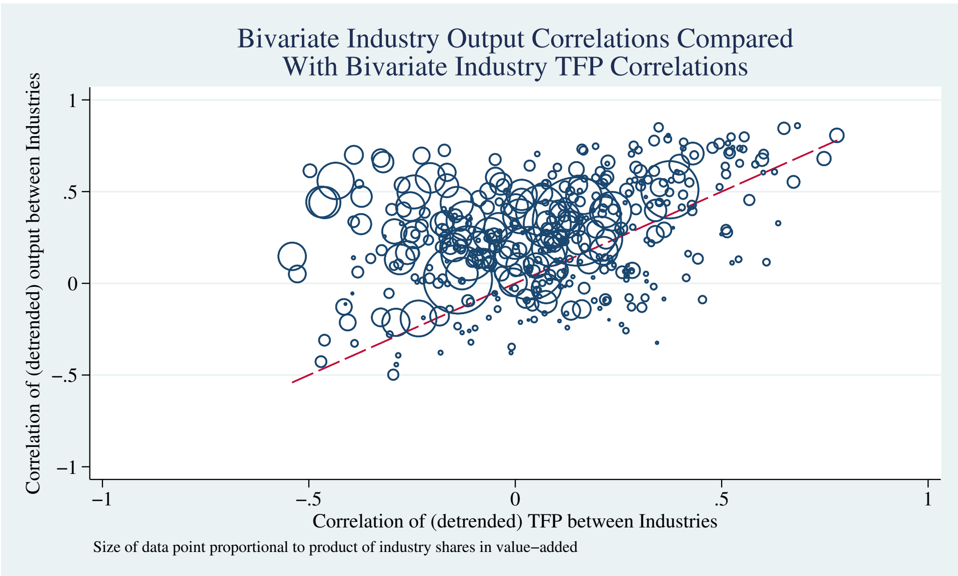

Figure 1: Bivariate Industry-by-Industry correlations in Output and Total Factor Productivity. Excess comovement is represented by the cluster of correlations above the 45-degree line.

Figure 1 shows that this comovement puzzle is ubiquitous. For each pair of industries, we compute the correlation of output, and the correlation of TFP. As the figure shows, for all but a few small industry-pairs, the correlation of TFP is significantly larger than the correlation of output. This figure allows us to distinguish our interpretation of *excess comovement* from simple measurement error in our measures of total factor productivity. Specifically, excess comovement would lead the data to be clustered above the 45-degree line, while while classical measurement error would attenuate bivariate TFP correlations, leading the data to be clustered above the 45-degree line for industries with positively correlated TFP, but clustering of data *below* the 45-degree line for industries with negatively correlated TFP. Yet the data are (roughly) uniformly clustered above the 45-degree line.

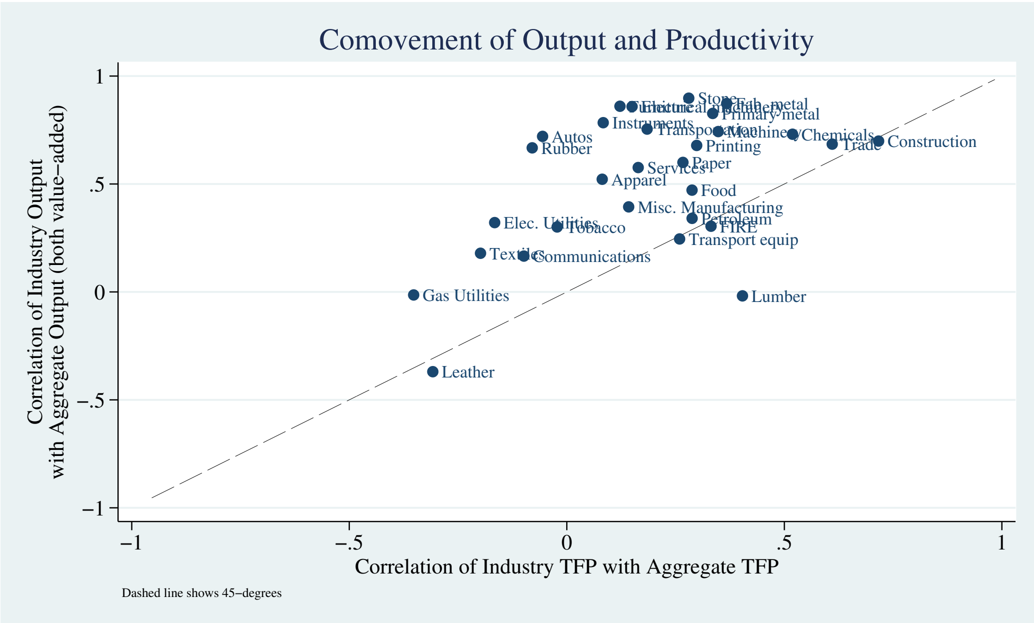

Figure 2: The Facts: Output Comovement v. TFP Comovement
Excess comovement is represented by the cluster of correlations above the 45-degree line.

Figure 2 shows the general pattern we are trying to match. In our simulations, we will construct our productivity shocks to match industry correlations with the common shock, and assess our fit in terms of how well the model matches the correlation of output with aggregate output. Two points are particularly worth emphasizing. First, all but a handful of sectors lie above the 45-degree line, suggesting generalized *excess comovement.* And second, both industries that receive a positive and a negative loading on the common productivity shock appear to experience more positive (or less negative) loadings on the common output factor. We are not after a mechanism that amplifies comovement. In the sections that follow, our goal is to develop a mechanism in which correlation in output is systematically larger than that in productivity growth.

2 An Island Model of Information-Driven Comovement

In order to isolate the mechanism that is new to this paper, we begin with a model in which information is the only source of interaction between industries. There are N industries, each of which is an island populated by a representative agent. There are no trade or production linkages between industries; workers on each island consume what they produce. Information matters because island productivity is unknown at the start of each period. Moreover, before the island's inhabitant makes her labor/leisure choice, she can purchase (imperfectly) informative forecasts of either island-specific, or aggregate productivity.

We use simple functional forms, which allow for tractable analytic expressions. Islanders have exponential utility, with constant absolute risk aversion, ρ, and preferences defined over consumption c and labor n:

$$U_i = -E[exp\left(-\rho(c_i - \psi n_i)\right)]. \tag{1}$$

Production in each industry is linear in labor, with marginal product z_i:

$$y_i = z_i n_i. \tag{2}$$

Importantly, labor's marginal product z_i is unknown. The first-order condition for labor yields:

$$n_i^* = \frac{1}{\rho Var[z_i|\mathcal{I}_i]}(E[z_i|\mathcal{I}_i] - \psi) \tag{3}$$

where $\mathcal{I}_i$ describes the information available on island i. Thus, labor effort is a function of beliefs about productivity, and is increasing in expected productivity, but decreasing in the level of uncertainty.

Each agent has a prior belief about productivity, which she may update in light of signals purchased in the information market. More specifically, each industry's productivity has an aggregate component which is known, μ_z, an aggregate component which is unknown but learnable, $\bar{z}$, an industry-specific component that is unknown but learnable, η_i, and an industry-specific component that unknown and unlearnable, e_i:

$$z_i = \mu_z + \beta_i \bar{z} + \eta_i + e_i, \tag{4}$$

where μ_z is common knowledge, $\bar{z} \sim N(0, \sigma_z^2)$, $\eta_i \sim N(0, \sigma_n^2)$ and $e_i \sim N(0, \phi_j^2)$. All three random variables are mutually independent and η_i and e_i are i.i.d. across industries. Like the β of a financial asset, an industry's β measures the extent to which it covaries with the aggregate. Each industry's β is common knowledge.

Information Markets Three features of information are crucial. First, information is produced according to a fixed-cost technology. A signal s_j can be discovered at the beginning of the period at a fixed cost χ. This can be interpreted as the cost of hiring an economist to make a productivity estimate for an industry, a set of industries, or the economy as a whole. Information producers can choose to either produce a signal about the aggregate economy, s_0, or about a specific sector s_i. The information, once discovered, can be distributed at zero marginal cost. Second, reselling purchased information is forbidden. In reality, intellectual property rights prohibit this. Third, there is free entry into the provision of information. Any agent (on any island) can invest in the production of information at any time.

For simplicity, we consider information suppliers competing on price in a perfectly contestable market.[5] As such, profits from information discovery depend on the price charged and demand for information, given the pricing strategies of other agents. One way to ensure that the market is contestable is to force information producers to choose prices in a first stage and choose entry in a second stage. Let the number of the agents that demand signal s_j, be λ_j. This depends on the

[5]This market structure is used because it produces a simple pricing formula. Veldkamp (2006) shows that Cournot or monopolistically competitive markets also produce information prices that decrease in the quantity sold.

price information producer j charges p_j, and on all other posted prices for information. The profit from information production is price times demand, minus the fixed cost: $\pi_j = p_j \lambda_j - \chi$.

If an information producer invests in learning about aggregate productivity, she learns a signal

$$s_0 = \bar{z} + e_0, \tag{5}$$

where the noise $e_0 \sim N(0, \phi_0^2)$. If she chooses to learn about industry i's productivity, she observes an industry-specific signal, s_i, that is the sum of the noisy signal of aggregate productivity, plus the learnable industry-specific shock:

$$s_i = \beta_i(\bar{z} + e_0) + \eta_i. \tag{6}$$

This information structure ensures that any specific sector will prefer to learn its sectoral forecast than the aggregate forecast and in turn, will prefer to learn the aggregate forecast over another industry's sectoral forecast. Moreover, conditional on an own-sectoral forecast, there is little useful information in the aggregate forecast, and conditional on the aggregate forecast, there is no useful information in another sector's forecast. Therefore, we examine sectors who choose to buy either no signal, only the aggregate signal, or only their sector-specific signal. (While we can relax the signal structure and still generate our main results, they simplify the choice problem.)

Updating Beliefs Given the various forms of uncertainty shown in (4), a sector's prior beliefs about its productivity, are $z_i \sim N(\mu_z, \beta_i^2\sigma_z^2 + \sigma_\eta^2 + \phi_i^2)$, $\forall i$. The information contained in a signal depends on what kind of signal it is. Own-industry signals contain the most precise information about industry-specific productivity: $s_i \sim N(z_i - \mu_z, \beta_i^2\phi_0^2 + \phi_i^2)$. Aggregate signals contain strictly less precise information about industry-specific productivity: $\beta_i s_0 \sim N(z_i - \mu_z, \beta_i^2\phi_0^2 + \sigma_\eta^2 + \phi_i^2)$. Other-industry signals contain the least precise information:$(\beta_i/\beta_j)s_j \sim N(z_i - \mu_z, \beta_i^2(\phi_0^2 + \phi_j^2/\beta_j^2) + \sigma_\eta^2 + \phi_i^2)$.

To form posterior beliefs, agents combine their prior beliefs and signals, according to Bayes' law. In this simple case, posteriors are simply a precision-weighted average of priors and signals. For the agents who do not observe any signal, their posterior beliefs are the same as their prior beliefs. Those who observe their industry-specific signal have posterior beliefs about their productivity that are normally distributed with mean and variance:

$$E[z_i|s_i] = \mu_z + \frac{s_i(\beta_i^2\phi_0^2)^{-1}}{(\beta_i^2\sigma_z^2 + \sigma_\eta^2)^{-1} + (\beta_i^2\phi_0^2)^{-1}} \tag{7}$$

$$Var[z_i|s_i] = \left((\beta_i^2\sigma_z^2 + \sigma_\eta^2)^{-1} + (\beta_i^2\phi_0^2)^{-1}\right)^{-1} + \phi_i^2. \tag{8}$$

For firms observing only the aggregate signal, their posterior beliefs are normally distributed with mean and variance:[6]

$$E[z_i|s_0] = \mu_z + \frac{\beta_i s_0 \phi_0^{-2}}{\sigma_z^{-2} + \phi_0^{-2}} \tag{9}$$

$$Var[z_i|s_0] = \beta_i^2\left(\sigma_z^{-2} + \phi_0^{-2}\right)^{-1} + \sigma_\eta^2 + \phi_i^2. \tag{10}$$

Definition of Equilibrium

1. Information producers announce prices p_j, at which they are willing to sell each signal s_j. After observing the prices posted by their competitors, they choose whether or not to incur the fixed cost to produce each signal, taking as given the action of other agents.

2. Taking information prices and availability as given, agents choose what signals to purchase.

3. Agents choose consumption and labor. All decisions maximize (1), given all signals they have discovered or purchased, and subject to their budget constraint. Agents in each industry consume what they produce, plus the information market profits they earn, minus the cost of any information they buy: $c_i = z_i n_i + \sum_j(\pi_j - \tau_j L_{ij})$, where $L_{ij} = 1$ if agent i buys signal j and 0 otherwise.

[6] Were firms to observe other-industry signals, they would update in a similar fashion to those observing the aggregate signal; for their purposes an other-industry signal is simply the aggregate signal plus noise. To adjust posterior mean and variance in (9) and (10), replace the aggregate signal noise ϕ_0^2 with the higher-variance noise $(\phi_0^2 + \sigma_\eta^2/\beta_j^2)$ and the aggregate signal realization s_0 with the other-industry signal s_j.

3 Main Results

3.1 Aggregate Information Generates Comovement

The only stochastic component of the model is the level of productivity, z_i. While z_i is not an input into production decisions, $E[z_i|\mathcal{I}_i]$ is the key driving force (equation 3). Thus, with no information markets, the firm's decisions would be the same every period. The addition of the information market ensures that $E[z_i|\mathcal{I}_i]$ is shaped by the information purchased, and this is the source of the model's excess comovement. For two firms that both observe their industry-specific signal, the correlation of their conditional expectations is dictated by the correlation of their observable fundamentals. In contrast, when two firms observe the aggregate signal, their common source of information gives them more highly correlated conditional beliefs.

Proposition 1 *If $\beta_i\beta_j > 0$, the correlation of labor input for any two industries is higher if those industries observe the aggregate signal only, than it would be if they observed their industry-specific signal: $corr(n_i^a, n_j^a) \geq corr(n_i^i, n_j^j)$. This inequality is strict if $\sigma_\eta^2 > 0$.*

Proof: in appendix A.1. The only force causing labor input to vary over time is the realization of the common signal. Since the only driving force is a common one, the labor input of two of these aggregate-informed industries is perfectly correlated. An industry that observes only aggregate information has labor supply that depends only on the aggregate signal s_0, we can write:

$$n_i^A = \alpha_i(s_0 + \gamma_i) \tag{11}$$

where $\gamma_i = (\mu_z - \psi)(\phi_0^2 + \sigma_z^2)/(\beta_i\sigma_z^2)$, $\alpha_i = \beta_i/(\rho Var[z_i|s_0]) * \sigma_z^2/(\phi_0^2 + \sigma_z^2)$, and $Var[z_i|s_0]$ is given in equation (10).

The resulting covariances of output are derived in appendix A.2. Because output is a product of two normal variables, labor and productivity, its second moments are far less tractable. While output covariances with aggregate and firm-specific information cannot be compared analytically, we will compare comovement numerically when we simulate the model in section 3.3.

3.2 Equilibrium Information Provision

In equilibrium, the price of a piece of information is the fixed cost of discovering it, divided by the number of agents who demand the signal: $p_j = \chi/\lambda_j$. Free entry at the stage where information prices are set ensures zero profit for information suppliers. If they made profits, other suppliers would enter the market. That would not be an equilibrium. Zero profit means that the price of information times the quantity demanded equals the cost of discovery: $c_j\lambda_j = \chi$. Thus, each information supplier prices at average cost.

Proposition 2 *A firm will purchase the aggregate signal s_0 if two conditions are satisfied:*

1. *Buying the aggregate signal at price χ/λ yields higher utility than buying the industry signal, at the higher cost χ:*

$$\frac{1}{2\rho}\log\left(\frac{Var(z_i)}{Var(z_i|s_0)}\right) - \frac{\chi}{\lambda} \geq \frac{1}{2\rho}\log\left(\frac{Var(z_i)}{Var(z_i|s_i)}\right) - \chi.$$

2. *Buying the aggregate signal yields higher utility than not purchasing any information:*

$$\frac{1}{2\rho}\log\left(\frac{Var(z_i)}{Var(z_i|s_0)}\right) - \frac{\chi}{\lambda} \geq 0.$$

See appendix A.3 for proof.

Because of the assumption of a nested information structure, an agent who buys information is always deciding between only two signals: either the own-industry-specific signal or the aggregate signal. No agent will ever purchase multiple signals. The industry-specific signal contains all the information contained in other signals, to the extent that they relevant for this industry. Likewise, other-industry signals are only noisy approximations to the information in the aggregate signal. So, no agent who could observe the aggregate signal would learn any additional relevant information from an other-industry signal. The only time agents might purchase multiple signals is if other industry-signals were cheaper than the aggregate signal. If this were the case, one of the signal providers could switch to providing the aggregate signal, for the same price, and make a profit.

As the economy becomes large ($N \to \infty$) and information becomes expensive ($\chi \to \infty$), industry-specific information becomes more and more costly and its demand falls to zero. All agents purchase either aggregate information (at a price χ/λ which is stationary for a given fraction of islands purchasing information λ/N), or no information. With high variance of productivity z_i, information will be valuable and not learning will be a costly choice. This is the type of environment where many agents choose to observe aggregate information and the strongest aggregate shocks emerge.

3.3 Simulating the model

Choosing parameter values To match the model and data, we give each of our islands the characteristics of one of the 2-digit industries described in section 1. Specifically, we construct the aggregate TFP process to match the variance of aggregate TFP in the data (σ_z=0.4 log points).[7] The industry TFP processes are constructed to match the variance of each industry's TFP in the data, and also to ensure that the covariance of each industry's TFP with aggregate TFP matches the data. This involved estimating a one-factor model, $TFP_{it} = \alpha_i + \beta_i \tilde{TFP}_{agg,t}$, and equating two features of the model and data: the loading on the aggregate factor β_i and the sum of the firm-specific shock variances ($\sigma_\eta + \phi_{ii}$). The relevant parameters for each industry are described in appendix B. Thus, basic patterns in the data drive the pattern of shocks in our simulations.

One feature of the model that the data cannot inform us about is how much of each shock is learnable by information producers. For the aggregate shock, we assume the the variance of the noise is equal to the variance of the true shock ($\phi_0^2 = \sigma_z^2$). The equivalent assumption for the industry specific shock is that the observable shock and the unobservable shock have equal variance ($\sigma_\eta^2 = \phi_{ii}^2$). In both cases, the signal-to-noise ratio is one.

We set other parameters at standard values: absolute risk aversion ($\rho = 4$); a disutility of labor ($\psi = 0.96$) which matches the relative volatility of labor hours in the data $std(n)/std(y) = 0.8$ (Benhabib et al. 1991); and a cost of information ($\chi = 0.2$) chosen to induce some industries to

[7] Aggregate TFP is constructed as the weighted average of industry TFP, where weights reflect each industry's share in total value-added

make each of the three possible information choices. Section 5.3 explores other information costs.

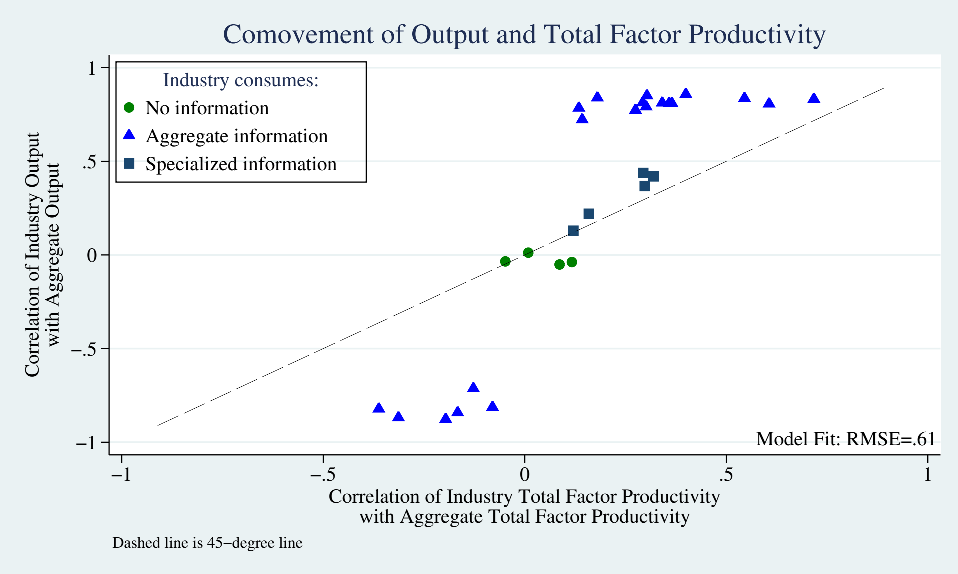

Figure 3: Output Comovement v. TFP Comovement in the Island Model
Excess comovement is represented by the cluster of correlations above the 45-degree line.

Results Figure 3 illustrates the comovement in each simulated sector. The important feature of this graph is that the industries that observe the aggregate signal have significantly higher output correlations, in excess of their TFP correlations. The average correlation of an industry with aggregate output is 47%, compared to 51% in the data. For productivity, this average correlation is 17%, equal to the data by construction. Of the 47% output correlation, 7% is really *excess* correlation – the model's average correlation is 0.07 larger than it would be if all industries observed their industry-specific signal.[8] The industries that observe aggregate information exhibit stronger excess comovement, with correlations 0.09-0.12 higher in absolute value than they would be with full information. All other industries have excess correlation that is less than 1%.

One obvious failing of this model is its prediction that all industries with counter-cyclical TFP $\beta_i < 0$ have counter-cyclical output. In the data, more than half of these industries have pro-cyclical TFP. What this model does is make a heterogeneous shock setting look like one with one aggregate

[8]Another natural benchmark would be to give all industries perfect foresight about their true productivity. The problem with that benchmark, in this setting, is that it would lead all industries to choose an infinite amount of labor. If we switch to CES preferences or include a labor market, we could use perfect-foresight as a benchmark.

shock. In that sense, it achieves its goal. But a one-shock model would also predict that the output of such industries is counter-cyclical. One way to remedy this problem is to introduce a second aggregate shock, for example, oil prices. Since this is a shock relevant to all sectors, many will choose to learn about it and oil information should also be inexpensive. If negative β industries are more sensitive to oil price than to aggregate TFP (which is possible because many of these industries have small TFP-loadings), then the effect of oil shocks might dominate the effect of TFP for these firms. Even firms with counter-cyclical TFP can potentially have pro-cyclical output. An example of this comes in section 4.4.

One of the reasons that it is important to understand comovement is because it helps to explain the volatility of business cycles. Fluctuations in output are more volatile than what measured changes in productivity can account for. If sectors' output covaries highly, then the sum, aggregate output, will have higher volatility. Our model produces additional volatility. In fact, it produces too much of it, a 9.5% standard deviation of log output. There are at least two simple reasons model output is too volatile. First, there are no decreasing returns. The linearity of the production function simplifies the analysis, but makes labor fluctuate excessively. Second, there is no capital. Capital, unlike labor, is a slow-moving stock that must be built up over time. Its presence would dampen output fluctuations.

Although the model's output variance does not match the data, its fraction of variance that comes from sectoral covariance does. Using the Shea (2002) decomposition, section 5 argued that 83% of variance in aggregate output is due to sectoral comovement. Applying the same decomposition to the simulated model reveals that 77% of the model's variance comes from its sectoral comovement.

This model illustrates how information markets dampen the effect of heterogeneous information and transmit more aggregate information. In this instance, the aggregate information is aggregate productivity. But the mechanism is more general than that. It filters out all kinds of industry-specific and firm specific information and delivers aggregate shocks to beliefs. These shocks to beliefs show up in the data as shocks to endogenous choice variables, just as they do in the data.

4 Adding a Market For Labor

The island model of section 2 illustrates why the non-rival nature of information produces complementarity in information acquisition, and why this can induce comovement in industry output. However, that model is missing many realistic features of the aggregate economy such as labor markets or tradeable goods. This might be a cause for concern: Market prices that aggregate information have been the achilles' heel of other information friction models. It also leaves unanswered questions about how inter-island linkages can affect information transmission and output comovement. In this section, we show that the information mechanism that filters out heterogeneous information and transmits aggregate shocks to choice variables still functions, albeit with some modifications, in the presence of a perfectly efficient market price.

We now change the island model by allowing island workers to supply labor to other islands, at a market wage. That wage reveals all information. In standard business cycle models, such a factor market typically serves only to *deepen* the comovement puzzle: Positive shocks to one sector may lead employers to bid labor away from other sectors, decreasing output elsewhere. While the cyclical wage problem does arise here, applying a well-known solution to that problem allows our information effect to continue operating, even strgoner than before.

The public good nature of information rules out the possibility information-cost sharing through an information market: No one will share the cost of a signal they will otherwise observe for free. However, a few large industries underwrite public provision of some information. For smaller or less volatile industries, it is more economical to infer their productivity from this free other-industry information, than to discover their industry-specific signal. Beliefs based on common, public information comove, more than TFP alone would predict. Thus, the model's mechanism is robust to both a labor market and the unravelling of all private information.

Setup Each agent i is endowed with a technology z_i and 1 unit of time, which she supplies to a labor market, or consumes as leisure $l_i < 1$. Agents have exponential preference for consumption c.

$$U = -E[\tilde{\xi}(1 - l_i)^2 \exp(-\rho c)]. \tag{12}$$

The form of utility over leisure needs to change from the previous model because the payoff to supplying labor is no longer random. Whereas before, the effective wage was the marginal product z_i, which was unknown, now the wage w is known when l_i, n_i are chosen. Using the previous utility formulation would yield an indeterminate labor supply with a non-random payoff. This form of utility ensures the labor supply is a linear function of the wage and keeps the model tractable.

Production requires combining labor n, which can be hired at an endogenous wage w, and technology to get output of sector i: $y_i = z_i n_i$.

Agents can also decide whether to discover information about their sector $\lambda_i = 1$, or not $\lambda_i = 0$. Discovering information about your sector means that the signal $s_i = \beta_i \bar{z} + \eta_i$ becomes common knowledge. As explained before, because information is a public good, sectors cannot commit to share the cost of discovering information about $\bar{z}$. Without cost-sharing, no industry would ever prefer to acquire the aggregate or an other-industry signal, because those do not contain any information that is not already in the own-industry signal.

The agent's budget constraint is that she can eat what she produces, minus the cost of the labor, net of labor supplied, and the cost of information discovery:

$$c_i = z_i n_i - w n_i + w(1 - l_i) - \chi \lambda_i. \tag{13}$$

Equilibrium An equilibrium is a set of labor $\{n_i \geq 0\}$, leisure $\{l_i\} \in [0, 1]$, consumption $\{c_i \geq 0\}$, and information choices $\{\lambda_i\} \in \{0, 1\}$ that maximize (12) subject to (13), and a market wage w that clears the labor market: $\sum_i n_i = \sum_i (1 - l_i)$.

4.1 Results with Costly Information but No Home Production

The first-order condition tells us that the optimal labor demand in industry i is

$$n_i^* = max \left\{ \frac{E[z_i | \mathcal{I}_i] - w}{\rho Var[z_i | \mathcal{I}_i]}, 0 \right\}. \tag{14}$$

The first-order condition for leisure dictates the labor supply.

$$1 - l_i = \frac{\rho}{2\tilde{\xi}} w \equiv \xi w \tag{15}$$

where $\xi \equiv \rho/(2\tilde{\xi})$. Substituting (14) and (15) into the labor market clearing condition delivers the equilibrium wage:

$$w = \frac{\sum_{i=1}^{N} E[z_i|\mathcal{I}_i]/Var[z_i|\mathcal{I}_i]}{\sum_{i=1}^{N} 1/Var[z_i|\mathcal{I}_i] + \rho\xi} + \zeta. \tag{16}$$

where $\zeta = 0$ if the non-negativity constraints on n_i do not bind. Since all information is public, this wage is known to all agents.

An agent that discovers their industry signal believes that their productivity is $z_i \sim N(\mu_z + s_i\phi_i^{-2}v_i, v_i)$, where $v_i = 1/(\phi_i^{-2} + (\sigma_z^2 + \sigma_\eta^2)^{-1}))$. For an agent who infers their sector productivity from others's signals, the precision of their information depends on how many of those signals were observed. Suppose that S signals are in the public domain: $\{s_1, \ldots, s_S\}$. Each one is an independent signal about $\bar{z}$ with variance σ_η^2/β_i^2. Thus, $E[\bar{z}|s_1, \ldots, s_S] = \mu_z + \sigma_\eta^{-2}(\sum_{i=1}^{S} \beta_i^2 s_i)Var[\bar{z}|s_1, \ldots, s_S]$ and $Var[\bar{z}|s_1, \ldots, s_S] = (\sigma_\eta^{-2}\sum_{i=1}^{S} \beta_i^2 + \sigma_z^{-2})^{-1}$. Since agents who did not discover their industry signal have no information about the industry-specific component of their productivity, their expected value of their own z_i and $\bar{z}$ are the same. But their beliefs about their own industry have higher variance: $Var[z_i|s_1, \ldots, s_S] = Var[\bar{z}|s_1, \ldots, s_S] + \sigma_\eta^2 + \phi_i^2$.

Since all agents that do not discover information have identical beliefs about their productivity, they have perfectly correlated labor decisions, just like in section 2. The only difference here is that whether labor decisions are perfectly positively or perfectly negatively correlated depends on whether the industry's TFP is more or less procyclical than the wage.

Proposition 3 ***Correlation of labor inputs.*** *Suppose that the non-negativity constraint on labor does not bind ($\xi = 0$). If only one industry l chooses to observe its industry-specific productivity, then $corr(n_i, n_j) = 1$ or -1, for all firms i and j.*

If more than one industry chooses to observe its industry-specific productivity, but industry i and industry j both choose not to, then $corr(n_i, n_j) = 1$ iff $\beta_i = \beta_j$.

Proof in appendix A.4. When there is only one firm learning in the economy, there is only one shock that determines all firms' beliefs and the wage. Since $E[z_i|\mathcal{F}_i] - w$ is proportional to the same random variable, for every firm, all firms have perfectly correlated labor inputs. When more than one firm learns, the wage and the posterior beliefs depend on the realized signals in slightly different ways. Therefore, each firm's labor inputs are a different linear combination of these two shocks. That linear combination is the same only when both firms are uninformed and have the same loading on aggregate productivity.

Information Choice and the Free-Rider Effect When labor prices and quantities fully reveal the information others observe, information becomes a public good. This introduces a free-rider problem that was not present in the baseline model. But this 'problem' actually strengthens our result. Free-riding makes firms not want to learn, when one or more other firms are learning. It is these firms that decide not to learn that base their actions on aggregate information and exhibit the excess comovement. Thus, the more industries free-ride off the information of others, the stronger comovement becomes.

Simulation With one exception, the parameter values are identical to those in section 3.3. The information cost needs to be lower for some industries to acquire information because the benefits to public information are lower than the benefits to the private information in section 2. We set the new information cost to $\chi = 0.01$.

In figure 4, output comovement is near zero (-4%), on average. The problem is that highly-cyclical (high-β) industries demand lots more labor in booms. This demand drives up the wage. Less-cyclical (low-β) industries, seeing mild cyclical increases in productivity but large wage increases, decide to hire fewer workers. Their output declines. This makes all the industries whose expected productivity is less cyclical than the wage have negative output correlations with aggregate output. Even mild positive correlation from productivity is swamped by the substitutability in production that arises from the cyclical wage effect. This problem is common to all standard RBC models, even after they assume the presence of large, aggregate shocks.

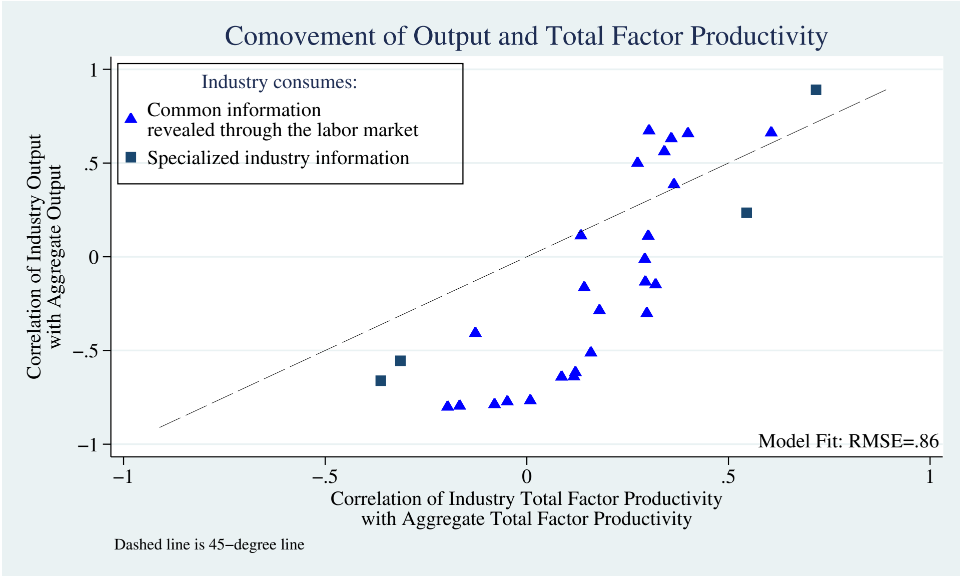

Figure 4: Simulated model: Incorporating a labor market, costly information but no home production.

4.2 Results with Home Production and Costless Information

To solve the cyclical wage problem, we use the fix developed by Benhabib et al. (1991): a large, not highly cyclical, home production sector. Because this sector has productivity shocks that are not very correlated with the aggregate productivity, it makes the wage less cyclical. It absorbs lots of labor when aggregate productivity is low, keeping the wage up, and sheds workers when aggregate productivity is high, keeping the wage from rising.

In this subsection, we add this one additional industry, to have 30 in total. We also turn off the information friction by making information costless ($\chi = 0$). This highlights what the effect the home production sector alone has. In the next subsection, we will examine the full model with home production and information frictions.

Simulation The introduction of one new sector leaves 2 new parameters to be chosen. The loading of the home production industry on aggregate productivity (β_h) is 0.05 and the variance of the home production shock is 0.34%. This β_h allows the standard deviation of aggregate market labor, relative to the data to match the data (0.8, as reported in Benhabib et al. (1991)). The industry-specific variance ϕ_h^2 is chosen to equate the time spent on home production and on market labor, similar to the division of time in the data (Benhabib et al. 1991).

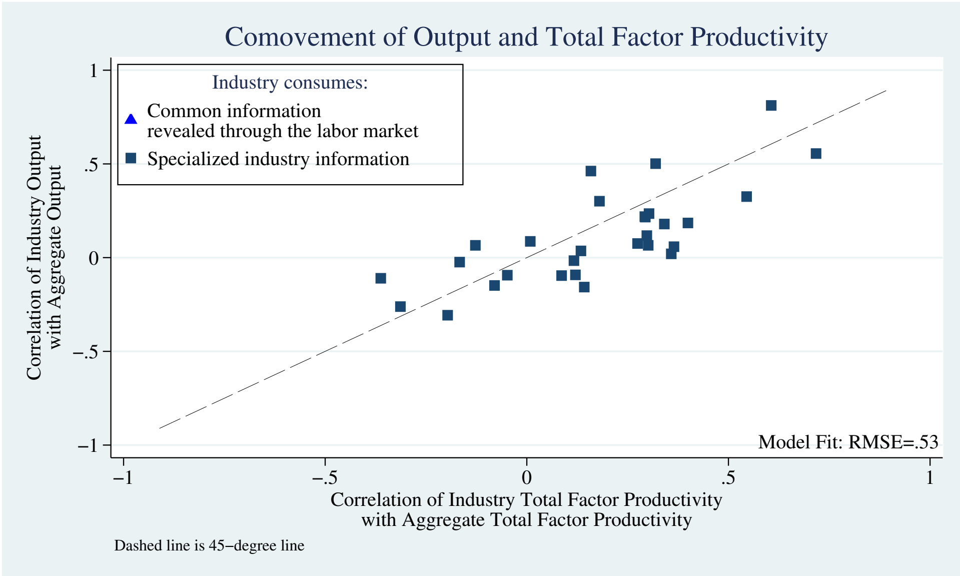

Figure 5: Simulated model: Incorporating a labor market and home production, but no information frictions.

Figure 5 shows that the average correlation of each industry's output with the aggregate (37%) is lower than the 51% correlation in the data. Even more striking is that less than half (47%) of the variation in output comes from comovement, compared to 83% in the data. Adding home production is clearly an improvement because without it, average comovement is close to zero. But, home production alone cannot explain the large output correlations in the data.

4.3 Results with Home Production and Costly Information

Results of the previous two subsections have demonstrated that replicating the high output comovement in the data will require both solving the cyclical wage problem and generating some aggregate shocks. This model puts the two pieces together and achieves high output comovement. The setting is exactly the same as before, but with a positive information cost ($\chi = 0.01$).

For many industries, output correlation in the model matches or exceeds that in the data (figure 6). The strength of information frictions in generating comovement is just as strong with

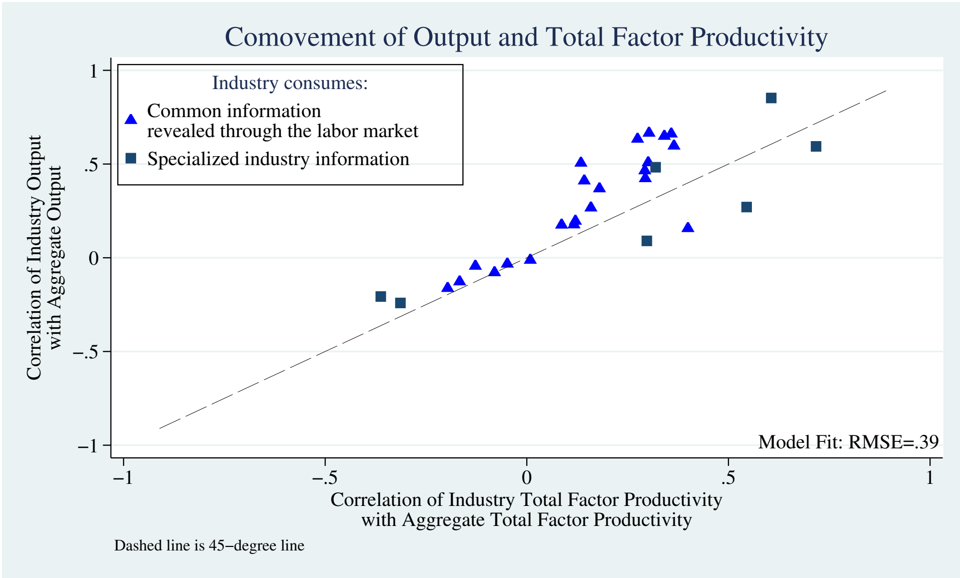

Figure 6: Simulated model: Incorporating a labor market, a home production sector, and costly information.
Excess comovement is represented by the cluster of correlations above the 45-degree line.

full-informative prices, as it is in the island model. The average sector's correlation with aggregate output is 44%, slightly less than the 51% in the data. Likewise, the Shea decomposition tells us that fraction of aggregate output variance from comovement is 69%, compared to 83% in the data. Yet there is one remaining problem: sectors with counter-cyclical productivity also have counter-cyclical output. In the data, most of these sectors have pro-cyclical output. Next, we examine a second aggregate shock that can solve this problem

4.4 A Second Aggregate Shock

A simplifying assumption of this model is that there was one common factor $\bar{z}$ that all sector's productivities were related to. The one-factor model cannot explain why TFP and output correlations sometimes have different signs. It can only magnify or dampen the correlation in fundamentals. Another possibility is that there are multiple common factors. If two sectors both load positively on a factor they learn about, this introduces positive correlation in their beliefs and in their input decisions. Even if another factor makes the sectors' fundamental productivity negatively correlated, if they do not learn much about that factor, it does not undo the positive correlation in their actions. With multiple factors, sign reversals are possible: labor inputs can comove positively, even if productivity has a negative correlation.

Simulation The only difference between this simulation and the previous one is that the info cost is now higher ($\chi = 0.05$). Because information is more expensive, only 1 market industry learns. The non-learning firms can use only this one signal to make inference about aggregate TFP. Therefore, their inferences about aggregate TFP are very noisy. Non-learning sectors don't react strongly to noisy info. However, the home-production sector's productivity is also observed. While this shock is specific to the home sector's productivity, the home sector is so large, that a change in its productivity affects the wage. This is a form of aggregate shock that all market industries load on with the same sign: When wages are higher, every industry produces less than they otherwise would. Because firms are reacting less to aggregate TFP, the effect of the wage shock becomes more dominant when information cost is high. Because all sectors react the same way to wages shocks, they comove, even if their TFP's are negatively correlated.

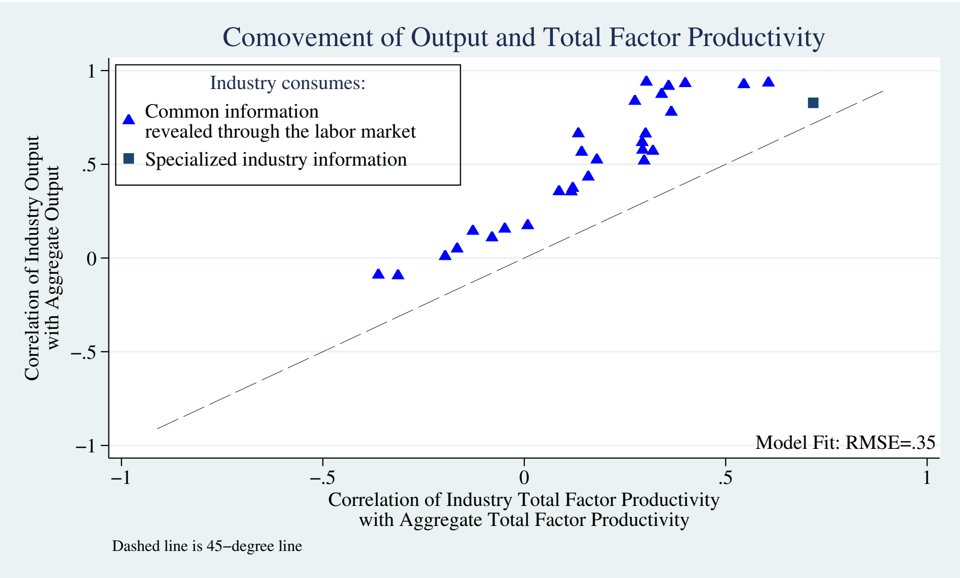

Figure 7: Correlation of industry and aggregate productivity and output, with a labor market, a home production sector, and a higher information cost. Excess comovement is represented by the cluster of correlations above the 45-degree line.

When firms can choose whether on not to purchase information in the high-information-cost model, only one market firm acquires their industry-specific signal. The resulting pattern of comovement is illustrated in figure 7. Information choice causes the average correlation of output with the market to be 61%, 10% higher than in the data. The fraction of aggregate output variance explained by comovement is 87% in this model, surpassing the 83% in the data. Pairwise correlations also reveal strong excess comovement: The average *pairwise* correlation of all industries output is 60%, while the average pairwise correlation of TFP is 8%.

This exercise is not meant to persuade the reader that home production shocks are an important driver of business cycles. In reality, the other important aggregate shocks are the usual suspects: inflation risk, oil prices, shocks to foreign markets. The point this exercise makes is that information markets can transmit the aggregate information in these kinds of shocks as well. This can make negative-β industries exhibit positive comovement.

5 Empirical Support for the Theory

The challenge in testing a theory based on informational scarcity is that the signals agents chose to acquire are not directly observable or measurable. Instead, we must rely on indirect measures of information quantity. One such measure is the information content of a firm's equity price. Another approach is to let the model predict which firms should learn more. Evidence from both approaches supports the theory.

5.1 Information Comovement: Evidence from Financial Markets

The efficient markets hypothesis says that equity prices summarize available information regarding a firm's profitability. Thus equity prices inform us about what information firms might have. If prices predicted future earnings precisely, we could infer that firms are well-informed. This idea that equity prices inform firms' input choices is supported by Chen, Goldstein and Jiang (2006).

Our model predicts that equity prices should reflect more cheap, aggregate information than expensive industry- or firm-specific information. Empirical finance studies confirms this prediction:

equity prices of different firms and sectors comove more than corporate earnings. That is, prices are driven more by aggregate than firm-specific information.

Durnev, Morck, Yeung and Zarowin (2003) argue that this over-weighting of aggregate information comes from an information friction. Consistent with this interpretation, they note that prices which are most strongly driven by the aggregate or common component are also the worst predictors of future earnings. At the industry level, greater industry-specific price variation (and hence less reliance on aggregate signals) is also correlated with the existence of a larger number information-producing analysts (Piotroski and Roulstone 2003). These facts support our prediction that when information is scarce, it has more aggregate content. When information is abundant, firms have access to signals with relatively more firm-specific content.

There is a further parallel between the uninformed firms in our model, and those empirical firms whose equity prices show little firm-specific variation: both also make less efficient input choices. Durnev, Morck and Yeung (2004) find that firms with more firm-specific equity price variation make more efficient real investments. In our model, firms whose signals contain more industry-specific information make more efficient labor input decisions.[9]

For instance, when no industries are informed, the average correlation between productivity z_i and labor input n_i in our model is zero. When all firms are informed, that correlation is 74%. If half the firms are informed, then the average correlation for informed firms is 71% and for uninformed firms is 2%.

5.2 Output Comovement: Evidence from Manufacturing Data

According to proposition 3.2, sectors with more sector-specific productivity variation (high $Var(z_i|s_0)$) value sector-specific information more. If such sectors acquire more sector-specific information, then their excess comovement will be low. This is not saying that more idiosyncratic variation in in-

[9] To verify that a similar result obtains in our model – for output, rather than equity prices – we compute Durnev et al. (2004)'s comovement statistic for informed and uninformed firms' output, in the simulated model. Their measure is based on R^2, calculating the contribution of industry j to comovement as the difference in the fraction of industry output variation explained by aggregate output and the fraction explained by the aggregate less industry j. In the simulated labor model (section 4.3), only industries with that obtain sector-specific information have positive R^2 measures. The output of industries with only aggregate signals contains no information beyond that contained in the output of informed firms ($R^2 = 0$).

dustry TFP implies lower correlation between sectoral and aggregate TFP: that is a mechanical relationship. Rather, the model predicts that such sectors should have lower output correlation, after accounting for the lower correlation of productivity.

This prediction is borne out in U.S. data on output and TFP across the 459 4-digit manufacturing sectors covered in the NBER-CES Manufacturing Industry Database.[10] We approximate $Var(z_i|s_0)$ by taking the industry-specific residuals from an estimated one-factor TFP model. Analyzing detrended annual data from from 1958-1996, we then estimated:

$$corr(output_{ind}, output_{agg}) - corr(TFP_{ind}, TFP_{agg}) = \underset{(0.006)}{0.048} - \underset{(2.89)}{5.46} \cdot Var(TFP_{ind}|TFP_{agg}). \quad (17)$$

We find that high levels of idiosyncratic TFP variation—which in the model would be associated with greater demand for industry-specific information—is associated with a smaller gap between the correlation between industry and aggregate output, and the correlation between industry and aggregate TFP. To get a sense of the relevant magnitudes for instance, note that the difference between a firm at the 25th percentile of idiosyncratic TFP variance (0.04%) and a firm at the 75th percentile (0.15%) is about a 12% decline in excess comovement. This effect is also statistically significant at the 90% confidence level. Finally, a simulation exercise shows that if there is measurement error in TFP, our estimates understate the true relationship between idiosyncratic variance and excess comovement.

5.3 The Long-Run Fall in Comovement

Over the last 30 years, firm-level volatility increased and aggregate volatility decreased. Comin and Philippon (2005) show these two facts imply a decrease in firm comovement. Our model could explain this trend from a decreasing cost of information over time. According to the model, a

[10] These data come from the NBER-CES Manufacturing Industry Database, by Eric J. Bartelsman, Randy A. Becker, and Wayne B. Gray, June 2000 (http://www.nber.org/nberces/nbprod96.htm). We analyze these detailed sectoral data rather than the 2-digit data emphasized earlier in the paper, because the 29 industries offered too few data points to estimate any effect precisely.

falling information cost causes more firms to acquire firm or industry-specific signals. This moves the economy closer to the full-information economy, which exhibits no excess comovement.

Using the calibrated model, we illustrate how small changes in the cost of information can replicate the comovement decline observed in the data. Figure 8 illustrates this effect.

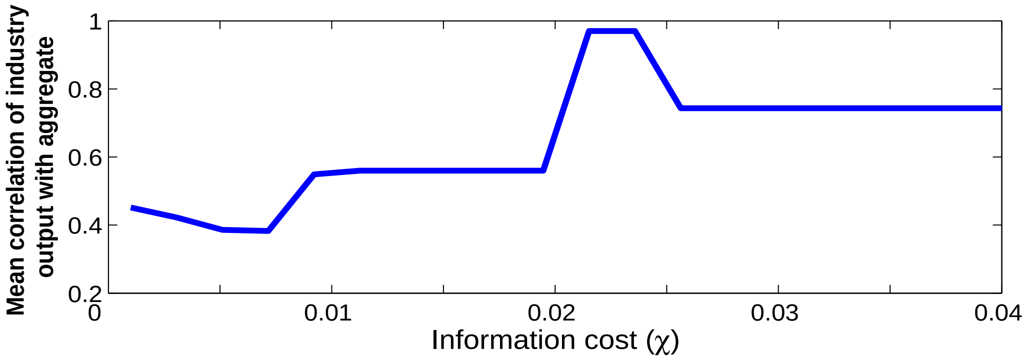

Figure 8: A falling information cost makes comovement increase, then decrease. Average correlation of industry and aggregate output for the simulated labor market model with home production. Parameters are the same as in previous island and labor market simulations. The total amount paid for all information varies between 0.05% and 0.13% of aggregate GDP.

When information costs are very low, this is the full-information model of section 4.2. Because each sector gets its sector-specific information, there are no aggregate shocks introduced by information. As the information cost rises, firms economize on information costs by purchasing cheaper, aggregate information. Aggregate information introduces aggregate shocks, the source of comovement. When information becomes very expensive, little information is acquired. Less information has less effect on agents' beliefs. As the aggregate shock to beliefs diminishes, comovement declines. In the extreme, if neither the market nor the home sector were to acquire any information, there would be no movement in beliefs, output correlation would be determined only by TFP correlation, and there would be zero excess comovement.

If the economy started somewhere to the left of the peak in comovement, then arbitrarily small decreases in information cost have the potential to dramatically decrease output comovement. The opposite prediction, that a decline in information costs would increase comovement, would require that information is currently so scarce as to paralyze decision-making. While this is theoretically possible, it is not realistic. A model with such limited information would never produce sufficiently volatile investment. Furthermore, free data about the aggregate economy, in practice, is not scarce. Finally, the asset price facts (section 5.1) tell us that low-information signals lack firm-specific information, but do contain aggregate information. Therefore, we conjecture that the economy is to the left of the peak in figure 8 and that decreases in information costs would cause comovement to fall.

6 Conclusion

Industry comovement in business cycles may arise from firms' desires to economize on information costs. Learning aggregate, rather than firm-specific information allows firms to share the costs of aggregate information with other firms, or to free-ride off information other firms acquire. Both of these possibilities arise because of the non-rival nature of information. Because information used by one firm can also be used by another firm, whereas capital or labor cannot be shared in such a way, information is a natural candidate for a source of hidden complementarities.

The information that producers purchase does not have to be productivity information. Anything that has a firm-specific and an aggregate component to it and is relevant to production decisions could cause comovement. Alternatives include demand, wage, or price information. Also, the theory could explain firm comovement within industries. We chose to focus on industry comovement because in noisy firm-level data, it is less clear that a comovement puzzle exists.

Romer (1990) and Lucas (1988) taught us that information production was critical to sustain long run growth. Because information is non-rival, accumulating information can achieve what accumulating physical goods cannot. Despite the fact that real business cycle models were designed to explain short-run and long-run growth with the same tools, most have neglected information. Given that production of non-rival information was the key to understanding long run growth, why wouldn't it play a key role in business cycles as well?

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A Appendix

A.1 Proof of proposition 1

Using equation (4), the covariance of productivity is $\beta_i\beta_j\sigma_z^2$. For a given information choice, $Var[z_i|\mathcal{F}_i]$ is not random. The only random variable in (3) is $E[z_i|\mathcal{F}_i]$. Since correlations are invariant to linear transformations, $corr(n_i, n_j) = corr(E[z_i|\mathcal{F}_i], E[z_j|\mathcal{F}_i])$.

For firms with aggregate information, the conditional expectation is given by equation (9); the only random variable is s_0, the common signal both agents observe. The aggregate signal s_0 enters in both conditional expectations linearly. Thus, $corr(E[z_i|s_0], E[z_j|s_0]) = corr(s_0, s_0) = 1$, and therefore $corr(n_i^a, n_j^a) = 1$. Since the correlation of the informed firms labor input cannot exceed one, the correlation of aggregate-information labor input must be weakly greater.

To establish strict inequality, we must compute the correlation of informed firms' labor, using (3) and (7): $corr(n_i^{FI}, n_j^{FI}) = \beta_i\beta_j\sigma_z^2[(\beta_i^2\sigma_z^2 + \sigma_\eta^2)(\beta_j^2\sigma_z^2 + \sigma_\eta^2)]^{-1/2}$. Note that the denominator is strictly larger than the numerator, and thus the correlation is strictly less than one whenever $\sigma_\eta^2 > 0$. Therefore $corr(n_i^a, n_j^a) > corr(n_i^{FI}, n_j^{FI})$ whenever $\sigma_\eta^2 > 0$.

A.2 Output Covariance in the Island Model

Corollary 1 *When any two industries observe the aggregate signal only (AG), the covariance of their output is*

$$cov(y_i^{AG}, y_j^{AG}) = \alpha_i\alpha_j\left\{\beta_i\beta_j\sigma_z^2(3\sigma_z^2 + \phi_0 + \gamma_i\gamma_j) + \mu_z\sigma_z^2(\mu_z - \gamma_i\beta_i - \gamma_j\beta_j) + \phi_0^2\mu_z^2\right\}. \tag{18}$$

For two industries that observe their industry-specific signal, the industry-information (II) output covariance is

$$cov(y_i^{II}, y_j^{II}) = \frac{\alpha_i^{II}\alpha_j^{II}}{\rho^2 Var[z_i|s_i]Var[z_j|s_j]}\left\{\sigma_\eta^4 + \sigma_\eta^2\sigma_z^2(\beta_i + \beta_j) + \beta_i\beta_j\mu_z^2(\sigma_z^2 + \phi_0^2)\right. \tag{19}$$

$$\left. + (\beta_i\beta_j)^2\sigma_z^2(3\sigma_z^2 + \phi_0^2) + \frac{\beta_i\beta_j\sigma_z^2}{\alpha_i^{II}\alpha_j^{II}}(\mu_z - \psi)(\mu_z(1 + \alpha_i^{II} + \alpha_j^{II}) - \psi)\right\}$$

With Aggregate Signal For firms that observe the aggregate signal, their labor input is given by (11). Combining with the expression for z_i from (4) and substituting in the definition of s_0:

$$z_i n_i = \alpha_i(\beta_i\bar{z} + \eta_i + e_i)(\bar{z} + e_0 + \gamma_i) \tag{20}$$

After removing additive constant terms, the covariance is

$$cov(y_i, y_j) = \alpha_i\alpha_j\beta_i\beta_j\{E[(\tilde{z} + \mu_z)^2)(\tilde{z} + e_0 + \gamma_i)(\tilde{z} + e_0 + \gamma_j)] - E[\tilde{z}^2 + \mu_z\gamma_i]E[\tilde{z}^2 + \mu_z\gamma_j]\} \tag{21}$$

where $\tilde{z}$ is the mean-zero variable $\bar{z} - \mu_z$. Taking expectations, using the fact that $E[\tilde{z}^4] = 3\sigma_z^2$, $E[\tilde{z}^3] = 0$, $E[e_0] = \phi_0^2$ and rearranging delivers the expression in the corollary.

With Full Information The full-information optimal labor supply is $n_i = (\beta_i \bar{z} + \eta_i - \psi)/(\rho\phi_i^2)$. Combining this with the expression for z_i in (4) yields $z_i n_i = (\beta_i \bar{z} + \eta_i + e_i)(\beta_i \bar{z} + \eta_i - \psi)/(\rho\phi_i^2)$. Expected output is $E[z_i n_i] = (\beta_i^2(\sigma_z^2 + \mu_z^2) - \psi\beta_i\mu_z + \sigma_\eta^2)/(\rho\phi_i^2)$.

To compute output covariance, we first take $E[y_i y_j] - E[y_i]E[y_j]$ and cancel out the cross-terms equal to zero, in expectation. This leaves us with

$$cov(y_i, y_j) = \frac{1}{\rho^2\phi_i^2\phi_j^2}\{E[(\beta_i^2\bar{z}^2 + +\eta_i + \psi\beta_i\bar{z})(\beta_j^2\bar{z}^2 + +\eta_j + \psi\beta_j\bar{z})] \tag{22}$$

$$(\beta_i^2(\sigma_z^2 + \mu_z^2) - \psi\beta_i\mu_z + \sigma_\eta^2)(\beta_j^2(\sigma_z^2 + \mu_z^2) - \psi\beta_j\mu_z + \sigma_\eta^2)\}$$

Simplifying this expression and using the formulas for the higher moments detailed above, we get the expression in the corollary.

A.3 Proof of proposition 3.2 (Derivation of information value)

Substituting the optimal labor choice in the utility function and applying the law of iterated expectations yields

$$U = E[E[-exp\left(-\rho(z_i - \psi)\frac{1}{\rho Var[z_i|\mathcal{I}_i]}(E[z_i|\mathcal{I}_i] - \psi)\right)|E[z_i|\mathcal{I}_i]]] \cdot K \tag{23}$$

where $K = exp(\rho\sum_j(-\pi_j + L_{ij}p_j))$ is the utility benefit from information sales or cost of purchases. That part of utility is deterministic. Inside the inner expectation, the only random variable is z_i, which is normally distributed about $E[z_i|\mathcal{I}_i]$ with variance $Var[z_i|\mathcal{I}_i]$. Applying the formula for the expectation of a log normal variable, and combining terms yields

$$U = E[-exp\left(-\frac{1}{2}\frac{(E[z_i|\mathcal{I}_i] - \psi)^2}{Var[z_i|\mathcal{I}_i]}\right)] \cdot K. \tag{24}$$

The one random variable left in the expectation is $E[z_i|\mathcal{I}_i]$. Because beliefs are a martingale, its expectation must be equal to the prior mean μ_i. The variance of beliefs after observing the signal is $\sigma_i^2 - Var[z_i|\mathcal{I}_i]$. Using the moment-generating formula for a non-central chi-square, the expectation can be re-written as

$$U = -\left(\frac{Var[z_i|\mathcal{I}_i]}{\sigma_i^2}\right)^{1/2}\exp\left(\frac{-1}{2\sigma_i^2}(\mu_i - \psi)^2\right) \cdot K. \tag{25}$$

The exponential term contains only parameters and prior beliefs. Information only affects utility multiplicatively. The lower the standard deviation of posterior beliefs, the less negative utility is.

To derive the willingness to pay for information, substitute back in the constant K. For an agent the purchases a signal s_j at cost p_j

$$U(s_j) = -\left(\frac{Var[z_i|s_j]}{\sigma_i^2}\right)^{1/2}\exp\left(\frac{-1}{2\sigma_i^2}(\mu_i - \psi)^2\right) \cdot \exp\left(-\rho\sum_k \pi_k + \rho p_j\right). \tag{26}$$

For the agent that does not purchase a signal, the posterior and prior variances are equal:

$$U_{no\ info} = -\exp\left(\frac{-1}{2\sigma_i^2}(\mu_i - \psi)^2\right) \cdot \exp\left(\rho\sum_k \pi_k\right). \tag{27}$$

Information increases expected utility when $U(s_j) > U_{no\ info}$, which is true when

$$-\left(\frac{Var[z_i|s_j]}{\sigma_i^2}\right)^{1/2} \exp\left(\rho p_j\right) > -1. \tag{28}$$

Rearranging and taking logs on both sides yields the condition in the text. □

A.4 Proof of proposition 3

Part I: If only one industry l chooses to observe its industry-specific productivity, but industry i and industry j both choose not to, then $corr(n_i, n_j) = 1$ or -1.

If l learns, then $(z_l + \eta_l)$ is the public signal about aggregate productivity. Posterior beliefs are $\hat{\hat{z}} = (z_l + \eta_l)\phi_l^{-2}/(\phi_l^{-2} + \sigma_z^{-2})$. Note that this posterior is comprised of known constants and $(z_l + \eta_l)$, and is linear in $(z_l + \eta_l)$.

Substituting these posteriors into equation (16), tells us that the wage is

$$w = 1/K_1[\sum_{i \neq l} \beta_i \hat{\hat{z}}/V_i + (z_l + \eta_l)/V_l] + \mu_z$$

where K_1 is a known constant, as are the posterior variances V_i and V_l. Since $\hat{\hat{z}}$ is linear in $(z_l + \eta_l)$, we can rewrite $(z_l + \eta_l) = K_2\hat{\hat{z}}$. Thus,

$$w = 1/K_1[\sum_{i \neq l} \beta_i/V_i + K_2/V_l]\hat{\hat{z}} + \mu_z.$$

Substituting the posterior and the wage into equation (3) tells us that labor inputs in an uninformed sector i are

$$n_i = 1/(\rho V_i)((\beta_i - 1/K_1(\sum_{i \neq l} \beta_i/V_i + K_2/V_l))\hat{\hat{z}} + \mu_z)$$

as long as the non-negativity constraints on n_i don't bind. The labor input of sector j is defined analogously. Since both are linear functions of one random variable $\hat{\hat{z}}$, their correlation is 1 if $(\beta_i - 1/K_1(\sum_{i \neq l} \beta_i/V_i + K_2/V_l)$ and $(\beta_j - 1/K_1(\sum_{i \neq l} \beta_i/V_i + K_2/V_l)$ have the same sign and -1 otherwise.

There is a knife-edge case where $(\beta_i - 1/K_1(\sum_{i \neq l} \beta_i/V_i + K_2/V_l) = 0$ for either industry, in which case the correlation will be zero. Since with any random draw of parameters, this is a measure-zero event, the proposition focuses on the other two cases.

Part II: If more than one industry chooses to observe its industry-specific productivity, but industry i and industry j both choose not to, then $corr(n_i, n_j) = 1$ iff $\beta_i = \beta_j$.

Let $\hat{\hat{z}}$ be the posterior belief about aggregate technology, derived from the public signals. Equation (16), tells us that the wage is

$$w = 1/K_1[\sum_{i \in Un} \beta_i \hat{\hat{z}}/V_i + \sum_{l \in In} (z_l + \eta_l)/V_l] + \mu_z$$

where K_1 is a known constant, as are the posterior variances V_i and V_l, Un represents the set of firms who are uninformed and In is the set of informed firms. The two sum terms can be rewritten as $K_2\hat{\hat{z}}+e_z$, where $K_2 = 1/K_1(\sum_i \beta_i/V_i)$ and $e_z = 1/K_1 \sum_{l\in In}(z_l+\eta_l-\hat{\hat{z}})/V_l$, which is independent of $\hat{\hat{z}}$.

Substituting the posterior and the wage into equation (3) tells us that labor inputs in an uninformed sector i are

$$n_i = 1/(\rho V_i)((\beta_i - K_2)\hat{\hat{z}} + e_z + \mu_z)$$

as long as the non-negativity constraints on n_i don't bind. The labor input of sector j is defined analogously.

Labor covariance is

$$cov(n_i, n_j) = (\beta_i - K_2)(\beta_j - K_2)Var(\hat{\hat{z}}) + Var(e_z).$$

The product of standard deviations of labor input is

$$std(n_i)std(n_j) = ((\beta_i - K_2)Var(\hat{\hat{z}}) + Var(e_z))^{1/2}((\beta_j - K_2)Var(\hat{\hat{z}}) + Var(e_z))^{1/2}.$$

The necessary condition for a correlation of 1 is that $cov(n_i, n_j) = std(n_i)std(n_j)$. This is the case, if an only if $\beta_i = \beta_j$. □

B Data Description

Figure 9 highlights the basic facts, showing the low comovement of business-cycle variation in value-added across industries (top panel). The bottom panel shows business cycle variation in these detrended total factor productivity series. While there is clearly some comovement in productivity, these data are quite clearly less correlated across sectors than outputs.

Table 1 provides greater detail about the cyclical behavior of these industries. Column one shows the correlation of sectoral value-added with aggregate value-added, while column two shows the correlation of sectoral input use with aggregate input use.

Industry	Correlation of industry data with aggregates.		
	Value-added	Index of inputs	TFP
Construction	0.70	0.79	0.72
Food	0.47	0.09	0.29
Tobacco	0.30	-0.12	-0.02
Textiles	0.18	0.68	-0.20
Apparel	0.52	0.40	0.08
Lumber	-0.02	0.76	0.40
Furniture	0.86	0.84	0.12
Paper	0.60	0.70	0.27
Printing	0.68	0.61	0.30
Chemicals	0.73	0.55	0.52
Petroleum	0.34	0.30	0.29
Rubber	0.67	0.83	-0.08
Leather	-0.37	0.53	-0.31
Stone	0.90	0.85	0.28
Primary metal	0.83	0.81	0.34
Fab. metal	0.87	0.86	0.37
Machinery	0.74	0.82	0.35
Electrical machinery	0.86	0.80	0.15
Autos	0.72	0.56	-0.06
Transport equip	0.25	0.35	0.26
Instruments	0.78	0.65	0.08
Misc. Manufacturing	0.39	0.56	0.14
Transportation	0.75	0.91	0.18
Communications	0.17	0.37	-0.10
Elec. Utilities	0.32	0.29	-0.17
Gas Utilities	-0.01	0.17	-0.35
Trade	0.68	0.84	0.61
FIRE	0.30	0.12	0.33
Services	0.58	0.61	0.16
Simple average	0.51	0.57	0.17
Share-weighted average	0.58	0.61	0.32

Table 1: Coherence of Output, Inputs and TFP across industries.
Each cell shows the correlation of industry output, inputs or TFP with the corresponding aggregate.

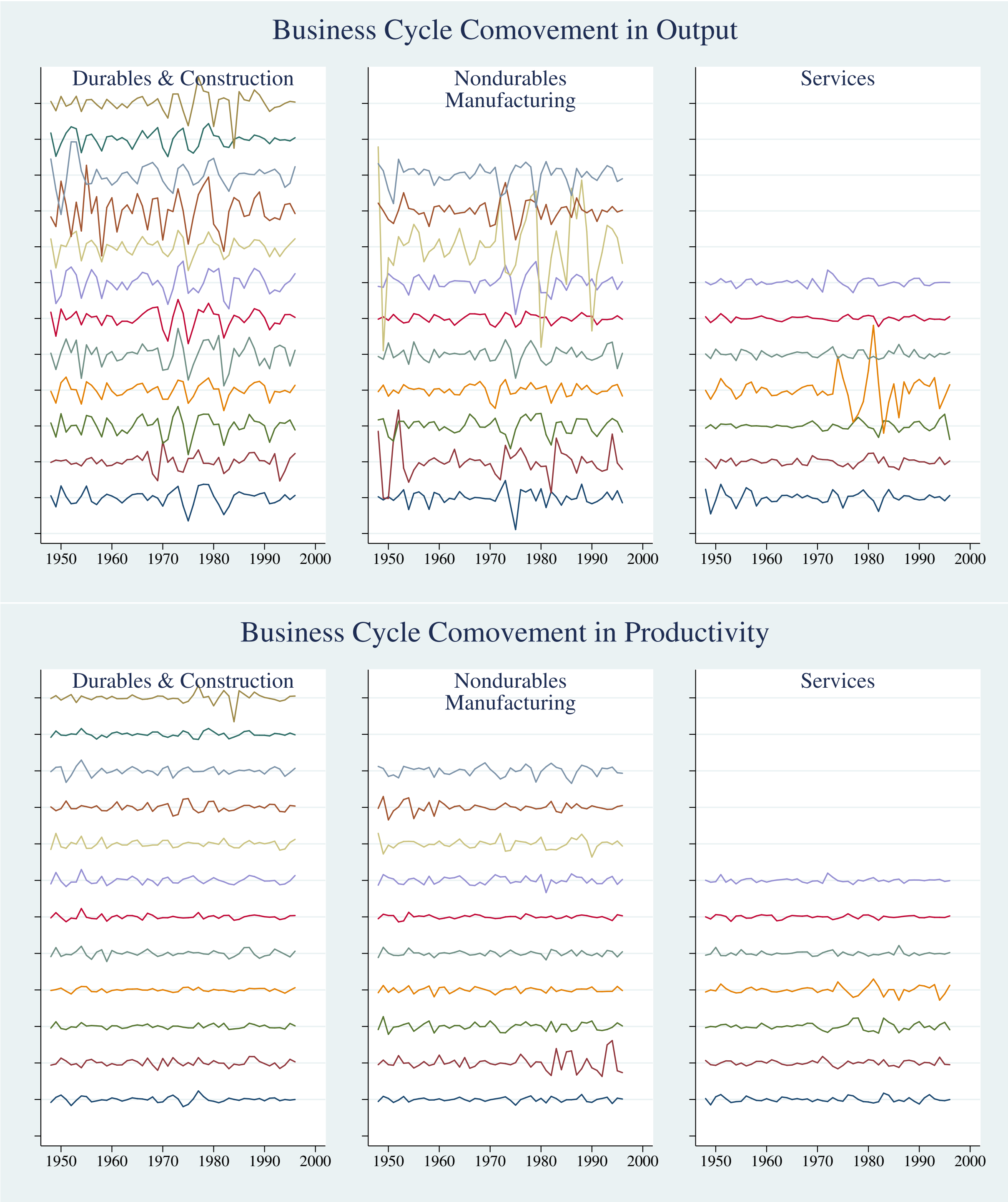

Figure 9: Comovement of output across industries and lesser comovement of total factor productivity across industries.

Analyzing Basu et al. (2006)'s "purified" measures of technology by industry.

	Summary stats		Regression Results					Single factor: TFP growth in the rest of the economy		Dependent variable: Industry TFP growth		Residuals: Industry-specific shock		Fitted values	
Industry	Observations	Average output share	Industry Beta	(se)	Industry Fixed Effects	(se)	R-sq.	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Construction	48	7.3%	1.10	0.20	-0.5%	0.2%	30.7%	0.4%	1.2%	-0.1%	2.3%	0.0%	1.9%	-0.1%	1.3%
Food	48	2.8%	0.16	0.27	1.1%	0.4%	1.5%	0.3%	1.4%	1.1%	1.9%	0.0%	1.9%	1.1%	0.2%
Tobacco	48	0.3%	-0.05	0.88	0.1%	1.3%	0.0%	0.3%	1.4%	0.1%	6.9%	0.0%	6.9%	0.1%	0.1%
Textiles	48	0.7%	0.23	0.53	1.8%	0.8%	0.9%	0.4%	1.5%	1.9%	3.8%	0.0%	3.8%	1.9%	0.4%
Apparel	48	1.4%	0.55	0.38	1.4%	0.6%	9.6%	0.4%	1.5%	1.6%	2.6%	0.0%	2.5%	1.6%	0.8%
Lumber	48	0.9%	0.71	0.47	1.0%	0.7%	13.3%	0.4%	1.5%	1.2%	2.9%	0.0%	2.7%	1.2%	1.1%
Furniture	48	0.5%	0.18	0.61	0.8%	0.9%	1.9%	0.4%	1.5%	0.8%	1.9%	0.0%	1.9%	0.8%	0.3%
Paper	48	1.3%	0.59	0.39	0.2%	0.6%	12.9%	0.4%	1.4%	0.4%	2.3%	0.0%	2.2%	0.4%	0.8%
Printing	48	1.8%	0.38	0.33	0.3%	0.5%	10.9%	0.3%	1.4%	0.5%	1.7%	0.0%	1.6%	0.5%	0.5%
Chemicals	48	2.8%	0.82	0.28	-2.0%	0.4%	8.5%	0.4%	1.3%	-1.7%	3.7%	0.0%	3.5%	-1.7%	1.1%
Petroleum	48	0.9%	0.43	0.48	0.2%	0.7%	2.1%	0.3%	1.4%	0.3%	4.3%	0.0%	4.2%	0.3%	0.6%
Rubber	48	0.9%	0.15	0.46	1.4%	0.7%	0.3%	0.3%	1.4%	1.4%	3.9%	0.0%	3.9%	1.4%	0.2%
Leather	48	0.3%	0.20	0.80	-0.9%	1.3%	0.6%	0.6%	1.5%	-0.8%	3.9%	0.0%	3.9%	-0.8%	0.3%
Stone, clay, glass	48	1.1%	0.40	0.42	0.1%	0.6%	15.4%	0.4%	1.5%	0.3%	1.5%	0.0%	1.4%	0.3%	0.6%
Primary metal	48	2.3%	0.71	0.32	-0.2%	0.5%	11.7%	0.5%	1.4%	0.1%	2.9%	0.0%	2.7%	0.1%	1.0%
Fabricated metal	48	2.4%	0.58	0.29	0.0%	0.4%	14.1%	0.3%	1.4%	0.2%	2.2%	0.0%	2.0%	0.2%	0.8%
Machinery	48	3.3%	0.36	0.25	0.6%	0.4%	2.3%	0.3%	1.4%	0.7%	3.4%	0.0%	3.3%	0.7%	0.5%
Electrical Machinery	48	2.4%	0.21	0.29	1.4%	0.4%	0.9%	0.3%	1.4%	1.4%	3.2%	0.0%	3.2%	1.4%	0.3%
Motor Vehicles	48	2.0%	-0.17	0.31	0.1%	0.5%	0.6%	0.4%	1.5%	0.0%	3.2%	0.0%	3.2%	0.0%	0.3%
Transport equip	48	1.9%	0.80	0.33	0.4%	0.5%	13.0%	0.3%	1.4%	0.6%	3.1%	0.0%	2.9%	0.6%	1.1%
Instruments	48	1.4%	-0.05	0.39	1.8%	0.6%	0.1%	0.2%	1.4%	1.8%	2.3%	0.0%	2.3%	1.8%	0.1%
Misc Manufacturing	48	0.6%	0.36	0.57	0.5%	0.9%	1.9%	0.4%	1.5%	0.6%	3.9%	0.0%	3.9%	0.6%	0.5%
Transportation	48	5.7%	-0.05	0.18	0.9%	0.3%	0.1%	0.3%	1.5%	0.9%	2.2%	0.0%	2.2%	0.9%	0.1%
Communications	48	2.9%	-0.17	0.26	-0.7%	0.4%	1.1%	0.4%	1.4%	-0.8%	2.3%	0.0%	2.3%	-0.8%	0.2%
Electric Utilities	48	2.3%	-0.31	0.29	-2.0%	0.4%	2.2%	0.4%	1.4%	-2.1%	3.0%	0.0%	3.0%	-2.1%	0.4%
Gas Utilities	48	0.7%	-0.68	0.51	0.1%	0.8%	7.9%	0.4%	1.5%	-0.2%	3.5%	0.0%	3.4%	-0.2%	1.0%
Trade	48	19.5%	-0.30	0.11	0.9%	0.1%	3.3%	0.1%	1.4%	0.9%	2.2%	0.0%	2.2%	0.9%	0.4%
FIRE	48	11.7%	0.10	0.14	1.2%	0.2%	0.8%	0.1%	1.4%	1.2%	1.5%	0.0%	1.5%	1.2%	0.1%
Services	48	18.2%	-0.39	0.11	-1.5%	0.2%	9.4%	0.9%	1.4%	-1.9%	1.8%	0.0%	1.7%	-1.9%	0.6%

Figure 10: Descriptive statistics for industry TFP 1-factor model.

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