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Firm Size, Capital Investment, and Debt Financing over Industry Business Cycles

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Abstract

We find that capital investment and net debt issuance of large firms are, on average, more sensitive to industry business cycles than those of small firms, in stark contrast to the effect of size on investment sensitivity to macroeconomic cycles. We theoretically examine the role of firm size on firms' responses to industry shocks. Consistent with our theoretical predictions, we find that large firms exhibit greater sensitivity to industry cycles than small firms in their investment and net debt issuance only in industries with low cyclical variability of markups and production growth, high fixed cost intensity, high market-to-book, and high markups.

I. Introduction

An important strand of the macroeconomic *real business cycle* literature highlights the rising contributions of industry (or sectoral) shocks in explaining aggregate fluctuations (Long and Plosser (1987), Foerster, Sarte, and Watson (2011)), establishing the presence of disaggregated industry business cycles (Forni and Reichlin (1998)). An extensive microeconomic literature (at the level of the firm) provides the microfoundations of real industry business cycles, and attributes these to technological innovation shocks (Schumpeter (1942), Gort and Klepper (1982), Jovanovic (1982), and Klepper (1996)) and changing consumer preferences (Gompers and Lerner (2003)). But while there is a large literature on how firms vary their capital investment and financing policies over the aggregate business cycle, we know little about how they respond to business cycle fluctuations in their own industry. We attempt to fill this gap in this article, by examining, both theoretically and empirically, the effects of industry business cycle fluctuations on firm-level investment and debt financing policies, while controlling for the effect of the aggregate cycle.

We find that capital investment and net debt issuance of large firms are, on average, more sensitive to industry business cycle fluctuations compared to those of small firms. These results are in stark contrast to the stylized facts established in the

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literature that the investment of small firms is more sensitive to the aggregate (or macroeconomic) business cycle compared to that of large firms (Gertler and Gilchrist (1994), Crouzet and Mehrotra (2020)); and that the debt issuance of small firms is also more sensitive to the aggregate business cycle than that of large firms (Covas and Den Haan (2011), Begenau and Salomao (2019)). The greater sensitivity of small firms to the aggregate business cycle attracts substantial attention from policymakers as well, and is generally taken as evidence that credit market imperfections amplify the real and financial effects of aggregate shocks (Bernanke and Gertler (1989), Kiyotaki and Moore (1997)). Thus, it is striking that on average large firms exhibit greater sensitivity to their industry business cycles than small firms.

Our empirical analysis is guided by predictions from a simple framework of corporate investment in which the firm's marginal profit (or price–cost markup) is affected by separate aggregate and industry-specific shocks. Consistent with the literature, our framework does not impose any exogenous restriction on the relation of firm size and markup. In this setup, there are conflicting effects of size on firms' investment sensitivity to industry shocks. With a downward-sloping industry demand curve, the effect of a given increase in production capacity (i.e., investment) on the markup is ceteris paribus more negative for larger firms, suggesting a negative relation of size and investment sensitivity to the industry shock. But since the negative effect of higher output on industry price is softened in industry expansions and exacerbated in downturns, larger firms increase (contract) investment more in expansions (downturns) relative to smaller firms. We find that the latter effect dominates the former when there is low variability of markups and production growth with respect to the industry-specific shock. Thus, the model predicts that firm size will have a positive effect on investment sensitivity to the industry business cycle in industries with *low variability* of markups and production growth over the industry cycle.

We take these novel predictions of our framework to the data. However, we recognize that cyclical variations in markups and production growth over the industry cycle are not directly observable industry characteristics, but likely reflect underlying industry product and technology characteristics. In particular, there is a strong economic intuition that industries producing goods that are not easily substitutable (i.e., have low elasticity of substitution) will tend to have milder downturns in terms of markups or production, other things being equal. Examples of such industries would include food and tobacco, chemicals, and computer and electronic products. It follows that such industries will have higher markups on average; and low exposure of markups to industry cyclical risk would result in higher industry median market-to-book. Yet another perspective is based on the recent literature that ascribes the observed trend in increased markups (Autor, Dorn, Katz, Patterson, and Van Reenen (2020), De Loecker, Eeckhout, and Unger (2020)) to labor-substituting technological changes, such as automation and computerization, that have increased fixed costs relative to marginal costs (Berry, Gaynor, and Morton (2019)). This argument implies that low cyclical variation in markups would be linked to higher fixed-cost industries. We therefore also empirically test the size effect on investment sensitivity to industry business cycles in terms of industry-level market-to-book, fixed cost intensity, and markup levels.

In our empirical analysis, we apply the regime-switching approach (Hamilton (1989)) to identify the industry business cycle phases for various industry groups within the U.S. manufacturing sector for which we have time-series data on industrial production. To separate the effects of industry and aggregate cycles, we also use the regime-switching approach to identify the aggregate business cycle phases using time-series data on the U.S. gross national product.[1] An important advantage of the regime-switching approach is that it allows for the generation of coincident indicators and inferred probabilities of a downturn in the next quarter for the U.S. economy and for each of the industry groups in our sample. By contrast, the widely used NBER recession classification identifies downturns after they materialize, and does not reflect business cycle fluctuations at the industry level, which is the main focus of our study. Because industry cycles are components of the aggregate cycle, we orthogonalize the probability of industry downturn with respect to the probability of aggregate downturn in our empirical analysis.

We employ panel regressions with firm fixed effects to identify the *within-firm* variation in capital investment over the industry and aggregate business cycles. As expected, we find that the capital investment is procyclical with respect to both the industry and aggregate business cycles. Consistent with the key prediction of our theoretical framework, we find that capital investment of larger firms is more sensitive to the industry business cycle than that of small firms only in industries with relatively low variation of markups and production growth over the industry cycle. On the other hand, there is no significant effect of size on investment sensitivity to the industry business cycle in industries with relatively high cyclical variation of markups and production growth.

Of course, as noted above, cyclical variation of markups and production growth are model-based estimates and are not directly observable.[2] Hence we test the model's predictions in terms of observable industry characteristics, such as fixed cost intensity, market-to-book, and markup. Consistent with the model's predictions we find that large firms exhibit greater sensitivity to industry cycles only in industries with high fixed cost intensity, high market-to-book, and high markup. On the other hand, firm size does not affect sensitivity of capital investment to industry cycles in industries with low fixed-cost intensity, low market-to-book, and low markup.

A large literature points to the importance of internal cash and debt in financing of firms' capital investment (e.g., Myers (1984), Drucker and Puri (2006), and Duchin, Ozbas, and Sensoy (2010)). Therefore, the sufficient condition for positive relation of size and capital investment sensitivity to industry shocks should apply as well to positive relation of size and sensitivity of net debt issuance to industry

[1]This differentiates our paper from prior studies that use the NBER recession indicator as a proxy for the aggregate business cycle (e.g., Erel, Julio, Kim, and Weisbach (2012), Dangl and Wu (2016)). Hamilton (1989) highlights that the regime-switching approach generates additional aggregate downturn phases that are not captured by the NBER indicator, because the latter only identifies recessions that actually materialize whereas the former also identifies fears of a likely aggregate downturn.

[2]We use estimates of the regime-switching model for each industry to estimate the cyclical variation of production growth in that industry. Similarly, we use time-series data on an industry's markup—measured using Compustat data following the approach suggested by Bustamante and Donangelo (2017)—to estimate the variation in industry markup.

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cycles. Indeed, we find that the net debt issuance of larger firms is more sensitive to the industry business cycle than that of small firms only in industries with relatively low variation of markups and production growth over the industry cycle. On the other hand, there is no significant effect of size on the sensitivity of net debt issuance to the industry business cycle in industries with relatively high cyclical variation of markups and production growth.

Our article is related to the large literature which examines the effect of the aggregate real business cycle on firm-level investment (e.g., Gertler and Gilchrist (1994), Crouzet and Mehrotra (2020)), financing policies (e.g., Covas and Den Haan (2011), Erel et al. (2012), and Begenau and Salomao (2019)), and capital structure dynamics (e.g., Hackbarth, Miao, and Morellec (2006), Bhamra, Kuehn, and Strebulaev (2010)). There is also a related literature which examines the effect of financing shocks, as opposed to real shocks, on capital investment (e.g., Dell'Ariccia, Detragiache, and Rajan (2008), Duchin et al. (2010), and Lemmon and Roberts (2010)). We complement this literature by examining the sensitivity of firm-level capital investment and debt financing to real industry business cycles, and how these sensitivities vary with firm size. We focus on the role of firm size because the greater sensitivity of small firms to the aggregate business cycle is a well-established stylized fact, and attracts substantial attention from researchers and policymakers. By contrast, we show that firm size has a positive effect on the sensitivity of capital investment and net debt issuance to industry business cycles in an empirically significant group of manufacturing industries, in a manner consistent with the predictions of our theoretical framework. Our analysis thus indicates that recognizing firms' differential sensitivity to industry and aggregate real business cycles is important in understanding their dynamic investment and financing policies.

The rest of the article is structured as follows: We describe the data and the methodology for identifying industry and macroeconomic business cycles in Section II. We develop a simple conceptual framework and derive testable predictions in Section III. We present the main empirical results in Section IV and conclude the article in Section V.

II. Data and Methodology

A. Data Sources

We obtain data on industrial production for industry groups in the manufacturing sector (NAICS 31–33) from the Board of Governors of the Federal Reserve System. We use the "Industrial Production and Capacity Utilization – G.17" series on Federal Reserve's web page (https://www.federalreserve.gov/releases/g17/download.htm) to obtain quarterly data on seasonally adjusted industrial production for 33 industry groups in the manufacturing sector. Most of the industry groups are defined at the 3-digit NAICS level and may include either a single industry or a group of related industries, although a few industry groups are defined at the 4-digit NAICS industries. We provide details of these industry groups in Table 1. The data spans the time period from the first quarter of 1972 to the first quarter of 2019.

TABLE 1

Description of Industry Groups

Table 1 describes the industry groups in the manufacturing sector (NAICS 31–33) that are tracked under the "Industrial Production and Capacity Utilization – G.17" series maintained by the Federal Reserve. Most of the industry groups are defined at the 3-digit NAICS level, and may include either a single industry or a group of related industries, although a few industry groups are defined at the 4-digit NAICS industries. We provide summary statistics on the (annualized) quarterly growth over the period from 1972:Q1 to 2019:Q1.

		Growth Rate (Annualized)				
NAICS	Industry Description	Mean	Std. Dev.	Median	p10	p90
311,2	Food, beverage, and tobacco	0.012	0.021	0.011	−0.011	0.037
313,4	Textiles and products	−0.010	0.076	0.001	−0.105	0.068
315,6	Apparel and leather goods	−0.042	0.082	−0.032	−0.139	0.035
321	Wood product	0.005	0.086	0.026	−0.095	0.087
322	Paper	0.005	0.051	0.006	−0.039	0.061
323	Printing and related support activities	0.008	0.049	0.011	−0.042	0.071
324	Petroleum and coal products	0.010	0.047	0.005	−0.038	0.073
325	Chemical	0.016	0.052	0.017	−0.039	0.074
326	Plastics and rubber products	0.022	0.075	0.026	−0.060	0.099
327	Nonmetallic mineral product	0.005	0.071	0.020	−0.089	0.064
331	Primary metal	−0.003	0.117	0.011	−0.106	0.116
332	Fabricated metal product	0.009	0.069	0.023	−0.070	0.081
333	Machinery	0.012	0.092	0.034	−0.104	0.104
334	Computer and electronic product	0.118	0.097	0.122	0.006	0.250
335	Electrical equipment, appliance, and component	0.005	0.077	0.015	−0.089	0.075
3361–3	Motor vehicles and parts	0.022	0.142	0.037	−0.159	0.152
3364–9	Aerospace and misc. transportation equipment	0.014	0.084	0.009	−0.085	0.129
337	Furniture and related product	0.007	0.083	0.016	−0.070	0.078
339	Miscellaneous	0.020	0.044	0.022	−0.038	0.076

The Federal Reserve also provides data on industrial production for industry groups in the utility sector (NAICS 22) and for the mining sector as a whole (NAICS 21). We exclude these from our analysis although all our results are robust to the inclusion of these sectors. We exclude utility industries because these are highly regulated, and may not have the flexibility to respond to the business cycle. The drawback with the data on the mining sector is that it is not disaggregated by subgroups, such as coal, oil & gas, and metals.

We obtain data on U.S. gross national product (GNP) from the FRED Economic Data maintained by the Federal Reserve Bank of St. Louis (https://fred.stlouisfed.org/). We use the GNPC96 series which provides quarterly and seasonally adjusted data on the Real GNP of U.S. (in billions of 2012 dollars). This data is available from the first quarter of 1947 onward. We also use the FRED database to obtain data on several benchmark interest rates.

We obtain firm financial information from the Compustat Quarterly files and stock market data from CRSP. Our sample comprises of U.S. firms that belong to industry groups in the manufacturing sector, for which we have information on industrial production from the Federal Reserve.[3] There are 4,654 firms that meet this requirement. We provide details of the number of firms in each industry group in Table 1. We use this data to construct a firm-level panel data set spanning the time

[3]We classify a firm as U.S.-based by applying the following criteria. First, we check for U.S. incorporation by verifying that the firm's FIC variable in Compustat is set to "USA." Next, we verify that the main stock exchange on which the firm trades (EXCHG variable in Compustat) is a U.S. exchange, which corresponds to the condition 11 ≤ EXCHG ≤ 18. Finally, we check the firm's STATE is within the United States.

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period from 1980:Q1 to 2019:Q1, in which each observation corresponds to a firm-fiscal quarter combination.

B. The Regime-Switching Model

We use the regime-switching model of Hamilton (1989) to identify business cycle phases at the industry level. Hamilton's model specifies a parametric time series model in which the mean growth rate switches between two regimes: high and low (or expansions and downturns). The timing of these regimes and the within-regime growth rates are then estimated from data. An important advantage of this approach is that it allows for the generation of coincident indicators and inferred probabilities of expansions and recessions.

Formally, let y_{it} denote the growth rate of industrial production in industry group i in time period t. We consider the following simple model for y_{it}:

$$\begin{aligned} y_{i,t} &= \mu_{i,S_{i,t}} + \varepsilon_{i,t}, \\ \varepsilon_{i,t} &\sim \text{i.i.d. } N\left(0, \sigma^2_{\varepsilon,i}\right), \\ \mu_{i,S_{i,t}} &= (1 - S_{i,t}) \cdot \mu_{i,\text{high}} + S_{i,t} \cdot \mu_{i,\text{low}},\ \mu_{i,\text{low}} < \mu_{i,\text{high}}, \end{aligned} \tag{1}$$

where $\mu_{i,S_{i,t}}$ denotes the mean growth rate, which is permitted to switch between a high and low value ($\mu_{i,\text{high}}$ and $\mu_{i,\text{low}}$) based on the realization of the latent state variable $S_{it} \in \{0,1\}$. A natural interpretation is that $S_{it} = 1$ denotes a downturn in industry i because $\mu_{i,\text{low}} < \mu_{i,\text{high}}$. Equation (1) is estimated with the assumption that S_{it} is a first-order 2-state Markov chain, where the probability process driving S_{it} is governed by the transition probabilities

$$p_{i,jk} \equiv \Pr[S_{it} = k | S_{i,t-1} = j],\ j,k \in \ell, h. \tag{2}$$

The model provides estimates of the expected growth rates, $\mu_{i,\text{low}}$ and $\mu_{i,\text{high}}$, the variance $\sigma^2_{\varepsilon,i}$, and the transition probabilities, $p_{i,hh}$ and $p_{i,\ell\ell}$, for each industry group i. For each t, the model also provides 1-step-ahead predicted probability that the industry will be in the downturn state (i.e., $S_{i,t+1} = 1$). We refer to this variable as Pr(IND_DOWNTURN) and note that a low value of this variable denotes that the industry is expected to be in an expansionary phase in the next period. Accordingly, we define the following dummy variables: IND_DOWNTURN which identifies time periods during which Pr(IND_DOWNTURN) ≥ 0.75 and denotes that an industry downturn is highly likely next period; and IND_EXPANSION which identifies time periods during which Pr(IND_DOWNTURN) ≤ 0.25 and denotes that an industry expansion is highly likely next period.

We also use a variant of the model in equation (1), with growth in U.S. real GNP as the dependent variable, to identify business cycle phases at the aggregate level. As with the industry-specific measures, we estimate Pr(AGGR_DOWNTURN) which denotes the probability that the aggregate economy will be in the downturn state next period, and define the following dummy variables: AGGR_DOWNTURN which identifies time periods during which Pr(AGGR_DOWNTURN) ≥ 0.75 and denotes that an aggregate downturn is highly likely next period; and AGGR_EXPANSION which identifies time periods during

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TABLE 2

Industry Business Cycle Phases

Panel A of Table 2 provides an industry-wise description of the estimated model parameters of the regime-switching model (1). Panel B provides pairwise correlations between the various industry business cycle measures and aggregate business cycle measures in our firm-level panel data. Please see Appendix A for definitions of all variables. *p < 0.1.

Panel A. Industry-Wise Estimates of Model Parameters

NAICS	$\mu_{i,\text{low}}$	$\mu_{i,\text{high}}$	σ_i^2	$p_{i,hh}$	$p_{i,\ell\ell}$
311,2	0.000	0.030	0.015	0.875	0.793
313,4	−0.137	0.009	0.057	0.857	0.980
315,6	−0.246	−0.022	0.051	0.875	0.988
321	−0.160	0.031	0.055	0.742	0.960
322	−0.165	0.012	0.037	0.710	0.989
323	−0.012	0.055	0.038	0.975	0.944
324	−0.012	0.054	0.035	0.889	0.771
325	−0.101	0.027	0.038	0.744	0.976
326	−0.152	0.038	0.054	0.792	0.982
327	−0.149	0.026	0.041	0.772	0.970
331	−0.298	0.022	0.077	0.725	0.977
332	−0.130	0.028	0.046	0.773	0.969
333	−0.162	0.039	0.062	0.782	0.967
334	0.042	0.191	0.062	0.949	0.950
335	−0.146	0.028	0.050	0.780	0.968
3361–3	−0.230	0.061	0.101	0.802	0.971
3364–9	−0.049	0.081	0.052	0.919	0.919
337	−0.258	0.020	0.059	0.767	0.989
339	−0.020	0.045	0.030	0.862	0.919

Panel B. Pairwise Correlations of Business Cycle Measures

	Pr (IND_DOWNTURN)	Pr (AGGR_DOWNTURN)	IND_DOWNTURN	AGGR_DOWNTURN
Pr(IND_DOWNTURN)	1.000			
Pr(AGGR_DOWNTURN)	0.315*	1.000		
IND_DOWNTURN	0.912*	0.280*	1.000	
AGGR_DOWNTURN	0.301*	0.897*	0.271*	1.000
NBER_RECESSION	−0.008*	0.315*	−0.038*	0.263*
GNP_GROWTH	−0.241*	−0.741*	−0.175*	−0.643*
IND_GROWTH	−0.240*	−0.404*	−0.224*	−0.385*

which Pr(AGGR_DOWNTURN) ≤ 0.25 and denotes that an aggregate expansion is highly likely next period.

C. Industry Business Cycle Phases

We provide an industry-wise description of the estimated model parameters in Table 2. Note that the estimate of $\mu_{i,\text{low}}$ is either negative or zero for all industries, with the exception of "Computer and electronic products" (NAICS 334) for which it is positive. On the other hand, the estimate of $\mu_{i,\text{high}}$ is positive for all industries, with the exception of "Apparel and leather goods" (NAICS 315,6) for which $\mu_{i,\text{high}}$ is negative, and "Textiles and products" (NAICS 313,4) for which it is zero. Therefore, in most industries, it is reasonable to refer to the low and high states as downturn and expansion, respectively.[4] We note that industries differ substantially in their estimates of $\mu_{i,\text{high}}$ and $\mu_{i,\text{low}}$, as well as in the spread between these expected

[4]The apparel and leather goods industry and the textile industry are obvious exceptions because the expected growth rate is negative or zero even when these industries are in the high state. These estimates are consistent with the well-known long-run decline in U.S. textile and apparel industries, whose onset precedes our sample period by many decades (Howell (1964)). We verify that all our results are robust to the exclusion of these industries.

growth rates (i.e., $\Delta_{i,\text{Cycle}} \equiv \mu_{i,\text{high}} - \mu_{i,\text{low}}$). We use $\Delta_{i,\text{Cycle}}$ as a measure of variation in growth rates over the industry cycle.

Estimates of the transition probabilities, $p_{i,\ell\ell}$ and $p_{i,hh}$, suggest that both industry downturns and expansions are highly persistent. The median values of $p_{i,\ell\ell}$ and $p_{i,hh}$ across all industry groups are 0.823 and 0.968, which suggests that, on average, industry expansions are more persistent than industry downturns. The corresponding transition probabilities for the aggregate economy are 0.912 and 0.925, respectively.

We list the pairwise correlations among the various business cycle measures in our firm-level panel data set in Panel B of Table 2. It is evident from Panel B that industry business cycles do not covary perfectly with the aggregate business cycle. For instance, the correlation between Pr(IND_DOWNTURN) and Pr(AGGR_DOWNTURN) is only 0.315, and the correlation between IND_DOWNTURN and AGGR_DOWNTURN is only 0.271. Nevertheless, we orthogonalize Pr(IND_DOWNTURN) with respect to Pr(AGGR_DOWNTURN), and create a variable called $\widehat{\text{Pr}}$(IND_DOWNTURN) which we use in our regression analysis. By design, $\widehat{\text{Pr}}$(IND_DOWNTURN) has zero correlation with Pr(AGGR_DOWNTURN) which allows us to interpret it as an *industry-specific* business cycle measure that is independent of the aggregate business cycle.

III. Conceptual Framework

In this section, we present a simple and parsimonious model of capital investment when firms are exposed to separate industry-specific and aggregate profit shocks. We use this model to generate testable predictions, regarding the effect of firm size on the sensitivity of investment to the industry shock, to guide our empirical analysis in the next section.

The economy is composed of multiple industries, each industry producing a homogeneous good. The typical industry has a large number of unlevered firms with heterogeneous production capacities, which can be adjusted over time through capital investment. For simplicity we focus on the investment decisions of a generic firm, indexed n, in a typical industry in a 2-period model, $t = 1, 2$. At the beginning of $t = 1$, the firm is endowed with initial capacity $\bar{K}_n$. Subsequently, there is a joint realization of (random) industry-specific and economy-wide profit shocks, denoted by θ and ϕ, respectively. These shocks are drawn from a general joint distribution (i.e., they can be correlated).

Conditional on the profit shocks, firms in each industry independently and simultaneously choose their capital investment I_n, which determines their capital stock K_{n2} at the beginning of $t = 2$ according to

$$K_{n2} = (1-\delta)\bar{K}_n + I_n, \tag{3}$$

where δ denotes the rate of depreciation of capital in the industry. For convenience, and following the applied capital investment literature, we assume quadratic capital adjustment costs of the form $0.5\lambda I_n^2$, for all firms in the industry. The firm's output at $t = 2$ is given by a strictly increasing and concave production function $q_{n2}(K_{n2}) = 2\sqrt{K_{n2}}$.

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The firm's profit at $t = 2$ is given by

$$\pi_{n2}(\theta,\phi) = 2[a_n(\phi) + p(Q_2,\theta) - h_n] \cdot \sqrt{K_{n2}}, \tag{4}$$

where $a_n(\phi)$ is an increasing function of the aggregate shock ϕ; $p(Q_2,\theta)$ is the industry inverse demand curve or price function that is strictly decreasing in the industry output, $Q_2 = \sum_n q_{n2}$, but is increasing in the industry shock θ; and h_n is the firm's marginal cost which we assume is a constant for simplicity. It is also reasonable to assume that $\frac{\partial}{\partial\theta}\left(\frac{\partial p(Q_2,\theta)}{\partial Q_2}\right) > 0$, (i.e., the negative effect of output on industry price is diluted during industry expansions). These properties are satisfied, in particular, by the following commonly used linear demand function:

$$p(Q_2,\theta) = \gamma(\theta) - (\psi/\theta)Q_2, \tag{5}$$

where $\gamma(\theta)$ is an increasing function of θ, and $\psi > 0$ is a demand elasticity parameter. We will adopt this demand parameterization below to allow convenient derivation of the main predictions of the model. Finally, firms are liquidated and profits are distributed to the equity holders at the end of $t = 2$.

The specification of industry demand curve above is separable in the effects of industry and aggregate shocks, which is analytically convenient for focusing on the effects of industry shocks on firms' optimal investment policy. But we also choose this specification because both casual empiricism and the industrial organization literature suggest that industry expansions and downturns are driven by shifts in industry fundamentals, such as technological innovation shocks and shifting consumer tastes (e.g., Schumpeter (1942), Gort and Klepper (1982), and Gompers and Lerner (2003)). Therefore, the demand curve shifts outward during industry expansions and inward during industry downturns. While the macroeconomic business cycle affects the intensity of these shifts, the shifts in the industry demand curve are largely driven by shocks to the industry fundamentals. For example, the hi-tech industry expansion of the 1980s and 1990s was primarily driven by innovations in microprocessors and software; the state of the aggregate economy, for example, the recession in early 1990s followed by the boom in the later part of 1990s, influenced the intensity of the industry expansion but did not replace the underlying industry cycle. Consistent with this motivation, aggregate shocks in equation (4) only shift the industry demand curve.[5]

With this basic set-up in hand, we can turn to analyzing the optimal investment policy of firms. Each firm independently chooses its investment taking into account the effect of their output on the industry price. Thus, the investment choice of firm n can be written as

$$\max \Phi_n(I_n) = 2[a_n(\phi) + p(Q_2,\theta) - h_n] \cdot \sqrt{K_{n2}} - \left(I_n + 0.5\lambda I_n^2\right), \tag{6}$$

where K_{n2} follows the law of capital evolution (equation (3)) and $Q_2 = \sum_n q_{n2}$.[6] We analyze the the firm's optimal investment policy and undertake comparative statics

[5]However, the main predictions of our analysis below remain qualitatively similar for more general specifications of industry demand.

[6]This formulation of firms' optimal investment strategy appears appropriate in our setting of a large but finite number of firms, when the set of firms is generally evolving. In particular, the notion of

with respect to the industry shock θ (see Appendix B for detailed proofs). Not surprisingly, optimal investment is procyclical with respect to the industry shock.

We then examine the effect of initial firm size, $\bar{K}_n$, on the sensitivity of the optimal investment to the industry shock θ. This analysis yields the main prediction of our framework:

Proposition 1. The sensitivity of optimal capital investment to the industry shock is increasing in firm size if there is a low variability of price–cost markups over the industry business cycle.

Intuitively, there are conflicting effects of large size on firms' investment sensitivity to industry shocks. Because of downward-sloping industry demand curves, the effect of a given increase in production capacity (i.e., investment) is more negative for larger firms, other things being equal. This suggests a negative relation of size and investment sensitivity to industry shocks. On the other hand, the negative effect of higher output on industry price is softened in industry expansions and exacerbated in downturns. Therefore, larger firms increase (decrease) investment more in expansions (downturns) relative to smaller firms, which implies a positive relation of firm size and investment sensitivity to industry cycles. Low variability of markups across the industry business cycles is sufficient to ensure that the latter (positive) effect of size on investment sensitivity to industry cycle dominates. This prediction is novel because it provides sufficient conditions for the size-sensitivity of capital investment to industry shocks to *reverse* from the existing macroeconomic business cycle literature.[7]

Notably, this prediction is derived from a specification of firms' profits (see equation (4)) that is consistent with the standard neoclassical formulation of decreasing returns to scale with respect to production capacity (or size). And, as we mentioned earlier, we impose no exogenous assumption on the relation of size and markups, which is consistent with the received literature. In particular, there may be a positive relation of size and markups if size is correlated with market power or if large firms benefit from scale economies in innovation (Schumpeter (1942), Cohen and Klepper (1996)). On the other hand, smaller firms are typically the engines of "creative destruction" in established industries (Schumpeter (1942), Christensen (1997)) and, hence, can earn local monopoly rents by specializing in niche markets. Consistent with the conceptual ambiguity, the evidence on the relation of size and markups is mixed (Berry et al. (2019), Mertens and Mottironi (2023)).

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strategic interaction among firms with common knowledge of all firms' investment strategies is not economically appealing here. There is a large literature that acknowledges the informational demands of Nash equilibrium (such as Cournot outcomes), which are typically satisfied in games with complete information (e.g., see Harsanyi (1967)) or repeated interaction among a small and fixed number of players (e.g., see Kalai and Lehrer (1993)).

[7]Not surprisingly, perhaps, the effect of size on investment sensitivity to aggregate shocks is also generally theoretically ambiguous. However, we show in Appendix B that it will be negative if the $a_n(\phi)$ term in equation (4) is highly sensitive to the aggregate shock ϕ. Thus, our framework accommodates differential effects of size on investment-sensitivity to aggregate and industry-specific shocks.

We can enhance the empirical content of our analysis by formulating the prediction in terms of production growth rates used in Section II to identify industry cycles. Notice that in the linear demand parameterization at hand, the variability of markups over the industry cycle (i.e., over the support of θ) will be positively related to variability of production growth over industry cycles. Hence, we can also derive the following prediction:

Proposition 2. The sensitivity of optimal capital investment to the industry shock is increasing in firm size if there is a low variability of industrial production growth over the industry cycle.

The sufficient conditions in Propositions 1 and 2 are stated in terms of cyclical variation of markups and production growth which, as noted above, are model-based estimates and are not directly observable. Thus, prior to empirical tests, it is important to develop intuition on *economic fundamentals* associated with such industries. It is helpful to consider the polar cases of high and low variation of markups (or production growth) over industry cycles. Compared to the former, low cyclical variation industries may exhibit higher markups or production growth during long-duration expansions with mild markup or production growth reductions during short-duration downturns.

As we mentioned earlier, there is a strong economic intuition that industries producing goods that are not easily substitutable will tend to have milder downturns in terms of markups or production, other things being equal. With low substitutability, demand for the industry's base product would ceteris paribus be expected to rebound relatively quickly following any downturns, resulting in relatively mild downturns in terms of markups or production. Building on this intuition, we expect firms in low cyclical growth variation industries to exhibit higher average markups and market-to-book ratios (or Tobin's Q) relative to other industries.

Another perspective on low cyclical variation in markups is provided by the recent literature that highlights trends in markups due to technological changes that have increased fixed costs relative to marginal costs. Specifically, increased automation and computerization in essentially substitute capital for labor, thereby raising the fixed-to-marginal cost ratio in production. Berry et al. (2019) argue that such technological changes will tend to raise firms' markups for recovery of higher fixed costs; they thus attempt to explain the noted upward trend in U.S. markups (Autor et al. (2020), De Loecker et al. (2020)) to labor-saving or capital-enhancing technological change. Because recovery of fixed costs is acyclical by definition, this argument suggests that industries with high fixed costs per unit assets will tend to have relatively low cyclical variability of markups, other things being equal.

In our subsequent analysis, we will empirically test Propositions 1 and 2. We will also empirically examine whether size has a positive effect on the investment sensitivity to industry shocks in industries with high fixed cost intensity, high market-to-book, and high markup levels.

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IV. Empirical Results

A. Empirical Framework

We estimate panel regressions with firm fixed effects to examine how firm-level capital investment and debt financing vary over the industry business cycle, after controlling for the effect of the aggregate business cycle. Formally, we estimate variants of the following regression on a panel spanning the time period 1980:Q1 to 2019:Q1 in which each observation corresponds to a firm-quarter pair:

$$Y_{ij,t} = \alpha + \beta \times \text{Business cycle}_{i,t} + \gamma X_{j,t-1} + \mu_j + \varepsilon_{j,t}. \tag{7}$$

In equation (7), subscript "j" denotes the firm, "i" denotes the industry to which it belongs, and "t" denotes the time period. The dependent variable $Y_{ij,t}$ is a measure of firm-level capital investment or debt financing. We measure capital investment using CAPEX, which is obtained by scaling the firm's capital expenditure during the current fiscal quarter by net property, plant, and equipment (PP&E) outstanding at the end of the previous fiscal quarter.[8] We measure debt financing using ΔNET_DEBT, which is defined as the change in net debt (i.e., total debt minus cash and equivalents) from the previous fiscal quarter scaled by total assets at the end of the previous fiscal quarter.

The main regressor of interest is the state of the real business cycle in the firm's industry, which we proxy for using the forward-looking and probabilistic measures of industry business cycle derived from the regime-switching framework (see Section II.B; i.e., $\widehat{\text{Pr}}$(IND_DOWNTURN), IND_DOWNTURN, or IND_EXPANSION).[9] We control the regression for forward-looking measures of the aggregate business cycle, namely, Pr(AGGR_DOWNTURN), AGGR_DOWNTURN, or AGGR_EXPANSION. In some specifications, we also control for the aggregate business cycle using the NBER_RECESSION dummy, although a criticism of the NBER recession dating mechanism is that it is backward-looking and deterministic. We include firm fixed effects (μ_j) in the regression so that the coefficients on the business cycle variables capture the *within-firm* variation in capital investment and debt financing over the industry and aggregate business cycle.

We control for the following important firm-level determinants ($X_{j,t-1}$) of capital investment that are standard in the literature (e.g., see Fazzari and Petersen (1993)): Q, which is obtained by dividing the sum of market value of equity and the book value of interest-bearing debt with the sum of the book values of equity and interest-bearing debt; SIZE; NET_LEVERAGE, which is the ratio of total debt minus cash to assets[10]; cash flow position using CASH_FLOW, which is the ratio of the sum of net income before extraordinary items and depreciation and amortization

[8]We scale with lagged net PP&E because that is the standard practice in the literature on capital investment. We obtain qualitatively similar results if we scale with lagged assets instead of lagged net PP&E.

[9]We obtain qualitatively similar results if we use Pr(IND_DOWNTURN) instead of the orthogonalized measure, $\widehat{\text{Pr}}$(IND_DOWNTURN).

[10]Our results do not change if we use debt and cash as controls separately, instead of combining them into a net leverage term.

TABLE 3
Summary Statistics

Table 3 provides summary statistics for the firm-level panel data, in which each observation corresponds to a firm-fiscal quarter combination. The panel data includes all publicly listed firms in the manufacturing sector and spans the period 1980–2018. All variables are defined in Appendix A.

	Mean	Median	Std. Dev.	p25	p75	No. of Obs.
Firm Characteristics (Compustat)						
ASSETS (in $ million)	2,122.987	168.538	1,0831.102	41.154	838.322	171,396
SIZE	5.246	5.127	2.198	3.717	6.731	171,396
PROFIT	0.014	0.041	0.155	−0.002	0.090	134,389
LEVERAGE	0.158	0.099	0.181	0.001	0.256	169,665
Q	2.742	1.880	2.533	1.226	3.173	161,924
CASH	0.225	0.123	0.247	0.031	0.343	171,209
CASH_FLOW	−0.354	0.080	1.772	−0.029	0.184	155,161
SALES	2.302	1.354	2.944	0.753	2.469	170,876
RATED	0.199	0.000	0.399	0.000	0.000	171,396
CAPEX × 100	7.421	4.665	8.399	2.486	8.791	145,098
ΔNET_DEBT × 100	−0.109	−0.032	11.005	−2.838	3.653	144,212
Industry Characteristics						
IND_SG&A	0.160	0.146	0.094	0.079	0.223	171,386
IND_Q	1.986	1.909	0.588	1.540	2.342	171,372
IND_MARKUP	0.410	0.413	0.120	0.334	0.514	171,396
Δ_{Cycle}	0.149	0.149	0.059	0.129	0.173	171,396
Δ_{Markup}	0.177	0.201	0.057	0.115	0.201	171,396
Business Cycle Variables						
NBER_RECESSION	0.117	0.000	0.322	0.000	0.000	171,396
GNP_GROWTH	0.027	0.028	0.018	0.019	0.039	171,396
IND_GROWTH	0.044	0.031	0.098	−0.003	0.076	171,396
Pr(IND_DOWNTURN)	0.266	0.050	0.356	0.025	0.575	171,396
Pr(AGGR_DOWNTURN)	0.534	0.640	0.403	0.068	0.946	171,396
$\widehat{\text{Pr}}$(IND_DOWNTURN)	−0.001	−0.106	0.338	−0.271	0.279	171,396
IND_DOWNTURN	0.209	0.000	0.406	0.000	0.000	171,396
AGGR_DOWNTURN	0.447	0.000	0.497	0.000	1.000	171,396
IND_EXPANSION	0.708	1.000	0.455	0.000	1.000	171,396
AGGR_EXPANSION	0.381	0.000	0.486	0.000	1.000	171,396

to net property, plant, and equipment (PP&E); SALES, which is defined as the ratio of sales to net PP&E, and serves as a control for certain omitted aspects of the "true" Q or cash flows; and RATED, which is a dummy variable that identifies if the firm has a long-term credit rating. In the regression with ΔNET_DEBT as the $Y-$variable, we drop NET_LEVERAGE and SALES as controls, and replace CASH_FLOW with PROFIT, which is defined as the ratio of earnings before taxes to assets, to be more consistent with the capital structure literature.

We provide summary statistics of firm characteristics, industry characteristics, and business cycle variables in our firm-level panel data set in Table 3. Recall that each observation in the panel corresponds to a firm-fiscal quarter combination, and includes all publicly listed firms in the U.S. manufacturing sector over the time period from 1980:Q1 to 2019:Q1. As in other sectors of the economy, the size distribution of firms in the manufacturing sector is highly skewed, with the average firm being more than 12 times as large as the median firm in terms of the book value of total assets. There is significant cross-sectional variation in capital expenditure across firm-quarters. While the median firm's quarterly CAPEX is 7.4% (as a fraction of its lagged PP&E), the 25th− and 75th−percentile values of CAPEX are 2.5% and 8.8%, respectively. There is also significant cross-sectional variation in net debt issuance across firm-quarters. Please see Appendix A for detailed definitions of all variables.

B. Capital Investment over the Industry Cycle

We present the results of regression (7) with CAPEX as the dependent variable in Table 4. In column 1, we use $\widehat{\Pr}$(IND_DOWNTURN) as the measure of the industry business cycle, and control for the aggregate business cycle using Pr(AGGR_DOWNTURN). The negative and significant coefficient on $\widehat{\Pr}$(IND_DOWNTURN) indicates that firms invest significantly less when the likelihood of their industry downturn increases, even after controlling for the effect of the aggregate cycle. This effect is economically significant: an inter-quartile increase in $\widehat{\Pr}$(IND_DOWNTURN) is associated with a 0.86% decrease in (quarterly) CAPEX, which is significant compared to the mean (median) CAPEX of 7.42% (4.67%). As can be seen from the row titled $\beta_i - \beta_a$, the difference in coefficients between $\widehat{\Pr}$(IND_DOWNTURN) and Pr(AGGR_DOWNTURN) is not statistically significant.

TABLE 4

Capital Investment over the Industry Cycle

Table 4 presents the results of regression (7) with CAPEX × 100 as the dependent variable, aimed at investigating how firm-level capital investment varies over the industry business cycle. We include firm fixed effects in all specifications. All variables are defined in Appendix A. Standard errors (reported in parentheses) are robust to heteroskedasticity, and are clustered by firm. We use ***, **, and * to denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Dependent Variable: CAPEX × 100			
	1	2	3	4
$\widehat{\Pr}$(IND_DOWNTURN): β_i	−1.533*** (0.122)			
Pr(AGGR_DOWNTURN): β_a	−1.731*** (0.098)			
IND_DOWNTURN: β_i		−0.793*** (0.085)		−1.239*** (0.087)
AGGR_DOWNTURN: β_a		−1.190*** (0.073)		
IND_EXPANSION: β_i			1.318*** (0.087)	
AGGR_EXPANSION: β_a			0.724*** (0.075)	
NBER_RECESSION: β_a				−0.198** (0.089)
SIZE	−0.026 (0.081)	−0.041 (0.081)	−0.120 (0.080)	−0.278*** (0.079)
Q	0.505*** (0.026)	0.517*** (0.026)	0.514*** (0.026)	0.526*** (0.027)
NET_LEVERAGE	−5.325*** (0.258)	−5.292*** (0.258)	−5.308*** (0.258)	−5.267*** (0.260)
RATED	0.066 (0.133)	−0.000 (0.134)	0.070 (0.135)	0.073 (0.137)
CASH_FLOW	−0.155*** (0.052)	−0.152*** (0.052)	−0.145*** (0.052)	−0.129** (0.053)
SALES	0.182*** (0.010)	0.180*** (0.010)	0.179*** (0.010)	0.174*** (0.010)
Constant	5.734*** (0.436)	5.597*** (0.441)	4.087*** (0.458)	6.419*** (0.437)
$\beta_i - \beta_a$	0.198 (0.152)	0.397*** (0.121)	0.594*** (0.123)	−1.041*** (0.117)
No. of obs.	127,665	127,665	127,665	127,665
R^2	0.299	0.298	0.298	0.296
Firm FE	Yes	Yes	Yes	Yes

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Does the relative sensitivity of firm-level capital investment to industry and aggregate business cycles vary across the extremes of these business cycles (i.e., high likelihood of downturns vs. high likelihood of expansions?) We investigate these questions in columns 2 and 3. In column 2 the main explanatory variable of interest is the IND_DOWNTURN dummy which identifies that an industry downturn is highly likely (i.e., probability weakly exceeds 0.75) next period; we control for the high likelihood of an aggregate downturn next period using the AGGR_DOWNTURN dummy. In column 3 the main explanatory variable of interest is the IND_EXPANSION dummy which indicates that an industry expansion is highly likely next period; we control for the high likelihood of an aggregate expansion next period using the AGGR_EXPANSION dummy.

The results in column 2 show that firms decrease their CAPEX significantly more in response to a highly likely aggregate downturn than a highly likely industry downturn. Specifically, the negative coefficient on AGGR_DOWNTURN has a larger magnitude than the coefficient on IND_DOWNTURN, and the difference $(\beta_i - \beta_a)$ is statistically significant at the 5% level. On the other hand, the results in column 3 indicate that firms increase their CAPEX significantly more in response to a highly likely industry expansion than a highly likely aggregate expansion. Specifically, the positive coefficient on IND_EXPANSION is almost twice as large as the coefficient on AGGR_EXPANSION, and the difference $(\beta_i - \beta_a)$ is statistically significant at the 1% level.

In column 4, we repeat the regression in column 2 after replacing AGGR_DOWNTURN with the NBER_RECESSION dummy which indicates if the U.S. economy was classified to be in a recession for any time during the firm's fiscal quarter. Recall that a criticism of the NBER recession dating mechanism is that it is backward-looking and deterministic, whereas AGGR_DOWNTURN indicates that an aggregate downturn is highly likely in the next quarter. Unlike in column 2, we find that the coefficient on IND_DOWNTURN is several times larger in magnitude than the coefficient on NBER_RECESSION and the difference is statistically significant, which suggests that a forward-looking assessment of an industry downturn has a much greater impact on capital investment than the NBER recession classification.

In sum, the empirical analysis in Table 4 indicates that firm-level capital investment is procyclical with respect to both the industry and aggregate business cycles. On average, firms increase their capital investment more in response to highly likely industry expansions compared to highly likely aggregate expansions, but decrease capital investment more in response to highly likely aggregate downturns compared to highly likely industry downturns. It is also noteworthy that the effect of the NBER recession dummy is significantly weaker compared to that of the regime-switching measures of industry and aggregate business cycle.

C. Firm Size and Cyclical Properties of Capital Investment

We now test the predictions of Propositions 1 and 2 regarding the contrasting effects of firm size on the sensitivity of capital investment to industry and aggregate cycles. To test these predictions, we classify firms into three size categories in each time period as follows: SMALL and LARGE are dummy variables which identify

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firms that are in the smallest and largest size quartiles, respectively, within their industry; and MIDSIZE is a dummy variable to identify firms that are neither small nor large. We then estimate regression (7) with CAPEX as dependent variable after augmenting the regression with the MIDSIZE and LARGE dummies and their interactions with the industry and aggregate cycle measures. Note that the omitted category in this regression is SMALL, which identifies firms in the lowest size quartile. Therefore, the coefficients on the business cycle variables capture the effects for the small firms, whereas the interaction terms capture the incremental effects for midsize and large firms with respect to the small firms.

The results of these regressions are presented in Table 5. To conserve space, we only report the coefficients on the business cycle measures and their interactions with the size category dummies, and suppress the coefficients on the firm-level controls and the size category dummies. We estimate the regression on our entire panel data in column 1. The negative and significant coefficients on MIDSIZE $\times$ $\widehat{\text{Pr}}$(IND_DOWNTURN) and LARGE $\times$ $\widehat{\text{Pr}}$(IND_DOWNTURN) indicate that, on average, the capital investment of midsize and large firms is significantly more sensitive to the industry cycle compared to that of small firms. By contrast, the positive and significant coefficient on LARGE $\times$ Pr(AGGR_DOWNTURN) indicates that the capital investment of large firms is significantly less sensitive to the aggregate cycle compared to that of small firms, which is consistent with the results documented in the literature (Crouzet and Mehrotra (2020)).

Proposition 1 predicts that the sensitivity of capital investment to industry shocks is increasing in firm size in industries with low cyclical variability of markups. Following the approach used in Bustamante and Donangelo (2017) and Saidi and Streitz (2021), we use Compustat data to define an industry's markup in a given fiscal year-quarter as the sum of firms' sales minus the sum of firms' cost of goods sold, scaled by the sum of firm's sales.[11] We measure cyclical variability of an industry's markups using Δ_{Markup}, which is defined as the inter-quartile spread (i.e., difference between the top-quartile and bottom-quartile values) in the time series of the industry's markup scaled by the industry's median markup. We divide industries into two groups based on whether their Δ_{Markup} is higher than ("High-Δ_{Markup}" group) or lower than ("Low-Δ_{Markup}" group) the median Δ_{Markup} across all industries. We then estimate the regression in column 1 separately for these two groups, and present the results in columns 2 and 3.

In support of the prediction in Proposition 1, we find that the coefficients on MIDSIZE $\times$ $\widehat{\text{Pr}}$(IND_DOWNTURN) and LARGE $\times$ $\widehat{\text{Pr}}$(IND_DOWNTURN) are negative and significant only in the low-Δ_{Markup} group in column 3. By contrast, for the high-Δ_{Markup} group in column 2, we find a strong negative coefficient on $\widehat{\text{Pr}}$(IND_DOWNTURN) and insignificant coefficients on the interaction terms, which indicates that, in industries with high markup variability, investment of all firms is highly sensitive to the industry cycle and there are no differential effects for midsize and large firms relative to small firms.

[11]Although Compustat covers only public firms, Bustamante and Donangelo (2017) show that the correlation between Compustat-based markup measures and alternative measures based on Census data (comprising both private and public firms) is high.

TABLE 5

Firm Size and Cyclical Properties of Capital Investment

Table 5 presents the results of regression (7) with CAPEX × 100 as the dependent variable, aimed at investigating how small, midsize, and large firms differ in their responses to their industry business cycle. LARGE and MIDSIZE are dummy variables to identify firms in the largest and the two intermediate size quartiles, respectively, within their industry; the omitted category is SMALL which identifies firms in the smallest size quartile. We estimate the regression on the entire sample in column 1. We then estimate the regression separately for industries with high and low Δ_{Markup} in columns 2 and 3, respectively; for industries with high and low Δ_{Cycle} in columns 4 and 5, respectively; for industries with high and low IND_SG&A in columns 6 and 7, respectively; for industries with high and low IND_Q in columns 8 and 9, respectively; and for industries with high and low IND_MARKUP in columns 10 and 11, respectively. All variables are defined in Appendix A. We include firm-level controls and firm fixed effects in all specifications, but suppress the coefficients on firm-level controls and size category dummies to conserve space. Standard errors (reported in parentheses) are robust to heteroskedasticity, and are clustered by firm. We use ***, **, and * to denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Dependent Variable: CAPEX × 100				
		INDUSTRYΔ_{Markup}		INDUSTRYΔ_{Cycle}	
	All	HIGH	LOW	HIGH	LOW
Sample:	1	2	3	4	5
$\widehat{\text{Pr}}$(IND_DOWNTURN)	−0.592**	−1.002**	−0.488	−1.364***	−0.366
	(0.252)	(0.412)	(0.305)	(0.437)	(0.306)
MIDSIZE × $\widehat{\text{Pr}}$(IND_DOWNTURN)	−1.215***	0.223	−1.622***	−0.005	−1.611***
	(0.280)	(0.427)	(0.342)	(0.461)	(0.347)
LARGE × $\widehat{\text{Pr}}$(IND_DOWNTURN)	−1.288***	0.459	−1.731***	−0.047	−1.705***
	(0.313)	(0.467)	(0.377)	(0.478)	(0.381)
Pr(AGGR_DOWNTURN)	−1.653***	−1.973***	−1.530***	−1.686***	−1.617***
	(0.217)	(0.412)	(0.252)	(0.285)	(0.293)
MIDSIZE × Pr(AGGR_DOWNTURN)	−0.201	0.078	−0.269	0.116	−0.306
	(0.239)	(0.432)	(0.280)	(0.310)	(0.323)
LARGE × Pr(AGGR_DOWNTURN)	0.560**	1.267***	0.374	0.722**	0.502
	(0.260)	(0.486)	(0.300)	(0.349)	(0.345)
Constant	5.774***	8.092***	5.188***	7.459***	5.253***
	(0.455)	(0.917)	(0.513)	(0.794)	(0.541)
No. of obs.	127,665	28,422	99,243	39,439	88,226
R^2	0.312	0.336	0.305	0.303	0.299
Firm controls and FE	Yes	Yes	Yes	Yes	Yes

	Dependent Variable: CAPEX × 100					
	IND_SG&A		IND_Q		IND_MARKUP	
	HIGH	LOW	HIGH	LOW	HIGH	LOW
Sample:	6	7	8	9	10	11
$\widehat{\text{Pr}}$(IND_DOWNTURN)	−0.432	−0.793**	−0.828**	−0.450	−0.349	−1.174***
	(0.353)	(0.315)	(0.395)	(0.318)	(0.356)	(0.323)
MIDSIZE × $\widehat{\text{Pr}}$(IND_DOWNTURN)	−1.647***	−0.359	−1.908***	−0.364	−1.714***	−0.253
	(0.397)	(0.340)	(0.444)	(0.341)	(0.399)	(0.336)
LARGE × $\widehat{\text{Pr}}$(IND_DOWNTURN)	−1.665***	−0.489	−1.758***	−0.496	−1.653***	−0.406
	(0.433)	(0.358)	(0.489)	(0.363)	(0.431)	(0.376)
Pr(AGGR_DOWNTURN)	−1.686***	−1.566***	−1.837***	−1.652***	−1.751***	−1.573***
	(0.329)	(0.265)	(0.340)	(0.255)	(0.319)	(0.269)
MIDSIZE × Pr(AGGR_DOWNTURN)	−0.295	0.101	−0.006	0.196	−0.199	0.088
	(0.363)	(0.286)	(0.376)	(0.278)	(0.350)	(0.298)
LARGE × Pr(AGGR_DOWNTURN)	0.543	0.763**	0.979**	0.692**	0.567	0.682**
	(0.387)	(0.320)	(0.395)	(0.303)	(0.373)	(0.324)
Constant	5.430***	6.863***	5.354***	6.533***	4.890***	7.789***
	(0.594)	(0.660)	(0.615)	(0.628)	(0.572)	(0.681)
No. of obs.	77,034	50,628	68,622	59,043	78,822	48,843
R^2	0.285	0.364	0.305	0.357	0.293	0.382
Firm controls and FE	Yes	Yes	Yes	Yes	Yes	Yes

Meanwhile, Proposition 2 predicts that the sensitivity of capital investment to industry shocks is increasing in firm size in industries with low cyclical variability of production growth. We measure cyclical variability of an industry's production growth using $\Delta_{\text{Cycle}} = \mu_{\text{high}} - \mu_{\text{low}}$, which is the difference in the estimated average growth rates for that industry in the high and low states. To test this prediction in Proposition 1, we divide industries into two groups based on whether their Δ_{Cycle} is higher than ("High-Δ_{Cycle}" group) or lower than ("Low-Δ_{Cycle}" group) the median Δ_{Cycle} across all industries. We then estimate the regression in column 1 separately for these two groups, and present the results in columns 4 and 5.

Consistent with Proposition 2, we find that the coefficients on MIDSIZE $\times \widehat{\text{Pr}}$(IND_DOWNTURN) and LARGE $\times \widehat{\text{Pr}}$(IND_DOWNTURN) are negative and significant only in the low-Δ_{Cycle} group in column 5. By contrast, for the high-Δ_{Cycle} group in column 4, we find a strong negative coefficient on $\widehat{\text{Pr}}$(IND_DOWNTURN) and insignificant coefficients on the interaction terms, which indicates that, in industries with high cyclical variability of production growth, investment of all firms is highly sensitive to the industry cycle and there are no differential effects for midsize and large firms relative to small firms.

The results in columns 2 through 5 are consistent with the predictions of Propositions 1 and 2 that large firms exhibit greater sensitivity to industry cycles in industries with low cyclical variability of markups (Δ_{Markup}) and production growth (Δ_{Cycle}). However, as we noted in Section III, Δ_{Cycle} and Δ_{Markup} are model-based estimates and are not directly observable industry characteristics. Therefore, we now examine the effect of the following underlying industry characteristics which we argued are associated with low Δ_{Markups} and low Δ_{Cycle} (see the discussion following Proposition 1): high fixed cost intensity, high market-to-book, and high level of markups.

Following Chen, Harford, and Kamara (2019) we use sales, general, and administrative (SG&A) expenses to proxy for fixed costs, and measure industry fixed cost intensity as the median value of the ratio of SG&A expenses to assets for firms within the industry (IND_SG&A). We classify industries as high fixed cost industries if they are in the top quartile by IND_SG&A across all industries during that time period, and as low fixed cost industries otherwise. We then estimate the regression in column 1 separately for firms in high and low-fixed cost intensity industries in columns 6 and 7, respectively. We find that large firms exhibit greater sensitivity to industry cycles only in industries with high fixed cost intensity (column 6) but not in industries with low fixed cost intensity (column 7).

We measure IND_Q as the median Q for firms within the industry. In each time period, we classify industries as high-Q industries if they are in the top quartile by IND_Q across all industries, and as low-Q industries otherwise. We then estimate the regression in column 1 separately for firms in high-Q and low-Q industries in columns 8 and 9, respectively. We find that large firms exhibit greater sensitivity to industry cycles only in high-Q industries (column 8) but not in low-Q industries (column 9).

Finally, in each time period, we classify industries as high markup industries if they are in the top quartile by IND_MARKUP across all industries, and as low markup industries otherwise. We then estimate the regression in column 1 separately for firms in high and low markup industries in columns 10 and 11, respectively. We find that large firms exhibit greater sensitivity to industry cycles only in high markup industries (column 10) but not in low markup industries (column 11).

D. Net Debt Issuance over the Industry Cycle

A large literature points to the importance of internal cash and debt in financing of firms' capital investment (e.g., Myers (1984), Drucker and Puri (2006), and Duchin et al. (2010)). Therefore, we now estimate regression (7) with ΔNET_DEBT as the dependent variable to examine how net debt issuance of firms varies over the industry and aggregate business cycles. We control the regression for the following firm characteristics: SIZE; Q; PROFIT which is defined as the ratio of earnings before taxes to assets; and the RATED dummy. The results of these regressions are presented in Table 6.

The negative and significant coefficient on $\widehat{\mathrm{Pr}}$(IND_DOWNTURN) in column 1 indicates that firms decrease their net debt issuance when the likelihood of their industry downturn increases, even after controlling for the effect of the aggregate

TABLE 6

Net Debt Issuance over the Industry Cycle

Table 6 presents the results of regression (7) with ΔNET_DEBT × 100 as dependent variable, aimed at investigating how net debt issuance varies over the industry business cycle. We include firm fixed effects in all specifications. All variables are defined in Appendix A. Standard errors (reported in parentheses) are robust to heteroskedasticity, and are clustered by firm. We use ***, **, and * to denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Dependent Variable: ΔNET_DEBT × 100			
	1	2	3	4
$\widehat{\mathrm{Pr}}$(IND_DOWNTURN): β_i	−1.108***			
	(0.107)			
Pr(AGGR_DOWNTURN): β_a	−0.906***			
	(0.084)			
IND_DOWNTURN: β_i		−0.612***		−0.733***
		(0.079)		(0.076)
AGGR_DOWNTURN: β_a		−0.346***		
		(0.067)		
IND_EXPANSION: β_i			0.946***	
			(0.081)	
AGGR_EXPANSION: β_a			0.424***	
			(0.071)	
NBER_RECESSION: β_a				0.063
				(0.086)
SIZE	0.657***	0.601***	0.633***	0.538***
	(0.066)	(0.066)	(0.066)	(0.064)
Q	−0.637***	−0.627***	−0.635***	−0.622***
	(0.033)	(0.033)	(0.033)	(0.033)
PROFIT	2.608***	2.758***	2.660***	2.864***
	(0.487)	(0.487)	(0.487)	(0.487)
RATED	−1.116***	−1.107***	−1.103***	−1.069***
	(0.111)	(0.112)	(0.111)	(0.112)
Constant	−0.936***	−0.862**	−2.140***	−0.691*
	(0.358)	(0.359)	(0.378)	(0.357)
$\beta_i - \beta_a$	−0.202	−0.266**	0.522***	−0.796***
	(0.137)	(0.117)	(0.121)	(0.109)
No. of obs.	139,908	139,908	139,908	139,908
R^2	0.060	0.059	0.060	0.059
Firm FE	Yes	Yes	Yes	Yes

cycle. Although the coefficient on $\widehat{\Pr}$(IND_DOWNTURN) appears to be larger in magnitude than the coefficient on Pr(AGGR_DOWNTURN), the difference is not statistically significant as can be seen from the row titled $\beta_i - \beta_a$.

The results in column 2 indicate that firms decrease their net debt when an industry downturn or aggregate downturn is highly likely, and this effect is stronger for industry downturns compared to aggregate downturns. Similarly, the results in column 3 indicate that firms increase their net debt when an industry expansion or aggregate expansion seems highly likely, and this effect is stronger for industry expansions compared to aggregate expansions.

In column 4 we repeat the regression in column 2 after replacing AGGR_DOWNTURN with NBER_RECESSION. In contrast to the negative and significant coefficient on AGGR_DOWNTURN in column 2, we find that the coefficient on NBER_RECESSION is statistically insignificant. That is, firms decrease their net debt in anticipation of an aggregate downturn in the future but do not decrease net debt after a recession actually materializes.

E. Firm Size and Cyclical Properties of Net Debt Issuance

As we mentioned above, the existing literature highlights that the debt issuance for small firms is more procyclical with respect to macroeconomic business cycles compared with large firms (Covas and Den Haan (2011), Begenau and Salomao (2019)). We now examine whether small and large firms differ in terms of how they vary their net debt issuance over the industry business cycle. The empirical approach we use is very similar to that in Table 5. The results of these tests are presented in Table 7. To conserve space, we only report the coefficients on the business cycle measures and their interactions with the size category dummies, and suppress the coefficients on the firm-level controls and the size category dummies.

We estimate the regression on our entire panel data in column 1. The negative and significant coefficient on LARGE × $\widehat{\Pr}$(IND_DOWNTURN) indicates that, on average, the net debt issuance of large firms is significantly more sensitive to the industry cycle compared to that of small firms. When we distinguish between industries based on their variability of markups (i.e., Δ_{Markup}), we find that the greater sensitivity of large firms to the industry cycle is present only for firms in low-Δ_{Markup} industries (column 3) but not for firms in high-Δ_{Markup} industries (column 2). Similarly, when we distinguish between industries based on their cyclical variability of production growth (i.e., Δ_{Cycle}), we find that the greater sensitivity of large firms to the industry cycle is present only for firms in low-Δ_{Cycle} industries (column 5) but not for firms in high-Δ_{Cycle} industries (column 4). Overall, the results in columns 2–5 are similar to the corresponding results with CAPEX in Table 5, and are broadly consistent with the predictions of Propositions 1 and 2.

In the remaining columns of Table 7, we classify industries into high and low groups based on the following underlying industry characteristics: fixed cost intensity (columns 6 and 7), Q or market-to-book (columns 8 and 9) and markups (columns 10 and 11). We find that the greater sensitivity of large firms to the industry cycle in terms of their net debt issuance is present only in industries with high fixed cost intensity (column 6), high Q (column 8), and high markups (column

TABLE 7

Firm Size and Cyclical Properties of Net Debt Issuance

Table 7 presents the results of regression (7) with ΔNET_DEBT × 100 as dependent variable, aimed at investigating how small, midsize and large firms differ in their responses to their industry business cycle. LARGE and MIDSIZE are dummy variables to identify firms in the largest and the two intermediate size quartiles, respectively, within their industry; the omitted category is SMALL which identifies firms in the smallest size quartile. We estimate the regression on the entire sample in column 1. We then estimate the regression separately for industries with high and low Δ_{Markup} in columns 2 and 3, respectively; for industries with high and low Δ_{Cycle} in columns 4 and 5, respectively; for industries with high and low IND_SG&A in columns 6 and 7, respectively; for industries with high and low IND_Q in columns 8 and 9, respectively; and for industries with high and low IND_MARKUP in columns 10 and 11, respectively. All variables are defined in Appendix A. We include firm-level controls and firm fixed effects in all specifications, but suppress the coefficients on firm-level controls and size category dummies to conserve space. Standard errors (reported in parentheses) are robust to heteroskedasticity, and are clustered by firm. We use ***, **, and * to denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Dependent Variable: ΔNET_DEBT × 100				
		INDUSTRYΔ_{Markup}		INDUSTRYΔ_{Cycle}	
	All	HIGH	LOW	HIGH	LOW
Sample:	1	2	3	4	5
$\widehat{\Pr}$(IND_DOWNTURN)	−0.881***	−1.091**	−0.842***	−1.606***	−0.582*
	(0.261)	(0.446)	(0.315)	(0.438)	(0.331)
MIDSIZE × $\widehat{\Pr}$(IND_DOWNTURN)	−0.185	0.522	−0.415	0.279	−0.586
	(0.292)	(0.528)	(0.346)	(0.509)	(0.375)
LARGE × $\widehat{\Pr}$(IND_DOWNTURN)	−0.531*	0.333	−0.737**	0.181	−1.037***
	(0.301)	(0.536)	(0.358)	(0.509)	(0.378)
Pr(AGGR_DOWNTURN)	−0.957***	−0.607*	−1.044***	−0.889***	−0.965***
	(0.196)	(0.368)	(0.231)	(0.253)	(0.272)
MIDSIZE × Pr(AGGR_DOWNTURN)	0.092	−0.823*	0.369	−0.083	0.181
	(0.228)	(0.423)	(0.270)	(0.301)	(0.312)
LARGE × Pr(AGGR_DOWNTURN)	0.126	−0.367	0.227	0.158	0.074
	(0.232)	(0.417)	(0.276)	(0.298)	(0.321)
Constant	−0.927**	0.430	−1.265***	1.148*	−1.505***
	(0.391)	(0.829)	(0.442)	(0.599)	(0.487)
No. of obs.	139,908	31,075	108,833	43,652	96,256
R^2	0.060	0.050	0.063	0.045	0.065
Firm controls and FE	Yes	Yes	Yes	Yes	Yes

	Dependent Variable: ΔNET_DEBT × 100					
	IND_SG&A		IND_Q		IND_MARKUP	
	HIGH	LOW	HIGH	LOW	HIGH	LOW
Sample:	6	7	8	9	10	11
$\widehat{\Pr}$(IND_DOWNTURN)	−0.886**	−1.085***	−1.145**	−1.253***	−0.744*	−1.307***
	(0.384)	(0.311)	(0.464)	(0.308)	(0.392)	(0.339)
MIDSIZE × $\widehat{\Pr}$(IND_DOWNTURN)	−0.316	−0.013	−0.727	0.663**	−0.536	0.350
	(0.435)	(0.344)	(0.530)	(0.328)	(0.440)	(0.387)
LARGE × $\widehat{\Pr}$(IND_DOWNTURN)	−0.746*	−0.382	−1.002*	0.454	−0.972**	0.039
	(0.435)	(0.369)	(0.538)	(0.344)	(0.443)	(0.406)
Pr(AGGR_DOWNTURN)	−0.766**	-1.035***	−1.168***	−1.195***	−0.945***	−0.897***
	(0.313)	(0.224)	(0.330)	(0.236)	(0.309)	(0.232)
MIDSIZE × Pr(AGGR_DOWNTURN)	−0.060	0.212	0.075	0.326	0.116	−0.013
	(0.356)	(0.264)	(0.374)	(0.279)	(0.350)	(0.271)
LARGE × Pr(AGGR_DOWNTURN)	−0.129	0.324	0.051	0.468*	−0.151	0.377
	(0.364)	(0.268)	(0.383)	(0.275)	(0.361)	(0.274)
Constant	−1.895***	1.421***	−1.966***	1.296**	−1.899***	1.174**
	(0.544)	(0.505)	(0.594)	(0.516)	(0.532)	(0.544)
No. of obs.	83,929	55,973	75,680	64,228	86,009	53,899
R^2	0.070	0.084	0.080	0.074	0.072	0.085
Firm controls and FE	Yes	Yes	Yes	Yes	Yes	Yes

10); but is not present in industries with low fixed cost intensity (column 7), low Q (column 9), and low markups (column 11).

V. Conclusion

The stylized fact established in the literature that the investment and debt financing of small firms is more sensitive to the aggregate (or macroeconomic) business cycle compared to that of large firms attracts substantial attention. However, firm's investment and debt financing are also likely to be affected by persistent industry-specific shocks to profitability, which may arise due to shifts in consumer tastes and technological innovations. Yet, we know relatively little about how firms vary their capital investment and debt financing in response to business cycle fluctuations in their own industry. We examine these issues both empirically and theoretically in this article.

Our empirical analysis is guided by predictions from a simple conceptual framework of corporate investment in which a firm's marginal profit (or price–cost markup) is affected by separate aggregate and industry-specific shocks. Consistent with the literature, our framework does not impose any exogenous restriction on the relation of firm size and markup. Our conceptual framework predicts that firm size has a positive effect on investment sensitivity to industry shocks in industries with low cyclical variability of markups and production growth, high fixed cost intensity, high market-to-book, and high markups. Because cash and debt are primary financing sources for capital investment, these conditions are also sufficient for firm size to have a positive effect on sensitivity of net debt issuance to industry shocks.

We test these predictions using measures of industry-specific and aggregate business cycles derived from the regime-switching approach of Hamilton (1989). Our main empirical finding is that capital investment and net debt issuance of large firms is, on average, more sensitive to industry business cycle fluctuations compared to that of smaller firms. This result is in contrast to the stylized fact established in the literature that the investment and debt financing of small firms is more sensitive to the aggregate business cycle compared to that of large firms. Consistent with the predictions of our conceptual framework, we find that large firms exhibit greater sensitivity to industry cycles than small firms in their investment and net debt issuance only in industries with low cyclical variability of markups and production growth, high fixed cost intensity, high market-to-book, and high markups.

Appendix A: Definitions of Variables

Firm-Level Variables

We indicate the corresponding Compustat Quarterly variable names in quotes within parentheses. To mitigate the effect of outliers, we winsorize all firm financial ratios other than LEVERAGE and CASH at the 1% level in both tails. We winsorize LEVERAGE and CASH at the 1% level in the right tail only.

CAPEX: Capital expenditure during the current fiscal quarter ("capxy" for the first fiscal quarter, and "capxy" minus lagged "capxy" for the other fiscal quarters) scaled by net property, plant, and equipment at the end of previous quarter (i.e., lagged “ppentq”).

ΔNET_DEBT: Change in net debt (i.e., total debt minus cash and equivalents) from the previous quarter scaled by lagged assets.

SIZE: Natural logarithm of total assets (“atq”). LARGE and SMALL dummies identify firms that are in the top and bottom quartile, respectively, by SIZE within their industry during the given quarter; MIDSIZE dummy identifies firms in the two intermediate size quartiles, and denotes firms that are neither large nor small.

Q or Market-to-Book: Ratio of sum of the market value of equity (i.e., “prccq” × “cshoq”) and book value of debt (i.e., “dltt” + “dlc”) to the sum of book values of equity and debt (i.e., “seqq” + “dltt” + “dlc”).

CASH_FLOW: Ratio of the sum of net income before extraordinary items (“ibq”) and depreciation and amortization (“dpq”) to the net property, plant, and equipment (“ppentq”).

LEVERAGE: Ratio of long-term debt (“dltt”) to total assets (“atq”).

CASH: Ratio of cash and equivalents (“cheq”) to total assets (“atq”).
NET_LEVERAGE equals LEVERAGE−CASH

SALES: Ratio of net sales (“saleq”) to the net property, plant, and equipment (“ppentq”).

PROFIT: Ratio of earnings before taxes (“piy”) to total assets (“atq”).

RATED: A dummy variable that identifies firms with a long-term credit rating from S&P.

Business Cycle Measures

We use the regime-switching model (1) to estimate: i) business cycle phases for industry groups within the U.S. manufacturing sector using time-series data on industrial production; and ii) aggregate business cycle phases using time-series data on U.S. gross national product. The model yields the following estimates: mean growth rates in the low and high states (μ_{low} and μ_{high}), variance σ^2, and the Markov transition probabilities (p_{hh} and $p_{\ell\ell}$).

Pr(IND_DOWNTURN): A 1-step-ahead predicted probability that the industry will be in the downturn state next quarter.

Pr(AGGR_DOWNTURN): A 1-step-ahead predicted probability that the U.S. economy will be in the downturn state next quarter.

IND_DOWNTURN: A dummy variable to identify periods during which Pr(IND_DOWNTURN) ≥ 0.75 for the industry, and denotes that an industry downturn is highly likely next period.

IND_EXPANSION: A dummy variable to identify periods during which Pr(IND_DOWNTURN) ≤ 0.25 for the industry, and denotes that an industry expansion is highly likely next period.

AGGR_DOWNTURN: A dummy variable to identify periods during which Pr(AGGR_DOWNTURN) ≥ 0.75, and denotes that an aggregate downturn is highly likely next period.

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AGGR_EXPANSION: A dummy variable to identify periods during which Pr(AGGR_DOWNTURN) ≤ 0.25, and denotes that an aggregate expansion is highly likely next period.

$\widehat{\text{Pr}}$(IND_DOWNTURN): The predicted residual from a regression of Pr(IND_DOWNTURN) against Pr(AGGR_DOWNTURN).

Industry Characteristics

IND_SG&A: Median value of the ratio of sales, general and administrative expenses ("xsgaq") to assets ("atq") across all firms in the industry during the fiscal year-quarter.

IND_Q: Median value of Q (see definition above) across all firms in the industry during the fiscal year-quarter.

IND_MARKUP: Sum of firms' sales ("saleq") minus sum of firms' cost of goods sold ("cogsq"), scaled by sum of firm's sales for all firms in the industry during the fiscal year-quarter.

$\Delta_{i,\text{Markup}}$: The difference between the top-quartile and bottom-quartile values in the time series of the industry's markup scaled by the industry's median markup.

$\Delta_{i,\text{Cycle}}$: Defined as $\mu_{i,\text{high}} - \mu_{i,\text{low}}$ using the output of the regime-switching model (1); denotes the cyclical variability of an industry's production growth.

Appendix B: Proofs

Proof of Proposition 1. The optimization problem is

$$\max_{\{I_n\}_n} \Phi_n(I_n) = 2[a_n(\phi) + p(Q_2,\theta) - h_n]\sqrt{K_{n2}} - I_n - 0.5\lambda I_n^2, \tag{B.1}$$

subject to the constraint that $Q_2 = 2\sum_{n=1}\sqrt{K_{n2}^m}$. Substituting this constraint in equation (B.1) yields the first-order optimality condition for the typical firm as

$$\Phi_n'(I_n) = [a_n(\phi) + p(Q_2,\theta) - h_n](K_{n2})^{-0.5} - 2\frac{\psi}{\theta} - (1 + \lambda I_n) = 0. \tag{B.2}$$

The second order condition is

$$\begin{aligned} \Phi_n''(I_n) &= -0.5(K_{n2})^{-1}\left[(a_n(\phi) + p(Q_2,\theta) - h_n)(K_{n2})^{-0.5} + 2\frac{\psi}{\theta}\right] - \lambda \\ &= -0.5(K_{n2})^{-1}\left[4\frac{\psi}{\theta} + 1 + \lambda I_n\right] - \lambda < 0, \end{aligned} \tag{B.3}$$

where we have substituted the first-order condition (B.2) in (B.3).

Now, put $p_\theta(Q_2,\theta) = \left(\gamma'(\theta) + \frac{\psi}{\theta^2}Q_2\right)$. Then applying the implicit function theorem to the optimality condition (B.2) gives

$$\text{(B.4)} \qquad \frac{\partial I_n}{\partial \theta} = \frac{\left[p_\theta(Q_2,\theta)(K_{n2})^{-0.5} + 2\frac{\psi}{\theta^2}\right]}{-\Phi_n''(I_n)} > 0.$$

That is, optimal investment is procyclical in terms of industry shocks. To analyze the effect of *initial* (or a given) firm size $\bar{K}_n$ on the sensitivity of optimal investment to the industry shock, we first compute

$$\text{(B.5)} \qquad \frac{\partial K_{n2}}{\partial \bar{K}_n} = (1-\delta) + \frac{\partial I_n}{\partial \bar{K}_n},$$

where from (B.2) and applying the implicit function theorem and (B.3),

$$\text{(B.6)} \qquad \frac{\partial I_n}{\partial \bar{K}_n} = \frac{-(1-\delta)(K_{n2})^{-1}\left[0.5(a_n(\phi)+p(Q_2,\theta)-h_n)(K_{n2})^{-0.5} + \frac{\psi}{\theta}\right]}{-\Phi_n''(I_n)}$$
$$= \frac{-(1-\delta)\left[2\frac{\psi}{\theta} + 0.5(1+\lambda I_n)\right]}{\left[2\frac{\psi}{\theta} + 0.5(1+\lambda I_n)\right] + \lambda K_{n2}} < 0.$$

Substituting (B.6) in (B.5) gives,

$$\text{(B.7)} \qquad \frac{\partial K_{n2}}{\partial \bar{K}_n} = \frac{(1-\delta)\lambda K_{n2}}{\left[2\frac{\psi}{\theta} + 0.5(1+\lambda I_n)\right] + \lambda K_{n2}} > 0.$$

Returning to (B.4), we can then compute

$$\text{(B.8)} \qquad \frac{\partial}{\bar{K}_n}\left(\frac{\partial I_n}{\partial \theta}\right) \propto \left[\left(-0.5p_\theta(Q_2,\theta)(K_{n2})^{-1} + \frac{\psi}{\theta^2}\right)(K_{n2})^{-0.5}\frac{\partial K_{n2}}{\partial \bar{K}_n}\left(-\Phi_n''(I_n)\right) + \right.$$
$$\left.\left(p_\theta(Q_2,\theta)(K_{n2})^{-0.5} + 2\frac{\psi}{\theta^2}\right)\frac{\partial \Phi_n''(I_n)}{\partial \bar{K}_n}\right].$$

Next, from (B.3) and (B.6),

$$\text{(B.9)} \qquad \frac{\partial \Phi_n''(I_n)}{\partial \bar{K}_n} = -0.5\left(\frac{K_{n2}\frac{\partial I_n}{\partial \bar{K}_n} - \left[4\frac{\psi}{\theta} + 1 + \lambda I_n\right]}{(K_{n2})^2}\right) > 0.$$

Hence, returning to (B.8), recalling from (B.7) that $\frac{\partial K_{n2}}{\partial \bar{K}_n} > 0$, we find that the first term is generally ambiguous in sign (since $p_\theta(Q_2,\theta) > 0$), but the second term is positive. Therefore, $\frac{\partial}{\bar{K}_n}\left(\frac{\partial I_n}{\partial \theta}\right) > 0$ if $p_\theta(Q_2,\theta)$ is small, that is, if the price–cost markup is not too sensitive to the industry shock.

Finally, for the aggregate shock, we have

$$\text{(B.10)} \qquad \frac{\partial I_n}{\partial \phi} = \frac{a_n'(\phi)(K_{n2})^{-0.5}}{-\Phi_n''(I_n)} > 0.$$

Repeating the steps above we conclude that $\frac{\partial}{\bar{K}_n}\left(\frac{\partial I_n}{\partial \phi}\right)$ is generally ambiguous but is negative if $a_n'(\phi)$ is relatively large. ■

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Proof of Proposition 2. We recall that

$$p_\theta(Q_2,\theta) = \gamma'(\theta) + \frac{\psi}{\theta^2}Q_2. \tag{B.11}$$

Hence, taking the variance of $p_\theta(Q_2,\theta)$ with respect to the marginal probability density of θ over its support

$$\mathrm{var}_\theta(p_\theta(Q_2,\theta)) = \mathrm{var}_\theta(\gamma'(\theta)) + \mathrm{var}_\theta\left(\frac{\psi}{\theta^2}Q_2\right) + 2\mathrm{cov}_\theta\left(\gamma'(\theta), \frac{\psi}{\theta^2}Q_2\right), \tag{B.12}$$

which is increasing in $\mathrm{var}_\theta(Q_2)$, other things held fixed. ■

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