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Abstract

In this paper we analyze Minskian dynamics in the US economy via an empirical application of Minsky's financing regime classifications to a panel of nonfinancial corporations. First, we map Minsky's definitions of hedge, speculative and Ponzi finance onto firm-level data to describe the evolution of Minskian regimes. We highlight striking growth in the share of Ponzi firms in the post-1970 US, concentrated among small corporations. This secular growth in the incidence of Ponzi firms is consistent with the possibility of a long wave of increasingly fragile finance in the US economy. Second, we explore the possibility of short-run Minskian dynamics at a business-cycle frequency. Using linear probability models relating firms' probability of being Ponzi to the aggregate output gap, which captures short-term macroeconomic fluctuations exogenous to individual firms, we find that aggregate downturns are correlated with an almost zero increased probability that firms are Ponzi. This result is corroborated by quantile regressions using a continuous measure of financial fragility, the interest coverage ratio, which identify almost zero effects of short-term fluctuations on financial fragility across the interest coverage distribution. Together, these results speak to an important question in the theoretical literature on financial fragility regarding the duration of Minskian cycles, and lend support, in particular, to the contention that Minskian dynamics may take the form of long waves, but do not operate at business cycle frequencies.

JEL Codes: B5, E32, G30

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1 Introduction

In this paper we explore Minsky's Financial Instability Hypothesis through an empirical application of Minsky's financing classifications to firm-level financial statements. Minsky (1975; 1986; 1992) puts forward a theory of cycles defined by an economy's oscillation between periods of robust financing arrangements, and periods of financial fragility. Firms are categorized as hedge, speculative or Ponzi, based on the relationship between their cash inflows from operations and debt service requirements. Hedge structures are the most robust, generating more than sufficient operational cash flows to service both interest and principal obligations. Speculative firms, in contrast, must roll over principal on maturing debt, and Ponzi firms, which are the most fragile, must also roll over interest payments. Instability derives from an increase in the proportion of agents with fragile financial structures. Famously, 'stability breeds instability' as periods of robust finance lead to complacency, greater risk-taking and, over time, increasingly fragile finance.[1]

Minsky's work received widespread popular attention in both the press and the policy sphere after the 2008 crisis was hailed as a possible 'Minsky moment'. An article in *The Economist*, for example, writes that, after the crisis began in the US, "everyone was turning to his [Minsky's] writings as they tried to make sense of the mayhem. Brokers wrote notes to clients about the 'Minsky moment' engulfing financial markets. Central banks referred to his theories in their speeches. And he became a posthumous media star..." (The Economist, 2016). Describing the crisis in *The Financial Times*, Martin Wolf wrote, "What went wrong? The short answer: Minsky was right" (Wolf, 2008). In the policy realm, then-vice-chair of the Federal Reserve, Janet Yellen gave a speech saying, "To understand what went wrong [in 2008], I refer you to Hyman Minsky's pathbreaking work on speculative financial booms and busts" (Yellen, 2010).

This period also saw a surge in academic research on Minsky's Financial Instability Hypothesis and Minskian interpretations of the crisis (for example, Kregel, 2008; Whalen, 2008; Dymski, 2009; De Antoni, 2010; Behlul, 2011; Bellofiore and Halevi, 2011; Vercelli, 2011; Wray, 2011, 2016; Ryoo, 2016). This recent work builds on a long-standing theoretical literature, largely in the post-Keynesian tradition, that analyzes Minsky's approach to financial fragility and integrates Minskian dynamics into growth and distribution models (for example, Taylor and O'Connell, 1985; Lavoie, 1986; Gatti and Gallegati, 1990; Keen, 1995; Skott, 1995; Meirelles and Lima, 2006; Fazzari et al., 2008; Wray, 2009; Ryoo, 2010, 2013a,b). Outside the post-Keynesian literature, Bhattacharya et al. (2011) integrate Minskian dynamics with the literature on

[1] Minsky (1986) writes, "The mixture of hedge speculative, and Ponzi finance in an economy is a major determinant of instability. The existence of a large composition of positions financed in a speculative or a Ponzi manner is necessary for financial instability" (p. 232). Similarly, "the economy has financing regimes under which it is stable, and financing regimes under which it is unstable...[and] over periods of prolonged prosperity, the economy transitions from financial relations that make for a stable system to financial relations that make for an unstable system" (Minsky, 1992, p.8).

leverage cycles (Geanakoplos, 2010) to also emphasize financial sources of macroeconomic fluctuations.

Despite widespread attention, however, empirical applications of the Financial Instability Hypothesis are limited, particularly at the firm level.[2] This paper speaks to this gap in the literature via an empirical analysis of Minskian dynamics in the post-1970 US economy. Our analysis has three parts. First, we develop a methodology mapping Minsky's definitions of hedge, speculative and Ponzi finance onto firm-level accounts, and apply these definitions to a panel of US corporations drawn from Compustat. To the best of our knowledge, this mapping is the first direct application of Minskian definitions to firm-level data. Drawing on these classifications, our second contribution lies in a description of the incidence and evolution of Minskian regimes across US corporations since 1970. We document, most notably, a trend increase in the share of firms with Ponzi structures, concentrated among small corporations. This rising incidence of Ponzi firms occurs across sectors and, accordingly, does not reflect an expansion of sectors prone to Ponzi finance at the expense of more financially robust sectors. We augment this evidence with a discussion of the previous and subsequent states of Ponzi firms. We find that small firms are increasingly likely to *enter* the sample as Ponzi over the post-1970 period, whereas firms of above-median firm size are more likely to transition to Ponzi from a speculative regime. Furthermore, approximately 30% of spells of Ponzi finance end with the firm *exiting* the sample; notably, firms are relatively more likely to exit following a spell of Ponzi finance, than following a hedge or speculative regime. While the time dimension of available data on US firms is insufficient to definitively identify a long-term cycle, these results point to a secular expansion in fragility in the post-1970 US.

Third, we complement this evidence of a secular increase in the incidence of Ponzi finance with a set of econometric results suggesting that Minskian dynamics do *not* operate at a short-term (business-cycle) frequency in the US economy. We use linear probability models relating a firm's probability of being Ponzi to the aggregate output gap, which captures short-run fluctuations in macroeconomic conditions exogenous to individual firms. We find strongly statistically significant evidence that the output gap is correlated with an *almost zero* increase in the probability that a firm is in a more fragile financing regime (that a firm is Ponzi, or that a firm is speculative or Ponzi). This result is robust to a range of specifications, including variations measuring short-run fluctuations by real GDP growth and by sector-specific output gaps/growth,

[2] See Nikolaidi (2017), who argues that - going forward - empirical research has an important role to play in complementing the theoretical literature on Minsky. Recent examples of empirical work on Minsky generally emphasize the sector level. Mulligan (2013) finds that Minskian dynamics best-characterize leveraged sectors, and that crises spread from more to less leveraged sectors. However, Mulligan distinguishes industries that more or less strongly exemplify Minskian dynamics, but does not analyze the distribution of regimes across firms over time. Nishi (2016) analyzes Minskian dynamics in a sector-level analysis of the Japanese economy, and finds that – despite significant differences across sectors – speculative regimes are the most dominant in Japan. Notably, while few empirical papers directly engage the Financial Instability Hypothesis, Minsky is credited in a line of empirical research emphasizing financial factors in fixed investment (see Fazzari, 1999).

as well as to panel logit specifications. These results are, also, corroborated by quantile regressions using a continuous measure of fragility, the interest coverage ratio, which also identify small effects of the output gap on financial fragility across the interest coverage distribution.

Importantly, these results speak to a long-standing theoretical debate regarding the duration of Minsky cycles, which are sometimes identified as short- to medium-run cycles and sometimes as 'long waves'.[3] In particular, the analysis in this paper points to a *long wave* in the distribution of firms across Minskian regimes in the post-1970 US, rather than *short cycles* at business cycle frequencies. The distinction has important implications for understanding Minskian dynamics. On the one hand, short- to medium-run cycles would be characterized by many firms transitioning across regimes. Palley (2011), for example, writes: "The medium-term cycle is labeled the 'basic cycle' ... The 'basic cycle' involves the familiar process of evolution beginning with hedge finance, passing through speculative finance, and ending with Ponzi finance....[and] operates at the level of the individual enterprise" (p. 3). Similarly, "Within the Minskian framework, the *business cycle* is characterized by the gradual emergence of 'financial fragility', and this fragility ultimately causes the demise of the upswing" (p. 371) (Palley, 1994, emphasis added).

On the other hand, the view that Minskian dynamics take the form of 'long waves' emphasizes slower changes in institutions, regulations, and financing norms:

> "In the real world characterized by complexity and uncertainty, agents' financial practices are largely affected by norms and conventions.... Changes in these norms and conventions take time and tend to exhibit inertia. The long-term trend in these elements would not be greatly disturbed by ups and downs during the course of short-run business cycles (Ryoo, 2010, p. 163).

Wray (2009), similarly, contends that the 2008 crisis was not a 'moment', but instead the result of a long-term systemic increase in financial fragility. Notably, the distinction between short- and long-run dynamics is evident in Minsky's own work as well: while Minsky (1957, 1959) analyzes the business cycle, later work emphasizes long waves of institutional change and stages of capitalism (Minsky, 1964, 1995). Finally, still other authors consider 'twin cycles', wherein short-term Minskian cycles are nested within longer-run Minskian waves (Palley, 2011; Bernard et al., 2014). The results that we present in this paper contribute a novel set of empirical evidence to this debate.

The paper is organized as follows. Section 2 introduces the empirical definitions of Minskian regimes. Section 3 describes the post-1970 evolution of financing regimes across US corporations. Section 4 explores the possibility of business-cycle-length Minskian dynamics, and Section 5 concludes.

[3]See, for example, Ryoo (2010) who writes that "existing Minskian models do not distinguish long waves from short cycles and the periodicity of cycles in those models is ambiguous" (p. 164).

2 An application of Minskian financing regimes to firm-level data

The first step in our analysis is to map Minsky's definitions of financing regimes onto firm-level data, so as to classify each firm (in each year) as hedge, speculative or Ponzi. Following Minsky (1986), these classifications are based on the relationship between a firm's cash inflows from operations and its interest and principal obligations on outstanding debt.[4] For each firm-year observation we, therefore, identify net sources of cash for meeting financial obligations, and interest and principal commitments. In line with Minsky's definitions, summarized in Table 1, a firm-year observation is hedge if its sources of cash exceed both its interest and principal obligations; speculative if sources of cash cover interest but not principal commitments; and Ponzi if sources of cash are insufficient to cover *both* principal and interest payments. To complement these discrete classifications, we also construct a measure of interest coverage, defined as sources of cash less interest payments, scaled by total assets. This interest coverage ratio offers a continuous alternative to the discrete classifications of fragility: when interest coverage is lower, interest payments are higher relative to sources of cash, indicating higher fragility.

Table 1: Definitions of financing regimes

Regime	Definition of regime
Hedge	[Sources of cash $-$ Interest Payments $-$ Principal Payments] > 0
Speculative	[Sources of cash $-$ Interest Payments] > 0 *and* [Sources of cash $-$ Interest Payments $-$ Principal Payments] < 0
Ponzi	[Sources of cash $-$ Interest Payments] < 0

2.1 Data

These classifications are applied to a firm-level panel of publicly-traded US corporations drawn from Standard & Poor's Compustat Database. To clean the sample we exclude firms with negative recorded sales, assets, or interest payments, and limit the sample to firms incorporated in the US. We also exclude financial corporations, thereby restricting our analysis to the nonfinancial corporate sector. We do so for two reasons. First, the financial structure of financial and nonfinancial corporations is markedly different; commercial banks, for example, cannot be hedge units by definition, given their funding reliance on demand deposits. These differences in financial structure imply that including both financial and nonfinancial firms would obfuscate the interpretation of any effects we identify. Second, because nonfinancial corporations drive a

[4] See Minsky (1986, Ch. 9) for a complete discussion of these regimes. Note that, while Minsky distinguishes between expected and realized cash flows, our analysis is based on recorded cash flow data and, thus, realized cash flows.

significant proportion of real economic activity, these firms are of independent importance. The empirical definitions of cash inflows and cash commitments are introduced in detail in Sections 2.2 and 2.3 below and summarized, with Compustat reference numbers, in Table 2. Applying these definitions to the Compustat sample yields sufficient non-missing observations to construct a panel with discrete regime classifications between 1970 and 2014. Because interest coverage does not require data on principal payments, we can extend this portion of the analysis to 1950.

Table 2: Empirical definitions of financing regimes

	Compustat #
Sources of funds	
Funds from operations	
Income before extraordinary items[1]	18 + 15
Depreciation and amortization	14
Extraordinary items and discontinued operations	48
Deferred taxes[2]	126
Equity in net loss[2]	106
Sale of property, plant and equipment, and sale of investments (loss)[2]	213
Funds from investment activities	
Sale of property, plant and equipment[2]	107
Sale of investments[2]	109
Other funds from current activities[2]	218
Cash commitments	
Interest and Related Expenses	15
Debt in current liabilities – Total[3]	34
Notes payable	
Long-term debt due in one year	
Trade accounts payable[3]	70
Current liabilities - other[3]	72

Notes: [1] Income before extraordinary items is reported net of interest expense; we, therefore, add interest payments back into this income category to measure sources of cash available to meet financial obligations. [2] Items with zeros imputed for missing observations. [3] Items evaluated at the end of the previous year.

2.2 Sources of cash

The firm's relevant sources of funds are the cash inflows from operations that a firm can use to cover required financial commitments (interest and principal obligations). To align our regime classifications with Minsky's concepts, we define these sources of cash based on two principles. First, cash inflows are measured after accounting for expenses such as wages and salaries, which have a claim on cash flow prior to interest and principal. Second, we exclude cash inflows from activities like new borrowing, new equity issuance, or sales of financial assets. Doing so reflects that Minsky's taxonomy describes the extent to which discrepancies between sources of cash and required financial commitments give rise to new borrowing or financial asset sales.

Accordingly, we define a firm's net sources of cash as the *sum of funds from operations* (Compustat item #110), *other funds from current activities* (item #218), and *funds from investment activities* (items #107 and #109). *Funds from operations* constitute firms' primary source of cash. These inflows include both operating and non-operating income, which are net income concepts (i.e. net of operating expenses like salaries, and non-operating expenses like foreign exchange adjustments and moving expenses). Note that, because interest is an inflow from the *ownership*, rather than the *sale* of financial assets, we include interest income within sources of funds. We also add depreciation to a firm's sources of funds; while accounting conventions define depreciation as a cash outlay, depreciation is not an actual cash expenditure and, therefore, does not reduce firms' liquid cash inflows. *Other funds from current activities* include, for example, foreign currency exchange adjustments. Finally, *funds from investment activities* include net cash flows from the sale of property, plant and equipment, and the sale of other investments.

When using these three primary variables to define sources of funds, however, we confront two problems. First, a large share of observations for these aggregate measures are missing, including - most notably - over 77% of observations for *funds from operations* (item #110). These missing observations reflect that the less important components of the aggregate measure are often unreported, in which case Compustat assigns the observation a missing value. We, therefore, construct our own measure of funds from operations based on individual components, in which we take the main components of *funds from operations* 'as is' and impute zeros to missing observations for the remaining components. These adjustments reduce the share of missing observations for sources of funds to 12.25%.[5]

Second, it sometimes difficult to distinguish operational cash flows from new borrowing or asset sales due to financial distress. In particular, three aspects of our definition fall into a gray zone. First, the main subcategory of operating income, *extraordinary items and discontinued operations* (item #48), includes

[5]The main item used 'as is' is *income before extraordinary items* (item #18), which includes net income from operations and net non-operational income. Because *income before extraordinary items* is net of interest payments, we add *interest payments* (item #15) to this variable. The sum of *income before extraordinary items* and *interest payments* is the most relevant source of funds (both conceptually and quantitatively). We, similarly, take *depreciation and amortization* (item #14) and *extraordinary items and discontinued operations* (item #48) 'as is'. We impute zeros for missing observations for *deferred taxes* (item #126), *equity in net loss* (item #106, which is an adjustment for the unremitted portion of an unconsolidated subsidiary's earnings), and *sale of property, plant and equipment and sale of investments – loss* (item #213, which is an adjustment for gains/losses relative to the book value of sold assets). We follow a similar procedure for the two other components of sources of funds and, specifically, impute zeros for missing observations of *other funds from current activities*, and for *funds from investment activities/sale of property, plant and equipment* (item #107) and *sale of investments* (item #109).

inflows from extraordinary contingencies (like fire or flood) that are legitimate to include according to the principles laid out above. However, this category also includes cash flows that are likely derived from financial decisions (profit/loss on repurchase of debentures) or business decisions (profit/loss on the disposal of a division). Some part of these funds could, therefore, reflect the need to service financial obligations. Second, operating income includes a subcategory of net cash flows derived from *sale of property, plant and equipment* (item #107). Again, it is, in principle, impossible to determine if these non-recurring cash inflows from the sale of non-financial assets reflect standard operating decisions (e.g. selling a subsidiary because it is not profitable) or financial distress (e.g. selling a subsidiary to meet financial obligations). Third, cash inflows from the *sale of investments* (#109) include, among other things, the sale of stake in unconsolidated subsidiaries; it is again unclear if such divestment reflects business considerations or burdensome financial obligations. By including these three income categories, we define an upper bound on firms' relevant cash inflows. However, classifications excluding these three components co-move strongly with this baseline definition, reflecting in large part that the main component of sources of funds is *funds from operations*.

2.3 Cash commitments

Cash commitments include firms' *non-discretionary* financial obligations in each year: namely, interest payments on outstanding debt and principal payments due that year. This definition reflects that Minsky's taxonomy defines fragility by comparing the sources of funds a firm can use to service debt and the payments that must be made to service it. Accordingly, all *discretionary* uses of funds – capital investment, stock buybacks and dividend payments, or the acquisition of stakes in other firms – are excluded from financial commitments. Similarly, principal payments in excess of debt due that year are excluded from cash commitments, so as to disentangle required principal payments from a firm's (discretionary) decision to reduce its stock of long-term debt.[6]

We draw interest payments directly from Compustat (item #15); however, no Compustat variable directly captures principal payments. We, therefore, construct a measure of principal payments defined as the sum of short-term (current) liabilities (accounts payable, other current liabilities, and notes payable), and the

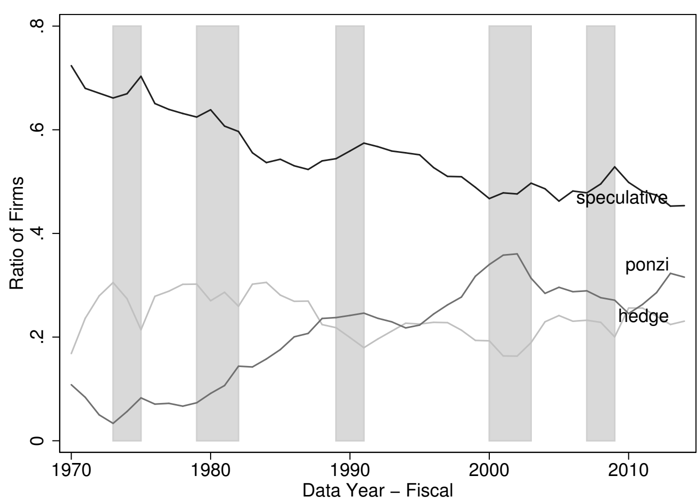
[6] Put differently, Minsky's taxonomy is defined by an *ex ante* comparison between the sources of funds a firm can rely on to service debt, and the payments needed to service this debt. It is, therefore, qualitatively different to classify a firm as Ponzi because it cannot generate cash from its operations to cover interest, than it is to say that it is 'Ponzi' when – even though it had plenty of cash inflows to cover interest obligations – it voluntarily reduces its liabilities, buys back stock, or accumulates physical capital such that, in the end, it has to borrow. This second firm is not Ponzi. Including discretionary expenditures would require us to assume that we can infer this *ex ante* relationship from an *ex post* comparison between all sources and all uses of funds.

portion of long-term debt due in that year (Compustat items #34, #70, and #72). Because these liabilities are end-of-period stocks, we define principal payments in year t as a function of these stocks in year $t-1$.

3 The incidence of Minskian regimes in the post-1970 US

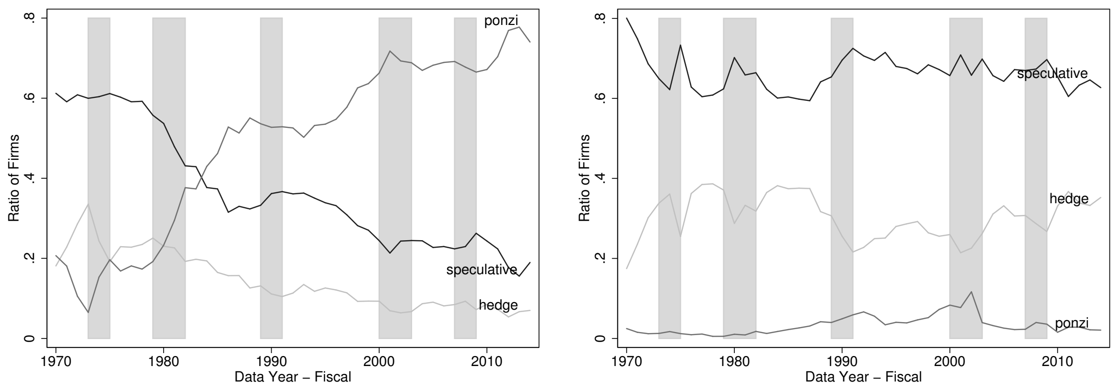
Applying these definitions to the Compustat data generates a firm-level panel in which each firm-year observation is classified as hedge, speculative or Ponzi. Based on these classifications we describe the incidence and evolution of financing regimes in the US nonfinancial corporate sector; analyze the sectoral composition of changes in the incidence of financing regimes; and identify both prior and subsequent states of the most financially fragile (i.e. Ponzi) firms. To begin, Figure 1 plots the incidence of hedge, speculative and Ponzi firms as a share of the total sample between 1970 and 2014. Most notably, Figure 1 captures secular growth in the share of Ponzi firms in the US nonfinancial corporate sector, from 10.8% in 1970 to 31.6% in 2014. This growth in Ponzi structures is concentrated during the 1980s and 1990s – during which time the share of Ponzi firms grows from 9.1% to 34.0% – and levels off in early 2000s, peaking at 36.1% of nonfinancial corporations in 2002. Concurrently, the share of speculative firms declines from 72.3% to 45.4% and, despite short-term oscillations, the share of hedge firms remains relatively constant at approximately a quarter of

Figure 1: Incidence of hedge, speculative and Ponzi financing regimes
Full sample of firms; 1970-2014



Notes: The figure shows the share of total firms under each financing regime. Shaded areas refer to full peak-to-trough periods for real GDP, obtained using the Hodrick-Prescott filter. GDP data is from the Bureau of Economic Analysis (chained dollar measure); for all other definitions and data sources, see Section 2.

Figure 2: Incidence of hedge, speculative and Ponzi financing regimes
By firm size; 1970-2014



(a) First Quartile

(b) Fourth Quartile

Notes: The figure shows the share of firms in the first and fourth quartiles of the asset distribution, respectively, under each financing regime. Quartiles are defined by percentile of the asset distribution in each year. Shaded areas refer to full peak-to-trough periods for real GDP, obtained using the Hodrick-Prescott filter. GDP data is from the Bureau of Economic Analysis (chained dollar measure); for all other definitions and data sources, see Section 2.

firms over the full period.

The increased share of Ponzi firms is primarily driven by growth in the number of *small* firms that are Ponzi. Figures 2a and 2b reproduce Figure 1 for firms in the top and bottom quartile of the asset distribution in each year. In the case of the largest quartile, Figure 2b illustrates that, on average, almost 70% of firms are speculative, and that the composition of financing regimes among this largest quartile of firms does not trend significantly over time. Growth in Ponzi finance over the post-1970 period is, instead, largely driven by an increased share of small firms with Ponzi structures, from 20.7% to 74.0% between 1970 and 2014.

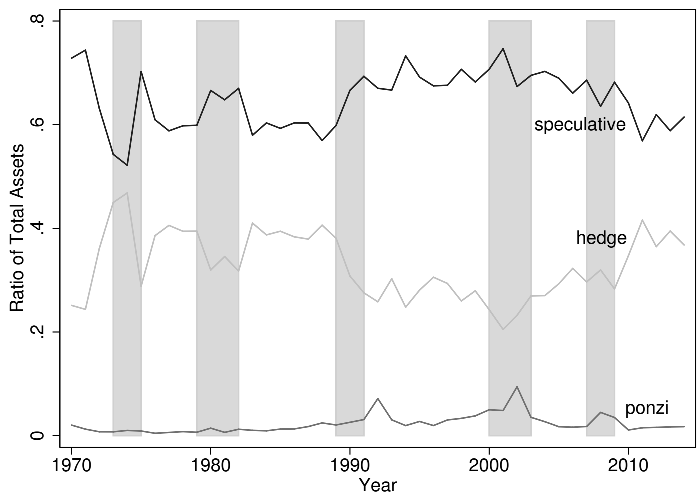
Importantly, small firms are most often Ponzi due to negative *sources* of cash, as opposed to high financial commitments. Table 3 summarizes the share of small Ponzi firms with negative values for our measure of sources of cash by decade, as well as the share of small Ponzi firms with, specifically, negative funds from operations. While 18.2% of firms in the bottom quartile of the asset distribution reported negative funds from operations in 1970, this proportion was 68.1% by 2014. Thus, Table 3 points to a growing share of small firms with negative sources of cash, largely due to negative operational income (*income before extraordinary items*), which, as described above, is firms' primary source of cash. This result is striking: a growing share of small firms effectively report losses after operational expenses are deducted from revenues. Given that these are firms that have had access to equity finance, this result suggests that sustained changes in financial practices are an important driver of the increased share of Ponzi firms (discussed further in Section 3.3).

Table 3: Negative sources of cash and negative funds from operations
Percentage of small Ponzi firms

	Sources of cash	Funds from operations	N
1970	18.2%	18.2%	849
1980	18.3%	23.6%	1315
1990	47.6%	50.6%	1448
2000	64.6%	67%	1851
2014	68.1%	69.6%	1216

Notes: The table describes the share of Ponzi firms in the first quartile of the yearly asset distribution with negative total sources of cash and with negative funds from operations (the main component of firms' sources of cash) by decade. N refers to number of firms. For definitions and data sources, see Section 2.

Figure 3: Hedge, speculative and Ponzi financing regimes as shares of total assets
By firm size; 1970-2014



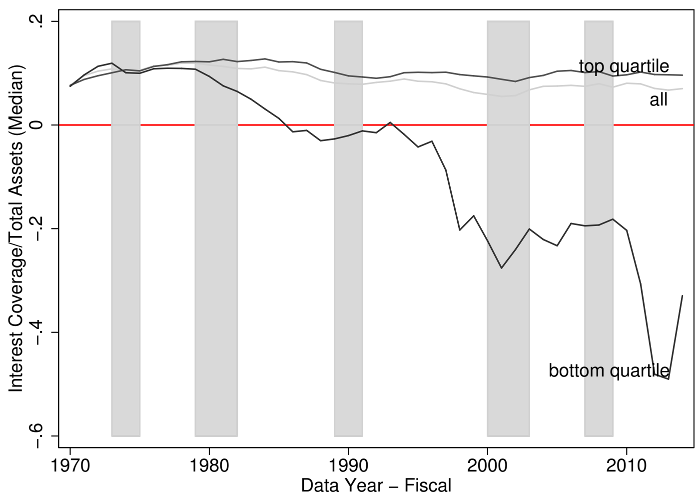
Notes: The figure shows the asset-weighted shares of all firms under each financing regime. Shaded areas refer to full peak-to-trough periods for real GDP, obtained using the Hodrick-Prescott filter. GDP data is from the Bureau of Economic Analysis (chained dollar measure); for all other definitions and data sources, see Section 2.

Figure 3 turns to the share of total assets under each financing regime. Consistent with the fact that the increased incidence of Ponzi finance is concentrated among small firms, Figure 3 illustrates that the share of total assets across financing regimes is relatively stable in the post-1970 US. Similarly, the share of total assets under Ponzi regimes is small, with at least 90.6% of assets under hedge or speculative regimes in each year.[7] Finally, Figure 4 extends this evidence to the interest coverage ratio, which provides a continuous counterpart to the discrete regime classifications in Figures 1-3. Figure 4 plots this measure of fragility between 1970 and 2014 for the full sample of firms, as well as for firms in the bottom and top quartile

[7] These patterns hold when hedge, speculative and Ponzi financing regimes are instead measured as shares of capital expenditures or sales, with the exception that, when measured relative to capital expenditures, the share of hedge firms rises relative to the share of speculative firms.

of the asset distribution. Consistent with the evidence in Figure 3 we note, first, that there is very little trend in the interest coverage ratio for the full sample of firms. Furthermore, Figure 4 reiterates substantial heterogeneity by firm size. Namely, while the largest quartile of firms closely follows the full sample trend, there is a marked decline in interest coverage among small firms, capturing increased fragility. Average interest coverage (as a ratio of total assets) among firms in the bottom quartile of the asset distribution is -0.076 (implying that the average small firm is in a Ponzi regime), but rises to approximately 0.10 among firms in the remaining quartiles. Thus, while we largely frame the discussion in this section in terms of the discrete regime classifications that are widely associated with Minsky's work, it is important to note that these discrete classifications present trends consistent with this alternative, continuous measure of financial fragility.

Figure 4: The interest coverage ratio
Full sample of firms, top and bottom quartile; 1970-2014



Notes: The figure shows median interest coverage as a ratio of total assets for the full sample of firms, and for firms in the top and bottom quartile of the interest coverage distribution. Interest coverage is defined as sources of cash less interest payments, normalized by total assets. Quartiles are defined by percentile of the asset distribution in each year. Shaded areas refer to full peak-to-trough periods for real GDP, obtained using the Hodrick-Prescott filter. GDP data is from the Bureau of Economic Analysis (chained dollar measure).

3.1 Do sectoral changes drive the growth in Ponzi firms?

While Figure 2 establishes a remarkable increase in the share of Ponzi firms in the 1980s and 1990s concentrated among smaller firms, public discourse often attributes changes in financing behavior to structural changes in the US economy, particularly the rise of information and communication technologies (ICT). Stories of startup firms raising funds on the stock market before turning a profit are familiar to most observers, and for good reason. Indeed, as of September 2016, there were 155 such startup companies valued at one billion dollars or more by their venture-capital backers (Austin et al., 2015). All these firms had access to equity financing. Since their current cash flows may fall short of their financial commitments, they may be classified as Ponzi in our analysis.

However, a sectoral decomposition indicates that growth in Ponzi firms is not driven by growth in ICT or, in fact, by any particular industry. Accordingly, the rising share of Ponzi firms primarily reflects changes within sectors (in proportion to their relative importance in the sample), rather than a large-scale expansion of sectors prone to Ponzi finance at the expense of more financially robust sectors. To show this, we decompose the change in the aggregate incidence of Ponzi regimes, by decade, into two components: a 'within-sector' component that measures changes in the incidence of Ponzi regimes within sectors, and a 'between-sector' or 'structural change' component that holds the incidence of Ponzi regimes within sectors fixed. Appendix A1 provides details on the sectoral classifications, as well as the shift-share methodology used in the sectoral decomposition.[8]

Table 4: Shift-share decomposition of changes in the aggregate share of Ponzi firms

	Δ Share of Ponzi Firms (p.p.)	Decomposition	
		Within-Sector (%)	Structural Change (%)
1970-1980	-1.7	95.5	4.5
1980-1990	15.0	96.9	3.1
1990-2000	9.8	85.2	14.8
2000-2014	-2.4	55.2	44.8

Notes: The first column shows the percentage point change in the aggregate share of Ponzi firms between the final year and the initial year of the period. The second and third columns show the decomposition of this change into the within-sector and the structural change components, as a percentage of the total change. For details on the sectoral decomposition and the shift-share methodology, see Appendix A1. For definitions and data sources, see Section 2.

Table 4 shows the results of this decomposition.[9] The first column shows the percentage point change in the aggregate share of Ponzi firms over each decade. Consistent with Figures 1 and 2, the lion's share of the increase in the share of Ponzi firms occurs in the 1980s (15 percentage points) and 1990s (9.8 percentage points). The percentage point changes in the share of Ponzi firms between 1970-1980 and 2000-2014 are, in contrast, slightly negative. The final two columns decompose the change in the aggregate share of Ponzi firms into within-sector and structural change components, each as a percentage of the aggregate change.

[8]We divide firms into thirteen sectors, based, first, on the Standard Industrial Classification (SIC) and also including, second, three 'high-tech' sectors: high-tech manufacturing, communications services, and software and computer-related services. The summary statistics in Appendix A1 point to substantial variation in the share of Ponzi firms both over time and across sectors (Table 13 in Appendix A1). Notably, nearly all sectors display an increased share of Ponzi between 1980 and 2000, when the bulk of the growth in Ponzi takes place.

[9]Figure 5 in Appendix A1 includes a visual representation of the decomposition that describes sectoral contributions to the change in the aggregate share of Ponzi firms by decade.

This decomposition highlights that – while both within-sector change and structural change contribute to the expansion of Ponzi finance during the 1980s and 1990s – the contribution of the within-sector component is clearly dominant in both decades, accounting for nearly 97% of the aggregate change between 1980 and 1990, and 85% between 1990 and 2000. Accordingly, most sectors contribute to the rising incidence of Ponzi regimes during the 1980s and 1990s.[10]

In the case of ICT, in particular, we note that – despite within-sector increases in Ponzi finance – the contribution of ICT sectors to growth in Ponzi finance during the 1980s is modest, reflecting that ICT constitutes a small share of the sample at this time. During the 1990s, in contrast, high-tech manufacturing and other ICT sectors contribute substantially to the expansion of Ponzi finance, with each exceeding 20% of the aggregate change. This contribution reflects, in part, the expansion of high-tech among publicly traded firms during the 1990s; for example, over a third of the contribution of software and computing services to the expansion of Ponzi finance stems from expansion of the sector (the structural change component). However, growth in the incidence of Ponzi is common across most other sectors during the 1980s and 1990s as well, reiterating the main conclusion that the expansion of Ponzi finance is a generalized phenomenon, reflecting mutually-reinforcing within-sector trends (where larger sectors have larger weights), and is not primarily due to increased access to equity finance by technology firms.[11]

3.2 Pre and post Ponzi history

Generalized growth in the share of financially fragile firms across sectors raises questions about both the previous and subsequent states of Ponzi firms. Does the increase in Ponzi finance reflect a trend wherein firms increasingly *enter* the sample as Ponzi, or do a significant proportion of firms transition into Ponzi from hedge or speculative regimes? Similarly, do Ponzi firms subsequently exit the sample, or do they transition back to other regimes? These questions are closely tied to the distinction between a 'basic cycle' in which Minskian dynamics are characterized by many firms passing through each regime (Palley, 1994, 2011) and

[10] Manufacturing contributes significantly to the increased aggregate incidence of Ponzi finance during both the 1980s and 1990s, reflecting in part manufacturing's large share of the nonfinancial corporate sector. During the 1980s, for example, traditional manufacturing makes the largest contribution to the increased aggregate share of Ponzi firms (34% of the observed increase), reflecting a large within-sector expansion of Ponzi firms (from 0.8% to 23%), but also that manufacturing is the largest sector in the sample. In the 1990s, as well, traditional manufacturing contributes just under 30% of the aggregate increase in Ponzi firms.

[11] While there is a small overall change in the aggregate share of Ponzi firms between 2000 and 2014, this is the only period with a sizable proportional contribution of structural change. During 2000-2014, most sectors — including ICT — record *negative* within-sector contributions to Ponzi. While these negative within-sector changes would have *lowered* the aggregate share of Ponzi firms by 6.8 percentage points between 2000 and 2014, the decline is almost entirely offset by an increased share of traditional manufacturing firms that are Ponzi. Thus, with the quantitatively important exception of manufacturing, there is suggestive evidence that, several years after the burst of the dotcom bubble in the early 2000s and the 2008 financial crisis, financial robustness increased in most sectors.

a long wave transformation of the economy towards increased fragility (Wray, 2009; Ryoo, 2010; Bernard et al., 2014).

Table 5: Status of firms in year before transitioning to Ponzi
Full sample and by size quartile

	Full sample	Quartile 1	Quartile 2	Quartile 3	Quartile 4
From missing	36.2%	50.1%	27.7%	15.6%	10.5%
Joined	17.7%	25.9%	11.9%	6.2%	4.3%
First after missing	13.8%	18.0%	11.6%	7.3%	4.5%
Reappear after missing	4.7%	6.2%	4.2%	2.1%	1.7%
Hedge	10.4%	9.7%	11.1%	10.5%	12.9%
Speculative	53.4%	40.2%	61.2%	74.0%	76.6%

Notes: Firms can transition to Ponzi from hedge or speculative finance, or from a previously missing observation. Previously missing observations can be divided between: (1) firms that join Compustat for the first time in t; (2) firms that were already in Compustat, are missing a regime classification in $t-1$, and are now receiving a regime assignment for *the first time*; and (3) firms that were already in Compustat, are missing a regime classification in $t-1$, but did have a regime classification in some previous period. Quartiles are defined by percentile of the asset distribution in each year. For definitions and data sources, see Section 2.

Firms that become Ponzi in year t can enter Ponzi from one of three previous states: (1) the firm can enter as Ponzi in t; (2) the firm can transition from being in a speculative regime in $t-1$, or (3) the firm can transition from being in a hedge regime in $t-1$. Table 5 summarizes the shares of each type of transition for the full sample and by firm size quartile for the full post-1970 period. These summary statistics, also, further divide firms entering as Ponzi in year t into three sub-categories: firms joining Compustat for the first time; firms already in the sample that did not have sufficient data for a regime assignment in year $t-1$; and firms already in the sample, also missing a regime classification in $t-1$, but that had a previous regime assignment in at least one year. Table 5 points to two different stories by firm size. Among large firms, as in the full sample, firms most often become Ponzi from a previously speculative state. In contrast, small firms are more likely to join the sample as Ponzi. It is, furthermore, notable that small firms have *increasingly* entered the nonfinancial corporate sector with fragile financing structures over the post-1970 period. In 1970-1974, 50.3% of firms in the smallest quartile became Ponzi from a previously speculative regime; this share falls to 23.4% in 2010-2014. In contrast, the share of firms in the first quartile entering Ponzi from 'missing' rose from 38.5% in 1970-1974 to 70.8% in 2010-2014.[12] This trend corroborates a hypothesis that the growing incidence of Ponzi firms reflects an increased number of small corporations that IPO with fragile financial structures (due to negative sources of cash).

[12]In 1970-74, 26% of Ponzi firms in the first quartile 'joined' the sample; 10.9% were 'first after missing', and 1.6% 'reappear after missing'. In 2010-14, 27.5% of Ponzi firms in the first quartile 'joined' the sample; 37.3% were 'first after missing' and 6.0% 'reappear after missing'.

An equally interesting question concerns what happens *after* a firm finds itself in a Ponzi regime. Table 6 summarizes the incidence of Ponzi firms' subsequent states for the full sample and by size quartile. These statistics highlight that, across firm size, a majority of spells of Ponzi finance (almost 60%) end when a firm transitions to a more robust financing regime, but that almost a third of Ponzi spells (30.2%) end with exit. This general pattern holds across firm size, with the notable exception that small firms more often exit the sample after a period of Ponzi finance than large firms. Table 6 also includes the possibilities that a firm is still Ponzi when the sample ends in 2014, and that Ponzi firms – after a spell of being Ponzi – have a missing observation for financing regime. Approximately 6% of spells of Ponzi finance were ongoing in the last year of our sample and, in a small number of cases, we cannot observe the post-switch state due to missing data (4.6%).

Table 6: Status of firms transitioning out of a Ponzi regime
Full sample and by size quartile

	Full sample	Quartile 1	Quartile 2	Quartile 3	Quartile 4
Hedge	9.3%	9.6%	9.3%	8.5%	8.9%
Speculative	49.8%	40.4%	54.3%	66.1%	73.3%
Exit	30.2%	36.1%	27.4%	21.1%	13.0%
End of sample	6.1%	8.3%	5.2%	1.7%	1.6%
Missing obs.	4.6%	5.8%	3.8%	2.6%	3.2%

Notes: Firms can transition out of Ponzi to a hedge or speculative regime; exit the sample; still be Ponzi in the last year for which we have available data; or have a missing regime classification following Ponzi finance. 'Exit' includes cases for which a Ponzi spell is followed by a missing observation, after which the firm exited the sample (2.7% of all transitions). The shares in this table are computed after adjusting the sample to exclude firms with gaps (0.64% of total firms). Quartiles are defined by percentile of the asset distribution in each year. For definitions and data sources, see Section 2.

While Table 6 indicates that Ponzi firms more often switch to a more robust regime than exit the sample, the question remains of whether firms are *more likely* to *exit* after a spell of Ponzi finance compared to firms in more robust regimes.[13] While a full econometric analysis of the determinants of exit hazard is beyond the scope of this paper, simple descriptive statistics suggest that a spell of Ponzi finance is associated with a greater likelihood of exiting the sample, as compared to being in a more robust regime – even when controlling for firm size quartile. To show this, we compare the distribution of regimes in the year before exit to the unconditional likelihood that a firm is Ponzi in any given year. Panel 1 of Table 7 shows the distribution of regimes among exiting firms in the year before they exit. The last column shows that, across firm size, 37.4% of exiting firms are Ponzi in the previous year. Panel 2 of Table 7 shows the unconditional likelihood that a firm is Ponzi in any given year. The last column shows that 21.5% of all firms are Ponzi in any given year. The 16 percentage point difference suggests that being in a Ponzi regime *enhances* the likelihood of

[13]Unfortunately, due to data limitations we cannot identify the reason for exit. A firm may exit because it has gone bankrupt; because it has merged with or been acquired by another firm; or because it has become privately held.

exiting the sample in the subsequent year, relative to other regimes. In contrast, the opposite relationship characterizes hedge and speculative regimes: the likelihood of being hedge or speculative is higher in any given year than it is in the year before exiting the sample.

Table 7: Distribution of financing regimes
Full sample and by size quartile

	Panel 1: Distribution of Finance Regimes in Year Before Exit				
	Size Quartiles				
	1	2	3	4	**Total**
Hedge	8.0%	19.0%	24.8%	27.1%	17.5%
Speculative	24.9%	48.7%	59.8%	65.5%	45.1%
Ponzi	67.1%	32.3%	15.3%	7.5%	37.4%
	Panel 2: Unconditional Distribution of Finance Regimes				
	Size Quartiles				
	1	2	3	4	**Total**
Hedge	13.5%	23.4%	27.7%	30.3%	23.6%
Speculative	35.3%	54.9%	63.9%	66.2%	54.9%
Ponzi	51.2%	21.7%	8.3%	3.5%	21.5%

Notes: The first panel shows the distribution of finance regimes in the year before firms exit the sample, when exit occurs before 2014. The first four columns further condition the distribution by size quartiles, while the last column shows the distribution across all exiting firms. The second panel shows the unconditional (on exiting) distribution of regimes. All entries are expressed as a percentage of the total non-missing observations for the finance regime. Quartiles are defined by percentile of the asset distribution in each year. For definitions and data sources, see Section 2.

Table 7, also, indicates that this pattern holds when conditioning on size quartiles. For example, we can compare the likelihood that a firm in the smallest quartile is Ponzi the year before it exits (67.2%) to the unconditional likelihood (51.2%) that a firm is Ponzi — again, a 16 percentage point difference. These probability differentials fall as size increases; however, the sign is preserved. Thus, across all quartiles, but more strongly so among smaller firms, firms are less likely to be hedge or speculative, and more likely to be Ponzi, the year preceding exit as compared to any given year.

3.3 A long wave of increasingly fragile finance?

The evidence in this section is consistent with the possibility of a long wave of increasingly fragile finance in the post-1970 US economy. In particular, the expanding share of Ponzi structures points to a secular shift in the structure of the nonfinancial corporate sector, extending across multiple business cycles, towards an increasing prevalence of fragile financial structures. Evidence regarding the previous and subsequent states of Ponzi firms further corroborate the possibility of a long Minskian wave. Perhaps most notably, a striking number of Ponzi firms *enter* the sample – i.e. *go public* – with a Ponzi structure due, in particular, to negative sources of funds.[14] This expansion of Ponzi entrants is arguably indicative of changing financial norms and conventions. More specifically, the fact that a growing share of (small) firms have access to equity finance *despite* negative operational income suggests that institutional changes in financial practices are an important driver of the increased share of Ponzi firms. Furthermore, the expansion of Ponzi – specifically among small firms – is due to 'new entry' as much as transitions from hedge and speculative regimes. Together with the finding that Ponzi firms are more likely to subsequently exit the sample as compared to hedge or speculative firms, these descriptive findings suggest that the primary source of Minskian dynamics in the post-1970 US does not lie in a 'basic cycle', wherein the expansion of financial fragility derives primarily from the movement of individual enterprises from hedge, through speculative, and to Ponzi finance (Palley, 2011), and instead corroborates the possibility of a long wave.

The sectoral decomposition further supports this possibility of a long wave. In particular, the expansion of Ponzi finance occurs across sectors, such that – rather than being indicative of structural change in the US economy wherein a financially fragile sector grows at the expense of a robust sector – there is a broad-based expansion of fragile structures. This widespread expansion in Ponzi structures again points to a broad change in financial norms and practices, wherein – across the US economy – the financial norms by which firms enter the sample of publicly-traded companies have changed. Together, the descriptive findings in Section 3 are consistent with a set of the literature on Minskian dynamics that emphasizes long waves in financing practices, defining, for example, long waves as stages of capitalism (Minsky, 1964, 1995; Wray, 2009; Ryoo, 2010; Bernard et al., 2014).

Thus, while the length of the available data on the US nonfinancial corporate sector makes it impossible to definitively identify a long wave, the descriptive evidence in this section establishes a set of stylized facts consistent with a long-term shift in financing norms towards an increasing *incidence* of financially fragile structures in the US nonfinancial corporate sector. Notably, however, because the expansion in Ponzi structures is concentrated among small firms, the *asset-weighted share* of firms in more fragile financing positions does not trend upwards over the same period. This low asset-weighted share of Ponzi raises an important question regarding whether the trends documented here point to greater *systemic* fragility. In this regard it is important to keep in mind that, in analyzing the nonfinancial *corporate* sector, 'small' firms are still relatively large.

It is also notable that Figure 3 captures a clear *lack* of an increased share of assets under financially fragile regimes (both speculative and Ponzi) after the onset of the 2008 crisis. Put differently, Figures 1-3

[14] This expansion of Ponzi entrants to the nonfinancial corporate sector occurs *despite* a marked decline in new entrants during this time period (Gutiérrez and Philippon, 2016).

do not point to a 'Minsky moment' within the nonfinancial corporate sector in 2008.[15] There are at least three possible interpretations of this finding. First, if Minskian dynamics take the form of long waves, the evolution of financial norms may be slow moving: even if norms begin to evolve after a crisis, regime shifts need not align with the business cycle. Second, and perhaps more important, this paper analyzes nonfinancial corporations, whereas the 2008 crisis was largely located in the household sector and was prompted by a housing price collapse (for a discussion of this point in a Minskian framework see Dymski, 2009).[16] In the context of nonfinancial firms, Minskian dynamics are most often located in investment booms. However, investment rates in the nonfinancial corporate sector slowed in the decades prior to 2008, despite rising profitability. This 'investment-profit puzzle' (Stockhammer, 2005; Van Treeck, 2008) suggests that – quite in contrast to an investment-led boom – the profit-investment link that is central to Minskian dynamics in the nonfinancial corporate sector, has *weakened* over the period of analysis. Financial firms, which were also central to the dynamics of the 2008 crisis, are similarly excluded from the sample.

It is, third, interesting to note that the majority of large firms are speculative and, therefore, rely on access to short-term financing to roll over debt. When the market for short-term corporate debt (commercial paper) froze during the financial crisis, these firms were directly vulnerable to the possibility that investors would be unwilling to refinance maturing commercial paper. Notably, however, the commercial paper market was supported during the crisis by direct (and unprecedented) Federal Reserve purchases of commercial paper (Kacperczyk and Schnabl, 2010). Thus, the policy response to the crisis conceivably mitigated the likelihood of a Minsky moment within the nonfinancial corporate sector – at least among these (primarily large) firms that are heavily reliant on short-term commercial paper for financing.

4 Short-term cycles? Financial fragility and the business cycle

The descriptive evidence in Section 3 points to a possible long wave of increasingly fragile financing arrangements in the post-1970 US economy; however, the possibility remains that shorter-term Minsky cycles are 'nested' within this long-term trend. In this section we, therefore, explore the possibility of short-term Minsky cycles by analyzing the link between macroeconomic fluctuations (at a business-cycle frequency) and a firm's probability of being in a more fragile financing regime. We present two sets of estimations: the first set uses the discrete classifications from the previous sections, and the second turns to the interest coverage ratio. Both sets of estimations point to an almost-zero contemporaneous relationship between the cyclical

[15] This conclusion is consistent with Behlul (2011) who finds, at the aggregate level, that the balance sheet of the nonfinancial corporate sector did not become more precarious following the crisis.

[16] See also Tymoigne (2014) for an analysis of increased financial fragility in residential housing beginning in the early 2000s.

component of output (the output gap) and financial fragility, suggesting that Minskian dynamics do not operate at a business-cycle frequency over this period in the US economy.

4.1 The probability of being Ponzi

To explore the impact of short-term business cycle fluctuations on firm-level financial fragility, we begin with a set of linear probability models estimating the relationship between fluctuations in economic conditions external to individual firms and the probability that a firm is Ponzi. We draw on two measures of business cycle fluctuations: the (normalized) cyclical component of US GDP extracted using the Hodrick-Prescott filter, and real GDP growth.[17] Results from these estimations are shown in Tables 8 and 9, respectively.

Table 8: Linear probability models, probability of being Ponzi
(Cyclical component of GDP)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Cyc output$_t$	-0.0052***	-0.0040***	-0.0059***	-0.0036***	-0.0074***	-0.0067***	-0.0069***	-0.0044***
	(0.0008)	(0.0008)	(0.0010)	(0.0010)	(0.0010)	(0.0010)	(0.0011)	(0.0011)
Cyc output$_{t-1}$					0.0066***	0.0065***	0.0061***	0.0062***
					(0.0010)	(0.0010)	(0.0012)	(0.0012)
Cyc output$_{t-2}$					0.0050***	0.0052***	0.0039***	0.0047***
					(0.0010)	(0.0010)	(0.0011)	(0.0011)
Avg growth (7yr)			0.8948***	0.2965**			0.7576***	0.1228
			(0.1187)	(0.1211)			(0.1217)	(0.1243)
Log total assets		-0.0267***		-0.0258***		-0.0251***		-0.0258***
		(0.0007)		(0.0011)		(0.0008)		(0.0011)
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	N	N	N	N	N	N	N	N
Firms	11232	11232	10196	10187	11232	11231	10196	10187
Avg. obs/firm	16.75	16.72	11.25	11.25	14.88	14.86	11.16	11.15
Std coeff (pp)	-0.45	-0.34	-0.50	-0.31	-0.63	-0.57	-0.59	-0.37
Uncond prob	17.5	17.5	17.5	17.5	17.5	17.5	17.5	17.5

Notes: The dependent variable is a binary variable indicating whether a firm is in a Ponzi regime in a given year. 'Cyc output' denotes the cyclical component of GDP obtained from the Hodrick-Prescott filter. 'Avg growth (7 yr)' denotes the average growth in aggregate GDP over the previous seven years. 'Std coeff (pp)' denotes the percentage point effect of a one standard deviation increase in 'Cyc output' on the probability of being Ponzi. 'Uncond prob' denotes the unconditional probability of being Ponzi. GDP data is from the Bureau of Economic Analysis (chained dollar measures); for all other definitions and data sources, see Section 2. The sample period is 1970-2014. Robust standard errors are in parentheses. *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

Table 8 begins with specifications using the cyclical component of output. This specification is premised on the assumption that the cyclical component of aggregate GDP reflects changes in economic conditions

[17]Both aggregate GDP and sector-level output series, introduced below, are normalized such that 2009, the base year, is equal to 100. Doing so ensures comparability between aggregate GDP and the sector-level output measures that are used in estimations in Appendix A2. Both aggregate GDP and sector-level output are drawn from the BEA (chained dollar measures). In all sets of regressions, we restrict the sample to only include firms with spells of at least seven consecutive observations; however, the results are strongly robust to varying this sample restriction.

that may affect financing structures, but that are exogenous to individual firms. Thus, the primary relationship of interest is between the contemporaneous cyclical component of GDP and the probability of being Ponzi, described by the coefficients in the first row of each column in Table 8. In particular, if business cycle fluctuations drive changes in firm financing regimes, we would expect that business cycle downturns (expansions) lead to an increase (decrease) in the probability that a firm is Ponzi.

Columns 1 and 2 begin with the most parsimonious specifications, estimating the relationship between the contemporaneous cyclical component of GDP and the probability of being Ponzi, both with and without a control for log of total assets to capture firm size. Each column also includes firm fixed effects that account for firm-specific factors (like sector of activity) that are not explicitly controlled for in the regression; because the aggregate output gap absorbs year-specific variation, year fixed effects are not included. As predicted by the hypothesis that Minskian dynamics describe short-term fluctuations, the key coefficient of interest in Columns 1 and 2 points to a negative and strongly statistically significant relationship between the contemporaneous cyclical component of output and the probability of being Ponzi.

Importantly, however, the magnitude of the estimated coefficient is small. To highlight economic magnitudes, standardized coefficients for cyclical output are included in the final row of Table 8. In Column 1, for example, a one standard deviation increase in the magnitude of the cyclical component of GDP leads to a 0.45 percentage point decline in the probability of being Ponzi. A comparison to the unconditional probability of being Ponzi (17.5%) highlights the small economic magnitude of the estimate. When also controlling for log total assets, a one standard deviation increase in the cyclical component of GDP leads to a 0.34 percentage point decline in the probability of being Ponzi. Thus, while – as expected – these results point to a negative contemporaneous relationship between the cyclical component of GDP and the probability of being Ponzi, the magnitude of this short run effect is quite small.

This result is corroborated by the remaining columns of Table 8. Columns 3 and 4 include a measure of seven-year average growth, defined by the average growth rate over the last seven years, to consider the possibility that periods of faster growth subsequently generate greater financial fragility. Columns 5-8 then replicate the four initial specifications, while also including two lags of the cyclical component of output. Thus, Column 8 presents the most exhaustive specification, which includes controls for two lags of the cyclical component of output, seven-year average growth, and log of total assets. Column 8 reiterates both the negative relationship between the cyclical component of GDP and the probability of being Ponzi, and the very small economic magnitude of this coefficient. Specifically, a one standard deviation increase in average growth is associated with a 0.62 percentage point increase in the probability of being Ponzi.

Two additional points are useful to note about Table 8. First, Columns 5-8 point to a positive relationship between the first and second lags of cyclical output and the probability of being Ponzi. These coefficients reflect mean reversal in the cyclical component of output, as measured by the Hodrick-Prescott filter. In particular, when holding the contemporaneous component of cyclical output fixed, subsequent lags of cyclical output capture this mean reversion, such that they are positively associated with the probability of being Ponzi. Finally, the coefficient describing the relationship between seven-year average growth and the probability of being Ponzi is positive and strongly statistically significant across specifications, suggesting that a spell of medium-run growth is associated with an increased likelihood that firms are Ponzi. This coefficient may, accordingly, suggest that sustained growth episodes breed 'exuberance' and, thus, the behavior that generates financial fragility. However, as with the contemporaneous cyclical component of output, the magnitude of the coefficient is, again, quite small. In Column 7, a one standard deviation increase in seven year average growth leads to a 0.65 percentage point increase in the probability of being Ponzi; when controlling for total assets (Column 8), the magnitude of this effect falls to 0.11 percentage points and becomes statistically insignificant.

Table 9: Linear probability models: probability of being Ponzi
Real GDP growth

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Δ(real gdp)$_t$	-0.2902***	-0.3636***	-0.4871***	-0.5175***	-0.3192***	-0.4044***	-0.4616***	-0.4900***
	(0.0343)	(0.0343)	(0.0448)	(0.0447)	(0.0382)	(0.0381)	(0.0463)	(0.0461)
Δ(real gdp)$_{t-1}$					-0.0599	-0.1039***	-0.1375***	-0.1327***
					(0.0386)	(0.0385)	(0.0471)	(0.0469)
Δ(real gdp)$_{t-2}$					0.1306***	0.0746**	0.0048	0.0171
					(0.0374)	(0.0373)	(0.0451)	(0.0449)
Avg growth (7yr)			1.0543***	0.5493***			1.1481***	0.6097***
			(0.1184)	(0.1199)			(0.1340)	(0.1355)
Log total assets		-0.0273***		-0.0265***		-0.0260***		-0.0262***
		(0.0007)		(0.0011)		(0.0008)		(0.0011)
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	N	N	N	N	N	N	N	N
Firms	11232	11232	10196	10187	11232	11231	10196	10187
Avg. obs/firm	16.75	16.72	11.25	11.25	14.88	14.86	11.16	11.15
$\sum$ Output Gap					-0.248	-0.434	-0.594	-0.606
p-value					1.51e-05	0	0	0
Std coeff (pp)	-0.58	-0.73	-0.97	-1.03	-0.64	-0.81	-0.92	-0.98
Uncond prob	17.5	17.5	17.5	17.5	17.5	17.5	17.5	17.5

Notes: The dependent variable is a binary variable indicating whether a firm is in a Ponzi regime in a given year. 'Δ(real gdp)' denotes real GDP growth. 'Avg growth (7 yr)' denotes the average growth in aggregate GDP over the previous seven years. 'Std coeff (pp)' denotes the percentage point effect of a one standard deviation increase in 'Δ(real gdp)' on the probability of being Ponzi. 'Uncond prob' denotes the unconditional probability of being Ponzi. GDP data is drawn from the Bureau of Economic Analysis (chained dollar measures); for all other definitions and data sources, see Section 2. The sample period is 1970-2014. Robust standard errors are in parentheses. *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

These results are corroborated by alternative specifications utilizing output *growth*, rather than the cyclical component of aggregate output. The results, shown in Table 9, indicate that a higher rate of GDP growth leads to a lower probability of being in a Ponzi regime, such that that expansions are associated with a decreased probability of fragile finance, whereas downturns increase firms' likelihood of being in a fragile regime. Like in Table 8, however, the coefficients in these estimations are small. In the most parsimonious specification in Column 1, for example, a one standard deviation increase in GDP growth leads to a 0.58 percentage point decline in the probability of being Ponzi; in Column 8 this magnitude is 0.98 percentage points. The magnitude of the sum of the lagged coefficients is, also, small; a one standard deviation increase in the sum of the lagged coefficients on real GDP growth is associated with a 0.97 percentage point decline in the probability of being Ponzi. In addition to these specifications, Appendix A2 includes analysis exploring the robustness of these results to panel logit specifications; specifications that use sectoral, rather than aggregate, output gaps and output growth; and specifications that consider the probability of being speculative *or* Ponzi. This robustness analysis corroborates our conclusion that the probability of being Ponzi – and the distribution of regimes more generally – are largely insensitive to short-run fluctuations in economic activity.[18]

4.2 A continuous measure of financial fragility

Finally, we consider the sensitivity of our conclusions to an extension that utilizes the interest coverage ratio. The interest coverage ratio allows us, first, to move beyond the question of how business cycle fluctuations affect binary financing classifications to an analysis drawing on the full distribution of a continuous measure of fragility. Second, we can analyze if the low estimated effects in Section 4.1 mask differential effects of business cycle conditions at quantiles of interest coverage away from the mean. Importantly, business cycle fluctuations are expected to impact firms differentially depending on the degree to which their cash inflows depend on current earnings from operations, which are likely more sensitive to business cycle variations than other cash inflows. Arguably, this is likely to be the case for the smaller firms in our sample; these firms are also more likely to be in lower quantiles of the interest coverage distribution. As was shown in Figure 4, the distribution of the interest coverage ratio is highly skewed, supporting the expectation of a different estimated effect at the mean than at the tails. Specifically, large firms are more likely to have positive

[18] In Appendix A2 we, first, show that the main results are robust to a panel logit specification (Table 14). We present linear probability models in the main text due to the relative ease of interpretation; however, because we have an unbalanced panel it is important that the results are robust to logit specifications. We, second, show that the results are robust to instead using a sector-specific – rather than aggregate – output gap (Table 15). By introducing variation masked in the cyclical component of aggregate output, these sector-level series allow us to consider the possibility that this sectoral variation increases the estimated magnitudes in Table 8. We, similarly, replicate the linear probability models that use GDP growth in Table 9 using sector-level output growth (Table 16). Finally, we estimate the probability of being *speculative or Ponzi*, rather than simply Ponzi, with linear probability models and panel logit specifications (Tables 17 and 18).

interest coverage and, accordingly, are less likely to be in a Ponzi regime. Larger firms are also arguably less dependent on current sales to generate cash flows, as opposed to non-operational sources of income stemming from the ownership of assets.

It is, therefore, plausible that the impact of current business cycle conditions on interest coverage differs at different quantiles of its distribution. To investigate this hypothesis we use the recentered influence function (RIF) regression to estimate the effect of the cyclical component of GDP (Table 10) and GDP growth (Table 11) at different quantiles of the interest coverage distribution (Firpo et al., 2009).[19] Like standard OLS regressions estimate the impact of an independent variable on the unconditional mean of the dependent variable, RIF-regressions estimate the impacts on unconditional quantiles of the dependent variable. Table 10 shows the effects of variation in the (normalized) cyclical component of aggregate GDP on the interest coverage ratio. Columns 1-2 shows the estimated effect on the mean, obtained from a standard fixed effects regression, and Columns 3-8 show estimates of the cyclical component of overall GDP on the 1st, 5th and 8th unconditional deciles, obtained from the RIF-regressions. These estimations suggest that changes in the cyclical component of GDP have a larger impact on lower deciles of the interest coverage measure than on the mean, the median, or upper deciles.[20]

Despite these differential effects, however, the quantile regressions again point to very small short-run effects of cyclical GDP on interest coverage and, by implication, on financial fragility. For example, Column 1 of Table 10 estimates that a one standard deviation increase in normalized GDP (0.73 in the 1950-2014 period) raises the mean of the interest coverage measure by only 0.002. In comparison to the unconditional mean of the interest coverage ratio of 0.06, the effect amounts to a 3.3% increase. Column 2, in turn, suggests that the same shock would raise interest coverage at the first decile by 0.0047. In our sample, the value of interest coverage at that quantile is -0.086, still a relatively small effect and certainly not one that would suffice to elicit a regime switch. In fact, empirically plausible cyclical fluctuations suggest a regime switch only for those firms that are already near the cut-off of zero interest coverage, beyond which they would switch from Ponzi to speculative. Interest coverage of (approximately) zero corresponds to the 16th percentile of the distribution; a one-standard deviation increase in cyclical GDP could cause many of those marginal firms to switch out of their Ponzi regimes. But, as suggested by the linear probability models

[19]Because interest coverage does not require data on principal payments, the quantile regressions cover 1950-2014. However, the results are qualitatively robust to excluding the pre-1970 period, thereby defining the sample period analagously to the period used in the linear probability models above.

[20]This finding is corroborated by the first panel of Figure 6 in Appendix A2, which presents estimates from the 10th to the 90th percentile in increments of five. Figure 6 shows a relatively smooth, monotonic decline in the estimated coefficient until approximately the median of the interest coverage measure, with the impact on the first decile estimated to be over three times larger than on percentiles above the median. Tables 19 and 20 in Appendix A2, furthermore, indicate that the results in Tables 10 and 11 are robust to the sectoral output gap and sectoral output growth, respectively.

Table 10: Effects of the output gap by quantile on the interest coverage ratio

	(1) Mean	(2) Mean	(3) Decile 1	(4) Decile 1	(5) Median	(6) Median	(7) Decile 8	(8) Decile 8
Cyc output$_t$	0.0031***	0.0039***	0.0066***	0.0073***	0.0019***	0.0021***	0.0019***	0.0021***
	(0.0005)	(0.0005)	(0.0008)	(0.0010)	(0.0002)	(0.0002)	(0.0004)	(0.0005)
Cyc output$_{t-1}$		-0.0037***		-0.0057***		-0.0017***		-0.0018***
		(0.0005)		(0.0010)		(0.0002)		(0.0006)
Cyc output$_{t-2}$		-0.0022***		-0.0053***		-0.0015***		-0.0020***
		(0.0005)		(0.0010)		(0.0002)		(0.0005)
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	N	N	N	N	N	N	N	N
Obs	226381	226381	226381	226381	226381	226381	226381	226381

Note: The dependent variable is interest coverage as a ratio of total assets. 'Cyc output' denotes the cyclical component of GDP obtained from the Hodrick-Prescott filter. Column (1)-(2) shows the estimated effect of the (normalized) cyclical component of overall GDP on the population mean of the dependent variable obtained through a standard fixed-effects regression. Columns (3)-(8) show the estimates of the overall output gap on the 10th, 50th and 80th unconditional percentiles of the interest coverage ratio, obtained through the Recentered Influence Function (Rif) regression. For computational efficiency, we use demeaned data in the estimations; the reported standard errors are adjusted to reflect the correct number of degrees of freedom. GDP data is from the Bureau of Economic Analysis (chained dollar measures); for all other definitions and data sources, see Section 2. The sample period is 1950-2014. Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 11: Effects of GDP growth by quantile on the interest coverage ratio

	(1) Mean	(2) Mean	(3) Decile 1	(4) Decile 1	(5) Median	(6) Median	(7) Decile 8	(8) Decile 8
Δ(real gdp)$_t$	0.1283***	0.1222***	0.2661***	0.2416***	0.1197***	0.1129***	0.0763***	0.0744***
	(0.0187)	(0.0183)	(0.0294)	(0.0302)	(0.0066)	(0.0069)	(0.0163)	(0.0169)
Δ(real gdp)$_{t-1}$		-0.0248		0.0383		0.0081		-0.0238
		(0.0155)		(0.0292)		(0.0069)		(0.0170)
Δ(real gdp)$_{t-2}$		-0.0959***		-0.1377***		-0.0427***		-0.0586***
		(0.0173)		(0.0286)		(0.0067)		(0.0166)
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	N	N	N	N	N	N	N	N
Obs	226381	226381	226381	226381	226381	226381	226381	226381
$\sum \Delta$ ln(rgdp)		0.00148		0.142		0.0782		-0.00797
p-value		0.968		0.00209		0		0.754

Notes: The dependent variable is interest coverage as a ratio of total assets. Δ(real gdp) denotes real GDP growth. Columns (1)-(2) show the estimated effect of real GDP growth on the population mean of the dependent variable, obtained through a standard fixed-effects regression. Columns (3)-(8) show the estimates of the overall output gap on the 10th, 50th and 80th unconditional percentiles of the interest coverage ratio, obtained through the Recentered Influence (Rif) regression. For computational efficiency, we use demeaned data in the estimations; the reported standard errors are adjusted to reflect the correct number of degrees of freedom. GDP data is from the Bureau of Economic Analysis (chained dollar measures); for all other definitions and data sources, see Section 2. The sample period is 1950-2014. Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

described above, their proportion as a share of the total number of Ponzi firms would be small.

Finally, Table 11 tells a qualitatively similar story for changes in real GDP growth.[21] Again, the coefficients on contemporaneous growth are about 2.5 times larger for the first decile than at the median and at larger quantiles. The impact of a one-standard deviation (calculated for the 1950-2014 period and measured in decimal points) increase in real GDP growth (0.023) on interest coverage is 0.006 on the first decile and 0.002 on the mean — in line with the effects obtained from the analysis of cyclical GDP.

5 Conclusions

In this paper we apply Minsky's definitions of financial fragility to firm-level financial statements to develop a picture of the incidence and evolution of Minsky's financing regimes across the nonfinancial corporate sector in the post-1970 US economy. The empirical mapping of Minskian concepts onto firm-level accounts provides, to the best of our knowledge, the first explicit empirical application of Minsky's taxonomy of financial fragility at the firm level. This mapping, in turn, provides an empirical basis for exploring two sets of questions. First, what is the incidence and distribution of Minsky's financing regimes across nonfinancial corporations in the post-1970 US economy? Second, are business cycle movements associated with changes in the probability of a firm being in a more/less fragile financing regime?

These questions contribute, first, to an empirical understanding of the incidence and evolution of Minskian regimes in the post-1970 US. While partly governed by data availability, the post-1970 period is nonetheless a natural choice for analysis, given widespread attention to this period as one during which much of the regulatory apparatus of the initial post-WWII period was dismantled, as well as due to a concurrent expansion in the size of finance and changes in the financial behavior of nonfinancial corporations. The empirical application of Minsky's taxonomy in this paper contributes to this discussion by providing a novel empirical application of this widely-studied approach to financial fragility. Importantly, despite a large theoretical literature in a Minskian tradition, empirical analyses are sparse; the firm-level description of the evolution and incidence of financing regimes over an extended period of time in the US, accordingly, contributes to this literature by providing empirical context for Minskian regimes in one country over an important period of time.

Additionally, this paper speaks to a long-standing point of ambiguity in the theoretical literature regarding the duration of Minskian cycles. Detailed firm-level data provide a unique forum to approach this debate.

[21] Again see Figure 6 in Appendix A2 for estimates across a range of percentiles.

In particular, firm-level data allow us to distinguish dynamics at the heart of short cycles versus longer waves: namely, by distinguishing cycles driven by frequent 'switching' between regimes at the firm level – from robust to fragile, and back to robust – from cycles characterized by a long-term widespread expansion of fragility at the sector level. These longer-term dynamics are characterized by changes in financial norms that operate across the sector. In the post-1970 US, for example, increased access to equity financing from venture capital is arguably linked to changing norms regarding the financial requirements an enterprise must meet before making an initial public offering.

We highlight, in particular, a secular expansion in the incidence of Ponzi finance in the post-1970 US, consistent with a *long wave* in the distribution of firms across Minksian financing regimes; however, we find evidence of only very small Minskian cycles at *short cycle* frequencies. Thus, while our results point to a build-up of fragility within the nonfinancial corporate sector over a series of business cycles, they do not lend strong support to approaching Minskian dynamics as a theory of the business cycle, or as theories of nested short- and longer-term Minskian cycles. Our results, therefore, build on a subset of the Minskian literature – including seminal contributions by Minsky himself – that emphasizes the operation of Minskian dynamics on a long-term basis.

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A Appendix

A.1 Details on the sectoral decomposition

To analyze the extent to which growth in Ponzi finance reflects changes in the sectoral composition of the nonfinancial corporate sector, versus changes in the distribution of financing regimes within sectors, we divide the sample into 13 sectors, summarized in Table 12. These sectors roughly correspond to the major divisions of the Standard Industry Classification (SIC) (at the 4 digit level), and also include three high-tech sectors, which are composite categories drawing from the other sectors (based on the legacy classification of the formerly TechAmerica, now CompTIA, foundation). The three 'high-tech' sectors include high-tech manufacturing, communications services, and software and computer-related services.[22]

Table 12: Sectoral Classification

Sector	SIC Code	Sector	SIC Code
Agriculture, Forestry and Fishing	0100-0999	Other Services	7000-8999[a]
Mining	1000-1499	Non-operating Establishments	9995
Construction	1500-1799	Conglomerates	9997
Manufacturing (excl. High tech.)	2000-3999[b]		
Transportation and Public Utilities	4000-4999[c]	High-technology Manufacturing	3571, 3572,3575,3577-3579,3651, 3652,3661,3663,3669,3671,3672, 3675-3679,3674,3821-3826,3829, 3827,3861,3812,3844,3845
Wholesale Trade	5000-5199		
Retail Trade	5200-5999		
		Communications Services	4812-4813,4841,4899
		Software and Computing Services	7371-7379

Notes: The SIC codes for High-technology Manufacturing, Communications Services, and Software and Computing Services follow the legacy classification suggested by the formerly TechAmerica (now CompTIA) foundation. The legacy classification is currently under revision, but it could be originally accessed at http://www.techamerica.org/sic-definition. For an example of a recent paper using this classification, see Engelen et al. (2016).

[a]Excludes the codes listed under Software and Computing Services.
[b]Excludes the codes listed under High-technology Manufacturing
[c]Excludes the codes listed under Communications Services.

Table 13 provides summary statistics by sector. The top panel shows the distribution of firms in the sample by sector over four periods: 1970-1980, 1980-1990, 1990-2000, 2000-2014. To ensure consistency with our decomposition procedure described below, Table 13 presents period averages computed as simple arithmetic averages of the values in the first and final year. Note that 'traditional' manufacturing firms (i.e. excluding high-tech manufacturing) account for almost half of all firms in 1970-1980 and, while this share declines to 35% by 2000-2014, the sector remains the largest throughout the sample period. The fastest rates

[22]Examples of high-tech manufacturing include industrial and consumer electronics, semiconductors, optical instruments and elctromedical equipment; examples of software and computer services include programming and systems design, information retrieval services, and prepackaged software.

of expansion are recorded by 'other' services, whose average share rose from 8.4% to 15.5%, and software and computing services, whose average share rose from 1.4% to 6.5%.

Table 13: Descriptive Statistics by Sector

	Sectoral Shares of Firms in Sample (Period Avg., %)			
	1970-1980	1980-1990	1990-2000	2000-2014
Agriculture	0.5	0.5	0.5	0.4
Mining	6.3	6.4	5.3	6.1
Construction	1.7	1.6	1.3	1.2
Manufacturing (excl. high-tech.)	47.8	37.7	33.8	35.3
Transportation and Pub. Utilities	8.5	11.5	9.9	9.4
Wholesale Trade	5.1	5.2	4.7	3.9
Retail Trade	9.0	8.1	7.5	6.8
Other Services	8.4	10.5	13.6	15.3
Non-operating Establishments	0.8	1.6	2.0	1.5
Conglomerates	0.1	0.1	0.1	0.1
High-technology Manufacturing	8.5	10.8	11.8	10.6
Communications	2.1	3.0	3.5	2.8
Software and Computing Services	1.4	3.1	6.2	6.5
	Share of Ponzi Firms in Sector (Period Avg., %)			
	1970-1980	1980-1990	1990-2000	2000-2014
Agriculture	9.4	21.9	27.6	21.2
Mining	13.8	16.6	25.1	32.0
Construction	7.9	17.3	20.9	14.0
Manufacturing (excl. high-tech.)	10.0	16.7	27.8	36.6
Transportation and Pub. Utilities	3.6	7.2	11.7	10.3
Wholesale Trade	9.7	16.6	23.4	19.5
Retail Trade	6.0	14.0	22.4	17.1
Other Services	11.4	18.9	32.6	35.3
Non-operating Establishments	14.7	36.5	57.9	77.1
Conglomerates	0.0	0.0	0.0	12.5
High-technology Manufacturing	17.9	21.9	34.4	33.9
Communications	3.5	12.4	36.0	38.3
Software and Computing Services	19.4	21.1	45.1	46.9
All Sectors	10.0	16.7	29.1	32.8

Notes: The top panel shows the distribution of the firms in the sample, while the bottom panel shows the share of Ponzi firms in each sector. All figures are period averages computed as simple arithmetic averages of the values recorded in the first and in the final years of the periods, to ensure consistency with our decomposition procedure. For a detailed description of the sectoral classification see the text in Appendix A1. For all other definitions and data sources, see Section 2.

The bottom panel of Table 13 shows the share of Ponzi firms in each sector across the same four periods. Two main patterns stand out. First, there is substantial variation over time and across sectors. A standard variance decomposition procedure applied to the period averages on Table 13 finds near identical values for both the within-sector and between-sector components of the overall standard deviation – about 10 percentage points each.[23] In addition to cross-sector variation, nearly all sectors display a noticeable increase

[23]The decomposition of the overall standard deviation uses the following transformation: $\tilde{P}_{i,p} = P_{i,p} - \bar{P}_i + \bar{P}$. Where P

in the share of Ponzi firms between 1970-1980 and 1990-2000. The share in the communications sector increases tenfold (from 3.5% to 36%), and nearly triples in manufacturing (excluding high-tech) and 'other' services sectors. The 2000-2014 trajectory shows more heterogeneity: there is a mix of increasing, stable and decreasing shares. The combined effect of these trends is, in part, responsible for the relative stability of the aggregate share of Ponzi firms after 2000.

We decompose the change in the aggregate incidence of Ponzi regimes in these four periods into a 'within-sector' component' (the change in the incidence of Ponzi regimes within sectors, holding the sectoral shares of the total number of firms fixed), and a 'between-sector' or 'structural change' component (the change in the sectoral shares, holding the incidence of Ponzi regimes within sectors fixed). We adopt a variation of a standard decomposition proposed by Timmer et al. (2014), which assigns a structural change component only to sectors that expand their share of total firms in the sample. Let J denote the set of sectors whose share fell between t and $t-k$, and let K denote the set whose share expanded. Then:

$$\Delta P_t = \sum_{i=1}^{N} \bar{S}_i \Delta P_{(i,t)} + \sum_{i \in K} \Delta S_{(i,t)} (\bar{P}_i - \bar{P}_J) \tag{1}$$

where i denotes sector; $P_{i,t}$ is the share of Ponzi firms in sector i at time t; $S_{i,t}$ denotes the share of sector i in total firms in the sample at time t, and $\bar{P}_J$ is the average share of Ponzi firms in shrinking sectors, weighted by the decline in each sector's employment share:

$$\bar{P}_J = \frac{\sum\limits_{i \in J} (S_i^T - S_i^0) \bar{P}_i}{\sum\limits_{i \in J} (S_i^T - S_i^0)} \tag{2}$$

The decomposition in Equation (1) assigns the structural change component only to expanding sectors, in proportion to the difference between a sector's average share of Ponzi firms and the average share of Ponzi firms in the shrinking sectors (given by Equation 2).[24] As an example, suppose the share of software firms

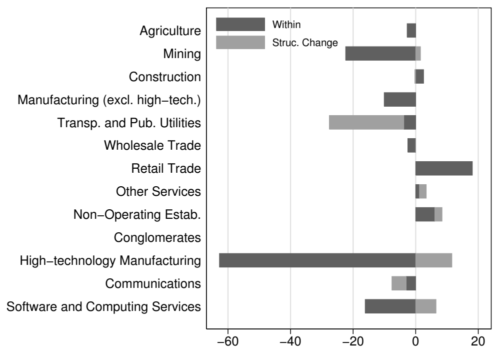
denotes the share of Ponzi firms, i denotes sectors, and p denotes periods. $\bar{P}_i$ denotes the average of P across periods in sector i, and $\bar{P}$ denotes the overall average of P. The within-sector standard deviation is the standard deviation of $\tilde{P}_{i,p}$; the between-sector standard deviation the standard deviation of $\bar{P}_i$ across all sectors.

[24]This decomposition is one example of a broader class of decompositions that can be expressed as:

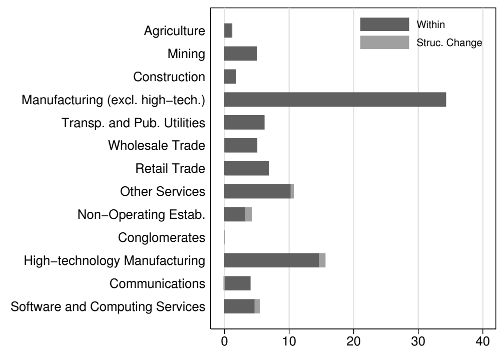
$$\Delta P_t = \sum_{i=1}^{N} \bar{S}_i \Delta P_{(i,t)} + \sum_{i=1}^{N} \bar{P}_i \Delta S_{(i,t)}$$

where P_t denote the aggregate share of Ponzi firms at time t. A bar over a variable denotes its average between times t and $t-k$. This equation(3) shows that the change in the aggregate share of Ponzi firms is equal to the sum of (1) within-sector changes in the share of Ponzi firms, weighted by the average sectoral shares between the two periods, and (2) the sum of changes in the sectoral shares in the total number of firms, weighted by the average share of Ponzi firms within each sector. The first term captures the within-sector component of the aggregate change, and the second captures the structural change component.

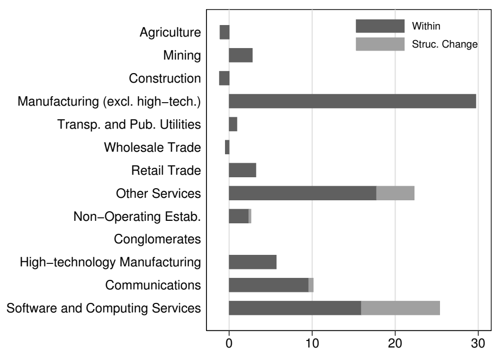
Figure 5: Sectoral contributions to change in aggregate share of Ponzi firms;
% of the observed change



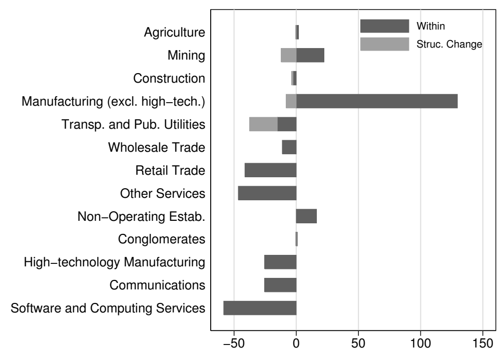
(a) 1970-1980



(b) 1980-1990



(c) 1990-2000



(d) 2000-2014

Notes: The figure shows sectoral contributions to the aggregate share of Ponzi firms for four sub-periods of the full sample period: 1970-1980; 1980-1990; 1990-2000; 2000-2014. All data are period averages computed as simple arithmetic averages of the values recorded in the first and in the final years of the periods, to ensure consistency with the decomposition procedure. For details of the sectoral classification and decomposition procedure used to generate these figures see the text in Appendix A1. For all other definitions and data sources, see Section 2.

increases at the expense of retail firms between 1980 and 1990, all else equal. In this case, the software sector is assigned a positive structural change contribution, as its average share of Ponzi firms is higher than that in retail in during the period (see Table 13). The retail sector is assigned a structural change contribution of zero. The results of this decomposition procedure are summarized in Table 4 in the text. Figure 5 provides a graphical presentation of these results, examining the contribution of each sector to observed changes in the aggregate share of Ponzi firms on account of the within-sector (the dark gray bars) and structural change components (the light gray bars). Individual contributions are shown as percentages of the change in the aggregate share of Ponzi firms in the period.

A.2 Additional regression results

Table 14: Marginal effects, logit estimations, probability of being Ponzi
(Cyclical component of GDP)

	(1)	(2)	(3)	(4)	(5)	(6)
Cyc output$_t$	-0.0158***	-0.0926***	-0.0746***			
	(0.0024)	(0.0123)	(0.0161)			
Cyc output$_{t-1}$		0.0829***	0.0889***			
		(0.0132)	(0.0166)			
Cyc output$_{t-2}$		0.0651***	0.0668***			
		(0.0128)	(0.0162)			
Δ(real gdp)$_t$				-3.7350***	-4.3726***	-6.4699***
				(0.4241)	(0.4916)	(0.6412)
Δ(real gdp)$_{t-1}$					-0.7987	-1.8234***
					(0.5050)	(0.6766)
Δ(real gdp)$_{t-1}$					1.9483***	0.7330
					(0.4868)	(0.6481)
Avg growth (7yr)			8.3424***			13.4385***
			(1.8080)			(1.9373)
Log total assets			-0.3303***			-0.3307***
			(0.0148)			(0.0147)
Firm FE	Y	Y	Y	Y	Y	Y
Year FE	N	N	N	N	N	N
Firms	6326	5898	3968	6326	5898	3968
Avg. obs/firm	17.16	15.58	14.12	17.16	15.58	14.12

Notes: The dependent variable is a binary variable indicating whether a firm is in a Ponzi regime in a given year. The estimations show the marginal effects from panel logit estimations: the change in the probability of being Ponzi for a 1% change in 'Cyc output' and 'Δ(real gdp)' respectively. 'Cyc output' denotes the cyclical component of GDP obtained from the Hodrick-Prescott filter. 'Δ(real gdp)' denotes real GDP growth. 'Avg growth (7 yr)' denotes the average growth in aggregate GDP over the previous seven years. Note that the logit estimations exclude all firms that do not see a transition into or out of Ponzi; as a result, the sample size is smaller than in the case of the linear probability models. GDP data is drawn from the Bureau of Economic Analysis (chained dollar measures); for all other definitions and data sources, see Section 2. The sample period is 1970-2014. Robust standard errors are in parentheses. $*p < 0.1$; $**p < 0.05$; $***p < 0.01$.

Table 15: Linear probability models, probability of being Ponzi
(Cyclical component of *sectoral* output)

Cyc output$_t$	-0.0015***	-0.0012***	-0.0026***	-0.0019***	-0.0023***	-0.0022***	-0.0030***	-0.0025***
	(0.0002)	(0.0002)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Cyc output$_{t-1}$					0.0014***	0.0015***	0.0013***	0.0013***
					(0.0003)	(0.0003)	(0.0004)	(0.0004)
Cyc output$_{t-2}$					0.0014***	0.0014***	0.0011***	0.0011***
					(0.0003)	(0.0003)	(0.0003)	(0.0003)
Log total assets		-0.0267***		-0.0230***		-0.0251***		-0.0232***
		(0.0007)		(0.0009)		(0.0008)		(0.0009)
Avg growth (7yr)			0.6355***	0.4291***			0.5810***	0.3959***
			(0.0712)	(0.0715)			(0.0729)	(0.0731)
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	N	N	N	N	N	N	N	N
Firms	11232	11232	11232	11223	11232	11231	11232	11223
Avg. obs/firm	16.75	16.72	12.41	12.40	14.88	14.86	12.02	12.01
Std Coeff (pp)	-0.43	-0.35	-0.74	-0.55	-0.66	-0.62	-0.85	-0.70
Uncond prob	17.5	17.5	17.5	17.5	17.5	17.5	17.5	17.5

Notes: The dependent variable is a binary variable indicating whether a firm is in a Ponzi regime in a given year. 'Cyc output' denotes the cyclical component of *sectoral* GDP obtained from the Hodrick-Prescott filter. 'Avg growth (7 yr)' denotes the average growth in aggregate GDP over the previous seven years. 'Std coeff (pp)' denotes the percentage point effect of a one standard deviation increase in 'Cyc output' on the probability of being Ponzi. 'Uncond prob' denotes the unconditional probability of being Ponzi. Sectoral GDP data is from the Bureau of Economic Analysis (chained dollar measures); there are nine sectors, based on standard SIC classifications. For all other definitions and data sources, see Section 2. The sample period is 1970-2014. Robust standard errors are in parentheses. *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

Table 16: Linear probability models, probability of being Ponzi
(Real *sector-level* output growth)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Δ(real gdp)$_t$	-0.1219***	-0.1289***	-0.1656***	-0.1564***	-0.1320***	-0.1483***	-0.1934***	-0.1905***
	(0.0150)	(0.0150)	(0.0174)	(0.0173)	(0.0164)	(0.0164)	(0.0190)	(0.0190)
Δ(real gdp)$_{t-1}$					-0.0462***	-0.0546***	-0.0997***	-0.0898***
					(0.0158)	(0.0157)	(0.0181)	(0.0181)
Δ(real gdp)$_{t-2}$					0.0115	0.0058	-0.0418**	-0.0331*
					(0.0160)	(0.0160)	(0.0180)	(0.0180)
Avg growth (7yr)			0.5238***	0.3808***			0.7327***	0.5901***
			(0.0656)	(0.0657)			(0.0760)	(0.0760)
Log total assets		-0.0270***		-0.0234***		-0.0255***		-0.0235***
		(0.0007)		(0.0009)		(0.0008)		(0.0009)
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	N	N	N	N	N	N	N	N
Firms	11232	11232	11232	11223	11232	11231	11232	11223
Avg. obs/firm	16.75	16.72	12.41	12.40	14.88	14.86	12.02	12.01
Industry-Year FE					N	N	N	N
$\sum$ Output Gap					-0.167	-0.197	-0.335	-0.313
p-value					1.56e-08	0	0	0
Std coeff (pp)	-0.55	-0.59	-0.75	-0.71	-0.60	-0.67	-0.88	-0.88
Uncond prob	17.5	17.5	17.5	17.5	17.5	17.5	17.5	17.5

Notes: The dependent variable is a binary variable indicating whether a firm is in a Ponzi regime in a given year. 'Δ(real gdp)' denotes sector-level real output growth. The cyclical component of *sectoral* GDP obtained from the Hodrick-Prescott filter. 'Avg growth (7 yr)' denotes the average growth in aggregate GDP over the previous seven years. 'Std coeff (pp)' denotes the percentage point effect of a one standard deviation increase in 'Δ(real gdp)' on the probability of being Ponzi. 'Uncond prob' denotes the unconditional probability of being Ponzi. Sectoral GDP data is from the Bureau of Economic Analysis (chained dollar measures); there are nine sectors, based on standard SIC classifications. For all other definitions and data sources, see Section 2. The sample period is 1970-2014. Robust standard errors are in parentheses. *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

Table 17: Linear probability model, speculative/Ponzi
(Cyclical component of GDP)

	(1)	(2)	(3)	(4)	(5)	(6)
Cyc output$_t$	-0.0124***	-0.0145***	-0.0134***			
	(0.0009)	(0.0012)	(0.0014)			
Cyc output$_{t-1}$		0.0103***	0.0099***			
		(0.0012)	(0.0014)			
Cyc output$_{t-2}$		0.0101***	0.0099***			
		(0.0012)	(0.0014)			
Δ(real GDP)$_t$				-0.9052***	-0.8404***	-0.9892***
				(0.0405)	(0.0454)	(0.0568)
Δ(real GDP)$_{t-1}$					-0.2879***	-0.3902***
					(0.0459)	(0.0578)
Δ(real GDP)$_{t-2}$					0.1379***	0.0387
					(0.0444)	(0.0553)
Avg growth (7yr)			0.9535***			1.8244***
			(0.1531)			(0.1668)
Log total assets			0.0052***			0.0038***
			(0.0013)			(0.0013)
Firm FE	Y	Y	Y	Y	Y	Y
Year FE	N	N	N	N	N	N
Firms	11232	11232	10187	11232	11232	10187
Avg. obs/firm	16.75	14.88	11.15	16.75	14.88	11.15
Std coeff (pp)	-1.06	-1.23	-1.14	-1.81	-1.68	-1.975
Uncond prob	75.5	75.5	75.5	75.5	75.5	75.5

Notes: The dependent variable is a binary variable indicating whether a firm is speculative *or* Ponzi in a given year. Note that one minus the probability of being speculative or Ponzi defines the probability of being hedge. 'Cyc output' denotes the cyclical component of GDP obtained from the Hodrick-Prescott filter. 'Δ(real gdp)' denotes sector-level real output growth 'Avg growth (7 yr)' denotes the average growth in aggregate GDP over the previous seven years. 'Std coeff (pp)' denotes the percentage point effect of a one standard deviation increase in 'Cyc output' or 'Δ(real gdp)' on the probability of being Ponzi. 'Uncond prob' denotes the unconditional probability of being speculative or Ponzi. GDP data is from the Bureau of Economic Analysis (chained dollar measures); for all other definitions and data sources, see Section 2. The sample period is 1970-2014. Robust standard errors are in parentheses. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table 18: Marginal effects, logit estimations, speculative/Ponzi
(Cyclical component of GDP)

	(1)	(2)	(3)	(4)	(5)	(6)
Cyc output$_t$	-0.0272***	-0.1360***	-0.1290***			
	(0.0020)	(0.0106)	(0.0133)			
Cyc output$_{t-1}$		0.0963***	0.0964***			
		(0.0111)	(0.0133)			
Cyc output$_{t-1}$		0.0888***	0.0901***			
		(0.0105)	(0.0125)			
Δ(real GDP)$_t$				-7.9101***	-7.5899***	-9.2355***
				(0.3554)	(0.4102)	(0.5376)
Δ(real GDP)$_{t-1}$					-2.4868***	-3.4082***
					(0.4063)	(0.5306)
Δ(real GDP)$_{t-2}$					1.2318***	0.3410
					(0.3886)	(0.5058)
Avg growth (7yr)			8.2515***			16.0901***
			(1.3720)			(1.5036)
Log total assets			0.0483***			0.0305***
			(0.0117)			(0.0117)
Firm FE	Y	Y	Y	Y	Y	Y
Year FE	N	N	N	N	N	N
Firms	7015	6446	4395	7015	6446	4395
Avg. obs/firm	18.84	17.57	16.41	18.84	17.57	16.41

Notes: The dependent variable is a binary variable indicating whether a firm is speculative *or* Ponzi in a given year. The estimations show the marginal effects from panel logit estimations: the change in the probability of being speculative *or* Ponzi for a 1% change in 'Cyc output' and 'Δ(real gdp)' respectively. Note that one minus the probability of being speculative or Ponzi defines the probability of being hedge. 'Cyc output' denotes the cyclical component of GDP obtained from the Hodrick-Prescott filter. 'Δ(real gdp)' denotes sector-level real output growth 'Avg growth (7 yr)' denotes the average growth in aggregate GDP over the previous seven years. Note that the logit estimations exclude all firms that do not see a transition into or out of Ponzi; as a result, the sample size is smaller than in the case of the linear probability models. GDP data is from the Bureau of Economic Analysis (chained dollar measures); for all other definitions and data sources, see Section 2. The sample period is 1970-2014. Robust standard errors are in parentheses. *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

Table 19: Effects of the sectoral output gap by quantile on the interest coverage ratio

	(1) Mean	(2) Mean	(3) Decile 1	(4) Decile 1	(5) Median	(6) Median	(7) Decile 8	(8) Decile 8
Cyc output$_t$	0.0007***	0.0011***	0.0017***	0.0021***	0.0005***	0.0007***	0.0004***	0.0009***
	(0.0002)	(0.0002)	(0.0002)	(0.0003)	(0.0001)	(0.0001)	(0.0001)	(0.0002)
Cyc output$_{t-1}$		-0.0009***		-0.0011***		-0.0004***		-0.0007***
		(0.0002)		(0.0003)		(0.0001)		(0.0002)
Cyc output$_{t-2}$		-0.0007***		-0.0012***		-0.0003***		-0.0004***
		(0.0002)		(0.0003)		(0.0001)		(0.0002)
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	N	N	N	N	N	N	N	N
Obs	226381	207770	226381	207770	226381	207770	226381	207770

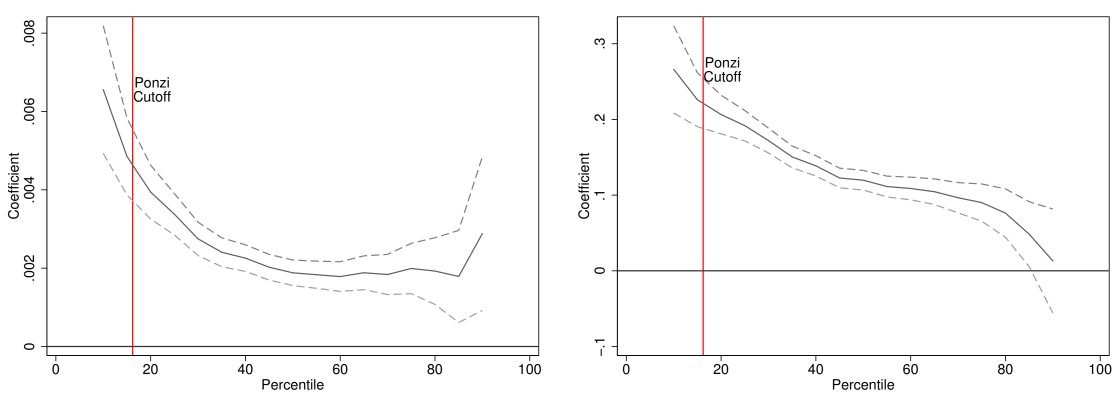
Note: The dependent variable is interest coverage as a ratio of total assets. 'Cyc output' denotes the cyclical component of *sectoral* output obtained from the Hodrick-Prescott filter. Column (1)-(2) shows the estimated effect of the (normalized) cyclical component of overall GDP on the population mean of the dependent variable obtained through a standard fixed-effects regression. Columns (3)-(8) show the estimates of the sectoral output gap on the 10th, 50th and 80th unconditional percentiles of the interest coverage ratio, obtained through the Recentered Influence Function (Rif) regression. For computational efficiency, we use demeaned data in the estimations; the reported standard errors are adjusted to reflect the correct number of degrees of freedom. Sectoral GDP data is from the Bureau of Economic Analysis (chained dollar measures); for all other definitions and data sources, see Section 2. The sample period is 1950-2014. Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 20: Effects of sectoral growth by quantile on the interest coverage ratio

	(1) Mean	(2) Mean	(3) Decile 1	(4) Decile 1	(5) Median	(6) Median	(7) Decile 8	(8) Decile 8
Δ(real gdp)$_t$	0.0623***	0.0695***	0.1119***	0.1089***	0.0492***	0.0516***	0.0400***	0.0436***
	(0.0075)	(0.0080)	(0.0132)	(0.0134)	(0.0030)	(0.0032)	(0.0073)	(0.0076)
Δ(real gdp)$_{t-1}$		0.0221***		0.0476***		0.0189***		0.0099
		(0.0073)		(0.0130)		(0.0031)		(0.0075)
Δ(real gdp)$_{t-2}$		-0.0049		0.0045		0.0060*		0.0055
		(0.0077)		(0.0129)		(0.0031)		(0.0075)
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	N	N	N	N	N	N	N	N
Obs	217596	197361	217596	197361	217596	197361	217596	197361

Notes: The dependent variable is interest coverage as a ratio of total assets. Δ(real gdp) denotes real GDP growth. Columns (1)-(2) show the estimated effect of real *sector-level* output growth on the population mean of the dependent variable, obtained through a standard fixed-effects regression. Columns (3)-(8) show the estimates of sectoral growth on the 10th, 50th and 80th unconditional percentiles of the interest coverage ratio, obtained through the Recentered Influence (Rif) regression. For computational efficiency, we use demeaned data in the estimations; the reported standard errors are adjusted to reflect the correct number of degrees of freedom. Sectoral GDP data is from the Bureau of Economic Analysis (chained dollar measures); for all other definitions and data sources, see Section 2. The sample period is 1950-2014. Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Figure 6: Effects of the output gap by quantile on the interest coverage ratio



(a) Cyclical component of GDP

(b) Real GDP growth

Notes: The figure shows the unconditional quantile regression estimates for the effect of the output gap and real GDP on interest coverage as a ratio of total assets. The dependent variable is interest coverage as a ratio of total assets. Estimates are shown of the overall output gap (panel (a)) and real GDP growth (panel (b)) across the distribution of the interest coverage ratio, obtained through the Recentered Influence (Rif) regression. For computational efficiency, we use demeaned data in the estimations; the reported standard errors are adjusted to reflect the correct number of degrees of freedom. GDP data is from the Bureau of Economic Analysis (chained dollar measures); for all other definitions and data sources, see Section 2. The sample period is 1950-2014. The dotted lines show 95% confidence intervals defined by robust standard errors.