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The Leading Premium

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Abstract

In this paper, we consider conditional measures of lead-lag relationships between aggregate growth and industry-level cash-flow growth in the US. Our results show that firms in leading industries pay an average annualized return 3.6% higher than that of firms in lagging industries. Using both time series and cross sectional tests, we estimate an annual pure timing premium ranging from 1.2% to 1.7%. This finding can be rationalized in a model in which (a) agents price growth news shocks, and (b) leading industries provide valuable resolution of uncertainty about the growth prospects of lagging industries.

JEL classification: G10; E32; E44.

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1 Introduction

Different macroeconomic aggregates go through economic cycles with different timings (see, among others, Stock and Watson, 1989, 2002; Estrella and Mishkin, 1998). Variables that respond promptly to exogenous shocks are denoted as "leading," whereas variables that adjust with delay are called "lagging."[1] Thus far, the empirical macroeconomic literature has focused mainly on leads and lags of aggregate indicators. Little is yet known about leads and lags across firms operating in different segments of the economy.

In this paper, we document the existence of a significant lead-lag structure in fundamental cash flows across industries. This structure is relevant to the explanation of the cross section of stock returns, as leading industries pay a higher average stock return than lagging industries, in the order of about 3.6% per year. After controlling for heterogeneous exposure to a large number of aggregate risk factors, we obtain an estimate of the pure timing premium, i.e., the premium on advance information (see Ai and Bansal, 2018; Binsbergen, Brandt, and Koijen, 2012; Binsbergen and Koijen, 2017), ranging from 1.2% to 1.7% per year.[2]

Specifically, we propose a novel model in which industries are ex-ante identical, but can ex-post either lead or lag the cycle. We postulate that industry cash flows are affected by infrequent industry-specific growth shocks that propagate slowly across all of the other industries. The industry that receives the shock 'first' ends up leading an aggregate cycle, and, since its shock slowly propagates to all the other industries, it eventually generates an aggregate fluctuation. In our empirical investigation, for example, we show that the IT sector was leading the cycle in the late 1990s, whereas real estate and banks were leading in

[1] For example, both bond yields and the stock market index tend to be leading indicators with respect to domestic output, as they forecast future recessions and booms. Unemployment, in contrast, is a lagging indicator.

[2] Consider a risk factor F_t, a leading firm (or industry) with cash flow growth $\Delta d_t^{Lead} = \mu + \lambda^{Lead} F_t$, and a lagging firm (or industry) with cash flow growth $\Delta d_t^{Lag} = \mu + \lambda^{Lag} F_{t-LL}$. The leading premium is a convolution of the heterogeneity in the timing of the exposure ($LL \neq 0$) and in the exposure itself ($\lambda^{Lag} \neq \lambda^{Lead}$). We control for heterogeneous exposure by considering several cycle-related risk factors and refer to the residual difference in the cost of equity of the two stocks, or sectors, as the (pure) timing premium.

the mid 2000s.

Under the aforementioned conditions, leading industries provide valuable anticipated resolution of uncertainty for industries that go through aggregate economic fluctuations with a delay. As a result, lagging firms bear less conditional cash-flow uncertainty and, by no arbitrage, have a higher price (or, equivalently, a lower yield) ceteris paribus. Leading firms, in contrast, play the role of early indicators like canaries in a coal mine and pay a higher equity yield. According to our model, the leading premium is (i) a conditional phenomenon as our industries are all ex-ante identical; and (ii) as high as 2% per year under a reasonable calibration of both industry cash flows and preferences for early resolution of uncertainty (Epstein and Zin, 1989).

In addition, our model suggests that we can identify leading and lagging firms just by computing conditional cross correlations with leads and lags of an indicator of economic activity. Equivalently, the leading premium can be measured even without full information on the entire cross section of industry-level shocks. This insight is relevant because it reduces estimation complexity. Inspired by our model, we compute conditional leading/lagging indices for industry-level cash flows with respect to US aggregate economic activity. We find substantial conditional variation in leads and lags across industries, but none over the long-run. Hence, in the US data, no industry is systematically leading/lagging the cycle, as in our model.

More specifically, we compute rolling-window correlations between US aggregate growth and leads and lags of operating income growth at an industry level. Data are quarterly and span the period 1972–2017. We consider 17,000 firms, which we aggregate to industries using the industry classification scheme obtained from Kenneth French's website.[3] In each quarter, we compute cross-correlograms and aggregate leads and lags in three different ways as described below in Section 3.1. We then assign the corresponding lead/lag indicator to

[3]See, for example, `http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/det_30_ind_port.html`.

the industry of interest. Note that this approach only uses past data to compute the cross-correlograms, and hence it can be used to construct an implementable investment strategy in real time.

Leading industries exhibit an average return that is approximately 3.6% higher than that of lagging industries. Even though leading industries are very similar to lagging industries across many dimensions, their cash flow helps in predicting the cash flows of lagging industries. Leading firms also lead in terms of employment and both equity and debt issuance policies. Furthermore, their price-dividends ratio has forecasting power on future industrial production and unemployment above and beyond that of other common forecasting factors. In addition, we show that our findings are statistically significant after double-sorting on the leag/lag (LL) exposure and either the book-to-market ratio or size, implying that the LL premium is a broad phenomenon in the cross section.

In the last part of our analysis, we run standard time-series and cross-sectional asset pricing tests. Our goal is not 'adding another factor to the zoo' (Feng, Giglio, and Xiu, 2020). We rather gather empirical guidance on the deeper economic concept highlighted in our model, that is, the size and relevance of the timing premium. After controlling for heterogeneous exposure to risk to several other risk factors (for example, investment minus consumption (Kogan and Papanikolaou, 2014), durability (Gomes, Kogan, and Yogo, 2009), industry-momentum (Moskowitz and Grinblatt, 1999), industry betting-against-beta (Asness, Frazzini, and Pedersen, 2014a), the five factors suggested by Fama and French (2015), the q-Factors (Hou, Xue, and Zhang, 2015a, b), and momentum (Carhart, 1997)), we find a pure annual timing premium of about 1.5%. This result conforms well with our model, and it provides additional and independent empirical evidence in favor of the relevance of advance information in the spirit of Ai and Bansal (2018). Equivalently, leads and lags in the diffusion of fundamental shocks across industries are an important dimension of equity pricing.

Related literature. As mentioned above, prior papers have already documented that heterogeneous exposure to contemporaneous news shocks can explain many cross sections of equity returns (see, among others, Bansal, Dittmar, and Lundblad, 2005). We differ from prior studies by showing that *heterogeneous timing* of exposure to news shocks explains a substantial share of the leading premium.

Kadan and Manela (2018) estimate the value of information using options. We empirically quantify the relevance of heterogeneity in the timing of exposure of cash flows to aggregate shocks for the cross section of equity returns. Our results are significant beyond announcement events (Patton and Verado, 2012; Savor and Wilson, 2013, 2016).

Koijen, Lustig, and Van Nieuwerburgh (2017) show that the Cochrane and Piazzesi (2005) factor is a strong predictor of economic activity, with a lead of up to 10 quarters relative to GDP growth. They provide evidence suggesting that this factor relates to a value-minus-growth stocks strategy. Similarly to them, we show that both the cash flows and the price-dividend ratio of leading firms forecasts economic activity, even after controlling for other common predictors. In addition, we show that the cash-flow of lagging firms is more predictable than that of leading firms. The same applies to employment and both equity and debt issuance.

Hong, Torous, and Valkanov (2007) investigate whether high-frequency industry *returns* can forecast excess returns on the CRSP market index. They find evidence of predictability, but only on very short horizons of one or two months. In contrast to previous studies, our empirical investigation is based on *cash-flow fundamentals* and focuses on longer time horizons. As a result, we are silent about the speed at which prices fully embody available information (Hou, 2007; Cohen and Frazzini, 2008). In our model, the endogenous cross section of *returns* features no lead-lag structure, that is, all returns move simultaneously, but with different endogenous sensitivities.

On the other side, our attention on leads and lags across industry-level cash flows is broad and does not hinge on specific network links, like for example customer-to-supplier (Cohen and Frazzini, 2008) or intermediate-to-final-producer (Gofman, Segal, and Wu, 2020). In addition, our leading and lagging portfolios have similar exposures to the concentration and the sparsity network factors proposed by Herskovic (2018), as well as similar markups (Gofman, Segal, and Wu, 2020). Future research should enrich our cash-flow models taking into account the results in Herskovic, Kelly, Lustig, and Nieuwerburgh (2020), and Ahern (2013).

We acknowledge that lagging firms can learn from the fundamentals of leading firms and adjust their investment decisions to endogenously alter their payouts (see, among others, Albuquerque and Miao, 2014). For the sake of tractability, however, we abstract away from investment decisions. By no-arbitrage, the portion of the leading premium driven by the timing premium depends on the spread between the equity and the risk-free bond yield curve. Richer settings like those suggested by Lettau and Wachter (2007, 2011), and Belo, Colin-Dufresne, and Goldstein (2014) are consistent with the empirical evidence in Binsbergen, Brandt, and Koijen (2012), Binsbergen, Hueskes, Koijen, and Vrugt (2013), and Binsbergen and Koijen (2017), but they would produce similar insights about the nature of the leading premium.

In the next section we provide intuition on our way to think of leads and lags across sectors. In Section 3 we describe our model. We present the setup and results of our empirical analysis in section 4. Section 5 concludes.

2 Intuition Based on No-arbitrage

Before presenting our DSGE model, we provide basic intuition in a simplified setting. Consider two stocks, denoted as *leading* and *lagging*. For the sake of simplicity, assume that they both pay dividends only once, n periods from now. From a time-0 perspective, the dividend of the leading firm, D_n^{lead}, is assumed to be unknown and random because the *leading* stock faces economic uncertainty. In order to abstract away from average growth, we assume $E_0[D_n^{lead}] = D_0^{lead}$. Consistent with our empirical analysis, we assume that the *leading* stock provides information about the future cash flow of the *lagging* firm. To make the intuition as crisp as possible, assume that $D_n^{lag} = D_0^{lead}$, that is, the future cash flow of the lagging stock is perfectly forecastable given the current cash flow of the leading firm.

Let $y_0(n)$ be the yield of a bond with maturity n and $v_0(n)$ be the dividend yield associated with the cash flow D_n^{lead}. Furthermore, assume for simplicity $D_0^{lead} = D_0^{lag} \equiv D_0$. By no arbitrage, the dividend yield for the lagging firm must be equal to $y_0(n)$, since its cash flow is known at time 0, so that $P_0^{lag} = D_0 e^{-y_0(n)n}$. In contrast, the leading firm must offer a yield of $v_0(n)$, i.e., $P_0^{lead} = D_0 e^{-v_0(n)n}$. This implies that the following holds:

$$\begin{aligned} \frac{P_0^{lag}}{D_0} \Big/ \frac{P_0^{lead}}{D_0} &= \frac{pd_0^{lag}}{pd_0^{lead}} \\ &= e^{(v_0(n)-y_0(n))n} \\ &= \frac{E_0[D_n^{lead}]}{F_{0,n}}, \end{aligned}$$

where $F_{0,n}$ is the future (or forward) price at time 0 for the dividend D_n^{lead} to be paid at time n, and pd_0^i is the price-dividend ratio of claim i at time 0. This implies

$$\frac{1}{n}\left(\log pd_0^{lag} - \log pd_0^{lead}\right) = v_0(n) - y_0(n),$$

i.e., the difference between the log valuation ratios of the lagging and the leading stock is equal to the forward equity premium (in the terminology of Binsbergen et al., 2012) for a maturity of n periods.

If investors are adverse to dividend uncertainty, we have $v_0(n) > y_0(n)$, and lagging firms are more valuable than leading firms. Equivalently, an investment strategy long in the leading and short in the lagging stock should pay a leading premium equal to the forward equity premium.

This result is important for two reasons. First, in this setting the leading premium features no time-discounting, as it is determined by the difference between the expected dividend at time n and the certain payoff $F_{0,n}$ paid at time n, i.e., it can be regarded as the price of a static lottery. Hence this premium is a pure measure of the value of advance information on n-period ahead cash flows.

Second, the leading premium equals the difference between equity and bond yields of the *same* maturity. Thus to obtain a positive leading premium we need a model that produces a significant positive gap between the yield curve of zero-coupon equities and that of bonds over the horizon for which leading industry cash flows predict lagging industry cash flows.

It is important to highlight that the existence of a leading premium depends on the spread between the equity and the bond yield curve, not on the *slope* of the equity curve. In the main text, we adopt an equilibrium model that delivers an upward sloping aggregate equity yield curve for the sole sake of analytical tractability. Richer settings like those of Lettau and Wachter (2007), Lettau and Wachter (2011), Croce et al. (2014), and Ai et al. (2018), which are consistent with the empirical evidence in Binsbergen et al. (2012), Binsbergen et al. (2013), and Binsbergen and Koijen (2017), would produce similar insights about the nature of the leading premium. In Section OL-C of the online appendix, we provide additional empirical support for this intuition.

3 An Equilibrium Model for the Leading Premium

In this section, we present a model that is instructive for our empirical investigation. The model clarifies under which conditions we should expect to observe a leading premium, and it enables us to obtain a list of testable hypotheses. In what follows, we (i) define our measures of leads and lags, (ii) describe our industry-level cash flow model, and (iii) look at asset pricing results. In the spirit of the literature, we use aggregate output to 'set the clock', i.e., aggregate output is used as a common reference to identify leading and lagging industries.

3.1 Measuring Leads and Lags

In this section, we discuss the measures that we adopt to identify leading and lagging industries. Since these measures are quite common in the macroeconomic literature, the readers familiar with cross-correlograms may want to go directly to the next section.

Consider the cash flow growth of industry i, ΔCF^i, and allow it to have a possibly time-varying lead-lag relation with output growth, ΔGDP. One way to identify the lead-lag link between aggregate output and the cash flow of this industry is to compute the following cross-correlogram over J periods

$$[\rho^i_{t,-J} \cdots \rho^i_{t,0} \cdots \rho^i_{t,+J}]$$

where

$$\rho^i_{t,j} = corr_{\{t-T \to t\}}(\Delta GDP_t, \Delta CF^i_{t-j})$$

is computed on a rolling window with $T > J$ observations. Since the cross-correlogram is of dimension $1 + 2J$, we use the following two ways to collapse it to a scalar, so that stocks can be easily sorted on it.

Maximum cross-correlation. Our first way to define our lead/lag indicator (LL) is

$$LL^i_t = \underset{-J \leq j \leq J}{\arg\max} |\rho^i_{t,j}|, \tag{1}$$

i.e., the indicator is given by the lead or lag for which the cross-correlation between cash flow and GDP growth peaks in absolute value. As an example, assume that (i) ΔGDP_t follows an $AR(1)$ with persistence $0 < \rho < 1$, and (ii) $\Delta CF^i_{t-5} = -\Delta GDP_t$, so that GDP lags by a fixed delay and with opposite sign. In this case, $\rho^i_{t,j} = -\rho^{|j-5|}$ and $LL^i_t = +5$, that is, our indicator detects that the cash flow is leading aggregate output by 5 periods.

Industry-level weighted average of leads and lags. When cash flows and GDP do not follow AR(1) processes, the previous measure may not be appropriate as it may disregard information contained in the whole cross-correlogram. One way to resolve this problem is to have an indicator that takes into account all possible leads and lags and gives more weight to the ones for which the cross-correlation is stronger in absolute value:

$$LL^i_t = \sum_{j=-J}^{J} \frac{|\rho^i_{t,j}|}{\sum_{j=-J}^{J} |\rho^i_{t,j}|} \cdot j. \tag{2}$$

3.2 The Cash Flow Model

We introduce a simple diffusion model to provide intuition about our way to identify conditionally leading and lagging industries. This model is stylized in many dimensions and is not meant to perfectly describe the data. Rather, our goal is to show that our cross-correlations have the potential to identify leading and lagging sectors when shocks diffuse across stocks with connected cash flows. Sorting on lead and lag indicators enables us to capture a sizeable conditional risk premium that we denote as the leading premium without running an industry-level structural estimation that would be subject to excessive estimation uncertainty.

For the sake of computational simplicity, we focus on an economy with three industries evenly spread out over a circle. Since we assume that it takes one period for an industry-specific shock to reach the next industry, $N = 3$ is equivalent to studying an economy in which there is at most a delay of one period in the transmission of a shock. We also look at the case $N = 4$, where it takes at most two periods before all locations (industries) are affected by a specific shock. Since we solve the model with an approximation of the fourth-order, choosing $N > 4$ exposes us to the curse of dimensionality. As a result, in our equilibrium model we have at most two periods of leads/lags.

We define aggregate output, Y_t, as the sum of the cash flows of our industries, D_t^i, i.e., $Y_t = \sum_{i=1}^N D_t^i$, hence the growth rate of output is simply equal to the weighted average of the growth rates of our industries (where lower-case letters denote logs):

$$e^{\Delta y_t} = \sum_{i=1}^{N} w_{t-1}^i e^{\Delta d_t^i}, \tag{3}$$

with $w_t^i = \frac{D_t^i}{Y_t}$. Industry-level (log) cash flow growth rates evolve according to the following equation,

$$\Delta d_t^i = \mu + x_{t-1}^i + \varepsilon_t^c - \tau \cdot (\ln w_t^i - \ln N), \quad i = 1, ..., N, \tag{4}$$

in which (i) expected growth, x^i, is industry-specific; (ii) we account for a common short-run shock to growth, $\varepsilon_t^c \overset{\text{i.i.d.}}{\sim} N(0, \sigma_c^2)$; and (iii) there exists co-integration across all industries, represented by setting $\tau > 0$.

Industry-level expected growth is modeled in order to (i) capture infrequent-but-sizeable industry-level cycles; and (ii) include spillovers across industries. Specifically, we assume that

$$x_t^i = \rho x_{t-1}^i + \lambda \cdot \left(\sum_{j \neq i} x_{t-1}^j \right) + J_t^i \cdot p_{t-1}^i \tag{5}$$

where

$$p_t^i = e^{\phi_2 \sum_{j \neq i} (x_t^j)^2}, \quad \phi_2 < 0. \tag{6}$$

In what follows, we explain the role of each variable in detail. We choose the autoregressive parameter $\rho \approx 1$, so that our infrequent shocks have long-lasting implications on growth, i.e., they produce relevant medium-term cycles. The second term on the right-hand side of equation (5) captures the spillover of the shocks that propagate from all industries $j \neq i$

towards industry i. These spillovers propagate forever along the circle with intensity λ and decay rate ρ.

For computational reasons, we mimic an infrequent 'jump' shock with the following continuous function:

$$J_t^i = \phi_0 \cdot \left(e^{\phi_1 u_{+,t}^i} - e^{\phi_1 u_{-,t}^i} \right),$$

where (i) both $u_{-,t}^i$ and $u_{+,t}^i$ are distributed as $i.i.d.N(0,1)$ shocks, and (ii) we set ϕ_0 (ϕ_1) to be a very small (large) positive number. This formulation enables us to use perturbation methods to solve our model.

In order to have well-defined industry-prompted cycles, we interact the shock J_t^i with the process p_{t-1}^i. We note that p_t^i is close to zero when other industries have already received shocks and hence their expected growth is far from their unconditional mean (i.e., $\phi_2 \sum_{j \neq i} (x_t^j)^2$ is a sizable negative number). This is a parsimonious way to represent the fact that different aggregate cycles are often driven by booms or busts in specific industries. In our empirical investigation, for example, we show that the IT sector was leading the cycle in the late 1990s, whereas real estate and banks were leading in the mid 2000s. Thanks to this assumption, a leading industry conveys relevant information about the cycle that other industries may experience (for additional details, see Appendix A).

Finally, we note that all of our industries are ex-ante identical and hence none of them are unconditionally leading or lagging. Equivalently, in this setting, the leading premium is solely a conditional phenomenon, consistent with our empirical findings. In addition, in our model all industries have the same network characteristics, such as upstreamness, again consistent with what we document in section 4.

3.3 Pricing Kernel

By no-arbitrage, our leading premium is connected to the spread between the equity yield curve and the bond yield curve (see section 2 for an example in which these two concepts perfectly coincide). Equivalently, the leading premium is partially a reflection of the timing premium. Hence any equilibrium asset pricing model able to deliver a substantial timing premium can produce a sizeable leading premium. In what follows, we focus on an equilibrium model featuring preferences sensitive to the timing of information about future growth.

Specifically, we assume that the representative agent has Epstein and Zin (1989) preferences, i.e.,

$$U_t = \left[(1-\delta)C_t^{1-\frac{1}{\psi}} + \delta E_t\left[U_{t+1}^{1-\gamma}\right]^{\frac{1-\frac{1}{\psi}}{1-\gamma}}\right]^{\frac{1}{1-\frac{1}{\psi}}}$$

and her stochastic discount factor is given as

$$M_t = \delta e^{-\frac{1}{\psi}\Delta c_t}\left(\frac{U_t}{E_{t-1}[U_t^{1-\gamma}]^{\frac{1}{1-\gamma}}}\right)^{1/\psi-\gamma}.$$

Since we focus on an endowment economy in which consumption equals output, consumption growth equals aggregate output growth and is determined according to equation (3).

3.4 Model Calibration and Results

In Table 1, we report our benchmark calibration as well as our targeted annualized moments. Our calibration of the preference parameters is consistent with that of Bansal and Yaron (2004). On the cash flow side, our calibration strategy differs in several dimensions. First, our industry-level expected quarterly growth process has a persistence ρ of 79%, a value lower than in a typical long-run risk model. After accounting for the diffusion of spillovers determined by λ, the overall persistence is consistent with the literature.

Table 1: Calibration

Panel A: Parameters

Cash Flows								Preferences		
μ	σ	ρ	λ	τ	ϕ_0	ϕ_1	ϕ_2	e^{δ}	γ	ψ
0.375%	0.0078	0.79	0.1	5e-5	2e-6	7.5	-100	0.997	10	1.5

Panel B: Cash Flow Moments

	Aggregate Output			Industry Cash Flow	
	St.Dev.	ACF(1)	Kurtosis	Rel. St.Dev.	Rel. Kurtosis
Data	5.00	0.48	7.30	1.34	1.48
	(0.70)	(0.17)	(2.47)	(0.14)	(0.44)
Model	3.70	0.67	2.55	1.07	1.10

Notes: Panel A reports our quarterly calibration. Panel B reports our targeted moments for both aggregate and industry-level cash flows. Entries for the model are obtained from repetitions of small samples. Aggregate annual per-capita GDP data start in 1930 and end in 2019. Industry-level cash flow refers to annual operating income from Compustat, 1960–2019. We focus on the Fama-French 30 industries and group them in three portfolios, each comprising 10 industries. The numbers in parentheses are HAC-adjusted standard errors.

Second, we model the infrequent arrival of sizeable shocks, as opposed to having a Gaussian diffusion. Because of these shocks, the distribution of growth rates features fatter tails than that of aggregate output. We calibrate the parameters ϕ_0 and ϕ_1 so that both the kurtosis and the volatility of each industry cash flow growth relative to that of aggregate output conforms to the data. Specifically, we use Compustat data to measure operating income for the Fama-French 30 industries. Since in our model we only have three industries, we group our 30 industries in three portfolios comprising an equal number of industries. In Table 1, we report both the volatility and the kurtosis of operating income growth aggregated at the portfolio level relative to the same moments computed on the growth of operating income aggregated across all firms in our dataset.[4] Additional details on the role of ϕ_0 and ϕ_1 are reported in section OL-A of the online appendix. We set τ to be small so that (i) the model feature balanced growth; and (ii) the cointegration of cash-flows across industries is not detectable in small sample, as in the data.

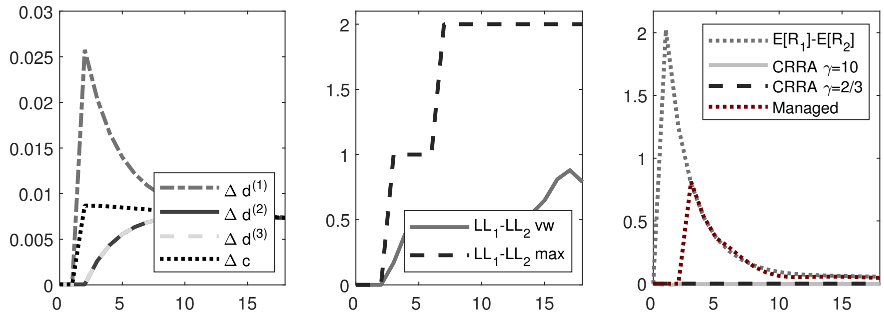
[4] We aggregate industries by sequentially assigning them to our three groups. For example, according to the Fama-French classification, our first group comprises 1. Food, 4. Games, ... The second group comprises 2. Beer, 5. Books, ... The third group includes 3. Smoke, 6. Household Consumer Goods...

We set the volatility of the common short-run shock, σ, to a value that makes aggregate output growth volatility very moderate compared to the data. We choose this strategy because we are aware that aggregate consumption growth has been half of that of output over the same long sample. An alternative way to keep the volatility of output on the low side would be to increase the number of industries at the cost of greatly increasing our computational time.

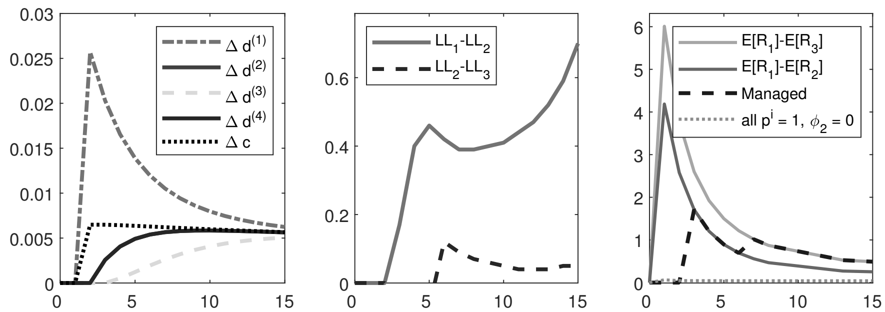
We solve our model using high-order perturbation methods and depict the impulse response function upon the realization of a positive growth shock to industry $i = 1$ in Figure 1. We start by discussing the case $N = 3$ (see Panel (a)). The growth increase in industry 1 is a leading indicator of the boom that the other industries will exhibit. In this specific calibration, industry 2 and 3 share the same growth path as industry 1 after approximately 12 quarters. The middle panel of this figure proves that our cross correlograms are able to correctly sort leading and lagging industries. The difference in the weighted averages of leads and lags starts to mean-revert after 16 periods, whereas the difference based on the maximum cross-correlation requires a longer time to mean-revert given that it takes discrete (i.e., integer) values.

We acknowledge that in very long samples a vector autoregression with time-varying coefficients may convey all of the relevant information dynamics about cash flows. In relatively short samples with a large cross section, however, estimating such a high-dimensional VAR with sufficient precision appears extremely challenging. Our simulation results suggest that cross-correlograms may be a useful non-parametric alternative tool to identify leading industries that have just received an infrequent growth shock.

In addition, in the rightmost panel we depict the expected return of a zero-dollar strategy long in leading and short in lagging industries. We consider both our benchmark calibration and two alternative calibrations in which $\gamma = 1/\psi$, that is, the agent has time-additive preferences with either high or low risk aversion. This panel shows three important results.



(a) N=3



(b) N=4

Fig. 1: The Leading Premium in the Model

Notes: This figure depicts impulse response functions upon the arrival of a positive shock to expected growth in industry $i = 1$. The shock arrives at $t = 1$ and affects cash-flows at $t = 2$. The left plot shows industry-level cash flow growth rates ($\Delta d^{(i)}$) as well as the growth rate of the aggregate cash flow (Δc). The middle plot shows the difference in our lead/lag indicators across industries. In panel (a), $N = 3$ and industry 3 behaves as industry 2. In panel (b), $N = 4$ and industry 2 and 4 have a similar behavior. In panel (a), we plot both the indicator based on the maximum cross-correlation ('max') and that computed as a weighted average of leads and lags ('vw'). The rightmost plot presents annualized conditional risk premia with either recursive preferences (benchmark) or time-additive preferences (CRRA). 'Managed' refers to an investment strategy that goes long (short) industries with higher (lower) LL indicator. When $\phi_2 = 0$, we have $p_t^i \equiv 1$.

First, as soon as an industry-cycle starts, the leading industry can feature a further conditional risk premium as large as 2%. An investment strategy based on our backward looking LL indicator would capture the variation in risk premia with delay and deliver a leading premium of about 0.9%. When $N = 4$ (see panel (b)), the cross section of leads and lags becomes wider and the leading premium becomes as large as 2% (dashed line, 'Managed'). As time goes by, our LL indicator correctly identifies the most leading and lagging industries, i.e., industry 1 and 3, respectively. As a result, the leading premium remains high and persistent.

Second, the leading premium is a relevant conditional phenomenon. On the one hand, as the cycle fully diffuses across industries, the implied leading premium declines to zero, i.e., it does not persist unconditionally. On the other hand, the premium is still sizeable after one whole year, meaning that its half-life is quite long.

Third, when $\gamma = 1/\Psi$ only short-run shocks are priced. Since our model features no leads/lags of short-run shocks, with time-additive preferences there is no leading premium. Consistent with what we presented above in Section 2, when $\gamma > 1/\Psi$ growth news shocks are priced and hence anticipated information about them generates a leading premium.

We conclude by noting two additional important aspects. Both the middle and the right-most panels of figure 1 remain unchanged if we explore the response to a negative shock to the expected growth of the cash flow in industry 1. On the one hand, this is consistent with the idea that in the model the leading premium is a pure reflection of the premium on the timing of information. On the other hand, this result proves that our study is not isomorphic to timing industries.

Second, if we were to set $\phi_2 = 0$, we would observe no leading premium. When $\phi_2 = 0$, we have $p_t^i = 1$ for all i and t, and hence it is no longer true that an industry-specific cycle provides useful information about the cycle of the other industries. This is because industry-driven cycles become equally likely across industries and over time. Equivalently, without heterogeneity in p_t^i across industries, there is no well-defined endogenous lead/lag structure (for additional details, see Appendix A).

3.5 Model-inspired Empirical Tests

Inspired by our model, in the next section, we ask the following questions. First, is there a relevant conditional variation in cash flow leads and lags across industries? What about unconditionally?

Second, assuming that we can identify leading and lagging industries, is there a sizable leading or lagging premium? Through the lens of our model, this exercise can inform us on the implied preference of investors for early resolution of uncertainty.

Finally, how large is the share of the leading premium that is solely driven by the timing premium? In order to address these questions, we use standard asset pricing techniques to control for heterogeneous exposure to risk to empirically identify the timing premium embedded in the industry cross section.

In what follows, we also report several robustness tests that link our empirical investigation to the narrative of our illustrative model.

4 Empirical Investigation

Data sources. In our empirical analysis, we use monthly stock returns from CRSP as well as the corresponding quarterly data from Compustat for the period from from 1967:Q1 to 2017:Q4. The quarterly data coverage in Compustat prior to 1967 is too limited for our investigation. We group firms into 30 industries following the classification scheme available on Kenneth French's website. We assign firms to industries using SIC codes from CRSP. We compute industry-level output by aggregating firms' operating income before depreciation and net of interest expenses, income taxes, and dividends (as in Acharya, Almeida, Ippolito, and Perez, 2014).[5] We also employ alternative measures in our robustness exercises, which we will describe in detail in the next sections. We use dummy variables to remove seasonality. We gather aggregate US consumption and output data from the National Income and Product Accounts (NIPA). All variables are seasonally adjusted and in real units. Inflation is computed using the Consumer Price Index (CPI).

[5] We do not use BEA industry data because they are coarser, based on NAICS definitions, and available only at an annual frequency prior to 1997.

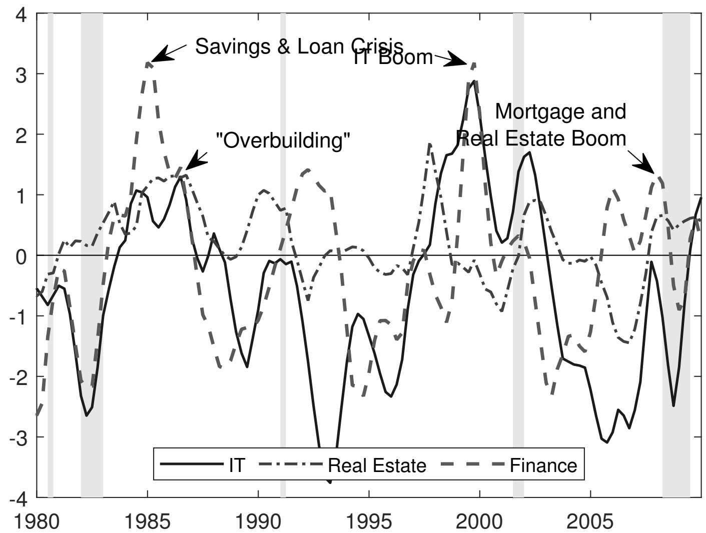


Fig. 2: Lead-Lag Indicator for Selected Industries

Notes: This figure depicts the lead-lag (LL) indicator for three major industries. The LL indicator is computed in two steps. First, for each industry, in each quarter we compute the ±4-quarter cross-correlation between industry-level output growth and the domestic output growth using 20-quarter rolling windows. Second, we compute the industry-level weighted average of leads and lags and assign it to the corresponding industry as its LL indicator. A positive (negative) LL indicator denotes an industry whose output growth leads (lags) GDP growth. Quarterly growth rates are adjusted for inflation and seasonality. Grey bars denote NBER recession periods.

LL indicators. For each industry, in each quarter, we compute the ±4-quarter cross-correlation between industry-level output growth and the domestic output growth using 20-quarter rolling windows. According to the methods described in the previous section, we then compute conditional quarterly lead-lag measures for each industry. This procedure generates a panel of industry-level lead-lag (LL) indicators spanning 51 years.

To provide economic guidance about our measure, in Figure 2, we report our industry-level weighted average LL indicators for the IT, the finance, and the real estate industry using observations starting from 1975. We focus on these industries because they have been important drivers of the last two main economic cycles in the US, and hence they represent a natural reference point for our methodology.

We find it reassuring that our methodology detects several well-known economic patterns.

For example, the IT industry became progressively more leading in the 1995-2000 subsample, that is, during the IT boom. The boom of the early 2000s, instead, was led by real estate, with finance becoming progressively more leading after 2005 and during the Great Recession. In Appendix B, we show that our correlograms are very distinct across lagging and leading industries (Figure B2). Furthermore, we list leading and lagging industries across 5-year subsamples (Table B1) and report the persistence of leading and lagging industries both in our data and from simulated date (Table B2). In the data, industries stay in the leading/lagging portfolio for 1.5 consecutive years on average. In the model, this figure is equal to about 1.8 years. In addition, we acknowledge that the data show a strongly time-varying composition of the leading industries that cannot be matched by our simple circle-shaped network.

4.1 Portfolio Sorting, Risk Premia, and Characteristics

Portfolio sorting. We start with the Fama-French 30-industry cross section. In each quarter, we sort firms grouped in our 30 industries according to their maximum correlation LL indicator value and divide them into three portfolios. Our lead (lag) portfolio contains on average the top six leading (lagging) industries and represents in each quarter at least 15% of total market capitalization, implying that our results are not driven by a fraction of small and potentially illiquid firms. Our results also hold when we form portfolios comprising either a fixed number of industries or different levels of capitalization (see Online Appendix, Tables OL-B1 and OL-B2, respectively).

For each portfolio, we compute value-weighted monthly returns and highlight the following relevant facts. First, we construct a lead-lag (LL) factor by considering the returns of a zero-dollar investment strategy long in the leading and short in the lagging portfolio. This strategy pays an average annualized excess return of 3.6%, as shown in Table 2.

Second, within each portfolio we identify the industries whose absolute value of correlation with output is above the median. We group the above-median industries in subportfolios

Table 2: Lead-Lag Portfolio Sorting

Panel A: returns (max correlation LL indicator)	Lead	Mid	Lag	LL	LL Strong
Avg Ex. Ret.	8.99***	6.64***	5.38*	3.60**	6.01***
	(2.11)	(2.37)	(2.81)	(1.79)	(2.32)

Panel B: comparison across LL indicators	Max Corr.	Industry-Weighted Avg.	Cross-Industr.
LL Ex. Ret. Volatility	12.90	12.09	11.45
LL Sharpe Ratio	0.28	0.30	0.35
Avg. LL Ex. Ret.	3.60**	3.65**	3.95***
	(1.79)	(1.74)	(1.44)
CAPM α	4.36**	4.03**	4.35***
	(1.84)	(1.89)	(1.50)
Portfolio Turnover	0.13	0.11	0.12
Industry migration	1.1	0.9	0.9
Ex-ante LL gap (quarters)	6.17	4.36	3.86
Ex-post LL gap (quarters)	3.70	3.78	3.37
Corr(Ex-ante LL, Ex-post LL)	0.41	0.85	0.60
Recession dummy	5.18	5.15	4.59
	(5.34)	(6.47)	(6.30)

Notes: Panel A provides annualized value-weighted returns of portfolios of firms sorted according to their industry-level lead-lag (LL) indicator based on maximum cross-correlation (see section 3.1). A positive (negative) LL indicator denotes an industry whose output growth leads (lags) GDP growth. Our Lead (Lag) portfolio contains the top (bottom) 20% of our leading industries. In each portfolio, we identify the industries with maximum cross-correlation above the portfolio's median and group them in a subportfolio denoted as 'Strong'. The LL Strong portfolio represents a zero-dollar trading strategy long in Lead Strong and short in Lag Strong. Panel B provides annualized value-weighted excess returns for an LL strategy across three different ways to compute the lead-lag indicator. Turnover measures the percentage of industries entering or exiting from a portfolio. Industry migration measures the median number of times an industry moves across portfolios in a year. Ex-ante (Ex-post) LL gap measures the average gap in the LL indicators across the Leading and Lagging portfolios at (after) formation. Return data are monthly over the sample 1972:01–2017:12. Industry definitions are from Kenneth French's website. CAPM α denotes average excess returns unexplained by the unconditional CAPM. The recession dummy measures variation in the average excess return of the LL portfolio during NBER defined recessions. The numbers in parentheses are standard errors adjusted according to Newey and West (1987). One, two, and three asterisks denote significance at the 10%, 5%, and 1% levels, respectively.

denoted as 'Strong', given that they feature a stronger and less noisy lead/lag connection with aggregate output. We then study the return of a zero-dollar investment strategy long in Lead-Strong and short in Lag-Strong. We obtain even stronger results (see Panel A of Table 2, right-most column).[6]

Third, these results are confirmed across our three ways to compute the LL indicator (see Table 2, Panel B). In addition to the measures defined in (1) and (2), our third LL indicator is denoted as 'cross-industry LL'. A possible concern about our previous indicators is that they do not adjust by the different predictive power that different industries may have. As an extreme example, one industry may lead GDP by four periods with a cross-correlation of 0.90 and be a much better predictor of the cycle ahead than an industry leading by four periods with a cross-correlation of 0.40. In order to address this concern, we also compute

$$LL_t^i = \sum_{j=-J}^{J} \frac{|\rho_{t,j}^i|}{\sum_{k=1}^{N} |\rho_{t,j}^k|} \cdot j,$$

where the weight assigned to lead/lag j of industry i depends on the cross-correlation of all of the other industries for the same lead/lag. In contrast to the industry-level weighted average of leads and lags, here we divide by the sum of $|\rho_{t,j}^k|$ across industries ($k = 1, .., N$), not across leads and lags ($j = -J, ..., J$).

The different versions of the LL factor generate Sharpe ratios ranging from 0.28 to 0.35, and their CAPM unconditional alphas range from 4% to 4.36%, a sizeable number. The average quarterly turnover is stable and very moderate at about 12%.[7] According to our methodology, industries move across portfolios at most once a year.

The next three rows in Table 2 confirm that the moderate migration of industries across portfolios is due to the persistence of our LL measures. In addition, across all possible indicators, the gap between the LL indicator of the leading industries and that of the lagging

[6]These empirical patterns are also present when we focus on equally weighted returns.

[7]In each quarter, we compute the market value of the firms that either exit or enter a given portfolio. We divide this number by two and report it as a fraction of the total market value. Expressing turnover in market value terms prevents our measure from being driven by many small industries frequently moving across portfolios.

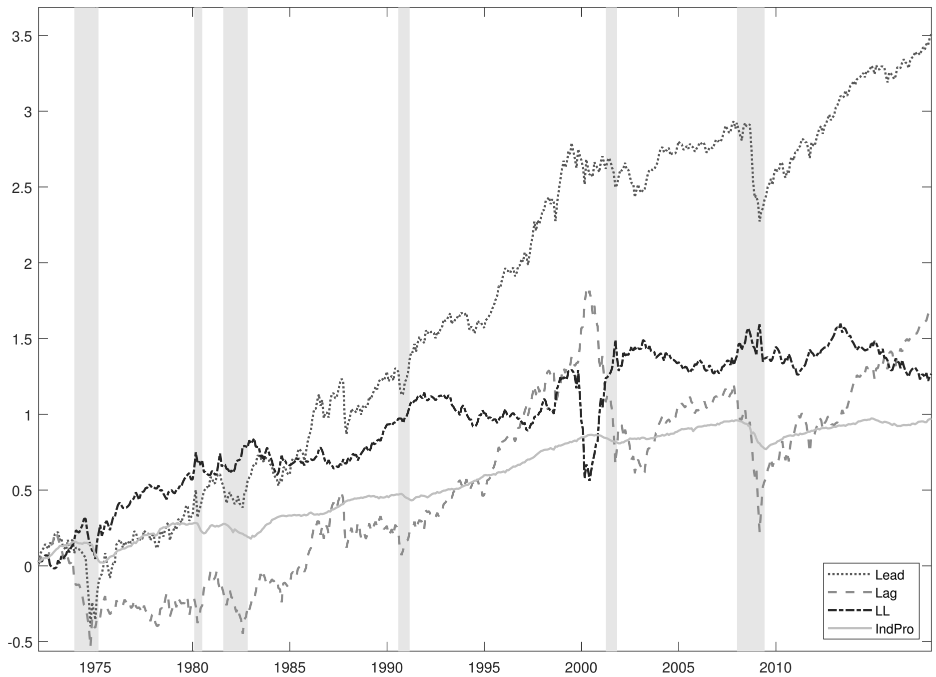


Fig. 3: Lead-Lag Cumulative Excess Return

Notes: This figure depicts cumulative log excess returns for our Leading and Lagging portfolios, as well for the Lead-Lag Factor. The solid line depicts the log of the industrial production series for the US. Shaded areas denote recession periods. Leads and lags are identified by maximum absolute value of cross correlations.

industries is very stable also at the end of the quarter in which the portfolio has been formed (ex-post measure).

We regress our LL return on a constant and on a dummy variable that takes a value of one during recession periods. In the last row of the table, we report our estimates and conclude that our returns are not significantly different during recessions. In addition, in Figure 3, we depict the cumulative log excess returns obtained investing in the leading and the lagging portfolio as well as the those from the Lead-Lag strategy. A visual inspection of the time path of our factor shows that it is acyclical, i.e., not synchronized with either industrial production or recession periods.

Given the similarity of our results across different measures of leads and lags, in what follows we keep the maximum cross-correlation as our benchmark.

Table 3: Dynamic and Static LL Portfolios Formation

	Avg. Excess Return	CAPM α	Gap in LL Indicator
Panel A: Dynamic portfolio formation			
Quarterly	3.60^{**}	4.36^{**}	6.17^{***}
	(1.79)	(1.84)	(0.13)
Annual	4.26^{**}	5.63^{***}	6.17^{***}
	(1.84)	(1.78)	(0.20)
Panel B: Static portfolio formation			
Initial Sorting	−1.77	−2.33	−0.11
	(1.70)	(1.79)	(0.23)
Unconditional LL	0.24	−0.88	0.07
	(1.46)	(1.63)	(0.24)

Notes: This table reports both annualized average value-weighted excess returns and CAPM α for a zero-dollar strategy long in leading industries and short in lagging industries. The lead-lag (LL) indicator is based on maximum cross-correlation (see section 3.1). The rightmost column reports the difference in the LL indicator across the leading and the lagging portfolios. In Panel A, we update the portfolios at the quarterly and annual frequency. In Panel B, the portfolios are formed at the beginning of the sample and rebalanced quarterly (i.e., we update their value weights keeping the industry composition constant). *Initial Sorting* refers to a portfolio constructed at the beginning of the sample using our standard procedure and it is never reformed. *Unconditional LL* is based on a full-sample computation of cross-correlations and an unconditional sorting. The column *LL indicator (Lead-Lag)* reports the average difference between LL indicators of industries in leading and lagging portfolios. Newey-West adjusted standard errors are reported in parentheses. Monthly data start in 1972:01 and end in 2017:12. Industry definitions are from Kenneth French's website. One, two, and three asterisks denote significance at the 10%, 5%, and 1% levels, respectively.

Conditional and unconditional sorting. In Table 3, we report both annualized average value-weighted returns and CAPM alphas for a zero-dollar strategy long in leading industries and short in lagging industries. The rightmost column reports the difference in the LL indicator across the leading and the lagging portfolios. In Panel A, we update our portfolios at either the quarterly or annual frequency. Our results do not hinge on high-frequency re-balancing and re-sorting. The leading premium can be captured even when we form our portfolios only once a year.

In Panel B, the portfolios are static, as they are formed only once and their weights are rebalanced quarterly. *Initial Sorting* refers to a portfolio constructed using our standard procedure over the first observations of our sample. Hence this portfolio refers to an implementable strategy. *Unconditional LL* refers to an investment strategy based on a full-sample computation of the unconditional leads and lags. Regardless of whether we use a static initial sorting or an unconditional one, the implied premium is statistically not different from zero. Hence the gap in the lead-lag indicators vanishes in these cases. In other words, our industries do not feature systematic differences in their leads/lags, and our leading premium is a conditional phenomenon.

Characteristics. In Table 4, we report key characteristics for our leading and lagging portfolios at both the industry and the firm level. Our leading premium is not driven by systematic differences in the upstreamness of our industries. Consistent with our model presented in Section 3, industries may be leading with respect to both upstream and downstream shocks (Herskovic et al., 2020; Cohen and Frazzini, 2008).

This result holds whether we measure upstreamness as in Antràs et al. (2012) or look at other indicators such as (i) the dollar value of goods supplied to other industries over the dollar value of goods used by a specific industry and (ii) the value of intermediate goods used by an industry over its total added value. In addition, we see no significant link between leading firms and investment-goods producers. Taking an industrial organization view, we document that leading stocks tend to be in industries featuring slightly more concentrated sales, i.e., industries where we have fewer but larger firms. After double-sorting on leads/lags and HHI, we see that the leading premium is concentrated among industries with a medium level of HHI (see Online Appendix, Table OL-B4). Equivalently, our leading premium is not due to extremely competitive or monopolistic industries. Furthermore, we see no difference in markups (De Loecker et al. 2020; Clara et al. 2021) across leading and lagging industries.

Turning our attention to firm-level characteristics, we point out that only tangibility is statistically different across leading and lagging firms. In one of our next empirical steps, we show that the leading premium remains relevant even after controlling for the tangibility factor (see Online Appendix, Table OL-B17). Looking at all the other variables, we find no

Table 4: Industry Characteristics across Leading and Lagging Portfolios

	Lead	Lag	Diff	p-value
Panel A: Industry-Level Characteristics				
Upstreamness	1.940	1.948	−0.008	0.887
Goods Supplied/Goods Used	1.441	1.488	−0.047	0.625
Interm. Goods Used/Total Output (excl. Labor)	0.679	0.662	0.018	0.251
HHI Sales	0.136	0.091	0.045	0.000
Investment Good Producer	0.154	0.130	0.025	0.430
$\log(\text{Markup}_1)$	0.357	0.329	0.028	0.213
$\log(\text{Markup}_2)$	0.148	0.123	0.025	0.270
Panel B: Firm-Level Characteristics				
Size, mln	1040.851	740.344	300.508	0.530
Market Leverage	0.262	0.264	−0.003	0.828
Tangibilty	0.250	0.220	0.030	0.034
Book-to-Market	0.723	0.720	0.002	0.918
R&D Expenses/Total Assets	0.070	0.065	0.005	0.268
Operating Income/Sales	0.152	0.148	0.004	0.657
Panel C: Portfolio-Level Characteristics				
Avg. of Inv./Tot. Assets	0.137	0.124	0.013	0.129
StDev of Inv./Tot. Assets	0.064	0.083	−0.019	0.000
$\beta^p_{N_C}$	−0.106	−0.086	−0.021	0.458
$\beta^p_{N_S}$	0.096	0.085	0.011	0.610

Notes: This table provides industry- and firm-level characteristics of companies allocated to the leading and lagging portfolios. In Panel A, we report industry-level measures. *Upstreamness* denotes the Antràs et al. (2012) measure of the industry's relative position in the supply chain. These variables are computed using the BEA input-output summary tables. *HHI Sales* represents the industry concentration as measured by Hirschman-Herfindahl Index of sales. *Investment Good Producer* refers to the share of firms producing investment goods as classified by Gomes et al. (2009). $Markup_1$ ($Markup_2$) includes (excludes) overhead costs. The firm-level variables are standard. Investment and total assets are aggregated at the portfolio level. The rightmost column reports p-values of the t-test between means using the standard errors adjusted according to Newey and West (1987).

systematic difference in financial leverage, growth opportunities, innovation intensity, and profitability.

We complete our analysis by comparing investment characteristics across leading and lagging portfolios. From a statistical point of view, firms in leading industries have an average investment intensity comparable to that of lagging firms. Lagging firms, however, adjust their investments more (as indicated by a higher standard deviation of the ratio of investment to total assets, $StD(I/A)$). These results are broadly consistent with the idea that lagging firms have time to process information about future fluctuations and use information to revise their investment plans.[8] In addition, our leading and lagging portfolios have similar exposures, $\beta^p_{N_C}$ and $\beta^p_{N_S}$, to the concentration and the sparsity network factor proposed by Herskovic (2018) (see Online Appendix, Table OL-B3, for additional details).

Leads, lags, and firm activity. Our model suggests that leading firms should be riskier than lagging firms because leading firm cash flows are less predictable than those of lagging firms. We explore this dimension by running forecasting regressions on both operating income and sales and we report our main results in Table 5 (top portion). In each Panel A, we use a set of common leading indicators (term spread, default spread, aggregate price-dividend ratio, inflation, and forward rate) in order to forecast the growth rate of the aggregated cash flows of both the leading and lagging portfolios. Consistent with the intuition of our model, the cash flows of the lagging industries are more predictable than those of the leading industries as they feature higher adjusted R^2 values across all forecasting horizons.

In Panels B and C, we strengthen our results by documenting that over longer horizons the growth rate of the cash flows of leading industries forecasts the cash flow growth of lagging industries, whereas the opposite is not true. In addition, at all horizons, the cash flows of lagging industries can be predicted by the growth rate of the cash flow of the industries in our leading portfolio with a sizeable adjusted R^2. Furthermore, for a given predictive horizon, the R^2 is always higher for the cash flows of the lagging portfolio.

We repeat the same steps with financing variables such as equity and debt issuance. We find very similar results, meaning that the financing activity of leading firms predicts that of lagging firms across different quarters. This regularity is also present when we look at

[8] We thank Laura Veldkamp for this insight. These results hold also when we exclude financial firms.

Table 5: Predictive Properties of Leading and Lagging Industries

	$h=1$	$h=2$	$h=3$	$h=4$		$h=1$	$h=2$	$h=3$	$h=4$
Cash-Flows Growth					**Sales Growth**				
Panel A: $y_{t+h}=\gamma_0+\gamma_h PF_t+\varepsilon_{t+h}$					*Panel A:* $y_{t+h}=\gamma_0+\gamma_h PF_t+\varepsilon_{t+h}$				
Adj. R^2 lead	0.093	0.082	0.073	0.077	Adj. R^2 lead	0.190	0.102	0.056	0.002
Adj. R^2 lag	0.184	0.204	0.245	0.103	Adj. R^2 lag	0.283	0.272	0.188	0.108
Panel B: $y^{lag}_{t+h}=\gamma_0+\gamma_h y^{lead}_t+\varepsilon_{t+h}$					*Panel B:* $y^{lag}_{t+h}=\gamma_0+\gamma_h y^{lead}_t+\varepsilon_{t+h}$,				
γ_h	0.398***	0.547***	0.465***	0.146	γ_h	0.677***	0.686***	0.586***	0.374**
	(0.142)	(0.184)	(0.151)	(0.143)		(0.065)	(0.071)	(0.155)	(0.172)
Adj. R^2	0.047	0.089	0.064	0.006	Adj. R^2	0.289	0.298	0.217	0.086
Panel C: $y^{lead}_{t+h}=\gamma_0+\gamma_h y^{lag}_t+\varepsilon_{t+h}$					*Panel C:* $y^{lead}_{t+h}=\gamma_0+\gamma_h y^{lag}_t+\varepsilon_{t+h}$				
γ_h	0.109*	0.101	0.025	−0.005	γ_h	0.310**	0.234*	0.130	0.101
	(0.059)	(0.072)	(0.066)	(0.054)		(0.146)	(0.132)	(0.110)	(0.084)
Adj. R^2	0.040	0.034	0.002	0.000	Adj. R^2	0.151	0.087	0.027	0.016
Equity Issuance					**Debt Issuance**				
Panel A: $y_{t+h}=\gamma_0+\gamma_h PF_t+\varepsilon_{t+h}$					*Panel A:* $y_{t+h}=\gamma_0+\gamma_h PF_t+\varepsilon_{t+h}$				
Adj. R^2 lead	0.070	0.046	0.052	0.043	Adj. R^2 lead	0.015	0.032	0.021	0.018
Adj. R^2 lag	0.255	0.265	0.269	0.207	Adj. R^2 lag	0.068	0.087	0.175	0.089
Panel B: $y^{lag}_{t+h}=\gamma_0+\gamma_h y^{lead}_t+\varepsilon_{t+h}$,					*Panel B:* $y^{lag}_{t+h}=\gamma_0+\gamma_h y^{lead}_t+\varepsilon_{t+h}$,				
γ_h	0.277***	0.212**	0.173***	0.265***	γ_h	0.034***	0.110***	0.031***	0.024**
	(0.073)	(0.097)	(0.061)	(0.090)		(0.012)	(0.028)	(0.011)	(0.011)
Adj. R^2	0.075	0.041	0.025	0.069	Adj. R^2	0.001	0.065	−0.000	−0.002
Panel C: $y^{lead}_{t+h}=\gamma_0+\gamma_h y^{lag}_t+\varepsilon_{t+h}$					*Panel C:* $y^{lead}_{t+h}=\gamma_0+\gamma_h y^{lag}_t+\varepsilon_{t+h}$				
γ_h	0.197**	0.127	0.036	−0.128	γ_h	0.122	0.097	0.120	0.066
	(0.099)	(0.095)	(0.098)	(0.089)		(0.127)	(0.094)	(0.087)	(0.060)
Adj. R^2	0.038	0.016	0.001	0.017	Adj. R^2	0.003	0.002	0.003	0.001

Notes: This table continues to the next page.

a flexible input of production such as labor.[9] For employment (bottom-right panel), we use annual data from Compustat, and hence we run our forecasting regressions only one period ahead. Interestingly, investment (bottom-left panel) is synchronized across leading and lagging firms. In the spirit of what is shown in Table 4, lagging firms have time to process information about future fluctuations and use it to revise their investment plans more aggressively and without waiting. This is an equilibrium outcome when (i) firms pre-

[9] We follow Ma (2019) in constructing quarterly series of firm-level financing and real policies. Equity issuance is defined as Compustat item SSTK scaled by lagged total assets. Debt issuance is non-negative. Annual employment growth is constructed using Compustat item EMP. Hiring is defined as non-negative employment growth.

Table 5(continued): Predictive Properties of Leading and Lagging Industries

Investment Growth

Panel A: $y_{t+h} = \gamma_0 + \gamma_h PF_t + \varepsilon_{t+h}$				
Adj. R^2 lead	0.318	0.309	0.217	0.104
Adj. R^2 lag	0.253	0.283	0.246	0.199
Panel B: $y^{lag}_{t+h} = \gamma_0 + \gamma_h y^{lead}_t + \varepsilon_{t+h}$,				
γ_h	0.717***	0.560***	0.350***	0.146
	(0.114)	(0.116)	(0.114)	(0.123)
Adj. R^2	0.440	0.265	0.098	0.011
Panel C: $y^{lead}_{t+h} = \gamma_0 + \gamma_h y^{lag}_t + \varepsilon_{t+h}$				
γ_h	0.586***	0.466***	0.291***	0.107
	(0.076)	(0.084)	(0.096)	(0.103)
Adj. R^2	0.393	0.248	0.096	0.013

Employment

Panel A: $y^{lag}_{t+1} = \gamma_0 + \gamma_1 y^{lead}_t + \varepsilon_{t+1}$		
	Emp growth	Hiring
γ_1	0.418***	0.406***
	(0.122)	(0.123)
Adj. R^2	0.131	0.127
Panel B: $y^{lead}_{t+1} = \gamma_0 + \gamma_1 y^{lag}_t + \varepsilon_{t+1}$		
	Emp growth	Hiring
γ_1	0.059	0.055
	(0.099)	(0.120)
Adj. R^2	0.004	0.003

Notes: This table reports results from h-quarter ahead predictive regressions. Panel A documents the adjusted R^2 from a model predicting growth of leading and lagging portfolios' variable of interest. PF comprises the following common predictive factors: term spread, default spread, aggregate price-dividend ratio, inflation, and forward rate. Panel B (Panel C) reports the estimation results when predicting cash-flow growth of lagging (leading) industries portfolio using cash-flow growth of leading (lagging) industries portfolio. The quarterly data start in 1972:Q1 and end in 2017:Q4. Numbers in parentheses are standard errors adjusted according to Newey and West (1987). One, two, and three asterisks denote significance at the 10%, 5%, and 1% levels, respectively. For employment, data are annual.

commit to investment, and (ii) adjusting investment afterward is increasingly costly (see our online appendix, section OL-D).

Our estimation results are stable across subsamples. We discuss this point further in our online appendix (see, for example, Figure OL-B2).

Predictability of aggregate activity. Our model suggests that leading industries convey news that are priced because they concern the future growth of the overall economy. In order to test this aspect of the model, we assess whether (i) the cash flows growth and (ii) the aggregate valuation ratio of our leading firms have predictive power for industrial production and unemployment beyond that of classical predictors. Specifically, we construct the price-dividend ratio for both the aggregate stock market and our leading portfolio and use these two ratios in standard forecasting regressions.

We report our findings in Tables 6 and 7 for cash flows and valuation ratios, respectively. We note three relevant results. First, as indicated by the results shown in Table 6, the growth rate of the cash flows of leading industries predicts future economic performance even after

Table 6: Predictive Properties of Leading Cash-Flow Growth

Industrial production growth				
	$h=1$	$h=2$	$h=3$	$h=4$
Eq. (1)-(2), γ_h	0.012*	0.015**	0.013**	0.007
	(0.007)	(0.007)	(0.007)	(0.007)
Adj. R^2	−0.001	0.059	0.084	0.129
Adj. R^{2*}	−0.009	0.045	0.074	0.130
Unemployment growth				
	$h=1$	$h=2$	$h=3$	$h=4$
Eq. (1)-(2), γ_h	−0.055**	−0.056**	−0.058**	−0.047*
	(0.028)	(0.028)	(0.026)	(0.025)
Adj. R^2	0.072	0.087	0.138	0.212
Adj. R^{2*}	0.058	0.072	0.122	0.203

Notes: This table reports loadings of industrial production growth and unemployment growth h quarters ahead on the cash-flow growth of industries in the leading portfolio. In particular, we estimate predictive regressions of the form:

$$\Delta g_{t+h} = \gamma_0 + \gamma_h \Delta CF_t^{lead} + \nu \Delta CF_t^{MKT} + \text{controls} + \epsilon_{t+h},\ h = 1,..,4 \quad (1)$$

$$CF_t^{lead} = \rho_0 + \rho_1 \Delta CF_{t-1}^{lead} + u_t \quad (2)$$

where Δg_{t+h} is the h-quarter ahead one-period growth rate of industrial production and unemployment. The set of controls includes the term spread, inflation, and federal fund rate. CF^{MKT} refers to the growth rate of the aggregate cash flows in our cross section. Estimated coefficients have been adjusted with the Stambaugh bias correction. Bootstrap standard errors are in parentheses. *Adj* $R^{2\,*}$ denotes adjusted R-squared for an equivalent regression where CF^{lead} is excluded. The quarterly data start in 1972:Q1 and end in 2017:Q4. One, two, and three asterisks denote significance at the 10%, 5%, and 1% level, respectively.

controlling for total cash flow growth in addition to other classical forecasting variables.

Second, Table 7 shows that our leading price-dividend ratio exhibits significant predictive power for both industrial production and employment. This result obtains while controlling for other well-known predictive factors, such as the aggregate price-dividend ratio, a measure for the aggregate credit spread, inflation, and the federal funds rate.

Third, the predictive power of the leading price-dividend ratio is increasing in the horizon of our regressions in terms of both coefficient magnitude (γ_h) and contribution to the adjusted R^2. This contribution is measured by the difference between the adjusted R^2 values with and without the leading price-dividend ratio included in the regression. Similar results are featured in Table 6 for our cash flows-based regressions. We note that we do not focus on

Table 7: Predictive Properties of Leading Price-Dividend Ratio

Industrial production growth				
	$h=1$	$h=2$	$h=3$	$h=4$
Eq. (1)-(3), γ_h	0.074^{***}	0.121^{***}	0.147^{***}	0.178^{***}
	(0.021)	(0.027)	(0.028)	(0.026)
Adj. R^2	0.253	0.073	0.041	0.102
Adj. R^2*	0.246	0.047	0.001	0.039
Eq. (2), γ_h	0.062^{***}	0.106^{***}	0.128^{***}	0.161^{***}
	(0.019)	(0.023)	(0.024)	(0.022)
Adj. R^2	0.249	0.077	0.065	0.133
Adj. R^2*	0.245	0.059	0.036	0.084
Unemployment growth				
	$h=1$	$h=2$	$h=3$	$h=4$
Eq. (1)-(3), γ_h	-0.046	-0.134^{***}	-0.227^{***}	-0.282^{***}
	(0.032)	(0.036)	(0.038)	(0.036)
Adj. R^2	0.251	0.016	0.042	0.117
Adj. R^2*	0.254	0.008	0.010	0.064
Eq. (2), γ_h	-0.046	-0.128^{***}	-0.219^{***}	-0.277^{***}
	(0.034)	(0.038)	(0.039)	(0.038)
Adj. R^2	0.239	0.006	0.043	0.117
Adj. R^2*	0.242	0.000	0.014	0.068

Notes: This table reports loadings of industrial production growth and unemployment growth h quarters ahead on the price-dividend ratio of the leading portfolio. In particular, we estimate predictive regressions of the form:

$$\Delta g_{t+h} = \gamma_0 + \gamma_h pd_t^{lead} + \delta pd_t^{MKT} + \alpha \Delta g_{t-1} + \varepsilon_{t+h},\ h = 1, .., 4 \qquad (1)$$

$$\Delta g_{t+h} = \gamma_0 + \gamma_h pd_t^{lead} + \delta pd_t^{MKT} + \alpha \Delta g_{t-1} + \text{controls} + \epsilon_{t+h},\ h = 1, .., 4 \qquad (2)$$

$$pd_t^{lead} = \rho_0 + \rho_1 pd_{t-1}^{lead} + u_t \qquad (3)$$

where Δg_{t+h} is the h-quarter ahead one-period growth rate of industrial production and unemployment. In the regressions, we control for the $(t-1)$-growth rate, Δg_{t-1}. The set of controls includes the default spread, inflation, and federal fund rate. Estimated coefficients have been adjusted with the Stambaugh bias correction. Bootstrap standard errors are in parentheses. *Adj* R^2* denotes adjusted R-squared for an equivalent regression where pd^{lead} is excluded. The quarterly data start in 1973:Q1 and end in 2017:Q4. One, two, and three asterisks denote significance at the 10%, 5%, and 1% level, respectively.

cumulative growth rates and hence we are not exposed to the potential problems pointed out by Valkanov (2003). Our estimates are adjusted for the Stambaugh (1986) bias, and our inference is based on a bootstrap procedure that mitigates the issues pointed out by Torous et al. (2004).

Leading Industry News Shocks (LINS). According to our equilibrium model, growth news shocks to the cashflow of leading industries represent the fundamental factor that matters for the leading premium. We recover the growth news shocks of the firms in the leading portfolio, $\hat{e}_t$, by estimating the following system of quarterly forecasting equations:

$$\begin{aligned} \Delta CF_{t+1}^{lead} &= \alpha + \beta X_t + \varepsilon_{t+1} \qquad (7) \\ g_t^{lead} &:= \alpha + \beta X_t \\ g_t^{lead} &= \rho_0 + \rho_1 g_{t-1}^{lead} + e_t. \end{aligned}$$

X comprises the price-dividend ratio of the leading portfolio as well as the following additional controls: term spread, default spread, aggregate price-dividend ratio, inflation, and federal funds rate.

According to the model, the excess returns of our leading industries should have higher exposure to growth news shocks than those of lagging industries. We test this assumption by regressing our LL financial factor, $r^{LL} := r^{lead} - r^{lag}$, on the LINS factor, $\hat{e}_t$,while controlling for the FF3 factors. The data support our model. This is also true when we include additional macroeconomic controls (see Table 8). We see this result as supportive of the mechanism implied by our equilibrium model. In section 4.3, we perform additional tests regarding the market price of risk of these factors.

4.2 Additional Dimensions

Robustness. In the online appendix OL-B, we show that our results are robust to many variations of our benchmark methodology. For example, we consider alternative ways to predict economic fluctuations, using consumption as opposed to output when constructing the LL indicators, using a wider range of leads and lags when computing the LL indicators,

Table 8: LL Exposure to Growth News Shocks

$r_t^{LL} := r_t^{lead} - r_t^{lag} = c_0 + (\beta^{lead} - \beta^{lag})\hat{e}_t + FF3_t + resid_t$		
	w. controls	w.o. controls
$\beta^{lead} - \beta^{lag}$	1.818***	0.600***
	(0.420)	(0.225)

Notes: The LL factor is constructed using our maximum correlation indicator and our benchmark cross section of 30 industries. The LINS factor is obtained by estimating the system of equations (7) and it captures growth news shocks to the cashflow of the industries in our leading portfolio. Quarterly data start in 1972 and end 2017. The effective sample is based on 176 observations. The factor $\hat{e}_t$ is estimated both with and without the addition of controls in equation (7). The controls are: term spread, default spread, aggregate price-dividend ratio, inflation, and federal funds rate. The numbers in parentheses are standard errors adjusted according to Newey and West (1987). One, two, and three asterisks denote significance at the 10%, 5%, and 1% level, respectively.

alternative cash flow measures, alternative granularities across industries, as well as double sorts on size and book-to-market.

Leading premium and cross section of risk factors. Given the way in which we form our LL factor, it is natural to ask whether it is connected to other well-known risk factors already explored in the literature. In this section, we run standard time-series tests in order to check whether: (i) other factors fully explain ours, and (ii) our factor explains other existing ones. We find it important to state that our goal is not 'adding another factor to the zoo' (Feng et al., 2020). Rather, we gather empirical guidance regarding the deeper economic concept highlighted in our model, that is, the size and relevance of the timing premium.

In addition, we note that in an economy in which shocks diffuse immediately across sectors, our lead-lag factor should not provide additional information, once we control for other aggregate factors. Equivalently, we should not expect to find a significant alpha. In many of our exercises, however, we find a strong disconnect between our leading premium and other well-known risk factors. We interpret these results as suggesting that existing risk factors are not enough to fully capture the role of the many shocks that affect our granular cross section of industries. We report our detailed results in the online appendix, section

OL-B.1.

4.3 The Timing Premium in the Cross Section

In this section, we perform a cross-sectional investigation in order to (i) test key predictions of our model, and (ii) better disentangle the portion of our leading premium that is associated exclusively with advance information and cannot be attributed to heterogeneous exposure to other factors connected to cyclical economic activity.

We use GMM to estimate the following linear pricing model

$$R^{ex}_{i,t} = a_i + \beta_i \cdot F_t + u_{i,t} \quad (8)$$

$$E[R^{ex}_{i,t}] = \beta_i \lambda + v_i, \quad (9)$$

in which R^{ex} denotes excess returns, i indexes the test assets, and the β and λ coefficients measure the exposure of returns to and the market price of risk of our factors, F_t, respectively.[10]

We estimate this model across many different cross sections of test assets using the FF3 model as baseline and we augment it with either our LL financial factor or our news shocks-based LINS factor. We use many different cross sections of test assets both for robustness and to address the criticism of Lewellen et al. (2010) related to the strong factor structure of the size and book-to-market cross-sections.

In Table 9, we report for each cross-section both the spread in the portfolio exposures to our LL-based factors and a measure of the implied timing premium, given by the spread in exposures multiplied by the market price of risk. On average, the timing premium ranges

[10] As in Cochrane (2005), we represent the discount factor as $m_t = \overline{m} - bf_t$, so that

$$b = E(f_t f_t')^{-1} \lambda. \quad (10)$$

Table 9: **Disentangling Timing Premium from Leading Premium**

	LL Factor		News Shocks Factor	
	$\Delta\beta_{LL}$	$\lambda_{LL} \cdot \Delta\beta_{LL}$	$\Delta\beta_{LINS}$	$\lambda_{LINS} \cdot \Delta\beta_{LINS}$
30 industries	0.456	2.08	0.642	1.90
38 industries	0.407	1.61	0.684	1.56
49 industries	0.454	2.34	0.729	2.42
BE/ME and Size (25)	0.165	0.67	0.397	1.44
BE/ME and OP (25)	0.196	0.68	0.406	1.87
OP and INV (25)	0.279	1.41	0.417	2.04
Size and OP (25)	0.271	1.36	0.602	2.10
Size and LT Reversal (25)	0.106	0.41	0.382	0.66
Size, BE/ME, INV, OP (40)	0.182	0.81	0.197	0.71
Size, OP, INV (32)	0.244	1.34	0.426	1.94
Size, BE/ME, INV (32)	0.142	0.60	0.354	1.05
Size, BE/ME, OP (32)	0.251	1.12	0.567	2.79
N. of time periods	552 (months)		176 (quarters)	
Mean	0.263	1.20	0.484	1.71

Notes: This table presents spreads in test assets' exposures to the the Lead-Lag factor, $\Delta\beta$, together with the product of these spreads and the corresponding factor risk premia, $\lambda \cdot \Delta\beta$. We consider both our financial factor (LL) and a macroeconomic factor that captures news shocks to the cashflow of leading industries ($LINS$). For the $LINS$ factor, data are quarterly. We employ the generalized method of moments (GMM) to estimate the linear factor model stated in equations (8)–(9). Monthly returns start in January 1972 and end in December 2017. At the bottom of the table, we report averages computed across different cross sections.

from 1.20% to 1.7% depending on whether we adopt our LL or our LINS factor. The middle point in this range is about 1.45% per year, i.e., about 40% of our leading premium of around 3.6% as documented in Table 2.[11]

Portfolios sorted on firm-level LL-exposure. Computing cross-correlograms on firm-level cash flows is impractical because these cash flows are too noisy. Consistent with prior literature, we use the firm-level returns exposure to our return-based factor to proxy the extent to which a firm leads/lags the cycle.

[11]When we use the LL factor, $\Delta\beta$ is obtained looking at 5th and the 95th percentile in the distribution of beta across test assets in each cross section. When we use the LINS factor, our estimates are based on a limited number of quarterly observations. Hence it is more common to obtain extreme estimates of betas. In this case, we use the 25th and the 75th percentile to be conservative.

Specifically, we start by taking our LL factor from our benchmark procedure that considers 30 industries. For each firm, we then compute its conditional exposure to the LL factor ($\beta_{LL,i,t}$) over a rolling-window that includes the past 60 months. We control for the FF3 factors in the regression and sort firms according to their $\beta_{LL,i,t}$ into 30 portfolios that we use as test assets. By grouping together all firms with strongly positive (negative) exposure, this procedure bundles the most leading (lagging) firms in the economy across industries. These portfolios are rebalanced once a year.

Our results are reported in Table 10 (top portion of each panel) and confirm what we had found in our previous analysis, namely that the LL factor is priced with a positive sign. Its annualized market price of risk is 3.36% (4.6%) when we use our LL (LINS) factor.

We then turn our attention to firm heterogeneity within industries. We focus on 38 (49) industries and sort firms within each industry in 3 (2) portfolios according to their $\beta_{LL,i,t}$ exposure. When we compute the $\beta_{LL,i,t}$ with 38 (49) industries we also use the benchmark LL factor that we obtained working with 30 industries. This procedure enables us to have a larger cross section of test assets and confirms that the LL factor is still priced in the cross-section.

In addition, both of our factors contribute to reducing our pricing errors. The LL factor reduces the average absolute pricing errors in a consistent way across cross sections by about 6%. The LINS factor is able to reduce our pricing errors by almost 20% in the cross section with 30 portfolios. In the other cross sections, the reduction in pricing errors is less sizeable.[12]

Additional results. Given the way in which we form our LL factor, it is natural to ask whether it is connected to other well-known risk factors already explored in the literature. In the online appendix, we run standard time-series tests in order to check whether: (i)

[12]Because of the curse of dimensionality, we are not able to replicate this asset pricing analysis using a large cross section of data simulated from our model. We refer the reader interested in this kind of exercise to a previous version of this manuscript (`https://www.nber.org/papers/w25633`) in which we have (i) exogenous cash-flows specified with an *exogenous* structure of leads and lags; and (ii) closed-form solutions.

Table 10: Prices of Risk in the LL Cross Section

Panel A: $E[R_i^{ex}] = \beta_{MKT}\lambda_{MKT} + \beta_{SMB}\lambda_{SMB} + \beta_{HML}\lambda_{HML} + \beta_{LL}\lambda_{LL}$ (monthly)

λ_{MKT}	λ_{SMB}	λ_{HML}	λ_{LL}	$H_0: PE^{LL} = 0$	$H_0: PE = 0$	$\Delta PE\%$
			30 LL-portfolios			
0.82***	0.68	0.13	0.28*	38.997	43.254	5.55%
(0.17)	(0.63)	(0.29)	(0.15)	[0.049]	[0.018]	
			38 Industry × 3 LL-portfolios			
0.71***	0.16	0.21	0.47***	46.341	48.868	6.26%
(0.22)	(0.20)	(0.42)	(0.18)	[0.582]	[0.478]	
			49 Industry × 2 LL-portfolios			
0.64***	0.61***	0.14	0.34***	102.241	104.489	3.20%
(0.11)	(0.13)	(0.09)	(0.11)	[0.112]	[0.085]	

Panel B: $E[R_i^{ex}] = \beta_{MKT}\lambda_{MKT} + \beta_{SMB}\lambda_{SMB} + \beta_{HML}\lambda_{HML} + \beta_{LINS}\lambda_{LINS}$ (quarterly)

λ_{MKT}	λ_{SMB}	λ_{HML}	λ_{LINS}	$H_0: PE^{LL} = 0$	$H_0: PE = 0$	$\Delta PE\%$
			30 LL-portfolios			
2.20***	2.24**	1.03	1.15***	32.567	45.794	18.50%
(0.61)	(0.92)	(0.92)	(0.29)	[0.175]	[0.013]	
			38 Industry × 3 LL-portfolios			
2.40***	0.39***	0.53***	0.45***	123.180	126.451	1.67%
(0.34)	(0.07)	(0.08)	(0.06)	[0.000]	[0.000]	
			49 Industry × 2 LL-portfolios			
1.78***	1.31***	1.07***	0.27***	246.041	249.908	0.63%
(0.12)	(0.04)	(0.02)	(0.04)	[0.000]	[0.000]	

Notes: This table presents market prices of risk for the FF3 factors (MKT, SMB, HML), our financial lead-lag factor (LL), and our leading industry news shocks factor ($LINS$). We employ the generalized method of moments (GMM) to estimate the linear factor model stated in equations (8)–(9). We use portfolios based on the individual firms' exposures to the LL factor ($\beta_{LL,i,t}$) estimated over the previous 60 months as our test portfolios. The top row of each panel presents results for 30 lead-lag portfolios. In the middle (bottom) row, the test portfolios are constructed by sorting firms on their $\beta_{LL,i,t}$ within each of 38 (49) industries into 3 (2) subgroups. Under the column $H_0 : PE^{LL} = 0$ ($H_0 : PE = 0$), we report the test statistics of the joint hypothesis of zero pricing errors including (excluding) the LL factor, $\Delta PE\%$. Associated p-values are in square brackets. The last column reports the relative increase in the average absolute pricing error when we exclude the LL factor. When we use our financial LL factor (panel A), we have monthly observations from January 1976 through December 2017. When we employ the LINS factor (panel B), the data are quarterly. The numbers in parentheses are standard errors adjusted according to Newey and West (1987). One, two, and three asterisks denote significance at the 10%, 5%, and 1% levels, respectively.

other factors fully explain ours, and (ii) our factor explains other existing ones. We find it important to state that our goal is not 'adding another factor to the zoo' (Feng et al., 2020). We gather empirical guidance on the deeper economic concept highlighted in our model, that is, the size and relevance of the timing premium.

5 Conclusion

In this study, we propose a novel rational equilibrium model in which (i) infrequent industry-level shocks diffuse slowly across other industries; and (ii) agents have a preference for early resolution of uncertainty, and hence they price advance information about future cash flows. In this setting, conditioning on the realization of industry-specific shocks, we can distinguish industries that are affected by shocks without delay (leading industries), and industries that will go through the same cycle but with delay (lagging industries). Along an industry-driven aggregate cycle, leading industries provide valuable advance information on the future cash flows of lagging firms and hence lagging firms are safer than leading firms. This implies that a conditional leading premium should exist.

In addition, our model suggests that we can identify leading and lagging firms just by computing cross correlations with leads and lags of a common indicator of economic activity. Equivalently, the leading premium can be measured even without full information on the entire cross section of industry-level shocks.

Inspired by our model, we compute conditional leading/lagging indices for industry-level cash flows with respect to US aggregate activity. We find that leading industries are riskier than lagging industries. More broadly, we provide two novel insights: (a) heterogeneity in the timing of exposure to shocks is an important dimension of the cross section of industry returns; and (b) asset prices are sensitive to the timing of economic fluctuations.

Future work should extend our investigation by including other potentially valuable sources of anticipated information. In addition, future studies should be consistent with the data and consider models with time-varying network linkages.

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APPENDIX

A The Role of p_t^i.

When $\phi_2 = 0$, we have that $p_t^i \equiv 1$ and the cash-flow model no longer features cycles driven by specific industries. To better see this point, note that industry-level expected growth then becomes

$$\begin{aligned} x_t^i &= \rho x_{t-1}^i + \lambda \cdot \left(\sum_{j \neq i} x_{t-1}^j \right) + J_t^i \\ J_t^i &\sim i.i.d., \end{aligned} \tag{A.1}$$

that is, all industries have the same conditional and unconditional probability of experiencing a growth cycle. Equivalently, it is no longer true that industries go over cycles sequentially ('one-at-a-time') and leading industries deliver anticipated information about lagging industries.

To visualize this concept, in Figure A1 we depict the expected response to positive shocks when $\phi_2 < 0$ (top panel) and when $\phi_2 = 0$ (bottom panel). In both cases, we assume that industry 1 has already been affected by a substantial positive shock, i.e., $x_0^1 >> 0$ whereas $x_0^i = 0$ for $i = 2, 3, ...$ Since we are only simulating exogenous cash-flows, the curse of dimensionality is not a problem and we can choose a larger number of industries. Here we have $N = 8$. As shown in the bottom panel, when $\phi_2 = 0$ all industries have the same probability to go through the same positive cycle *simultaneously.* Since we have assumed that $x_0^1 > 0$, the industries closer to industry 1 experience stronger spillovers and the magnitude of their growth is higher. Importantly, all industries adjust with the same timing, meaning that there is no clear leading/lagging industry.

In contrast, when $\phi_2 < 0$ our cash-flow model creates a well-defined cross section of leading and lagging cash-flows. This is because when $|x_0^1| >> 0$ and $x_0^i = 0$ for $i = 2, 3, ...,$ the following is true:

$$p_t^i \approx \begin{cases} 1 & i = 1 \\ 0 & i \neq 1. \end{cases} \tag{A.2}$$

Equivalently, industry 1 continues to drive the cycle and it is expected to get further shocks ($E_t \left[J_{t+1}^1 \right] p_t^1 \neq 0$) whereas the cash flows of the other industries will adjust mainly because of delayed spillovers ($E_t \left[J_{t+1}^i \right] p_t^i \approx 0 \quad i = 2, 3, ...$).

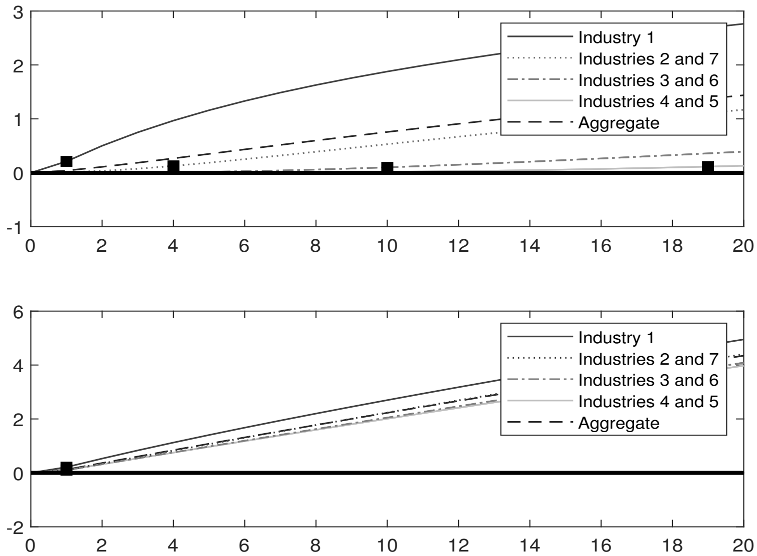


Fig. A1: The Role of p_t^i

Notes: This figure depicts simulated paths of industry cash flows as well as aggregate cash-flow in either our benchmark economy (top panel) or a setting in which $p_t^i = 1$, $\forall i \forall t$. In both cases, industry 1 is assumed to have received positive shocks prior to time 0, so that $x_0^1 > 0$ and $x_0^i = 0$ for $i = 2, 3, \ldots$. We then focus on the impulse response to an additional positive shock ($J_t^i = \phi_0 \cdot e^{\phi_1 u_{+,t}^i}$). In the bottom panel, filled boxes denote the first period in which an industry-specific cash-flow increases. In the top panel, filled boxes denote the period in which a specific industry cash-flow reaches the same level recorded at time $t = 1$ in the setting with $p_t^i \equiv 1$.

In other words, our model features a well-defined leading premium thanks to the fact that in each period t we have a well defined cross section of p_t^i values. Unfortunately, the cross section of p_t^i is not directly observable and so estimating the system of equations (3) – (5) is challenging given that the industry-specific shocks J_t^i are latent. Since we can think of p_t^i as the conditional probability of industry i to lead the aggregate cycle, in our empirical investigation we proxy for it with our LL indicators. According to our model, this approach is appropriate. As shown in Figure A2, our LL indicators are highly correlated with the true p_t^is. Since our LL indicators are computed on a backward-looking moving window of observations, they adjust with delay. As a result, it takes a few periods before an investor can properly identify leading and lagging industries. After allowing for a temporal delay ($h = 8$), however, the LL indicators move almost one-to-one with the true p_t^is.

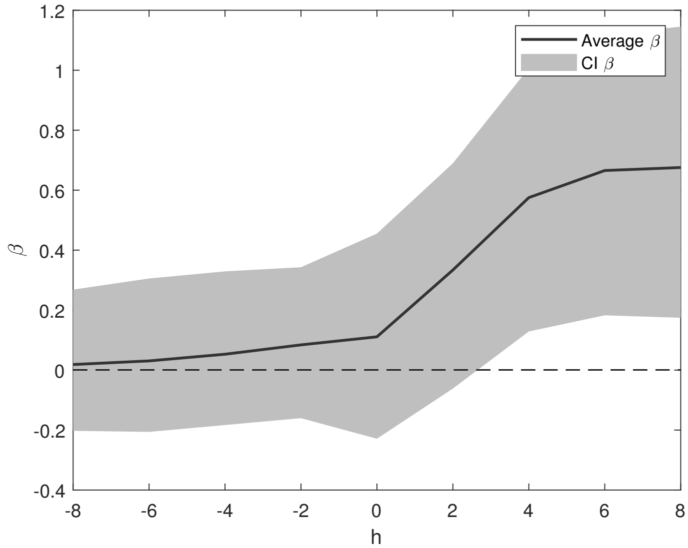


Fig. A2: p_t^i and the LL Indicators

Notes: This figure depicts the average β_h coefficient estimated from the following regression specification:

$$LL_{t+h,i} - LL_{t+h,i^*} = \alpha + \beta_h \left(p_{t,i} - p_{t,i^*}\right) + \varepsilon_{t+h,i},\ i \neq i^*$$

across 500 model simulations and $h = \pm 8$ quarters. $LL_{t+h,i} - LL_{t+h,i*}$ represents the difference between the LL indicator of industry i and a reference industry i^* computed using data simulated from our model. $p_{t,i}$ denotes the probability of a jump in the industry i's cash-flows at time t. The gray shaded area represents 90% confidence intervals.

B More about our LL Cross Section

To provide further economic guidance about our measure, in Figure B1 we report our maximum correlation LL indicators for the consumer goods, manufacturing, and business equipment sectors. We focus on these large aggregates because their average lead-lag structure has been documented in the literature (see, among others, Greenwood and Hercowitz (1991) and Gomme et al. (2001)), and hence they represent a natural reference point for our methodology.

Consistent with prior studies, the unconditional average of the LL indicators in our sample suggests that the consumer goods sector leads national output by a little more than a month (a lead of 0.38 quarters), whereas manufacturing lags it slightly (a lag of around 0.6 quarters). Business equipment, i.e., investment goods, lags consumer goods by almost three quarters, as it takes time for firms to adjust their investment orders. Our LL indicators suggest that the lead-lag structure across these sectors experiences fluctuations that are pronounced over time but moderate in the cross section.

Specifically, during recession periods both the consumer goods sector and the business

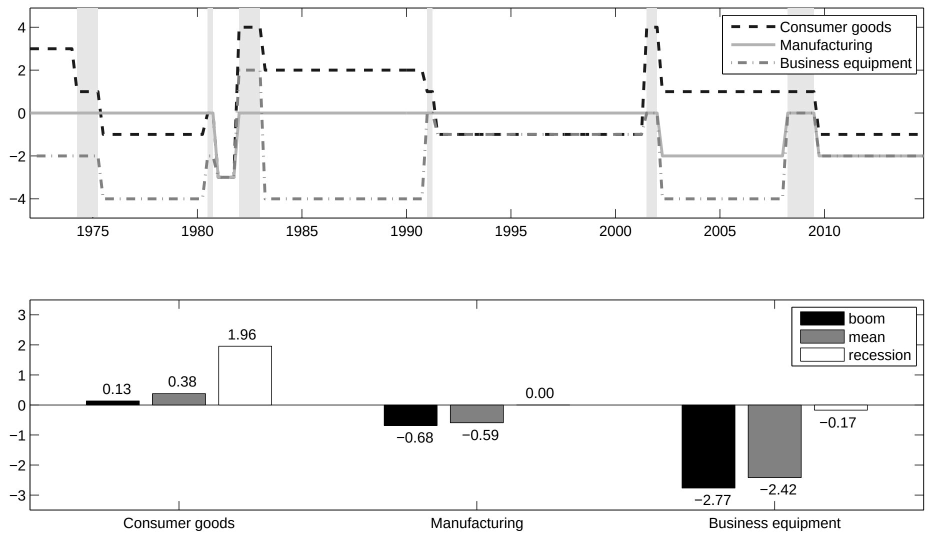


Fig. B1: Lead-Lag Indicator for Selected Industries

Notes: This figure depicts the lead-lag (LL) indicator for three major industries. The LL indicator is computed in two steps. First, for each industry, in each quarter we compute the ±4-quarter cross-correlation between industry-level output growth and the domestic output growth using 20-quarter rolling windows. Second, we identify the lead or lag for which the maximum absolute cross-correlation is attained and assign it to the corresponding industry as its LL indicator. A positive (negative) LL indicator denotes an industry whose output growth leads (lags) GDP growth. Quarterly growth rates are adjusted for inflation and seasonality. In the top panel, grey bars denote NBER recession periods. In the bottom panel, we report for each industry the average of the LL indicator over our entire sample (denoted as "mean"), and its average value during booms and recessions.

equipment sector tend to respond more promptly to shocks, as the former represents a stronger leading indicator, and the latter lags national output just by a few weeks. During booms, in contrast, both the consumer goods and the business equipment sectors lag the cycle by a longer period of time. The difference in the LL indicators of the two sectors, however, remains pretty stable, as it ranges from 2.13 quarters during recessions to 2.9 quarters during booms. In our main analysis with many industries, these cross sectional fluctuations become more relevant.

In Table B1, we report the most leading and lagging industries across different subsample. We note that IT is part of the 'Business equipment' industry and it is leading in 1996-2000. In Figure B2, we show that our average correlograms have very distinct patterns across leading and lagging industries, also accounting for sample uncertainty.

Table B1: Leading/Lagging Industries across Decades

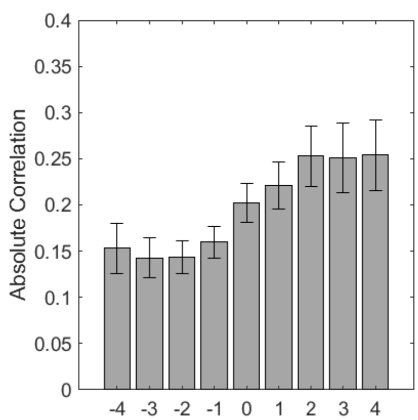
Subperiod	Leading	Lagging
1971–1975	Tobacco products	Fabricated products, machinery
	Chemicals	Business equipment
	Beer	*Printing, publishing*
	Printing, publishing	*Oil*
	Electrical equipment	*Utilities*
1976–1980	Printing, publishing	Wholesale
	Oil	Business equipment
	Coal	Fabricated products, machinery
1981–1985	Tobacco products	*Oil*
	Utilities	*Personal, business services*
	Automobiles	Wholesale
	Finance	
1986–1990	Wholesale	Business equipment
	Recreation	Business supplies
	Health	Coal
	Steel	
1991–1995	Tobacco products	Finance
	Utilities	Transportation
	Health	*Consumer goods*
		Textiles
		Meals
1996–2000	Utilities	Telecommunication
	Coal	Finance
	Construction	*Personal, business services*
	Steel	*Business supplies*
	Oil	
	Business equipment	
	Finance	
2001–2005	Electrical equipment	Utilities
	Health	Finance
	Steel	Chemicals
2006–2010	Health	Business equipment
	Clothes	Recreation
	Oil	*Personal, business services*
		Finance
2011–2015	Telecommunication	Business equipment
	Personal, business services	Personal, business services
	Coal	Electrical equipment
2016–2020	*Printing, publishing*	Personal, business services
	Retail	Construction
	Carry	*Tobacco products*
	Telecommunication	*Transportation*

Notes: This table provides for each decade the top-3 leading and lagging industries. This classification is based on our maximum correlation LL indicator described in section 3.1. If multiple industries appear in our leading/lagging portolio with the same frequency, we report them in *italics*.

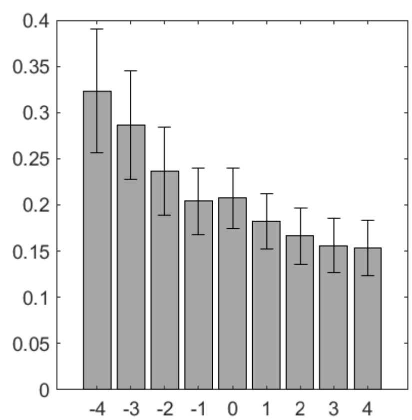
Table B2: Persistence in Leading/Lagging Industries

	Leading			Lagging		
	Mean	75th	Max	Mean	75th	Max
	Panel A: Quarterly Data, Duration in Quarters					
Data	2.35	3.01	7.43	2.14	2.53	6.83
Model	3.18	4.04	11.32	3.12	4.00	10.98
	Panel B: Annual Data, Duration in Years					
Data	1.46	1.65	2.07	1.22	1.38	1.70
Model	1.84	2.44	3.12	1.78	2.35	3.04

Notes: In panel A (panel B), we measure the average number of consecutive quarters (years) for which an industry is assigned to the leading/lagging portfolio. The entries for the data are based our benchmark cross section of 30 industries. In panel B, a year is included in the calculation if the industry is leading or lagging for at least three quarters during the calendar year. The entries for the model are based on simulated cash flows.



Panel A: Leading Industries



Panel B: Lagging Industries

Fig. B2: Average Cross-Crorrelogram for Leading and Lagging Industries

Notes: This figure depicts the average correlation between leads/lags of industry cash-flow growth and GDP growth across ±4 quarters. We identify leading and lagging industries according to our maximum correlation LL indicator (see section 3.1). The height of the gray shaded bars represents the average cross-correlogram for leading (left panel) and lagging (right panel) industries. The error lines depict 95%-confidence intervals using the HAC-adjusted standard errors.

ONLINE APPENDIX

OL-A The Role of ϕ_0

In figure OL-A1, we depict the implied conditional average of

$$J = \phi_0 e^{\phi_1 u}, \text{ with } u \sim N(0,1).$$

By setting ϕ_1 to a large number, the exponential function tends to be very steep and it mimics an 'L-shaped' function. We set ϕ_0 to a small number to make sure that our shocks have an average size of 0.8 for $u > 2.57$, that is, for realizations of a normal random variable that happen with a probability of 0.5%. Doubling (reducing by half) ϕ_0, doubles (reduces by half) the average size of our jump.

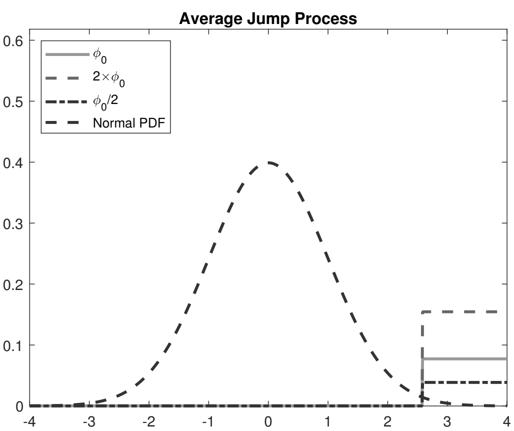


Fig. OL-A1: The Role of ϕ_0

Notes: This figure depicts $E[\phi_0 e^{\phi_1 u}|u < 2.57]$ and $E[\phi_0 e^{\phi_1 u}|u \geq 2.57]$ with $u \sim N(0,1)$. The parameters ϕ_1 and ϕ_0 are set as in our benchmark calibration. We also consider the cases in which ϕ_0 is either doubled or reduced by half.

OL-B Data Sources and Additional Tables

We use a cross section of monthly stock returns from the Center for Research in Security Prices (CRSP) and corresponding quarterly firm-level data from Standard & Poor's Compustat for the period Jan. 1967–Dec. 2017. Prior to 1967, the quarterly data coverage is modest. All growth rates are in real terms and seasonally adjusted. We retrieve macroeconomic data series for GDP, consumption, and CPI from the Federal Reserve Bank of St.

Louis. Industry definitions based on SIC codes are taken from Kenneth French's website. Table OL-B1 shows that our results are almost unchanged if we assign a fixed number of industries to our lead/lag portfolios.

Table OL-B1: Lead-Lag Portfolio Sorting (II)

	Lead	Mid1	Mid2	Mid3	Lag	LL
Avg. Ex. Ret.	9.81***	7.24***	8.52***	4.61*	6.97***	2.84**
	(2.12)	(2.33)	(2.55)	(2.76)	(2.58)	(1.44)
CAPM α	3.63***	0.52	1.77	−2.08*	0.00	3.63***
	(1.06)	(1.30)	(1.20)	(1.12)	(0.75)	(1.40)
FF3 α	3.27***	0.05	0.97	−2.34**	0.55	2.72*
	(0.98)	(1.16)	(1.33)	(1.13)	(0.97)	(1.55)
Avg. Mkt. Share	0.18	0.18	0.19	0.20	0.24	

Notes: This table provides both average excess returns and risk-adjusted returns on portfolios of leading and lagging industries. The notes of table 2 apply, with one exception: we sort industries into 5 portfolios comprising an equal number of industries in each quarter. *Avg. Mkt. Share* refers to the portfolio-level average market share.

Table OL-B2 shows that our results are robust with respect to changes in the market capitalization of our lead/lag portfolios.

Table OL-B2: Market Capitalization Share of Extreme Portfolios

Minimum share,%	10	15 (Benchmark)	20	25	30
Excess return	3.19	3.60**	3.09*	3.28**	2.34*
	(1.97)	(1.79)	(1.58)	(1.54)	(1.23)
CAPM α	3.96**	4.36**	3.81**	3.92**	2.91**
	(1.94)	(1.84)	(1.65)	(1.62)	(1.27)
FF3 α	3.20	3.68**	2.79**	2.88*	2.16*
	(2.07)	(1.80)	(1.42)	(1.47)	(1.24)

Notes: This table provides average value-weighted returns of the LL portfolio, that is, a zero-dollar strategy long in Lead and short in Lag industries as defined in section 4. The notes of table 2 apply, with one exception: we depart from our benchmark portfolio construction by varying the minimal share of market capitalization of our extreme portfolios. In the benchmark specification, both the Lead and Lag portfolios represent at least 15% of the total market value in each quarter.

Network-based factors. We collected data from the 'Summary use and supply' tables available on the BEA website in order to replicate the Herskovic (2018) methodology. Our annual sample spans twenty-one years (1997-2017), but we lose an observation because the Herskovic (2018)'s network factors—concentration and sparsity—are defined as annual variations. Let $\delta_{j,t}$ measure the output share of sector j at time t:

$$\delta_{j,t} = \frac{P_{j,t}Y_{j,t}}{\sum\limits_{i=1}^{n} P_{i,t}Y_{i,t}}$$

Then the network concentration factor is computed as:

$$\mathcal{N}_t^{\mathcal{C}} = \sum_{i=1}^{n} \delta_{i,t} \log \delta_{i,t}.$$

The network sparsity factor is given by

$$\mathcal{N}_t^{\mathcal{S}} = \sum_{i=1}^{n} \delta_{i,t} \sum_{j=1}^{n} \omega_{ij,t} \log \omega_{ij,t}.$$

where the network weight $\omega_{ij,t}$ is the elasticity of the investment of sector i with respect to input j. As in Herskovic (2018), we run the following regression at the stock-level

$$r_t^s = \alpha^s + \beta^s_{\mathcal{N}^{\mathcal{S}},t} \Delta \mathcal{N}_t^{\mathcal{S}} + \beta^s_{\mathcal{N}^{\mathcal{C}},t} \Delta \mathcal{N}_t^{\mathcal{C}} + \xi_t^i,$$

computing time-varying coefficients over a rolling window comprising 11 years. Let p denote a specific portfolio and S_t the set of stocks included in a specific portfolio at time t. The portfolio-level exposure coefficients are computed as follows:

$$\beta^p_{\mathcal{N}^{\mathcal{S}},t} = \sum_{s \in P_t} w_s \beta^s_{\mathcal{N}^{\mathcal{S}},t} \qquad \beta^p_{\mathcal{N}^{\mathcal{C}},t} = \sum_{s \in P_t} w_s \beta^s_{\mathcal{N}^{\mathcal{C}},t},$$

where w_s is either an equal weight or a value weight. We report our results in Table OL-B3. Leading and lagging firms do not feature systematic differences in their exposure to network factors in our data. After double-sorting on leads/lags and HHI, we find that the leading premium is concentrated among industries with a medium level of HHI (Table OL-B4).

Table OL-B3: Exposure to Sparsity and Concentration Factors

	Lead	Lag	Difference	p-value
		Panel A: Equally-Weighted		
$\beta^p_{N_C}$	−0.106	−0.086	−0.021	0.458
$\beta^p_{N_S}$	0.096	0.085	0.011	0.610
		Panel B: Value-Weighted		
$\beta^p_{N_C}$	−0.031	−0.045	0.014	0.445
$\beta^p_{N_S}$	0.066	0.097	−0.030	0.123

Notes: This table provides the average portfolio betas with respect to the network sparsity and concentration factors. The data are annual.

Table OL-B4: Double Sorting: the Role of HHI

	Low HHI	Mid HHI	High HHI
		Panel A: Excess Returns	
Avg. Ex. Ret.	1.41	5.27***	−1.15
	(1.66)	(1.51)	(2.01)
CAPM α	1.98	5.21***	−0.33
	(1.74)	(1.56)	(2.35)
FF3 α	0.33	4.82***	0.52
	(1.73)	(1.37)	(2.29)
Avg. Mkt. Share	0.36	0.34	0.10
		Panel B: Average log(Markup)	
Lead	0.43	0.45	0.43
Lag	0.52	0.42	0.46
Lead minus Lag	−0.09	0.03	−0.04
p-value	0.21	0.64	0.30

Notes: We form portfolios of firms double-sorted according to (i) their industry-level lead-lag (LL) indicator, and (ii) their industry-level sales HHI index. The LL indicator is based on maximum cross-correlation (see section 3.1). We identify high-, mid- and low-HHI industries among 12 most leading and lagging industries. The low-HHI (high-HHI) group comprises the top-25% (bottom-25%) competitive industries. Panel A provides both annualized average excess returns and risk-adjusted returns. Panel B reports average log-markups across portfolios. This measure includes overhead costs. The row 'p-value' refers to the null assumption that the lead and lag portfolios have the same average markup. The sample spans 1972:01–2017:12. One, two, and three asterisks denote significance at the 10%, 5%, and 1% level, respectively.

Table OL-B5: Lead-Lag Portfolio Sorting Using PD-ratio

	Lead	Mid	Lag	LL
Excess return	8.75***	6.40**	5.33**	3.42**
	(2.47)	(2.51)	(2.55)	(1.72)
CAPM α	3.11***	−0.34	−0.91	4.02**
	(1.18)	(0.55)	(1.16)	(1.68)
FF3 α	2.81**	−0.19	−1.65	4.45**
	(1.17)	(0.52)	(1.09)	(1.75)

Notes: This table provides annualized value-weighted returns of portfolios of firms sorted according to their β_t^i loadings obtained from this regression:

$$\Delta IP_{t+1} = \alpha_t^i + \beta_t^i pd_t^i + \epsilon_t^i,$$

where ΔIP stands for industrial production growth. For each industry i, in each quarter we estimate β_t^i using a 120-month rolling window. Our Lead (Lag) portfolio contains the top (bottom) 20% of industries sorted on their exposure β_t^i. These portfolios represent at least 15% of the total market value in each quarter. All other firms are assigned to the middle (Mid) portfolio. The LL portfolio reflects a zero-dollar strategy long in Lead and short in Lag. Return data are monthly over the sample 1972:01–2018:12. Industry definitions are from Kenneth French's website. CAPM α and FF3 α denote the average excess returns unexplained by the CAPM, and the Fama-French three-factor model, respectively. The numbers in parentheses are standard errors adjusted according to Newey and West (1987). One, two, and three asterisks denote significance at the 10%, 5%, and 1% levels, respectively.

Alternative way to predict economic fluctuations. Our previous exercise suggests that another way to identify leading industries may be through conditional predictive regressions. Specifically, one can run predictability regressions in which industry-level price-dividends are used to predict future aggregate activity (represented by industrial production) over rolling samples:

$$\Delta IP_{t+1} = \alpha_t^i + \beta_t^i pd_t^i + \epsilon_t^i. \tag{OL-B.1}$$

At the end of each quarter, industries with higher (lower) predictability power, β_t^i, can be considered as leading (lagging) and portfolios can be formed as we did with cross correlations.

Even though this procedure is not fully based on fundamental information about cash flows, it comes with an important advantage as it enables us to use monthly data, and hence it sharpens our sorting. We select a sample window of 120 months and allow for a quarter of delay in the formation of portfolios, meaning that we form portfolios, say, at the end of June using the betas computed at the end of March. By doing so, we make sure that all relevant information was available to investors. This procedure confirms the results obtained by using cash flows cross-correlations, as leading firms pay an average excess return that is 3.42% higher than that of lagging firms. We report detailed results in Table OL-B5.

We also note that if we repeat this procedure using industry returns as predictive variables in order to recover β_t^i, we find a zero leading premium. This is consistent with our economic model in which there is no information friction and returns of different industries adjust simultaneously—albeit to different extents—upon the arrival of news. That is, leads and lags in cash-flows do not necessarily imply leads and lags in the dynamics of returns. At higher frequencies, frictions that affect the speed of diffusion of news to prices may be relevant, but this dimension is not part of our investigation.

Consumption vs. output. In our endowment economy there is no distinction between consumption and output. In the data, however, these aggregates differ from each other. In Table OL-B6, we show that our results on the leading premium obtain also when we use aggregate consumption growth to compute our cross correlations as opposed to output growth.

Table OL-B6: Lead-Lag Portfolio Sorting with Consumption

	Lead	Mid	Lag	LL
Excess return	9.04***	6.11**	7.04**	2.01
	(2.27)	(2.42)	(2.83)	(1.87)
CAPM α	3.08***	−0.68	−0.24	3.32*
	(1.20)	(0.45)	(1.21)	(1.97)
FF3 α	3.70***	−1.00	−0.32	4.02**
	(1.18)	(0.52)	(1.31)	(1.89)
LL indicator	2.78	−0.24	−3.08	–

Notes: This table provides annualized value-weighted returns of portfolios of firms sorted according to their industry-level lead-lag (LL) indicator. A positive (negative) LL indicator denotes an industry whose output growth leads (lags) real consumption growth. Our Lead (Lag) portfolio contains the top (bottom) 20% of our leading industries. These portfolios represent at least 15% of the total market value in each quarter. All other firms are assigned to the middle (Mid) portfolio. The LL indicator row refers to the average portfolio-level lead-lag indicators. Turnover measures the percentage of industries entering or exiting from a portfolio. Return data are monthly over the sample 1972:01–2017:12. Industry definitions are from Kenneth French's website. CAPM α (FF3 α) denotes average excess returns unexplained by the CAPM (Fama-French three-factor model). The numbers in parentheses are standard errors adjusted according to Newey and West (1987). One, two, and three asterisks denote significance at the 10%, 5%, and 1% levels, respectively.

Long-run vs. short-run. In our model, we focus on growth news shocks that have a long-lasting impact on aggregate growth. Because of short-sample concerns, in our benchmark analysis we consider a limited number of leads and lags. In Table OL-B7, we show that our results are confirmed even when we focus on a wider range of leads and lags. Specifically, our results apply also when we look at leads and lags over 25 quarters in order to capture

Table OL-B7: Lead-Lag Portfolio Sorting - Longer Windows

	Lead	Mid	Lag	LL	LL Strong
Excess return	10.32***	7.20**	8.36**	1.96	9.59**
	(3.13)	(3.48)	(3.74)	(1.76)	(3.85)
CAPM α	3.65***	−1.08	0.02	3.63*	13.47***
	(1.33)	(0.67)	(1.38)	(1.90)	(3.74)
FF3 α	3.57***	−0.89	−0.78	4.35**	13.40***
	(1.07)	(0.57)	(1.36)	(1.78)	(4.00)
LL indicator	15.00	−3.45	−20.33	-	-
LL indicator (post-formation)	13.43	−3.34	−19.05	-	-

Notes: This table provides annualized value-weighted returns of portfolios of firms sorted according to their industry-level lead-lag (LL) indicator. First, for each industry, in each quarter we compute the ±25-quarter cross-correlation between industry-level output growth and the domestic output growth using 100-quarter rolling windows. Second, we identify the lead or lag for which the maximum absolute cross-correlation is attained and assign it to the corresponding industry as its LL indicator. A positive (negative) LL indicator denotes an industry whose output growth leads (lags) GDP growth. Our Lead (Lag) portfolio contains the top (bottom) 20% of our leading industries. These portfolios represent at least 15% of the total market value in each quarter. All other firms are assigned to the middle (Mid) portfolio. The LL portfolio reflects a zero-dollar strategy long in Lead and short in Lag. In each portfolio, we identify the industries with the absolute value of correlation above the portfolio's median and group them in a subportfolio denoted as 'Strong'. The LL Strong portfolio represents a zero-dollar trading strategy long in Lead Strong and short in Lag Strong. Return data are monthly over the sample 1992:01–2017:12. Industry definitions are from Kenneth French's website. CAPM α (FF3 α) denotes average excess returns unexplained by the CAPM (Fama-French three-factor model). The numbers in parentheses are standard errors adjusted according to Newey and West (1987). One, two, and three asterisks denote significance at the 10%, 5%, and 1% levels, respectively.

fluctuations in the spectrum of the medium cycle. We also confirm our results on the properties of the LL indicator measured after the formation of the portfolios.

Alternative cash flow measures. A possible concern with respect to our analysis is that our results are driven by the use of the Acharya et al. (2014) cash flow measure. Table OL-B8 confirms our findings on the leading premium also when we use operating income, earnings, or investment-based measures of fundamental cash flows (i.e., gross value of property, plant and equipment).

Leading premium vs. cash flow growth momentum. Another concern regarding our interpretation of the results is that they are possibly just the reflection of past cash flow growth momentum, rather than a phenomenon related to advance information. In order to address this concern, we sort firms according to the past growth rate of their industry-level cash flow. We form a winners-minus-losers investment strategy and look at the implied

Table OL-B8: Portfolio Sorting: Alternative Measures of Cash Flows

	OI		*PPEGT*		*Earnings*	
	LL	LL Strong	LL	LL Strong	LL	LL Strong
Excess return	4.19**	5.47**	2.21	4.19***	1.82	3.10
	(1.96)	(2.42)	(1.58)	(1.52)	(1.67)	(2.22)
CAPM α	5.13***	5.77**	3.27*	5.18***	2.20	3.97*
	(1.98)	(2.34)	(1.78)	(1.69)	(1.67)	(2.23)
FF3 α	5.49***	6.45***	3.49*	4.64**	2.91*	4.74**
	(2.09)	(2.48)	(1.84)	(2.05)	(1.74)	(2.26)

Notes: This table provides annualized value-weighted returns of portfolios of firms sorted according to their industry-level lead-lag (LL) indicator. The formation of portfolios is similar to our benchmark specification with the only difference being the industry cash flow measure we use to construct the LL indicator. In this table, we report results for LL and LL Strong portfolios using operating income (*OI*), gross value of property, plant and equipment (*PPEGT*), and earnings (*Earnings*) as our cash slow measures. Return data are monthly over the sample 1972:01–2017:12. Industry definitions are from Kenneth French's website. CAPM α (FF3 α) denotes average excess returns unexplained by the CAPM (Fama-French three-factor model). The numbers in parentheses are standard errors adjusted according to Newey and West (1987). One, two, and three asterisks denote significance at the 10%, 5%, and 1% levels, respectively.

factor. We find no significant spread, meaning that our lead-lag sorting is not a reflection of fundamental momentum. Equivalently, our leading (lagging) firms are not systematically winners (losers). See Table OL-B9.

Table OL-B9: Lead-Lag Portfolio Sorting: Cash Flow Momentum

	Winners	Mid	Losers	W-L
Excess return	7.14***	6.80***	6.82***	0.32
	(2.75)	(2.34)	(2.64)	(2.35)
CAPM α	0.08	0.26	−0.15	0.23
	(1.57)	(0.39)	(1.49)	(2.71)
FF3 α	−2.23	0.74**	−0.08	−2.15
	(1.32)	(0.36)	(1.35)	(2.42)

Notes: This table provides annualized value-weighted returns of portfolios of firms sorted according to their industry-level cash flow growth. First, in each quarter we compute the industry-level cash flow growth over past quarter. Our Winners (Losers) portfolio contains the top (bottom) 20% of industries with the highest (lowest) cash flow growth. These portfolios represent at least 15% of the total market value in each quarter. All other firms are assigned to the middle (Mid) portfolio. The W-L portfolio reflects a zero-dollar strategy long in Winners and short in Losers. Return data are monthly over the sample 1972:01–2017:12. Industry definitions are from Kenneth French's website. CAPM α (FF3 α) denotes average excess returns unexplained by the CAPM (Fama-French three-factor model). The numbers in parentheses are standard errors adjusted according to Newey and West (1987). One, two, and three asterisks denote significance at the 10%, 5%, and 1% levels, respectively.

Table OL-B10: Lead-Lag Portfolio Sorting – 38 and 49 Industries

	Panel A: 38 industries		Panel B: 49 industries	
	LL	LL Strong	LL	LL Strong
Excess return	3.92**	4.27**	4.05**	6.13***
	(1.80)	(2.05)	(1.78)	(1.99)
CAPM α	4.99***	4.88**	4.94***	7.30***
	(1.86)	(2.02)	(1.76)	(1.93)
FF3 α	4.28**	4.91**	5.06***	7.48***
	(1.93)	(2.12)	(1.71)	(2.14)

Notes: This table provides annualized value-weighted returns of portfolios of firms sorted according to their industry-level lead-lag (LL) indicator. The formation of the portfolios is identical to that described in the notes to table 2. In contrast to our benchmark specification that uses a 30-industry classification, this table documents results for 38 industries (Panel A) and 49 industries (Panel B). The LL portfolio reflects a zero-dollar strategy long in Lead and short in Lag. In each portfolio, we identify the industries with the absolute value of correlation *above the portfolio's median* and group them in a subportfolio denoted as 'Strong'. The LL Strong portfolio represents a zero-dollar trading strategy long in Lead Strong and short in Lag Strong. Return data are monthly over the sample 1972:01–2017:12. Industry definitions are from Kenneth French's website. CAPM α (FF3 α) denotes average excess returns unexplained by the CAPM (Fama-French three-factor model). The numbers in parentheses are standard errors adjusted according to Newey and West (1987). One, two, and three asterisks denote significance at the 10%, 5%, and 1% levels, respectively.

Granularity. We explore the role of granularity and report key results on the leading premium in Table OL-B10. Specifically, we adopt our sorting procedure after grouping firms into 38 and 49 industries, respectively. We point out the existence of a relevant tension between the number of industries and the precision of our ranking. On the one hand, considering more industries enables us to gain more power from the cross section. On the other, considering a more granular definition of industries makes our estimation of industry-level leads and lags more noisy and hence it makes our sorting less precise. We find it encouraging that our results on the leading premium are confirmed when working with both 38 and 49 industries.

Size and book-to-market. We double-sort the firms belonging to our lead and lag portfolios with respect to either their book-to-market (B/M) ratios, or their market capitalization (Size). As in Fama and French (2012), we choose the 30th and 70th percentiles of the book-to-market distribution as cutoff points to obtain low, medium, and high book-to-market portfolios. We do the same with respect to size and report our main results in Table OL-B11.

Our leading premium is sizeable and statistically significant for both low and medium

Table OL-B11: Lead-Lag Portfolio – Double Sort

	Panel A: LL and B/M			Panel B: LL and Size		
	Low	Mid	High	Small	Mid	Large
Excess return	3.43*	4.77**	0.51	4.20	1.99	4.91**
	(1.95)	(2.09)	(2.06)	(3.14)	(1.89)	(1.99)
CAPM α	4.44**	4.84**	0.38	3.72	2.16	5.55***
	(1.95)	(2.28)	(2.00)	(3.03)	(1.88)	(2.02)
FF3 α	3.66*	3.53*	−0.16	1.60	0.29	5.00***
	(1.94)	(1.97)	(2.25)	(3.83)	(2.25)	(1.93)

Notes: This table provides two decompositions of the annualized value-weighted returns of the LL portfolio constructed as described in table 2. In panel A, we decompose the LL return by double-sorting firms according to their book-to-market (B/M) ratio within the Lead and Lag portfolios. Our cutoff points are the 30th and 70th percentiles of the B/M distribution within each portfolio. Analogously, in panel B we decompose the LL return by double-sorting firms according to their market capitalization (Size) within the Lead and Lag portfolios. Our cutoff points are the 30th and 70th percentiles of the Size distribution within each portfolio. Return data are monthly over the sample 1972:01–2017:12. Industry definitions are from Kenneth French's website. CAPM α (FF3 α) denotes average excess returns unexplained by the CAPM (Fama-French three-factor model). The numbers in parentheses are standard errors adjusted according to Newey and West (1987). One, two, and three asterisks denote significance at the 10%, 5%, and 1% levels, respectively.

B/M firms. Among value firms, the premium is positive but measured with noise. This may be due to the fact that value firms in both the lead and lag portfolios count for just 2% of total market value, a very small fraction. Our leading premium is a broad phenomenon in the cross section of firms, as it applies to 80% of our firms that, in turn, represent between 28% and 38% of total market value. In a similar spirit, we note that our leading premium is not driven by small-cap firms, since our lead-lag structure in the cross section of industry cash-flows is mainly generated by large firms.

All of these results hold regardless of whether we use fixed 30%-70% cutoff levels computed from the full cross section of B/M and Size, or focus on the distribution of B/M and Size within each LL-sorted portfolio.

Robustness of predictive coefficients. In order to analyze the coefficients of the predictive regressions reported in table 5 in main text, we compute them dynamically over subsamples of increasing size. Specifically, we start with a subsample spanning the first 25 years in our dataset and then we keep adding 4 quarterly observations at the time. Our results are stable over time. See, for example, figure OL-B2 for results referring to the coefficients for cash flow growth (top-left portion of table 5, panel B).

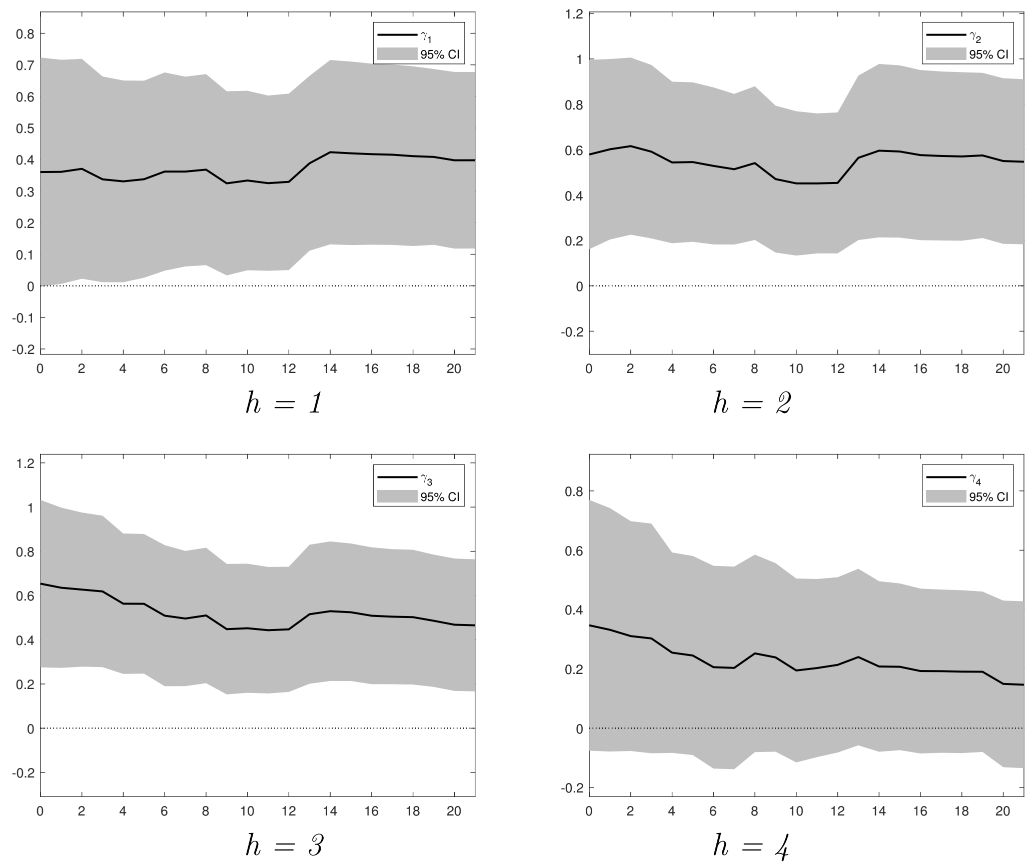


Fig. OL-B2: Predictive Regressions: Parameter Stability

Notes: This figure depicts estimates from the following regression:

$$\Delta y_{t+h}^{lag} = \gamma_0 + \gamma_h \Delta y_t^{lead} + \varepsilon_{t+h},\ h = 1, .., 4,$$

over subsamples with an increasing number of observations. The first estimate is computed using the first 25 years of data in our sample. We compute the subsequent estimates of γ_h by expanding the estimation window by four quarters at the time.

OL-B.1 The Leading Premium and the Cross Section of Risk Factors

Given the way in which we form our LL factor, it is natural to ask whether it is connected to other well-known risk factors already explored in the literature. In this section, we run standard time-series tests in order to check whether: (i) other factors fully explain ours, and (ii) our factor explains other existing ones. We find it important to state that our goal is not 'adding another factor to the zoo' (Feng et al., 2020). Rather we gather empirical guidance on the deeper economic concept highlighted in our model, that is, the size and relevance of the timing premium.

In addition, we note that in an economy in which shocks diffuse immediately across sectors, our lead-lag factor should not provide additional information once we control for other aggregate factors. Equivalently, we shall not expect to find a significant alpha. In many of our exercises, however, we find a strong disconnect between our leading premium and other well-known risk factors. We interpret these results as suggesting that existing risk factors are not enough to fully capture the role of the many shocks that affect our granular cross section of industries.

The LL's additional informativeness. Henceforth, we denote the Fama and French (1993) market, size, and value factors as, MKT, SMB, and HML, respectively. We consider also other financial factors that may be related to cyclical economic fluctuations, such as investment minus consumption proposed by Kogan and Papanikolaou (2014) (IMC), durability suggested by Gomes et al. (2009) (DUR), industry momentum constructed in the spirit of Moskowitz and Grinblatt (1999) (iMOM(6,6)), and industry betting-against-beta as suggested by Asness et al. (2014a) (iBAB).

In Table OL-B12, we show our conditional estimates (see Lewellen and Nagel, 2006) for the following regression:

$$LL_t = \alpha_{LL} + \gamma F_t + \varepsilon_t, \tag{OL-B.2}$$

where F_t comprises the factors mentioned above. Across all specifications, the intercept remains statistically significant and sizable, and the implied adjusted R^2 values are smaller than 11%. All of these results confirm that our factor goes beyond the role played by the FF3 factors, durability, investment shocks, industry momentum, and industry-level betting against the beta. The negative beta assigned to the IMC factor is fully consistent with Figure B1 in the appendix, as industries producing investment goods tend to lag the cycle. The statistically null link with the market is consistent with the a-cyclicality of our factor as per both our model and our results in Figure 3.

Untabulated results confirm that these conclusions can be obtained also when considering more granular cross sections with either 38 or 49 industries. Our results apply also when using different holding and formation periods for the construction of iMOM (see table OL-B13). Furthermore, our LL factor continues to have relevant information when we run our time-series tests on principal components that are extracted from all of these factors and explain up to 93% of their variation (see Table OL-B14).

We deepen our analysis by exploring the connection between the leading factor, the q-factors of Hou et al. (2015a, b), the FF5 factors of Fama and French (2015), and the Carhart

Table OL-B12: **The Disconnect between LL and Other Factors (I)**

	(1)	(2)	(3)	(4)	(5)	(6)
α_{LL}	3.96***	4.01***	3.04***	4.22***	3.48***	4.05***
	(0.81)	(0.70)	(0.58)	(0.50)	(0.47)	(0.62)
MKT	−0.08	−0.02	0.02	0.00	−0.05	−0.02
	(0.04)	(0.04)	(0.03)	(0.03)	(0.03)	(0.04)
SMB		−0.08**	0.01	−0.06*	−0.08**	−0.09**
		(0.03)	(0.04)	(0.03)	(0.03)	(0.03)
HML		−0.01	0.01	0.02	−0.00	−0.08
		(0.06)	(0.06)	(0.06)	(0.06)	(0.07)
IMC			−0.24***			
			(0.03)			
DUR				−0.11***		
				(0.02)		
iMOM					0.07**	
					(0.03)	
iBAB						0.15***
						(0.04)
Adj. R^2	0.02	0.04	0.10	0.05	0.04	0.05
# Obs.	552	552	552	552	552	492

Notes: This table reports the results from regressing the LL factor on other financial factors. We estimate conditional α_{LL} using 60-month rolling windows (Lewellen and Nagel, 2006) and controlling for the previous month market excess return (Dimson, 1979). Here, we consider market (MKT), size (SMB), value (HML), investment minus consumption by Kogan and Papanikolaou (2014) (IMC), durability by Gomes et al. (2009) (DUR), industry momentum by Moskowitz and Grinblatt (1999) (iMOM), and industry betting-against-beta by Asness et al. (2014a) (iBAB) factors. Newey-West adjusted standard errors are reported in in parentheses. Monthly data start in 1972:01 and end in 2017:12.

(1997) momentum factor. As shown in Table OL-B15, the alpha associated with our leading factor remains sizeable and significant across all cases considered. Even though our leading factor is related to cyclical measures like ROE and RMW, it is mostly unexplained by them. Untabulated results confirm that our results hold also when we sort industries according to their conditional forecasting power for future industrial production growth (see Equation (OL-B.1)).

Additional tests. We test whether our LL factor can explain other factors in the literature by checking whether their alpha is reduced when we add the time series of our LL factor to the set of our regressors. We report our formal results in Table OL-B16. We confirm a clear disconnect with our factor, that is, adding our LL factor to a large cross section of other risk

Table OL-B13: **LL Factor vs. Industry Momentum: Robustness**

	Industry Momentum (Lag, Hold)		
	(1,1)	(6,6)	(12,12)
		30-industries LL factor	
MKT+indMOM	3.30***	4.21***	4.00***
	(0.78)	(0.71)	(0.59)
FF3+indMOM	2.82***	3.48***	3.58***
	(0.61)	(0.47)	(0.48)
		38-industries LL factor	
MKT+indMOM	5.08***	4.86***	4.65***
	(0.86)	(0.87)	(0.79)
FF3+indMOM	3.81***	3.51***	3.60***
	(0.62)	(0.57)	(0.61)
		49-industries LL factor	
MKT+indMOM	4.53***	4.58***	5.53***
	(0.78)	(0.65)	(0.70)
FF3+indMOM	3.59***	3.89***	4.38***
	(0.79)	(0.73)	(0.71)

Notes: This table reports the intercept α_{LL} of the regression of the LL factor constructed from the cross section of 30, 38 and 49 industries on the corresponding industry momentum factor with different formation (Lag) and holding (Hold) periods (1 period means 1 month). The industry momentum is constructed following the methodology of Moskowitz and Grinblatt (1999). We report conditional α_{LL} using 60-month rolling windows (Lewellen and Nagel, 2006) and controlling for the previous month market excess return (Dimson, 1979). We control for the market factor (MKT) and Fama and French 3 factors (FF3). Newey-West adjusted standard errors are reported in in parentheses. Monthly data start in 1972:01 and end in 2017:12. One, two, and three asterisks denote significance at the 10%, 5%, and 1% levels, respectively.

factors change only marginally the estimated alphas.

In Table OL-B17, we show that our results are not subsumed by either the announcement risk factor of Savor and Wilson (2016) or the production network premium identified by Gofman et al. (2020). In addition, we show that even after controlling for tangibility our results hold.

Table OL-B14: LL Factor vs. Other Factors: Principal Component Analysis

α_{LL}	2.56***	2.30***	2.82***
	(0.58)	(0.70)	(0.82)
PC_1	−0.14***	−0.13***	−0.12***
	(0.02)	(0.02)	(0.02)
PC_2	0.01	0.02	0.01
	(0.03)	(0.03)	(0.03)
PC_3	0.10***	0.09***	0.08***
	(0.03)	(0.03)	(0.03)
PC_4		−0.09**	−0.05
		(0.04)	(0.03)
PC_5		−0.07***	−0.08***
		(0.02)	(0.03)
PC_6			0.01
			(0.04)
PC_7			−0.17***
			(0.04)
Expl. Var	64.1%	83.8%	94.7%
Adj. R^2	0.13	0.16	0.16
# Obs.	552	552	552

Notes: This table reports the results from regressing the benchmark LL factor constructed from the cross section of 30 industries on principal components extracted from Fama and French 5 factors, industry momentum (6,6) of Moskowitz and Grinblatt (1999), investment-minus-consumption, durability, quality-minus-junk, betting-against-beta, 30-industry momentum factors and q-factors. *Expl. Var.* shows how much of the variation in the factors is explained by the selected principal components. We report conditional α_{LL} using 60-month rolling windows (Lewellen and Nagel, 2006). Newey-West adjusted standard errors are reported in in parentheses. Monthly data start in 1972:01 and end in 2017:12. One, two, and three asterisks denote significance at the 10%, 5%, and 1% levels, respectively.

Table OL-B15: The Disconnect between LL and Other Factors (II)

FF5		HXZ q-factors		Carhart MOM			
α_{LL}	2.70***	α_{LL}	2.11**	α_{LL}	3.82***	4.39***	3.26***
	(0.63)		(0.93)		(0.76)	(0.74)	(0.56)
MKT	0.01	MKT	0.01	MKT		−0.11***	−0.03
	(0.03)		(0.03)			(0.04)	(0.03)
SMB	−0.02	ME	−0.03	MOM	0.05	0.05	0.09***
	(0.03)		(0.03)		(0.04)	(0.03)	(0.03)
HML	−0.14**	I/A	0.11	SMB			−0.09***
	(0.06)		(0.10)				(0.03)
RMW	0.10	ROE	0.11**	HML			0.03
	(0.06)		(0.05)				(0.06)
CMA	0.22***						
	(0.08)						
Adj. R^2	0.14	Adj. R^2	0.10	Adj.R^2	0.01	0.02	0.05
# Obs.	552	# Obs.	552	# Obs.	552	552	552

Notes: This table reports the results from regressing the LL factor on Fama and French 5 factors (FF5), the Hou et al. (2015a, b) q-factors, and the Carhart momentum factor (MOM). We estimate conditional α_{LL} using 60-month rolling windows (Lewellen and Nagel, 2006) and controlling for the previous month market excess return (Dimson, 1979). Newey-West adjusted standard errors are reported in parentheses. Monthly data start in 1972:01 and end in 2017:12.

Table OL-B16: Explaining Other Factors with LL Factor

Panel A: Q-Factors

	SMB	HML	IMC	DUR	BAB	iMOM	QMJ	RMW	CMA
α_0	0.52	0.85	0.24	−0.87	6.52***	−3.61*	3.11*	2.12**	0.68**
	(0.52)	(2.43)	(1.87)	(1.94)	(2.49)	(1.92)	(1.76)	(0.98)	(0.27)
α_1	0.44	0.72	0.09	−2.11	6.68***	−4.50**	3.07	2.24**	0.83***
	(0.57)	(2.42)	(2.20)	(2.38)	(2.54)	(1.98)	(1.89)	(0.95)	(0.26)
R_0^2	0.9232	0.4785	0.3521	0.2150	0.2181	0.0690	0.6618	0.4909	0.8460
R_1^2	0.9231	0.4814	0.3754	0.2171	0.2517	0.0679	0.6612	0.5143	0.8462

Panel B: Principal Components

	SMB	HML	IMC	DUR	BAB	iMOM	QMJ	RMW	CMA
α_0	0.21	0.68*	0.82***	−0.86**	−1.99**	−0.22	2.01*	0.22	1.57*
	(0.55)	(0.41)	(0.32)	(0.36)	(0.78)	(0.14)	(1.10)	(0.85)	(0.90)
α_1	0.02	1.06***	0.71*	−0.82**	−1.93**	−0.30*	1.99*	−0.04	1.36
	(0.68)	(0.39)	(0.41)	(0.41)	(0.87)	(0.17)	(1.18)	(0.87)	(1.20)
R_0^2	0.9702	0.8360	0.9870	0.9871	0.9127	0.9977	0.8161	0.7508	0.7324
R_1^2	0.9702	0.8358	0.9871	0.9871	0.9129	0.9977	0.8168	0.7552	0.7324

Notes: This table reports the results from explaining alphas of individual factors using the LL factor. Specifically we measure an incremental power of the LL factor relative to the Q-factors model of Hou et al. (2015a, b) (Panel A) and 7 principal components extracted from a large cross section of risk factors (Panel B). α_0 and R_0^2 denote the factor alpha and the implied adjusted R-squared for the baseline model which excludes our LL factor. α_1 and R_1^2 refer to a model augmented by the LL factor. We consider the size factor (SMB), the value factor (HML), the investment-minus-consumption by Kogan and Papanikolaou (2014) (IMC), the durability factor by Gomes et al. (2009) (DUR), betting-against-beta (BAB) by Asness et al. (2014a), industry momentum by Moskowitz and Grinblatt (1999) (iMOM(6,6)), quality-minus-junk (QMJ) by Asness et al. (2014b) and the Fama and French investment and profitability factors (RWA and CMA). We report conditional alphas using 60-month rolling windows (Lewellen and Nagel, 2006). Newey-West adjusted standard errors are reported in parentheses. Monthly data start in 1972:01 and end in 2017:12.

Table OL-B17: The Disconnect between LL and Other Factors (II)

Announcement Factor			Network Factor		Tangibility Factor	
α_{LL}	4.28**	4.56**	α_{LL}	6.56***	α_{LL}	3.34**
	(2.15)	(2.08)		(2.37)		(1.69)
MKT	−0.12	−0.12	MKT	−0.22***	MKT	0.00
	(0.08)	(0.08)		(0.06)		(0.12)
SMB	0.04	0.04	SMB	−0.23***	SMB	−0.11
	(0.08)	(0.08)		(0.06)		(0.19)
HML	0.05	0.05	HML	−0.55***	HML	0.08
	(0.15)	(0.15)		(0.17)		(0.35)
SW_e	−0.01		TMB	0.11*	TAN	−0.16
	(0.02)			(0.06)		(0.11)
SW_n		−0.03				
		(0.02)				
Adj.R^2	0.02	0.03	Adj.R^2	0.41	Adj.R^2	0.06
# Obs.	492	492	# Obs.	110	# Obs.	552

Notes: The left portion of this table reports the results from regressing the LL factor constructed from the cross section of 30 industry portfolios on Fama and French 3 factors, market (MKT), size (SMB), and value (HML), together with earnings announcement value-weighted returns from Savor and Wilson (2016) for announcers (SW_e) and non-announcers (SW_n). Monthly data start in 1972:01 and end in 2012:12. The middle portion of this table controls for the Top-Minus-Bottom (TMB) risk factor identified by Gofman et al. (2020) in production networks. The TMB factor is available starting from 2003:11. The right panel of the table controls for the tangibility factor constructed by sorting firms on their tangibility ratio (net property, plan and equipment over total assets). Monthly data for the tangibility factor start in 1972:01 and end in 2017:12. Newey-West adjusted standard errors are reported in parentheses.

OL-B.2 Additional Results in the Cross Section.

Additional tests. In Table OL-B18, we report our results for both the market prices of risk and the implied stochastic discount factor loadings associated with our four factors, that is, FF3 plus the LL factor. Since we take the concerns about spurious inference seriously, we also report the cross sectional improvement in GLS adjusted R^2 (GLS R^2+, see Lewellen et al. (2010)) and the mean scaled intercept (SI, see Harvey and Liu (2018)) statistics.[13]

We find that both the factor risk premium λ_{LL} and the pricing kernel loading b_{LL} are statistically significant at the 5% and often 1% level. The cross sectional R^2 improvement is sizeable and particularly so for the industry cross section. The $p-$value of the SI statistics is almost always smaller than or equal to 10%, implying that we can reject the null hypothesis that the LL factor is a lucky factor.

Hence, these tests confirm that our LL factor is relevant when it comes to pricing the cross sections of equity returns, including those in which portfolios are sorted with respect to investment (INV), operating profits (OP), long-term reversal (LT Reversal), and momentum (MOM).[14] We also show that these results are still significant, albeit at a higher significance level, when we add either momentum or durability to set of risk factors to study the cross section of industries (see Table OL-B19). These results reduce the concerns in Giglio et al. (2021).

[13]We follow Harvey and Liu (2018) in aggregating the results from 10,000 bootstrap samples of the entire cross section with replacement.

[14]Fama and French (1993) do not estimate market prices of risk as we do. We run the Fama-MacBeth regressions replication code choosing our industry portfolios as test assets. In this cross section, we obtained poorly identified, and often negative, market price of risk for both SMB and HML.

Table OL-B18: Prices of Risk and Pricing Kernel Loadings

Cross Section (# portfolios)	λ_{MKT}	λ_{SMB}	λ_{HML}	λ_{LL}	b_{MKT}	b_{SMB}	b_{HML}	b_{LL}	GLS R^2+	SI
30 industries	0.64***	−0.38	−0.09	0.38*	0.04***	−0.05*	−0.01	0.03*	0.12	−0.021
	(0.18)	(0.24)	(0.21)	(0.22)	(0.01)	(0.03)	(0.03)	(0.02)		[0.10]
38 industries	0.65***	−0.30	−0.01	0.33*	0.04***	−0.04	0.00	0.02*	0.12	0.013
	(0.18)	(0.19)	(0.23)	(0.18)	(0.01)	(0.03)	(0.03)	(0.01)		[0.13]
49 industries	0.66***	−0.34	−0.15	0.43*	0.04***	−0.05*	−0.02	0.03*	0.06	0.004
	(0.17)	(0.23)	(0.21)	(0.25)	(0.01)	(0.03)	(0.03)	(0.02)		[0.05]
BE/ME and Size (25)	0.52***	0.15	0.40***	0.34**	0.04***	0.02	0.06***	0.03***	0.05	−0.024
	(0.18)	(0.15)	(0.15)	(0.13)	(0.01)	(0.02)	(0.02)	(0.01)		[0.06]
BE/ME and INV (25)	0.59***	−0.14	0.27	0.31**	0.04***	−0.02	0.04*	0.02**	0.06	−0.037
	(0.18)	(0.25)	(0.19)	(0.14)	(0.01)	(0.03)	(0.02)	(0.01)		[0.08]
BE/ME and OP (25)	0.54***	−0.32	0.49***	0.29**	0.05***	−0.04	0.07***	0.02	0.04	−0.040
	(0.18)	(0.25)	(0.18)	(0.14)	(0.01)	(0.03)	(0.02)	(0.01)		[0.06]
OP and INV (25)	0.57***	−0.43**	0.64***	0.42***	0.06***	−0.05*	0.09***	0.02**	0.03	−0.089
	(0.19)	(0.22)	(0.22)	(0.14)	(0.01)	(0.03)	(0.03)	(0.01)		[0.08]
Size and LT Reversal (25)	0.58***	0.03	0.54***	0.32**	0.04***	0.01	0.08***	0.02**	0.06	−0.087
	(0.18)	(0.17)	(0.18)	(0.13)	(0.01)	(0.02)	(0.02)	(0.01)		[0.02]
Size, BE/ME, INV, OP (40)	0.57***	0.03	0.34**	0.39***	0.04***	0.00	0.05***	0.03***	0.05	−0.076
	(0.18)	(0.15)	(0.15)	(0.14)	(0.01)	(0.02)	(0.02)	(0.01)		[0.02]
Size, BE/ME, INV, OP, MOM (50)	0.56***	0.06	0.18	0.63***	0.04***	0.01	0.03	0.05***	0.03	−0.064
	(0.18)	(0.15)	(0.15)	(0.14)	(0.01)	(0.02)	(0.02)	(0.01)		[0.05]
Size, OP, INV (32)	0.55***	−0.03	0.82***	0.46***	0.05***	0.00	0.11***	0.03***	0.02	−0.069
	(0.18)	(0.15)	(0.20)	(0.15)	(0.01)	(0.02)	(0.03)	(0.01)		[0.12]
Size, BE/ME, INV (32)	0.58***	0.17	0.28*	0.35***	0.04***	0.02	0.05**	0.03***	0.05	−0.040
	(0.18)	(0.14)	(0.16)	(0.14)	(0.01)	(0.02)	(0.02)	(0.01)		[0.14]
Size, BE/ME, OP (32)	0.54***	0.06	0.47***	0.37***	0.04***	0.01	0.07***	0.03***	0.04	−0.085
	(0.18)	(0.14)	(0.17)	(0.14)	(0.01)	(0.02)	(0.02)	(0.01)		[0.07]

Notes: This table presents monthly factor risk premia and the exposures of the pricing kernel to both the FF3 and our lead-lag (LL) factors. We employ GMM to estimate the linear factor model stated in equations (8)–(10). GLS R^2+ denotes the improvement in GLS adjusted R^2 achieved by adding the LL factor to the FF3 factors. *SI* denotes the average scaled intercept of Harvey and Liu (2018). Associated p-values are in squared brackets. Our set of test assets consists of 30-, 38-, and 48-industry portfolios; portfolios sorted on book-to-market (BE/ME), market capitalization (Size), operating profits (OP), investments (INV); long-term (LT) reversal, and momentum (MOM). Our monthly sample is 1:1972–12:2017. The numbers in parentheses are Newey and West (1987) standard errors. One, two, and three asterisks denote significance at the 10%, 5%, and 1% levels, respectively.

Table OL-B19: Prices of Risk and Pricing Kernel Loadings

Momentum factor

$$E[R_i^{ex}] = \beta_{MKT}\lambda_{MKT} + \beta_{SMB}\lambda_{SMB} + \beta_{HML}\lambda_{HML} + \beta_{MOM}\lambda_{MOM} + \beta_{LL}\lambda_{LL}$$

λ_{MKT}	λ_{SMB}	λ_{HML}	λ_{MOM}	λ_{LL}
0.65***	-0.32	-0.06	-0.01	0.35*
(0.17)	(0.30)	(0.22)	(0.23)	(0.20)

$$m_t = \overline{m} - b_{MKT}MKT_t - b_{SMB}SMB_t - b_{HML}HML_t - b_{MOM}MOM_t - b_{LL}LL_t$$

b_{MKT}	b_{SMB}	b_{HML}	b_{MOM}	b_{LL}
0.05***	-0.04	0.00	-0.01	0.03*
(0.01)	(0.04)	(0.03)	(0.02)	(0.01)

Durability factor

$$E[R_i^{ex}] = \beta_{MKT}\lambda_{MKT} + \beta_{SMB}\lambda_{SMB} + \beta_{HML}\lambda_{HML} + \beta_{DUR}\lambda_{DUR} + \beta_{LL}\lambda_{LL}$$

λ_{MKT}	λ_{SMB}	λ_{HML}	λ_{DUR}	λ_{LL}
0.63***	-0.42	-0.12	-0.29	0.42**
(0.17)	(0.35)	(0.24)	(0.97)	(0.20)

$$m_t = \overline{m} - b_{MKT}MKT_t - b_{SMB}SMB_t - b_{HML}HML_t - b_{DUR}DUR_t - b_{LL}LL_t$$

b_{MKT}	b_{SMB}	b_{HML}	b_{DUR}	b_{LL}
0.04***	-0.06	-0.02	-0.01	0.03**
(0.01)	(0.04)	(0.05)	(0.06)	(0.02)

Notes: This table presents monthly factor risk premia and the exposures of the pricing kernel to the FF3 factors (MKT, SMB, HML), the Carhart (1997) momentum factor (MOM), the Gomes et al. (2009) durability factor (DUR) and our lead-lag factor (LL). We employ the generalized method of moments (GMM) to estimate the linear factor model stated in equations (8)–(9). Using a linear projection of the stochastic discount factor m on the factors ($m = \overline{m} - f'b$), we determine the pricing kernel coefficients as $b = E[ff']^{-1}\lambda$. Our sample consists of monthly returns for 30-industry portfolios from January 1972 through December 2017. The numbers in parentheses are standard errors adjusted according to Newey and West (1987). One, two, and three asterisks denote significance at the 10%, 5%, and 1% levels, respectively.

OL-C Intuition Based on No-arbitrage: Empirical Support

The derivations described in Section 2 suggest that lagging stocks should behave more like bonds, whereas leading stocks should behave more like uncertain aggregate equity. We provide further support for our analysis by estimating a quarterly VAR with three variables: aggregate bond yield, aggregate equity yield, and then the yield of either our lagging portfolio or our leading portfolio. The portfolio yields are computed in a standard way by using the cum- and ex-dividends return of our stocks. The bond yield is from the Fama-Bliss data set and is for a maturity of one year.

After imposing a lower-triangular structure on the covariance matrix of the shocks, we can identify the role played by bond-specific and equity-specific shocks in determining the variance of our lagging and leading dividend yields. Since our results do not change if we rank the aggregate equity yield first and the bond yield second in our VAR, we do not need to take a stand on causality of bond and equity shocks for the purpose of our exercise.

In Figure OL-C1, we show the variance decomposition for both our leading and lagging

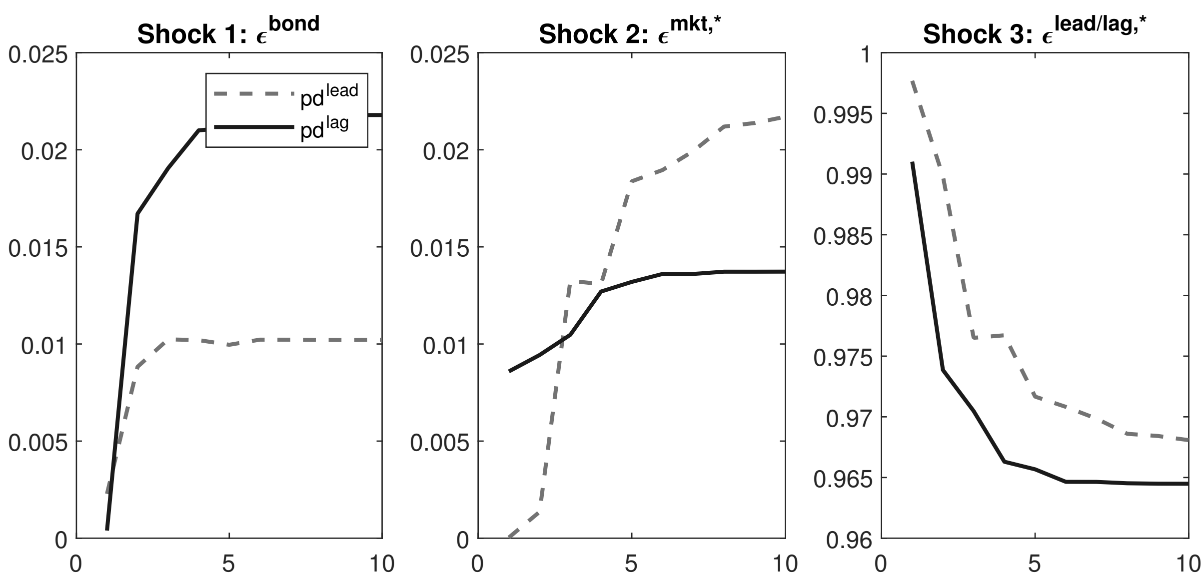


Fig. OL-C1: Variance Decomposition of Leading/Lagging Portfolio Yields

Notes: This figure depicts the variance decomposition of the forecast error of the leading and lagging portfolio log yields estimated from a VAR(3). The variables in the model are: one-year bond yield; aggregate equity market log price-dividend ratio; and either leading or lagging log price-dividend ratio. The data is quarterly and spans the period 1972Q1:2017Q4.

portfolios. Not surprisingly, given the persistence of dividend yields, the leading (lagging) yield-specific shock explains most of the variance of the leading (lagging) portfolio dividend yield (right panel). Most importantly, consistent with our intuition bond-specific shocks matter more than aggregate equity-specific shocks for our lagging portfolio (left panel). The opposite is true for our leading portfolio (middle panel).

OL-D Leads, Lags and Pre-Committed Investment

Consider an economy in which time $t = 1, 2, 3, 4$ is discrete, and expanding assets in place requires two consecutive periods of pre-committed investment. A leading firm decides to proceed with investment at time 1 and commits to investing $\overline{I}$ at both $t = 1$ and $t = 2$ in order to reach an ideal level of capital at time $t = 3$, denoted as $\overline{K} = 2\overline{I}$.

Consider also a lagging firm which is ex-ante identical to our leading firm and differs from it just because it proceeds with the same investment plan with a period of delay, i.e., it commits to investing starting from $t = 2$ and completing its project at $t = 4$.

Finally, assume at time $t = 2$ news arrives and the expected final value of installed capital changes compared to time $t = 1$.

The problem of the leading firm can be stated as follows:

$$\begin{array}{ll} \text{choose} & \Delta I_2^{lead} \\ \text{to max} & E_2[V(\Delta I_2^{lead})] - \beta_0 \cdot (\Delta I_2^{lead})^2, \end{array}$$

where $\Delta I_2^{lead} := I_2^{lead} - \overline{I}$ is the deviation in the investment at time $t = 2$ from its pre-committed level; $E_2[V]$ measures the variation in the expected value of the project under the information set at time $t = 2$; and the coefficient $\beta_0 > 0$ introduces a quadratic adjustment cost that depends on the variation from the pre-committed investment level.

At time $t = 2$, the investment that took place at $t = 1$ cannot be changed, and hence, for the leading firm, $\Delta I_1^{lead} = 0$. The lagging firm, in contrast, can change the entire sequence of investments. Its problem is stated as follows:

$$\begin{array}{ll} \text{choose} & \Delta I_2^{lag},\ \Delta I_3^{lag} \\ \text{to max} & E_2[V(\Delta I_2^{lag} + \Delta I_3^{lag})] - \beta_{-1} \cdot (\Delta I_2^{lag})^2 - \beta_0 \cdot (\Delta I_3^{lag})^2, \end{array}$$

where we assume that $0 \leq \beta_{-1} < \beta_0$, meaning that adjusting the scale of investment at the beginning of the project is cheaper than in the second part of its life.

Assume that $\beta_{-1} = 0$, then it is optimal to have $|\Delta I_2^{lag}| = |\Delta K|$ and $|\Delta I_3^{lag}| = 0$. That is, the full adjustment of the capital stock $|\Delta K|$ happens at time $t = 2$ by modifying I_2^{lag}. Simultaneously, because of the presence of adjustment costs, $|\Delta I_2^{lead}| < |\Delta K|$, meaning that both leading and lagging firms will adjust investment simultaneously but to different extents. Specifically, the adjustment is going to be stronger for the lagging firm.

By continuity, one can prove that $\exists \beta_{-1}^* < \beta_0$ such that, if $\beta_{-1} \in [0,\ \beta_{-1}^*]$, we obtain $|\Delta I_2^{lead}| < |\Delta I_2^{lag}|$. As stated in main text, lagging and leading firms adjust their investments simultaneously, but lagging firms do so more aggressively if the adjustment costs are increasing along the life of the project.

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