An empirical analysis of Minsky regimes in the US economy

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*** Very preliminary draft ***

Abstract

In this paper we empirically analyze Minskian dynamics in the US economy by applying Minsky's classifications of financing regimes to a firm-level panel of nonfinancial corporations. We first map Minsky's definitions of hedge, speculative and Ponzi finance into firm-level data, and describe the incidence and evolution of Minksian regimes across nonfinancial corporations since the early 1970s. Second, we explore the relationship between fluctuations in the aggregate economy and firms' likelihood of being in a fragile finance regime, and find evidence of small short-run Minsky cycles. To do so, we use linear probability models relating a firm's probability of being Ponzi to aggregate and sectoral output gaps, and find that these output gaps – which capture variations in macroeconomic conditions exogenous to individual firms – are correlated with an increased probability that a firm is Ponzi. These results are corroborated by quantile regressions based on a continuous financial fragility measure – the interest coverage ratio – that identify differential effects of business cycles on financial fragility at different quantiles of the interest coverage distribution.

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 (1986, 1992)

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puts forward a theory of cycles defined by the economy's oscillation between periods characterized by robust financing arrangements, and periods of increasing 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, as hedge firms generate more than sufficient operational cash flows to service both interest and principal obligations. Speculative firms, in contrast, roll over principal on maturing debt, and Ponzi structures are the most fragile, requiring firms to also roll over interest payments. At the aggregate level, financial 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, more risk-taking and, in turn, increasingly fragile finance.

A long-standing theoretical literature analyzes Minsky's approach to financial fragility and integrates Minskian dynamics into growth and distribution models (as examples, see Taylor and O'Connell, 1985; Skott, 1995; Ryoo 2010). There has also been a resurgence of both popular and academic interest in Minskian dynamics after 2008 received widespread attention as a possible "Minsky moment" (Kregel, 2008; Dymski, 2010; Ryoo, 2013). Empirical applications of Minsky's financial fragility hypothesis, however, are limited.[4] One exception is Mulligan (2013), who finds Minskian dynamics better-characterize over-leveraged sectors, and that crises spread from more to less leveraged sectors. At its core, however, Mulligan distinguishes industries that more or less strongly exemplify Minskian dynamics and, thus, neither explicitly analyzes the incidence of Minskian regimes in the US, nor how the incidence of these regimes correlate with macroeconomic conditions. Furthermore, Mulligan's criterion for classifying firms into different regimes is somewhat arbitrary, and does not map closely to Minsky's definitions. Firm-level data, however, provide a unique opportunity to analyze the dynamics of Minsky's financial instability hypothesis. Detailed cash flow data harness firm-level variation, and allow for an empirical complement to theoretical approaches surrounding Minskian dynamics, as well as to questions arising out of this theoretical literature such as the distinction between short-term cycles and longer-term waves.

In this paper we empirically analyze Minskian dynamics in the US economy by applying Minsky's classifications of financing regimes to a firm-level panel of nonfinancial corporations. Our first contribution lies in a set of descriptive results describing the incidence and evolution of Minksian regimes across nonfinancial firms since the early 1970s. We document a trend increase in the share of firms with Ponzi financing structures, driven by an increased share of small regimes among small firms, defined as those in the bottom quartile of the asset distribution.. We also document that small firms become

4 Note that, while few empirical papers directly engage Minsky's financial instability hypothesis, Minsky's work is credited in a line of empirical research emphasizing the role of financial factors in firm investment decisions (for a discussion see Fazzari 1999).

increasingly likely to enter the sample as Ponzi over the post-1970 period, but that firms with above-median firm size are more likely to transition to Ponzi from a previous speculative regime.

Second, we find robust and statistically significant evidence that economic contractions are correlated with an increased probability that a firm is in a more fragile financing regime. These results are based, first, on linear probability models that relate a firms' probability of being Ponzi to aggregate and sector-specific output gaps, which capture variations in macroeconomic conditions exogenous to the individual firm. Quantile regressions based on the interest coverage ratio – a continuous measure of fragility – corroborate these results, and highlight that short-run Minsky cycles operate more strongly at smaller quantiles of the interest coverage distribution as compared to the mean. The economic magnitude of this estimated effect is small, pointing to relatively small short-term Minsky cycles. {Finally, we show preliminary evidence of medium run cycles, wherein higher average sectoral growth is associated with an increased probability of Ponzi financing structures. This result suggests that sustained growth episodes breed 'exuberance' that leads, in turn, to growing fragility; however, the magnitude of the results are again small}.

The paper is organized as follows. Section 2 introduces our empirical application of Minskian regimes to firm-level data. Section 3 describes the incidence and evolution of financing regimes across the nonfinancial corporate sector since the early 1970s. Section 4 analyzes the short-run and medium-term relationship between the business cycle and the probability of Ponzi finance. Section 5 concludes.

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 the firm-level data, so as to classify firms as either hedge, speculative or Ponzi.[5] As noted in the introduction, these classifications are based on cash flows and, in particular, the relationship between a firm's cash inflows from operations and a firm's interest and principal obligations on outstanding debt.[6] To classify firms into financing regimes, we therefore identify a firm's (1) net sources of cash for meeting financial obligations, and (2) interest and principal obligations. Based on the relationship between these sources of funds and cash commitments we, first, apply Minsky's definitions of hedge, speculative and Ponzi financing regimes to individual firm-year observations in the firm-level data. In addition, we construct an interest coverage ratio, which provides a continuous counterpart to these discrete regime classifications, comparing sources of cash to interest payments.

5 See Minsky (1986, Ch. 9) for a complete discussion of these regimes.

6 Note that, while Minsky's writing distinguishes between expected and realized cash flows, our analysis is based on recorded cash flow data and, thus, realized cash flows.

2.1 Data

The regime classifications are applied to a firm-level panel of nonfinancial corporations in the US 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 limiting 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 describe a significant proportion of real economic activity, these firms are of independent importance.

2b. Sources of cash

The firm's relevant sources of funds are those cash inflows from operations that a firm can use to cover financial commitments, namely interest and principal obligations. To align our regime classifications with Minsky's definitions, we define these sources of cash on the basis of three principles. First, we define cash inflows after accounting for expenses such as wages and salaries, which have a prior claim on cash flow relative to interest and principal payments. Second, we only include sources of funds that generate liquid cash inflows; thus, we exclude, for example, depreciation. Third, we exclude cash inflows that result from activities such as new borrowing, new equity issuance, or the sale of financial assets. This restriction reflects that the point of Minksy's taxonomy of regimes is to indicate the extent to which discrepancies between sources of cash and required financial commitments give rise to new borrowing or financial asset sales.

Given these principles, we define a firm's net sources of cash to be 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 the primary component of a firm's relevant sources of cash. These cash inflows include both operating and non-operating income, which are defined as net income concepts (i.e. net of operating expenses such as salaries, and non-operating expenses such as foreign exchange adjustments and moving expenses). Note also that this category includes interest income; we include interest income because interest reflects a cash inflow from the *ownership* of financial assets, rather than the *sale* of financial assets. *Other funds from current activities* include, for example, foreign currency exchange adjustments. *Funds from investment activities* include net cash flows obtained from the sale of property, plant and equipment, and the sale of other investments.

When using the three aggregate variables above to construct our measure of sources of funds, however, we confront two problems. First, a large share of observations for the aggregate measures above are missing, including over 77% of the observations for *funds from operations* (item #110). The reason for so many missing observations is that many of the less important components of the aggregate measure are not reported, and in those cases the observation is assigned a missing value.

To work around this problem, we construct our own measure of *funds from operations* using its individual components (obtained from the income statement and from the statement of cash flows). Our procedure consists in using the main components of funds from operations *as is*, and then imputing zeros to missing observations for the remaining components. The main item used *as is* is *income before extraordinary items* (item #18). This item includes net income from operations and net non-operational income (see above). Since it is computed net of interest payments, we add to this variable *interest payments* (item #15). The sum of these two components is the most relevant (both conceptually and quantitatively) source of funds for our regime classification. The other items used *as is* exclude depreciation and amortization (item #14, which is added since it is a non-cash expense deducted from operational income), and extraordinary items and discontinued operations (item #48). The items with zeros imputed for missing observations include deferred taxes (item #126), *equity in net loss* (item #106, an adjustment for the unremitted portion of an unconsolidated subsidiary's earnings), *sale of property, plant and equipment and sale of investments – loss* (item #213, an adjustment for gains or losses relative to the book value of sold assets).

We follow a similar procedure for the two other components of our baseline measure of sources of funds: we impute zeros for missing observations of *other funds from current activities*, and we impute zeros for missing observations of the two subcomponents of *funds from investment activities/sale of property, plant and equipment* (item #107) and *sale of investments* (item #109). By making these adjustments, we reduce the proportion of missing observations for our baseline measure of sources of funds to 12.25%.

The second problem is that it becomes difficult to distinguish cash flow from operations from cash flows reflecting factors like new borrowing or asset sales due to financial distress. In particular, three aspects of the definition above fall into a gray zone. First, the main subcategory of operating income, as mentioned above, is *income before extraordinary items and interest payments* (item #18). This category includes inflows resulting from extraordinary contingencies (such as a fire or a flood) that are legitimate to include according to the principles laid out above. However, this category also includes flows that are likely derived from financial decisions (profit or loss on repurchase of debentures) or business decisions (profit or loss on the disposal of a division). Thus, some part of these sources of funds could, in principle, occur in response to the need to service financial obligations. Second, operating income similarly includes a subcategory of net cash flows derived from *sale of property, plant and equipment* (item #107). It is, in principle, impossible to tell whether these non-recurring cash inflows from the sale of financial assets are the result of standard operating decisions (e.g. I sell a subsidiary because it is not profitable) or the result of financial distress (e.g. I sell a subsidiary to meet my financial obligations). Third, cash inflows resulting from the *sale of investments* (#109) include, among other components, sale of stake in unconsolidated subsidiaries; it is unclear if such a divestment reflects business considerations, or burdensome financial obligations.

Our baseline definition of sources of cash, which includes these three components, therefore, reflects an upper bound on firms' relevant cash inflows. Thus, this definition effectively biases our firm classifications away from financial fragility, rather than towards financial fragility. To account for these ambiguities, however, we also compare this definition to alternative measures of cash inflows excluding these three sub-components. The alternative measures co-move strongly with our baseline definition and generate descriptive patterns that closely match those for the primary definition of sources of funds that we utilize, reflecting that the main component of our measure of firm's sources of funds is *funds from operations*.

2.3 Cash commitments

In accordance with Minsky, the firm's key cash commitments that define the robustness or fragility of its financial structure include interest payments on outstanding debt and principal payments. As noted above, operating and non-operating expenses have a first claim on cash prior to financial obligations, which are accounted for via deductions from the income items. Furthermore, all other 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 on debt in excess of the portion of long-term debt coming due in a particular year are excluded from the firm's cash commitments, thereby disentangling *required* principal payments from a firm's (discretionary) decision to reduce its stock of long-term debt.

Based on these considerations, we utilize data for interest and principal payments. We draw interest payments directly from the Compustat data (item #15). However, there is no Compustat variable that directly captures principal payments. To measure principal payments we construct a variable that is the sum of short-term (current) liabilities and that portion of long-term debt that comes due in year t. By this definition, principal payments include debt in current liabilities (accounts payable, other current liabilities, and notes payable), and the portion of long-term debt that is due that year. Finally, because these liabilities are defined as end-of-period stocks, we define principal payments in year t to be a function of these stocks in year $t-1$.

2.4 Hedge, speculative and Ponzi finance

The relationship between sources of funds, and interest and principal payments defines the regime classification of any firm-year observation. In line with Minksy's definitions, laid out above, a firm-year observation is classified into a particular financing regime based on the relationship between a firm's sources of funds and cash commitments: a firm is hedge if its sources of cash exceed both its interest and principal payments; speculative if sources of cash cover interest commitments but not principal commitments; and Ponzi if sources of cash are insufficient to cover both principal and interest payments. These definitions are summarized in Table 1. Based on these definitions, we have sufficient non-missing observations to generate a panel of regime classifications between 1970-2014. In addition to these discrete classifications, we construct an interest coverage variable, defined as sources of cash less interest payments, and scaled by total assets. Interest coverage provides an alternative, continuous measure of firm-level financial fragility. While we have insufficient non-missing observations to generate discrete regime classifications prior to 1970, interest coverage does not require data on principal payments such that we can extend it to 1950.

[Table 1 here]

3. The evolution and incidence of financing regimes

On the basis of these classifications, we turn to the incidence and evolution of financing regimes in the US nonfinancial corporate sector. Figure 1 plots the share of hedge, speculative and Ponzi firms in the total sample of nonfinancial firms between 1970 and 2014. Figure 1 points, most notably, to a post-1970 trend increase in the share of Ponzi firms in the US nonfinancial corporate sector – primarily prior to the early 2000s. Concurrent with this growth in the share of firms in Ponzi finance regimes, the share of total firms in speculative financing regimes declines. Finally, despite short-term oscillations, the share of hedge firms remains relatively constant.

[Figure 1 here]

[Figure 2 here]

Importantly, the increased share of Ponzi firms is largely driven by growth in the number of small firms that are Ponzi. To highlight this trend, Figure 2 decomposes Figure 1 for firms in the top and bottom quartile of the asset distribution. These sub-sample plots highlight two key points. First, firms in the largest quartile of the asset distribution are most commonly speculative, and the composition of financing regimes among this largest quartile of firms does not trend over time. Second, the increased number of Ponzi firms over the post-1970 period shown in Figure 1 is driven by an increased number of small firms with Ponzi financing structures. Because the increase in Ponzi structures are concentrated among small firms, the share of total assets under a Ponzi financing structure trends much less significantly over the post-1970 period than the share of total firms under Ponzi regimes. Figure 3 plots the share of total assets under Ponzi regimes, and indicates that – despite sharp spikes in 2001 and 2007 – the share of total assets under Ponzi financing regimes is relatively stable in the post-1970 US economy.

Note, furthermore, that small firms are Ponzi due, primarily, to negative *sources* of cash, as opposed to high financial commitments. The growing share of negative values for our baseline measure of sources of cash, in turn, is a result of an increase in the share of small firms with negative sales for *income before extraordinary items* (net of interest payments), which as described above is our primary source of cash. Indeed, in 1971, 19% of the firms in the bottom quartile of the asset distribution reported a negative value for this measure. In 2014, by contrast, that proportion was 79%.

[Figure 3 here]

These trends raise questions about the previous state of Ponzi firms. Namely, does the trend increase in Ponzi finance reflect the fact that more firms are *entering* the sample as Ponzi? Do a significant proportion of firms *transition* into Ponzi from other financing regimes, as a result of a combination of idiosyncratic firm-specific and external factors? Firms that become Ponzi in any given year, t, can have entered Ponzi from one of three previous states: (1) the firm may have entered the sample in year t; (2) the firm may have been speculative in year t, or (3) the firm may have been hedge in year t. Figure 4 plots the shares of Ponzi firms that became Ponzi from each of these three previous states for the smallest and largest quartile of firms between 1970 and 2014. The figure points to two different stories by firm size. First, small firms have increasingly *entered* the nonfinancial corporate sector with fragile financing structures – i.e. as Ponzi firms. This trend suggests that growth in the share of Ponzi firms reflects growth in the share of small corporations that IPO with fragile financial structures (due to negative sources of cash). Large firms, on the other hand, are more likely to become Ponzi from previously being speculative, such that large firms do in fact *switch* between more and less fragile financing regimes.

Table 2 summarizes these descriptive statistics by firm size, highlighting the status of Ponzi firms in the year before they transitioned to Ponzi for the full sample as well as for the smallest and largest quartile of firms. In the full sample, as among large firms, firms are most likely to switch into Ponzi from previously being speculative. Small firms, on the other hand, are more likely to join the sample as Ponzi. Note that Table 2 provides an additional level of detail as compared to Figure 3. In particular, Table 2 divides firms entering the sample into three sub-categories: firms that join for the first time; firms that were already in the sample but were missing data necessary for assigning a regime classification; and firms that were previously in the sample, exited and re-joined. Figure 4 combines these three ways of 'joining' the sample within the single category 'joined'.

[Figure 4 here]

[Table 2 here]

4. Financing regimes and the business cycle

In this section we present two sets of estimations that explore the link between fluctuations in macroeconomic conditions and a firm's probability of being in a fragile (specifically, Ponzi) financing regime. Accordingly, these estimations explore the possibility of short-term Minsky cycles in the US economy. First, we estimate the effect of the output gap on a firm's probability of being Ponzi using a series of linear probability models. Second, we turn to the (continuous) interest coverage ratio, and utilize quantile regressions to estimate the effect of the output gap on interest coverage across the distribution of the interest coverage ratio (i.e. as opposed to exclusively at the mean). With both methodologies we find evidence of a negative contemporaneous relationship between the cyclical component of output (the output gap) and financial fragility. These results suggest that economic contractions are associated with (small) increases in firm-level financial fragility, pointing to (small) short-run Minsky cycles in the US economy.

In these estimations we draw on two definitions of the output gap: one is defined as the cyclical component of US GDP extracted using the Hodrick-Prescott filter, and the other is based on the cyclical component of sector-level output series. The sector-level output gap introduces additional variation masked in the aggregate level output gap; because of significant co-movement between different sectors in the US economy, however, we find qualitatively similar results when using the two definitions of the output gap. Both the GDP and sector-level data are drawn from the BEA (chained dollar measures).[7]

4.1 Linear probability models, and the probability of being Ponzi

We begin with linear probability models estimating the relationship between fluctuations in economic conditions external to individual firms and the probability that a firm is Ponzi. These estimations explore the role of short-run business cycle fluctuations in firm-level financial fragility. Tables 3 presents these baseline regressions using the cyclical component of sector-level output. These regressions are premised on the fact that the cyclical component of sectoral output reflects changes in economic conditions that may affect financing structures, but that are exogenous to the individual firm. Thus, in each case, the primary relationship of interest is between the contemporaneous component of the cyclical component of GDP and the probability of being Ponzi, described by the coefficients in the first row of each. All specifications include firm-level fixed effects; note, however, that because the aggregate

7 There are 9 sectors, according to standard SIC definitions.

output gap absorbs year-specific variation, and because there is significant sector co-movement over time, time fixed effects are not included.

[Table 3 here]

The estimates in Table 3 point to a negative and statistically significant relationship between the contemporaneous cyclical component of output and the probability of being Ponzi in all specifications, such 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 specification, looking at 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. The relationship is negative and statistically significant at the 1% level. However, the economic magnitude of the estimated coefficient is small. In Column 2, for example, a one standard deviation increase in the magnitude of the cyclical component of GDP leads to a 0.31 percentage point decline in the probability of being Ponzi. Thus, the results point to small short run Minsky cycles, such that a 'larger contraction' leads to a larger likelihood of being Ponzi, although the magnitude of this short run effect is quite small.

This qualitative result is corroborated in the remaining columns of Table 3. First, Columns 3 and 4 include two additional lags of the cyclical component of GDP in the estimations, again with and without a control for total assets. Subsequently, the remaining columns include a control for longer-term average growth in the sector, defined by the seven-year geometric average growth rate. Thus, Columns 7 and 8 present the most exhaustive specification; in Column 8, in particular, we include controls for two lags of the sector-level output gap, seven-year average growth, and log of total assets. Column 8 again highlights the negative statistically significant relationship between the cyclical component and the probability of being Ponzi. While the coefficient has increased relative to the most parsimonious specification, the magnitude of the relationship remains small. In the specification including total assets (Column 8), a one standard deviation increase in average growth is associated with a 0.62 percentage point increase in the probability of being Ponzi. [The qualitative results hold, with similar magnitudes, if the regressions utilize GDP growth rather than the cyclical component of GDP; we will report the regressions using GDP growth in the next verison of this paper].

Finally, turn to the coefficients describing the relationship between seven-year average growth and the probability of being Ponzi. In each regression that includes the average growth variable, the coefficient on average growth is positive and strongly statistically significant. This result suggests that, in addition to short-run business cycle effects, Minskian financial instability may reflect medium-run cyclicality. In this case, the short-run cyclical effect may be nested within a medium-term cycle, during which sustained growth episodes breed 'exuberance' and, thus, behavior that generates financial fragility.

The final two columns of Table 3 estimate this effect independently, and corroborate the positive coefficient. However, the magnitude of the estimate is, again, small.

Table 4 compares the results in Table 3 to specifications including year fixed effects. These results are provided as a basis for comparison; however, as noted above, the fact that sectors in the US economy co-move so significantly suggests that year fixed effects may not be necessary insofar as they absorb a significant amount of the time-specific variation – for example in business cycle conditions – that is captured via the cyclical component of sectoral output.

[Table 4 here]

4.2 A continuous measure of financial fragility

Next, we extend this analysis to the continuous measure of interest coverage, defined – as noted in Section 2.4 above – as net sources of cash less interest payments, scaled by total assets. While these regressions move beyond the explicit application of Minsky's definitions, the interest coverage ratio has at least two advantages. First, we are able to exploit the variation inherent in a continuous measure of fragility. Second, one plausible reason for the low estimated effects of the current cyclical component of GDP on the probability of being Ponzi is that, given the descriptive statistics above, we may expect different effects of business cycle conditions on financial fragility at quantiles of the asset distribution distinct from the mean. In particular, business cycle fluctuations should impact firms differently depending on the degree to which their financing regime depends on current earnings from operations, which are presumably more sensitive to business cycle variations than other sources of cash inflows.

[Figure 5 here]

Importantly, the distribution of the interest coverage ratio is highly skewed. Figure 5 plots the interest coverage ratio over time for the full sample of firms, and for sub-samples describing the largest decile and the smallest quartile in the asset distribution in any given year. Because of the highly skewed distribution of the interest coverage ratio, we utilize quantile regressions (reflecting the fact that we expect a different estimated effect at the mean than at the tails). To account for outliers, the variable is trimmed.

[Table 5 here]

[Figure 6 here]

We explore this hypothesis by examining the effects of current business cycle conditions on our measure of interest coverage as a ratio of total assets (described in Section 2.4). Unlike the binary regime classification measures, the interest coverage measure is continuous. This fact allows us to test whether changes in the cyclical component of GDP or in current GDP growth have differential effects on different quantiles of the measure. As suggested by Figure 5, larger firms are more likely to have positive interest coverage – and, thus, are less likely to be in a Ponzi regime. Indeed, the average interest coverage measure (as a ratio to total assets) among firms in the bottom quartile of the asset distribution is -0.076, while it rises to about 0.10 among firms in the remaining quartiles. But larger firms are arguably less dependent on current sales to generate cash flows, as opposed to non-operational sources of income stemming from the ownership of assets. Thus, a plausible hypothesis is that the impact of current business cycle conditions on the interest coverage measure will differ at different quantiles of its distribution.

To investigate this hypothesis, we utilize the recentered influence function (RIF) regression to estimate the effect of the cyclical component of GDP and GDP growth on different quantiles of the distribution of the interest coverage measure (see Firpo et al., 2009). Just like standard OLS regressions produce estimates of the impact of an independent variable of interest on the unconditional mean of the dependent variable, RIF-regressions estimate the impacts of on given unconditional quantiles of the dependent variable.[8] Table 5 shows the effects of variation in the (normalized) cyclical component of GDP on interest coverage as a ratio to total assets. Column 1 shows the estimated effect on the mean, obtained from a standard fixed effects regression, while Columns 2-4 show the estimates of the cyclical component of overall GDP on the 1st, 5th and 8th unconditional deciles, obtained from the RIF-regressions. A comparison across columns suggests that changes in the cyclical component of GDP are estimated to have a larger impact on lower deciles of the interest coverage measure than on the mean, the median, or upper deciles. This finding is corroborated in the first panel of Figure 6, which shows the estimated effects for a range of percentiles – from the 10th to the 90th in increments of 5. Figure 6 shows a monotonic decline in the estimated coefficient until about 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.

Despite these differential effects, our quantile regressions show small short-run effects of cyclical GDP on interest coverage and, by implication, on a firm’s finance regime. For example, Column 1 of Table 5 suggests that a one standard deviation increase in normalized GDP (0.73 in the 1950-2014 period) is estimated to raise the mean of the interest coverage measure by only 0.002. In comparison with an unconditional mean of interest coverage as a ratio of total assets 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 ratio is -0.086, which still implies a relatively small effect and certainly not one that would suffice to elicit a regime switch.

Empirically plausible cyclical fluctuations only suggest a regime switch for those firms that are already near the cut-off of zero interest coverage, beyond which they would switch from Ponzi to

8 Note that this property differs from conventional quantile regressions, which estimate impacts on conditional (on the included covariates) quantiles of the distribution of the dependent variable.

speculative. Indeed, an interest coverage of (approximately) zero corresponds to the 16th percentile of the distribution (indicated by the vertical red line in Figure 1). Given the estimated coefficient at the 15th percentile (shown in the first panel of Figure 6), 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 described above, their proportion as a share of the total number of Ponzi firms would be small.

[Table 6 here]

Finally, Table 6 and the accompanying panel in Figure 6 tell a qualitatively similar story for changes in the rate of growth in real GDP. Again, the coefficients on contemporaneous growth are about 2.5 times larger for the first decline than for the median and above. 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 the interest coverage measure would be 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 generate a picture of the incidence and evolution of Minsky's financing regimes across the nonfinancial corporate sector in the post-1970 US economy. We ask two sets of questions. First, what is the incidence and evolution 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?

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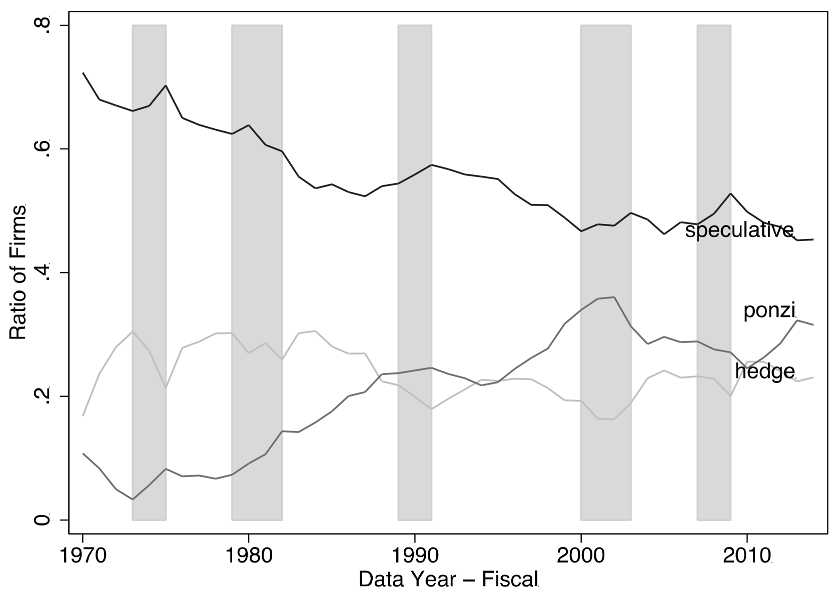
Tables and figures:

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
	[Sources of cash – Interest Payments – Principal Payments] < 0
Ponzi	[Sources of cash – Interest Payments] < 0

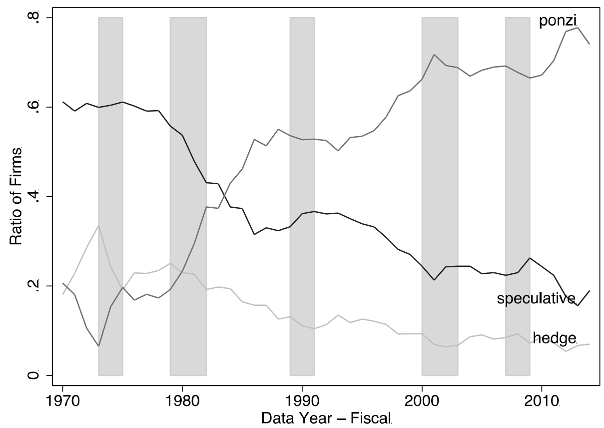
Figure 1: Incidence of hedge, speculative and Ponzi financing regime
Full sample of firms; 1970-2014



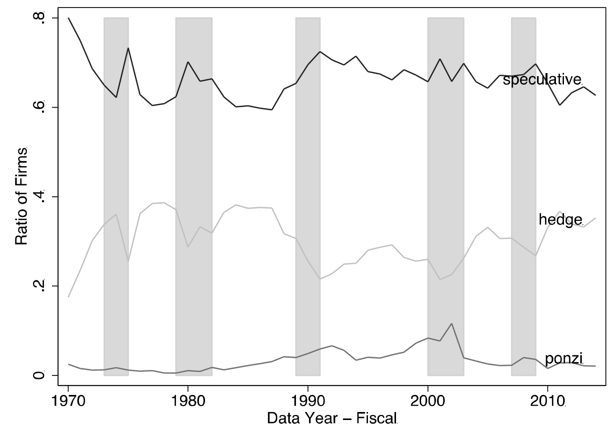
Notes: Shaded areas refer to full peak-to-trough periods for real GDP, obtained using the Hodrick-Prescott filter.

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

2a: First quartile

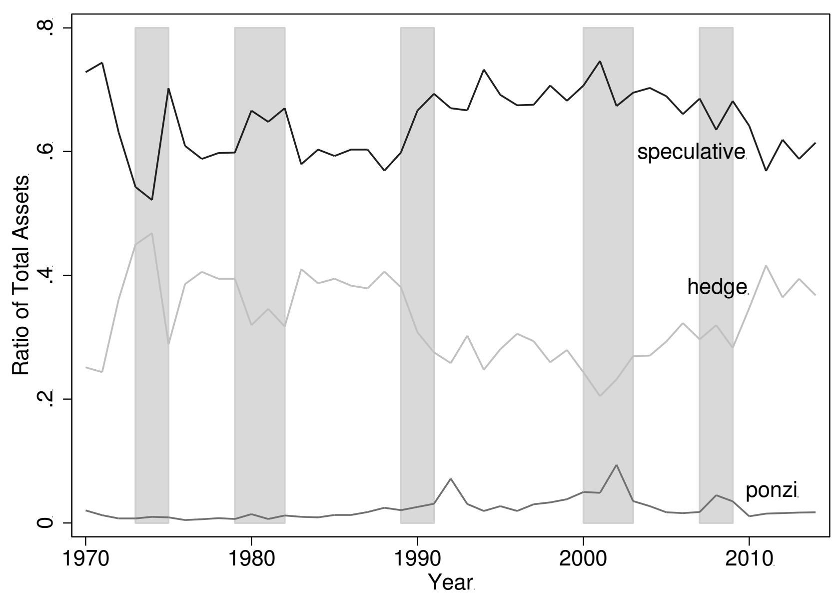


2b: Second quartile



Notes: Shaded areas refer to full peak-to-trough periods for real GDP, obtained using the Hodrick-Prescott filter. Quartiles are calculated on the basis of percentile of the asset distribution.

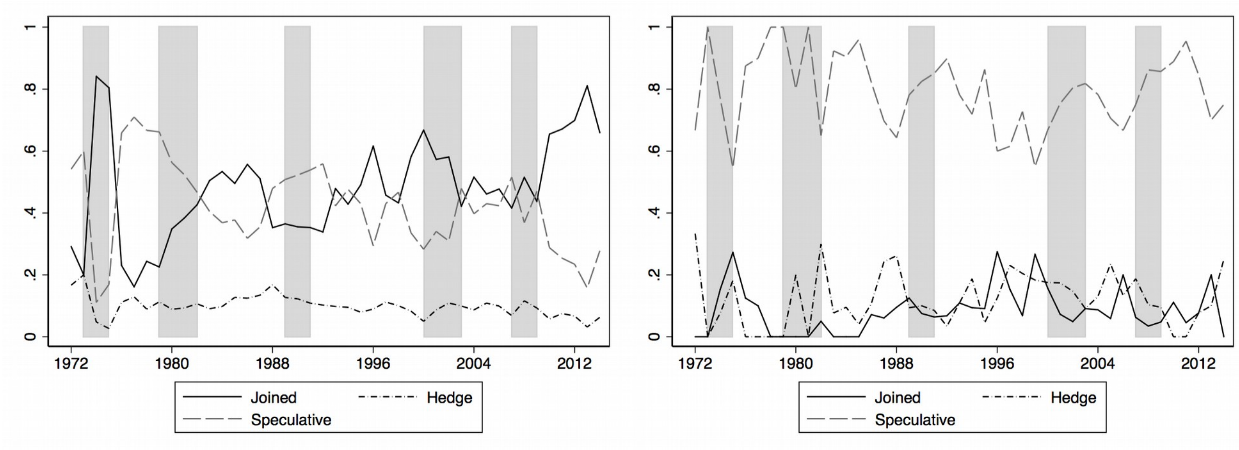
Figure 3: Hedge, speculative and Ponzi financing regimes as shares of total assets
Full sample of firms; 1970-2014



Notes: Shaded areas refer to full peak-to-trough periods for real GDP, obtained using the Hodrick-Prescott filter.

Figure 4: Status of firms before transitioning to Ponzi (% of total switches into Ponzi from a particular previous state)

4a: First quartile 4b: Fourth quartile



Notes: Shaded areas refer to full peak-to-trough periods for real GDP, obtained using the Hodrick-Prescott filter. These figures plot the *previous year's* state of firms that are Ponzi in year t (i.e. for firms that are Ponzi in year t, what was the state of these firms in year t-1?). For each firm there are three possibilities: the firm can either enter the sample in year t (did not exist in year t-1), have been speculative in year t, or have been hedge in year t.

Table 2: Status of firms in the year before transitioning to Ponzi (% of total switches into Ponzi from a particular previous state)

	All firms	1st Quartile	4th Quartile
Joined	36.2%	50.1%	10.5%
New firm	17.7%	25.9%	4.3%
1st after missing	13.8%	18.0%	4.5%
Rejoined	4.7%	6.2%	1.7%
Speculative	10.4%	9.7%	12.9%
Hedge	54.4%	40.2%	76.6%

Notes: For each firm there are three possibilities: the firm can either enter the sample in year t (did not exist in year t-1), have been speculative in year t, or have been hedge in year t. In this table, the "joined" category is, furthermore, divided into three categories: (1) a new firm; (2) 1st regime observation after missing regime observations; (3) a firm rejoined the sample after previously being missing.

Table 3: Linear probability models with cyclical component of sector-level output
Dependent variable: the probability of being Ponzi

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Cyclical output	-0.0014***	-0.0011***	-0.0022***	-0.0020***	-0.0027***	-0.0021***	-0.0033***	-0.0026***		
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0004)	(0.0004)		
L1.Cyclical output			0.0016***	0.0017***			0.0016***	0.0016***		
			(0.0003)	(0.0003)			(0.0003)	(0.0003)		
L2.Cyclical gap			0.0014***	0.0013***			0.0011***	0.0010***		
			(0.0003)	(0.0003)			(0.0003)	(0.0003)		
Avg growth (7 years)					0.6591***	0.4601***	0.5939***	0.3972***	0.3564***	0.2257***
					(0.0949)	(0.0944)	(0.0961)	(0.0957)	(0.0828)	(0.0819)
Log of total assets		-0.0272***		-0.0258***		-0.0231***		-0.0230***		-0.0237***
		(0.0012)		(0.0013)		(0.0016)		(0.0016)		(0.0015)
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	N	N	N	N	N	N	N	N	N	N
Firms	12358	12358	12355	12355	11203	11203	11203	11203	11203	11203
Avg. Obs. per Firm	15.74	15.74	14.80	14.80	11.81	11.81	11.72	11.72	11.81	11.81

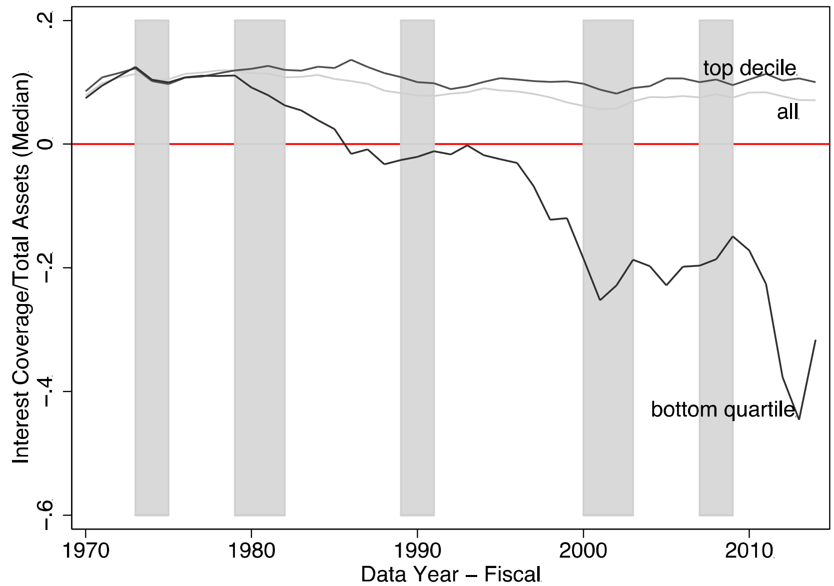
Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4: Linear probability models with cyclical component of sector-level output
Dependent variable: the probability of being Ponzi (including year fixed effects)

VARIABLES	(1)	(2)	(3)	(4)	(7)	(9)	(8)	(10)	(5)	(6)
Cyclical output	0.0000	-0.0002	-0.0001	-0.0003	-0.0010*	-0.0016***	-0.0011**	-0.0017***		
	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0006)	(0.0005)	(0.0006)	(0.0005)		
L.1 Cyclical output			0.0005	0.0003			0.0006	0.0004		
			(0.0004)	(0.0004)			(0.0005)	(0.0005)		
L.2 Cyclical output			-0.0001	-0.0004			0.0004	-0.0001		
			(0.0004)	(0.0004)			(0.0005)	(0.0005)		
Avg growth (7 years)					0.2676*	0.4048***	0.2256	0.4013***	0.1495	0.2177*
					(0.1502)	(0.1416)	(0.1534)	(0.1451)	(0.1229)	(0.1171)
Log of total assets		-0.0551***		-0.0552***		-0.0571***		-0.0573***		-0.0570***
		(0.0017)		(0.0018)		(0.0023)		(0.0023)		(0.0023)
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Firms	12358	12358	12355	12355	11203	11203	11203	11203	11203	11203
Avg. Obs. per Firm	15.74	15.74	14.80	14.80	11.81	11.81	11.72	11.72	11.81	11.81

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Figure 5: The interest coverage ratio
Full sample of firms, top decile and bottom quartile; 1970-2014



Notes: Shaded areas refer to full peak-to-trough periods for real GPP, obtained using the Hodrick-Prescott filter.

Table 5: Effects of the Output Gap by Quartile (RIF Regressions)

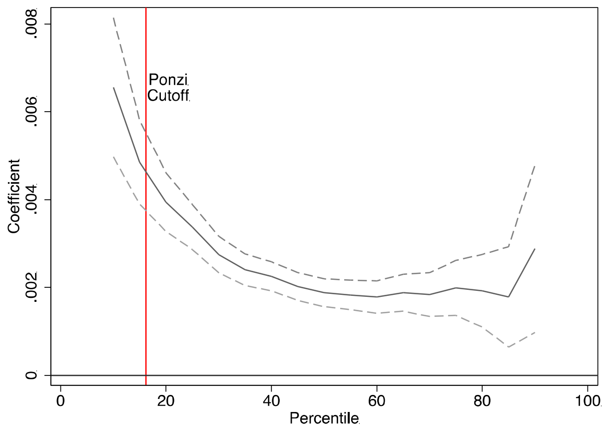
	(1) Mean	(2) 1st Decile	(3) Median	(4) 8th Decile
Cyclical GDP_t	0.00307***	0.00656***	0.00188***	0.00193***
	(0.00050)	(0.00081)	(0.00016)	(0.00042)
Firm FE	Y	Y	Y	Y
Year FE	N	N	N	N
Obs	226,381	226,381	226,381	226,381

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: The dependent variable is the interest coverage as a ratio to total assets. Column (1) 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 (2)-(4) show the estimates of the overall output gap on the 10^{th}, 50^{th} and 80^{th} unconditional percentiles of the interest coverage ratio, obtained through the Recentered Influence Function (Rif) regression. For a description of the methods and data sources, see the text.

Figure 6: Unconditional quantile regression estimates for the effect of the output gap and real GDP on interest coverage as a ratio of total assets

6a: Cyclical component of GDP



6b. Real GDP growth

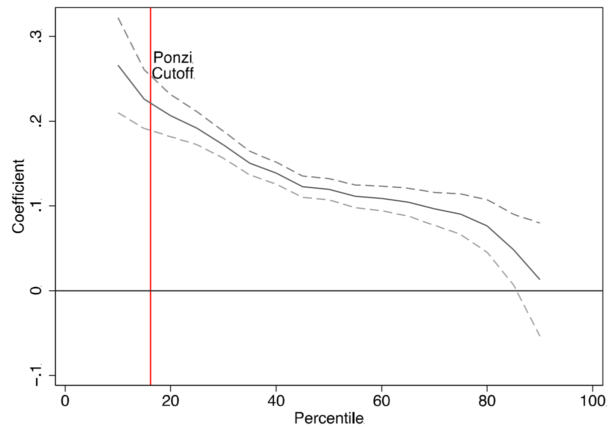


Table 6: Effects of the Output Gap by Quartile (RIF Regressions)

	(1) Mean	(2)	(3) 1st Decile	(4)	(5) Median	(6)	(7) 8th Decile	(8)
$\Delta \ln\left(real\ gdp\right)_t$	0.12831***	0.12219***	0.26613***	0.24159***	0.11970***	0.11290***	0.07627***	0.07440***
	(0.01866)	(0.01830)	(0.02860)	(0.02935)	(0.00644)	(0.00668)	(0.1587)	(0.01643)
$\Delta \ln\left(real\ gdp\right)_{t-1}$		-0.02481		0.03833		0.00808		-0.02378
		(0.01550)		(0.02838)		(0.00669)		(0.01657)
$\Delta \ln\left(real\ gdp\right)_{t-2}$		-0.09591***		-0.13766***		-0.04274***		-0.05859***
		(0.01730)		(0.02783)		(0.00652)		(0.01615)
$\Sigma\Delta \ln\left(real\ gdp\right)$		0.0858		0.142		0.0782		-0.00797
p-value		0.0192		0.00209		0		0.754
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	N	N	N	N	N	N	N	N
Obs	226,381	226,381	226,381	226,381	226,381	226,381	226,381	226,381

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: The dependent variable is the interest coverage as a ratio to total assets. 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 Function (Rif) regression. For a description of the methods and data sources, see the text.