# Small and Large Firms over the Business Cycle*

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This version: June 26, 2017

**Abstract**

We provide new evidence on the behavior of small and large firms over the business cycle. Drawing from confidential firm-level quarterly data from the US Census Bureau on the income statements and balance sheets of US manufacturing firms from 1977 to 2014, we show that sales, inventory growth, and investment rates are more cyclical among smaller firms. This excess sensitivity holds after controlling for industry effects, and is driven by the behavior of firms in the top 0.5% of the asset distribution. However, due to the skewness of the distribution of sales and investment, the excess sensitivity is insufficient in magnitude to substantially affect the cyclical behavior of aggregates. Moreover, we show that the excess sensitivity of small firms survives when directly controlling for firm leverage, liquidity, or bank dependency, suggesting that it may not be driven by differences in access to credit. Additionally, we find that independent of size, firms with zero debt do not exhibit less sensitivity to the business cycle than positive leverage firms. Our findings inform the debate on the role the financial accelerator at business-cycle frequencies.

Keywords: Firm size, business cycles, financial accelerator

JEL Classification: E23, E32, G30

*The views expressed in this paper are those of the author and do not represent the Federal Reserve System or the Federal Reserve Bank of Minneapolis. Any opinions and conclusions expressed herein are those of the authors and do not necessarily represent the view of the US Census Bureau, and all results have been reviewed to ensure that no confidential information is disclosed. We thanks seminar participants at Colby College, the Federal Reserve Board, the Inter-American Development Bank, the Minneapolis Fed, and Northwestern Kellogg for helpful comments, and Cristina Arellano, V.V. Chari, Jan Eberly, Mark Gertler, Kyle Herkenhoff, and Ellen McGrattan for helpful discussions.

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# 1 Introduction

This paper examines the cyclical behavior of small and large firms in the US. The size distribution of firms has received considerable attention in the literature on economic growth and in corporate finance, but differences in exposure to business cycle across the size distribution have received somewhat less attention. An influential early contribution by Gertler and Gilchrist (1994) argues that sales at small manufacturing firms in the US respond more strongly to monetary policy shocks (as captured by the Romer and Romer (1989) dates) than the sales of large manufacturing firms. More recently, Chari, Christiano and Kehoe (2013) examine the sales response of small and large manufacturing firms in recessions, finding mixed evidence that small firms exhibit greater cyclicality. Similarly, Kudlyak and Sanchez (2016) argue that sales of large firms actually fell faster than sales of small firms in the Great Recession. Whether there are differences in the cyclicality of firms across firm size remains an open area of research.

In this paper, we bring new evidence to bear on this topic. We are interested in three main questions. First, are small firms more cyclically sensitive than large firms, and if so, to what extent? Second, does this excess sensitivity substantially contribute to amplifying aggregate fluctuations? Third, is this excess sensitivity the manifestation of cross-sectional differences in access to finance?

Much of the literature on the cyclicality of small and large firms in US is built off public releases of US Census Bureau's Quarterly Financial Report (QFR), which provides information on sales and financial liabilities of manufacturing, retail and wholesale trade firms disaggregated by size classes. In this paper, we use the confidential firm-level microdata (income statements and balance sheets) that underlies the QFR public releases to determine the cyclicality of sales, inventories, investment, and various financial liabilities for small and large firms. We assemble a quarterly panel from 1977 to 2014 and use it to construct time series for various real and financial variable and estimate firm-level regressions to ascertain differences in cyclicality across firm size categories.

The firm-level microdata of the QFR carry several advantages relative to the publicly released data and alternative datasets for answering questions about the cyclicality of small and large firms. The publicly released data used in earlier studies uses aggregates within firm size classes (it reports, for example, total sales at manufacturing firms with over $1 billion in assets). Because these size classes are fixed in nominal terms, public releases can suffer from reclassification bias in recessions, as firms move across firm size categories; the panel aspect of the firm-level data allows us to address reclassification bias by classifying firms on lagged size or other lagged observables. Additionally, given the skewness of sales, investment, and liabilities over the firm size distribution, it is unclear how well these aggregates capture the behavior of the average or median firm within a size category. Finally, and most importantly, the firm-level data allows for a regression analysis where controls can be introduced for factors that may be correlated with firm size and account for any measured excess sensitivity of small firms.

Alternative firm-level datasets, such as Compustat also carry disadvantages relative to the QFR. Compustat is limited to publicly traded firms, and therefore provides a censored view of the cross-section of US firms. Additionally, it typically reports financial statements only annually, making it more challenging to use for business-cycle analysis. By contrast, the QFR is a stratified random sample of the population of manufacturing firms, with financial statements reported quarterly. Another advantage of the QFR is that is surveys firms' sources of debt financing (i.e. bank or bond market debt); it can therefore be used to measure the role of bank dependence and access to public markets in accounting for cyclical sensitivity. Finally, the QFR instructs respondents to report a domestic consolidation (i.e. financial statements for US operations only), in contrast with Compustat where financial statements reflect global operations.[1]

Using the QFR microdata, we find strong evidence for differences in business cycle sensitivity between small and large firms. Specifically, we find that sales and investment of firms in the bottom 99% of the distribution exhibit stronger contemporary correlations with GDP. Though particular episodes differ, over the five recession dates in our sample (which ranges from 1977 to 2014), sales at small firms contract more than sales at large firms. This pattern also holds in the four Romer and Romer (1989) dates that appear in our sample. Compared to earlier work based on public releases that looks at total sales of firm size classes, we measure average growth within firm size class. Our baseline estimate is that a 1% drop in GDP is associated with a 2.6% drop in sales in top 1% of firms, and a 3.1% drop in sales in the bottom 99%. The size asymmetry also appears in firm level regressions that control for industry and use a larger number of firm size bins. Interestingly, the size effect is concentrated in the top 0.5% of the size distribution; we find no evidence of any difference in the sales elasticity to GDP up to the 99.5th percentile.

The differential sensitivity we uncover for sales growth also holds for inventory growth and investment rates. Smaller firms exhibit stronger cyclical swings in inventory growth and investment, including both total investment and tangible investment (property, plant, and equipment). As with sales growth, the differential is concentrated at the top 0.5% of the asset distribution relative to all other firms. Within the bottom 99.5% of the firm size distribution, we find no difference in cyclicality. Despite differences in methodology, we find that the behavior of sales growth and inventory growth between small and large firms is consistent with the findings of Gertler and Gilchrist (1994). We find some evidence that tangible investment rates at the largest firms are countercyclical, though overall investment is cyclical reflecting the greater importance of intangible investment at large firms.

Despite uncovering differences for small and large firms in the cyclicality of sales, inventories, and investment, we find that these differences have very little effect on aggregates. Our data allows

[1] The QFR began during World War II and is used as an input into calculations of corporate profits in the National Income and Product Accounts. Section 2 provides a more detailed discussion of the dataset and its relationship to other firm-level data used in the literature.

us to construct counterfactual paths for aggregate sales growth, inventory growth and investment under the alternative assumption that firm-level cyclical sensitivities are equal in the cross-section, and plot this counterfactual against realized aggregate sales growth. As seen in Figure **??**, the difference between the two series is difficult to detect. The reason for this result is the extreme skewness of the distribution of sales and investment in the cross-section of firms. For instance, the top 0.5% of firms accounts for approximately 75% of total sales and 85% of total investment in the latter parts of the sample. While the size differences in cyclical sensitivities of are statistically significant, they are also not large enough in magnitude to counterbalance this skewness. To the extent that alternative monetary or fiscal policies could address this differential cyclicality, our results suggests that those policies would have little effect on aggregate fluctuations.

Our findings verifying the greater cyclicality of small firms beg the question of whether these differences in cyclicality are driven by a financial accelerator mechanism. Gertler and Gilchrist (1994) argued that small firms serve as a proxy for financially constrained firms as these firms exhibit greater bank dependence, cannot issue market debt, and face a higher degree of idiosyncratic risk. We verify that it is indeed the case that small firms do differ from large firms along these dimensions. However, several findings cast doubt on whether the size difference is driven by a financial accelerator mechanism. First, the measured cyclical behavior of debt across size groups is not fully consistent with the narrative put forward in the litterature on the financial accelerator. In particular, both small and large firms cut back on short-term borrowing during recessions, which is at odds with the view which emphasizes that small firms cannot access short-term financing in recessions, and are thereby forced to shed labor, reduce inventories, and lower investment relative to larger firms with better access to external financing.

Second, we introduce direct controls for balance sheet ratios emphasized in the financial frictions literature that should affect the cost and availability of external financing. We sort firms into leverage, liquidity and bank dependence categories. We also introduce dummies for whether a firm has accessed public debt markets in the past. None of these controls eliminates the size differential that we document. Moreover, only in the case of leverage classes are the signs consistent with the financial accelerator mechanism and statistically significant; that is, lower leverage firms are less sensitive to business cycles than higher leverage firms. However, the size effect remains (and is actually stronger) than in a regression with just size alone. The other proxies we use tend not to enter regressions with the correct sign; for instance, we show that past access to commercial paper or bond markets tends to heighten business-cycle sensitivity. At a minimum, this results suggests the size asymmetry may be driven by nonfinancial factors.

Lastly, we also directly examine the behavior of financially constrained v. unconstrained firms in the Great Recession. If we directly sort firms into zero leverage firms (firms with no debt) v. positive leverage firms, we find that sales for both these categories behaved almost identically in the Great Recession. This result is all the more striking because zero leverage firms are more likely to

be small firms. Given concerns that a substantial degree of propagation of the Great Recession was due to a disruption of credit supply that worsened the contraction for financially weak firms, our findings for sales and investment cast doubt on the relevance of this channel for the manufacturing sector. Importantly, a financial accelerator may still have effects on employment, and we cannot rule out larger effects for non-manufacturing firms, which account for a substantial fraction of value added and employment.[2]

The remainder of the paper is organized as follows. Section 2 details the construction of the QFR data set and provides summary statistics for small and large firms. Section 3 provides time series and regression evidence on the response of small and large firms over the business cycle, in recessions, and after Romer and Romer (1989) dates. Section 4 analyzes the aggregate implications of size asymmetries between small and large firms. Section 5 presents evidence on whether the size differences we document are evidence of a financial accelerator. Section 6 concludes.

### 1.1 Related Literature

Our analysis relates to several distinct strands of literature but most closely contributes to the literature examining the cyclicality of financial frictions. In addition to Gertler and Gilchrist (1994), Bernanke, Lown and Friedman (1991), Bernanke and Blinder (1992) and Kashyap, Lamont and Stein (1994) all consider the role of a credit channel in explaining specific downturns. More recently, evidence on differential sensitivity by firm size over the business cycle and its relation to the financial accelerator have been reevaluated by Chari, Christiano and Kehoe (2013) and Kudlyak and Sanchez (2016). Ivashina and Scharfstein (2010) provide evidence of tightening bank lending in the Great Recession. Recent work by Bergman, Iyer and Thakor (2015) investigates the presence of a financial accelerator in the farming sector using exogenous temperature shocks.

Given that employment data by firm size is relatively more plentiful than sales or investment data, a larger literature has examined size asymmetries in employment and job flows over the business cycle and sought to quantify the effects of credit supply shocks in the Great Recession. Moscarini and Postel-Vinay (2012) examines differences in job creation between small and large firms over the business cycle while Fort et al. (2013) consider the behavior of job creation by firm size and age. The latter argue that employment at small-young firms are more sensitive than large-mature firms and appear particularly sensitive to changes in house prices. Using Compustat data, Sharpe (1994) finds that higher leverage firms shed sales and employment faster than lower leverage firm while also finding evidence of a separate size asymmetry. Chodorow-Reich (2014) and Greenstone, Mas and Nguyen (2014) use firm-level and county-level data respectively to investigate the effect of shocks to credit supply on employment. Mehrotra and Sergeyev (2016) uses a

[2]However, it is worth emphasizing that non-manufacturing sectors are also far less cyclical than manufacturing, and account for a lower share of overall fluctuations in output.

heterogenous firm dynamics model to identify the contribution of shocks to credit supply on the decline in US employment in the Great Recession.

We also relate to a literature that investigates the cyclicality of firm financing and the relation to firm size. Jermann and Quadrini (2012) investigates the cyclicality of overall corporate debt and equity, while Covas and Den Haan (2011) argues that the cyclicality of equity financing differs with firm size. Begenau and Salomao (2015) analyze the cyclicality of financing in Compustat data and consider implications in a quantitative firm dynamics model, while Crouzet (2016) studies the implications of subsitution between bank and bond financing for aggregate investment. Likewise, Shourideh and Zetlin-Jones (2012) consider differences in the reliance on external financing of small and large firms and provide evidence on the financing of private firms in the UK. Gopinath et al. (2015) draws on balance sheet data for small firms in southern European countries to assess the role of integration and capital misallocation in the 2000s.[3] In contrast to these papers, our data set captures the cyclicality of financing at small, nonpublic firms in the US that are not present in Compustat.

# 2 Data

## 2.1 The Quarterly Financial Report

The Quarterly Financial Report (QFR) is a survey of firms conducted quarterly by the US Census Bureau. The survey covers several sectors of the US economy: mining, manufacturing, and wholesale and retail trade firms. Since 2009, the survey has been broadened to include a selected set of firms in service industries. Surveyed firms are required to report an income and balance sheet statement each quarter. Data collected by the QFR is used by Bureau of Economic Analysis as an input in estimates of corporate profits for the national income and product accounts, as well as in various other official statistical publications, such as the Flow of Funds.[4]

The QFR data is a stratified random sample. This sample is created using corporate income tax records provided by the Internal Revenue Service (IRS) to the Census Bureau. Any manufacturing firm that files a corporate income tax return (Form 1120) with assets over $250K may be included in the QFR sample. The random stratification is done by size, meaning that firms above certain size thresholds are included in the QFR sample with certainty, while smaller firms are sampled randomly. Since 1982, firms with more than $250 million in book assets are sampled with certainty; the microdata therefore includes the universe of such firms. Firms with between $250K and $250 million in assets are instead sampled randomly, so that the microdata contains only a representative sample. Specifically, each quarter, a set of firms with between $250K and $250 million in book

[3] See Kalemli-Ozcan et al. (2015) for details on the European firm level balance sheet data used in the paper.

[4] The QFR has its origins in World War II as part of the Office of Price Administration. The survey was administered by the Federal Trade Commission until 1982 when it was transferred to the Census Bureau.

assets is randomly drawn and included in the sample for the following 8 quarters. At the same time, approximately 1/8th of the existing sample stops being surveyed. For the $250K-$250 million dollar group, the microdata is thus a rotating panel, akin to the Current Population Survey (CPS). The exact coverage of the sample relative to the population of firms varies across quarters, but is typically in the neighborhood of 5-8%. For instance, in 2014q1 (the last quarter of our sample), the QFR surveyed 8122 manufacturing firms, out of an estimated population of 136205. Of these surveyed firms, 3700 had less than $10 million in assets, 2768 had between $10 and $250 million in assets, and 1654 had more than $250 million in assets.

Firms which are part of the rotating random sample receive a simplified ("short") form requiring them to report their income statement and balance sheet for the quarter. Firms which are sampled with certainty receive a somewhat more detailed ("long") form, which requires them to provide more information on the composition of their debt and their financial assets, as well as to report income of non-consolidated entities separately from the rest of non-operating income.[5] Based on the underlying sample frame, the Census Bureau then assigns sampling weights to each firm in order to generate population estimates of quantities of interest.[6]

## 2.2 Data construction

The micro files of the QFR required substantial initial work in order to construct a usable panel data set. This is because, in comparison to other Census datasets like the Longitudinal Business Database, the QFR microdata almost never been used by researchers, and to our knowledge, not at all since the move to the NAICS classification, in 2000.[7] The Census Bureau provided raw data files from 1977q1 to 2014q1, but these data files were not linked across quarters. To compute investment rates and growth rates, firms had to be linked across quarters. In general, a survey identifier was available; however, changes in the encoding format of the survey identifiers on a number of quarters required us to match firms based on other identifiers. To do so, we relied on the employer identification number (EIN) of firms along with matches based on firm name and location of firm headquarters.

Between 1994 and 2000, the raw Census data files were missing sampling weights. We used public releases of the QFR that contain statistics of the number of firms by strata to reconstruct

[5] The QFR short and long forms are available at http://www.census.gov/econ/qfr/forms.html.

[6] To be more precise, the QFR uses post-stratification sampling weights which are adjusted to reflect potential changes in the composition of size and industry stratum of the firm after the stratum is formed. As a result, sampling weights may vary slightly within firm over the duration of the panel. A detailed exposition of the survey stratification and the methodology used for estimating universe totals is available at https://www.census.gov/econ/qfr/documents/QFR_Methodology.pdf .

[7] The most recent instance of use of the QFR microdata of which we are aware is Bernanke, Gertler and Gilchrist (1996), which use the microdata to compare firm-level to aggregate growth in sales. It is also the only instance of use of the data of which we are aware.

sampling weights over this period.[8] These weights were also adjusted so that aggregate assets for manufacturing firms match assets as publicly reported by the Census Bureau. Between 1977 and 1994 and post 2000, we find that, using the Census Bureau's sampling weights, aggregate sales and assets match the publicly available releases.

In addition to linking the firm observations across quarters and imputing sampling weights, we also drop miscoded observations and keep only firms with strictly positive assets and balance sheet data that balances correctly.[9] Less than 0.1% of firm-quarter observations have balance sheet for which the sum of liabilities and equity does not match reported assets within less than 0.01%, suggestive that the data suffers from limited mis-reporting. The cleaned data set we work with contains about 1.5 million firm-quarter observations between 1977q1 and 2014q1, of which about 900K are manufacturing firms.[10]

In this paper, we will focus on two samples. The summary statistics and the time series that do not require the computation of growth rates are built off the full sample of approximately 900K firm-quarter observations for manufacturing firms. We use a different sample for computing growth rates or investment rates: we then require firms to have reported data for the four quarters prior to the observation date, in order to be able to compute the year-on-year changes in quantities of interest. For the majority of small firms, which are tracked for 8 quarters, taking year over year growth rates eliminates approximately half of the observations. This second sample with firm-level growth rates for manufacturing firms contains approximately 460,000 observations.[11]

### 2.3 Advantages of the QFR

Before discussing the summary statistics of the data set, it is worth comparing the QFR to alternative firm-level data sets and discussing some of its advantages and drawbacks.

The primary firm-level financial data set is Compustat. Relative to Compustat, the main advantage of the QFR is that it consitutes a representative sample of the population of US manufacturing firms, given that the sampling frame is drawn from IRS administrative data and response is manda-

[8] Aggregates of the QFR are publicly available at https://www.census.gov/econ/qfr/historic.html. In a given quarter, the Census Bureau releases a set of tables by asset size class and industry; one of these tables provides the number of firms by industry and asset size class. For an example, see Table L in http://www2.census.gov/econ/qfr/pubs/qfr09q1.pdf.

[9] A final issue was that the data did not have a codebook. Because the contents of variables in the micro-data files were not always named in an unambiguous manner, this meant that it was sometimes not possible to match with certainty variables to survey response items in the short and long form. In order to deal with this issue, we matched the exact dollar values of ambiguously named variables to public reports of corporations with similar consolidation rules as those required by the QFR.

[10] Currently, we have not analyzed the non-manufacturing part of the data set, since firms with less than $50 million in assets are not sampled, but we plan to do so in future work.

[11] The growth rate sample is more than half the full sample due to the presence of large, continually sampled (long-form) firms.

tory. In particular, it includes private, smaller, bank-dependent firms, which are not covered by Compustat but nevertheless constitute the typical firm in the population. Since these firms are those most likely to suffer from frictions arising from limited access to capital markets, the QFR is a particularly attractive source of information to answer the questions on which this paper focuses.

There are three other differences between Compustat and the QFR. First, the income and balance sheet data is reported at a quarterly frequency, which better allows for business cycle analysis. While a quarterly version of Compustat exists, most analyses (including those focusing on business-cycle facts) use the annual version of the data. The quarterly data in the QFR is updated by firms with at high frequency: for example, in any quarter less than 2% of (unweighted) firm-level inventory observations are identical to the previous quarter. Second, the QFR asks firms to classify their liabilities into bank and non-bank liabilities, and for larger firms, to provide estimates of bonds and commercial paper outstanding.[12] This additional firm-level data on the composition of debt by source is not directly available in standard annual versions of the Compustat data set, and requires further merges with other datasets in order to be computed. Lastly, as an input into the national accounts, the QFR asks firms for a domestic consolidation of the financial statements. For firms with significant global operations, a substantial fraction of income may be earned outside the US and a significant fraction of assets may be located outside the US. In principle, the QFR more accurately measures activity within the US relative to Compustat.

For smaller European firms, the Amadeus data set provides income and balance sheet data. In comparison to our data set, the Amadeus data set has greater industry coverage, but has a shorter time span (since 2000) and provides data at an annual frequency (see Kalemli-Ozcan et al. (2015)). Alternative US data sets that provide data on small, private firms includes the Survey of Small Business Finances and Sageworks (see Asker, Farre-Mensa and Ljungqvist (2011)). However, neither data set provides the coverage, frequency, or time horizon which the QFR does.[13]

### 2.4 Summary Statistics

Table 1 provides summary statistics on real and financial characteristics for small and large manufacturing firms. These statistics are constructed by groups firms into quantiles of current book assets, computing moments within bins, and averaging across quarters from 1977q1 to 2014q1. In contrast to public releases of the QFR, which are published by fixed nominal size bins, our definition of size groups adjusts over time with inflation and growth. All nominal values are deflated by the BEA price index for manufacturing, normalized to 1 in 2009q1.[14]

[12] The QFR also require larger firms to provide a highly detailed overview of their financial assets, including, among others, cash and demand deposits inside and outside the US and Federal and local government debt owned. We do not use this data in this paper.

[13] Asker, Farre-Mensa and Ljungqvist (2011) report that the Sageworks database contains financial statement data for about 95,000 firms from 2002 to 2007.

[14] The series is available at http://bea.gov/industry/gdpbyind_data.htm.

[Table 1 about here.]

Table 1 clearly illustrates the high degree of skewness in both sales and assets. The top 0.5% of firms in the size distribution have assets of $6.7 billion and sales of $ 1.5 billion annually. By contrast, firms within the bottom 90% of the size distribution have just $2 million in assets and $1.2 million in sales. The resulting extreme degree of concentration of sales and assets among the top 0.5% is discussed in more detail in section 4. As discussed there, investment is also very skewed. However, 1 shows that investment rates are comparable across size classes, so that the skewness of investment primarily reflects the skewness of the asset size distribution, rather than differences in investment intensity. Finally, note that sales growth is substantially faster at the largest manufacturing firms over this period; consequently, asset concentration in the manufacturing industry has increased markedly over the past 35 years.

Turning to capital structure, Table 1 provides standard balance sheet ratios by firm size categories. A standard measure of leverage - the debt to asset ratio — generally decreases across firm size categories. However, a standard measure of liquidity - the cash to asset ratio - is also highest among smaller firms. Overall, net leverage (debt less cash over assets) is fairly stable across size class providing no evidence that smaller firm carry greater leverage. However, we do find that smaller firms have more short-term debt and bank debt (as a share of total debt), and rely more on trade credit than larger firms.

One clear difference between large and small firms — particularly among the largest 0.5% of firms — is the intangible asset share. Firms in the survey report separately property, plant, and equipment (tangible assets) from other long-term assets. A high share of intangible assets likely reflects the accumulation of goodwill due to past acquisitions, so that the sharp increase in intangible asset share across size classes underscores the importance of acquisitions for growth at the very largest firms.[15]

It is worth emphasizing that, despite differences across size classes in various real and financial characteristics, there remains tremendous heterogeneity within size classes. Table ?? provides an approximate interquartile range for sales growth, leverage, and liquidity.[16] For sales growth and leverage, the approximate interquartile range within size bins dwarfs the differences across size bins. The interquartile range narrows for larger size classes, but nevertheless remain substantial. It is worth noting that a substantial fraction of firms carry zero leverage; these zero leverage firms tend to be concentrated in the bottom 90% of the size distribution.

[Table 2 about here.]

[15] Even for firms with low or zero intangible asset share, the market value of the firm may differ substantially from the book value of the firm. However, our data only contains book value of assets; for most firms in our sample, which are private, no ready measure of market value would be available.

[16] Due to data disclosure restrictions, we provide averages above and below the median within size classes, rather than the exact 25th and 75th percentiles.

To summarize, on average over the sample, small firms tend to have similar net leverage as large firms, but rely more extensively on bank debt, short-term debt and trade credit. Moreover, sales and assets display an extreme degree of concentration among the very largest firms, and increasingly so over time, given their faster average growth rate. We next turn to differences in cyclical behavior across these size groups.

# 3 The excess sensitivity of small firms

This section documents the fact that, relative to large firms, small firms display "excess sensitivity" to aggregate fluctuations. By "excess sensitivity" of small firms, we mean that a worsening (or an improvement) in aggregate conditions — as proxied, for example, by real GDP growth — is associated with systematically larger declines (or increases) in sales and investment.

## 3.1 Measurement framework

Appendix A provides the formal details for the measurement framework which we use in order to group firms by size categories and measure growth. This framework has two features which are worth emphasizing before reporting key results.

First, we focus on *firm-level* growth. This allows us to make full use of the firm-level data, and control for firm-level characteristics, in particular industry and capital structure. This is distinct from previous work using the public QFR releases, which were limited to focusing on the growth of aggregates by size group (based on nominal thresholds) due to the way the Census Bureau summarized and released the data. The connection between firm-level and aggregate growth, and the implications of differences in average firm-level growth for aggregates, are discussed in more detail in Section 4.

Second, we base our size groups on *quantiles* of the *lagged* empirical distribution of *book assets*. We use *quantiles* — for example, the bottom 99% versus the top 1% — because they are immune to long-run upward size drift due to inflation and real growth. This problem arises when using fixed nominal thresholds, which is the way that the publicly available QFR data defines size groups and reports variables of interest. Classifying firms by their *lagged* position in the size distribution helps alleviate the cyclical effects of reclassification bias emphasized in Moscarini and Postel-Vinay (2012).[17] Finally, we use *book assets* because, among the possible measures of size in our data, it is the most stable at higher frequencies; in particular, unlike sales, it does not display substantial seasonal variation at the firm level.

[17] Specifically, if firms tend to cross the threshold from small to large during expansions, this results in an upward bias of the growth rate of total sales of large firms (and, symmetrically, a downward bias in the growth rate of total sales of small firms).

In most of the discussion of the evidence below, we use a one-year lag for size, and define small firms to be the bottom 99% of lagged book assets.[18] This is with the exception of the regression results, which we report for more disaggregated size groups (retaining the one-year lag). However, as discussed in Section 3.5, the results are robust to using shorter lags or finer bins for the construction of size groups.

### 3.2 Sales

Figure 1 shows the time series for the average firm-level growth of sales of two size groups, the bottom 99% (denoted by $\hat{g}_t^{(\text{small})}$ in what follows), and the top 1% (denoted by $\hat{g}_t^{(\text{large})}$ in what follows).[19] By average firm-level growth, for any given quarter, we are computing year over year growth rates of sales at the firm level and averaging over firms (using Census sampling weights). The resulting time series is pasted together quarter to quarter.

The most striking feature of these two series is perhaps how closely they track each other (their sample correlation is 0.93). In particular, from 1987 to 1990, 1995 to 2000, and 2002 to 2007, it is difficult to distinguish growth rates across these groups visually. Nevertheless, there are periods of notable divergence. The two most striking ones are 1982q3-1984q1 - the recovery from the Volcker recessions - and 2008q3-2009q4 - the early stages of the Great Recession. In the first instance, the growth rate of small firms far outpaced that of large firms; in the second instance, it was markedly lower. The recovery of the 1990-1991 recession also features a slightly faster growth rate of small firms. Thus, even though visually the common cyclical component in small and large firms' growth stands out most, one cannot rule out that sales growth contains a size-dependent cyclical component.

[Figure 1 about here.]

Indeed, Figure 2 shows that the difference between small and large firms' average growth rate is positively correlated to GDP growth. This figure plots the time series $\Delta\hat{g}_t \equiv \hat{g}_t^{(small)} - \hat{g}_t^{(large)}$ against year-on-year changes in real GDP. The estimated slope coefficient of the bi-variate simple OLS between the two series is 0.60, with a White standard error of 0.11. The economic interpretation of this coefficient is that, for every percentage point decline in GDP, sales decline, on average, by 0.6% more among small firms than they do among large firms.

[Figure 2 about here.]

[18] The motivation for using this threshold is that firms in the bottom 99% account for approximately 30% of total sales in the early parts of the sample, analogous to Gertler and Gilchrist (1994). We discuss this issue in more detail in Section 4.

[19] Unless otherwise noted, all series are deflated by the BEA's chain type price index for manufacturing value added (bea.gov/industry/gdpbyind.htm) before computing growth rates.

Table 3 reports more formal estimates of the conditional elasticity of firm-level growth to GDP growth, and confirms the visual impressions conveyed by Figure 2. The first column of Table 1 shows estimates of the model:

$$\begin{aligned} g_{i,t} &= \alpha + \beta \log\left(\tfrac{GDP_t}{GDP_{t-4}}\right) \\ &+ \sum_{j\in\{(90,99),(99,99.5),(99.5,100)\}} \left(\gamma_j + \delta_j \log\left(\frac{GDP_t}{GDP_{t-4}}\right)\right) \mathbf{1}_{i\in\mathcal{I}_t^{(j)}} \\ &+ (\textit{Industry controls}) + \epsilon_{i,t} \end{aligned} \tag{1}$$

where the size groups $\mathcal{I}_t^{(j)}$ are given by

$$\begin{aligned} \mathcal{I}_t^{(90,99)} &= \left\{ \quad i \in \mathcal{I}_t \quad \text{s.t.} \quad a_{i,t-4} \in \left[\bar{a}_{t-4}^{(90)}, \bar{a}_{t-4}^{(99)}\right] \quad \right\}, \\ \mathcal{I}_t^{(99,99.5)} &= \left\{ \quad i \in \mathcal{I}_t \quad \text{s.t.} \quad a_{i,t-4} \in \left[\bar{a}_{t-4}^{(99)}, \bar{a}_{t-4}^{(99.5)}\right] \quad \right\}, \\ \mathcal{I}_t^{(99.5,100)} &= \left\{ \quad i \in \mathcal{I}_t \quad \text{s.t.} \quad a_{i,t-4} \in \left[\bar{a}_{t-4}^{(99.5)}, \infty\right[ \quad \right\}, \end{aligned} \tag{2}$$

$\bar{a}_{t-4}^{(k)}$ denotes the one-year lagged $k$-th percentile of the empirical distribution of book assets, and $\mathcal{I}_t$ denotes firm included in the sample (see appendix A for formal definitions of the size groups). The two main differences between this regression and the simple visual evidence are that this specifications allows for four different size groups (the bottom 90%, 90-99%, 99% to 99.5% and the top 0.5%), instead of two; and that it controls for industry effects with a dummy for durable manufacturing.[20] Excess sensitivity would be characterized by a statistically significant coefficients $\gamma_j$ for one or several of the size groups; the first column of table 3 reveals that this is the case, so that the size effect does not simply reflect cyclical differences across industries.

The results of table 3 also reveal that the cross-sectional differences in cyclical sensitivity are driven by the top 0.5%, which represents approximately 500 firms in each quarter. In particular, relative to the baseline group (in which firms have average of approximately $2m$\$ in book assets, expressed in 2014q1 dollars), the cyclical sensitivity of sales growth among in the 90-99% (where book assets average $49m$\$) is not statistically different; for the 99-99.5% (where book assets average $626m$\$), the cyclicality is slightly smaller, but the significance is marginal. It is really only at the very top that the difference emerges. Note that the slope in the simple OLS of Figure 2 is essentially the same as the difference in elasticities between the top 0.5% and the bottom 90%, approximately 0.6; thus, the simple bivariate OLS provides a good proxy for the excess sensitivity of small firms' sales, despite potential differences across industries. We have experimented with more size classes; within the bottom 90% of the firm size distribution, we find no evidence of differences in cyclical sensitivity. It is also worth noting that the adjusted R-squared for this regression is quite low indicating that, despite the obvious common component between small and large firms, there is considerable heterogeneity in sales growth at the firm level.

[20] Additionally, the regression framework allows to compute standard errors clustered at the firm level. We have also considered finer industry controls: 3-digit NAICS; results are unchanged.

[Table 3 about here.]

Figure 3 conveys a similar message, but reporting estimates of the absolute cyclical sensitivity of each size group, instead of differences in elasticities relative to the baseline. Specifically, Figure 3 reports the marginal effect of $\log\left(\frac{GDP_t}{GDP_{t-4}}\right)$ at the mean, for each size groups (including the 0-90% group), as well as the unconditional cyclical sensitivity (the red line). The only group with a statistically different elasticity from the unconditional cyclical sensitivity is the top 0.5%. Moreover, note that the absolute magnitude of the elasticities to GDP growth are substantially larger than the cross-group difference. This fact will be important in Section 4, when we consider the aggregate implications of the cross-group difference in elasticities for the aggregate behavior of sales.

[Figure 3 about here.]

A simple summary of the evidence on sales is the following: when GDP growth drops by 1%, the largest firms' sales drop by approximately 2.5%, while the smallest firms' sales drop by approximately 3.1%. This effect is statistically significant, and driven by differences between the top 0.5% and the rest of the firms. We next turn to the evidence on inventory and fixed investment.

### 3.3 Investment

The long time-series for inventory growth and investment in fixed assets, reported in Figure 4, also display comovement across small and large firms, but to a lesser extent than sales (the respective sample correlations between the small and large time series are 0.64 and 0.52).[21] For inventory, the episodes of notable divergence between small and large firms are two recoveries: the 1983-1985 recovery, and the aftermath from the Great Recession. These two episodes convey a mixed message: in particular, in the aftermath of the Great Recession, large firms' inventory investment actually recovered more quickly. For fixed investment, the most striking fact is that contractions in fixed investment seem to occur with a lag at larger firms. This is particularly visible during the Volcker recessions. Slowdowns in investment also persist longer; in the aftermath of the 2000-2001 recession, the turning point for investment among large firms occurred approximately 4 quarters later for large firms than for small firms.

[Figure 4 about here.]

The regression evidence, reported in Table 3, provides a clearer picture than the long time series. The second and third columns report estimates of model (2), when $g_{i,t}$ is either inventory growth (second column) or the fixed investment rate (third column). Just as was the case for sales, relative to the baseline 0-90% size group, inventory growth of the top 0.5% of firms has a significantly

[21] See Appendix A for details on the construction of inventory growth and investment rates for tangible capital.

smaller conditional elasticity to GDP growth.[22] The economic magnitude of the effect is large: for the bottom 90%, the average marginal effect at the mean of a 1% drop in GDP is a 1.9% drop in inventory; for the top 0.5% percent, the drop is only 1.1%. Inventory growth at the smallest firms is thus approximately twice as sensitive to aggregate conditions as at the largest firms.[23]

The results for fixed investment are, if anything, starker: the difference between the 99-99.5% and the 99.5-100% groups and the bottom group are both statistically significant. The economic magnitudes are large: for example, the average marginal effect of a 1% drop in GDP on fixed investment is a 0.7 percentage point reduction in the average investment rate among the 0-90%, but only a 0.15 percentage point reduction among the 99-99.5% group. This is relative to an average investment rate of 27.7% among the 0-90% group, and 22.0% among the 99-99.5% group. The small estimated elasticity of investment to aggregate conditions among larger firms is likely driven by the fact large firms seem to cut investment with a lag, as mentioned before. Nevertheless, the overall message is the same as for sales: inventory growth and investment rates among small firms are substantially more sensitive to business cycles than among large firms.

### 3.4 Recessions and recoveries

Is the excess sensitivity of small firms documented so far a fact about all stages of the business cycle, or is it specifically about recessions (or recoveries)? In order to shed some light on this question, we apply the methodology used in Gertler and Gilchrist (1994) and Chari, Christiano and Kehoe (2013), and construct estimates of the average cumulative decline (or increase) in sales, inventory and fixed capital after the initial (or final) quarter of the five NBER recessions in our sample.[24]

Figure 5 focuses on average cumulative declines after the beginning of the five recessions in our sample (the start dates are 1980q1, 1981q3, 1990q3, 2001q1 and 2007q3). We construct these cumulative declines in two different ways (appendix B provides a formal exposition of each). First, in the top row of Figure 5, we report a cumulative version of the average growth rates by size group reported in Figures 1 and 4, normalizing the series to 100 at the recession start date. Second, in the bottom row of Figure 5, we report the average within-firm change at different horizons, for the set of firms present in quarter 0 and which can be tracked for 10 continuous quarters around the beginning of the recession. The time-series in the top row are more directly comparable to the previous evidence, but the sets of firms used to construct them are not the same across quarters,

[22] As was also the case for sales, the estimated difference in elasticities between the bottom 90% and the top 0.5% lines up with the results of a simple OLS regression of the difference in inventory growth between the top 1% and the bottom 99%, which delivers a slope coefficient of approximately 0.7. Results are not reported but available upon request.

[23] These values are obtained by computing the average marginal effect of GDP growth on inventory growth, by size groups, as in (3).

[24] Gertler and Gilchrist (1994) examine the evolution of these variables after Romer and Romer dates while Chari, Christiano and Kehoe (2013) study recession dates.

and can be affected by reclassification across size groups. By contrast, the time-series in the bottom row are constructed using a unique set of firms, but suffer from attrition as firms drop out of sample.

[Figure 5 about here.]

Figure 5 suggests that the sales of small firms, as measured by the "cumulative" approach (top left panel), track closely those of large firms, although within-firm changes (bottom left panel) seem slightly larger for small firms at long horizons. Inventory declines, if anything, are larger at large firms at the onset of recessions. By contrast, under both approaches, fixed capital declines substantially more among small firms, consistent with the evidence provided above. The absence of a strong size effect in recessions could be expected given the time series reported in Figure 1.

This is in sharp contrast with the behavior of these variables during recoveries, which is documented in Figure 6.[25] The dates used here are 1980q3, 1982q4, 1991q2, 2002q1 and 2009q4. The figure shows that during recoveries, sales and inventories of small firms grow substantially faster, on average, than those of large firms; by contrast, the recovery of fixed capital is almost identical across size groups.

[Figure 6 about here.]

Taken together, Figures 5 and 6 indicate that the excess sensitivity of sales and inventory among small firms could be accounted for primarily by recoveries, while the excess sensitivity of investment could be accounted for primarily by recessions. However, we view this evidence as preliminary, and warranting further quantification in a regression framework. Indeed, there are only five recession/recovery in the sample, with substantial differences across episodes. Figure 7 gives an example. It reports the same time series as (5), but specifically for 2007q4, the date for the beginning of the Great Recession. During this recession, sales of small firms did contract substantially more than large firms', albeit with some delay (as the turning point in sales only occurs in 2008q3).

[Figure 7 about here.]

### 3.5 Robustness

We conclude this section by discussing the extent to which our results depends on two factors: the dates spanned by the sample; the proxy used for the state of the business cycle.

[25] This figure only reports the time series constructed by cumulating the average growth rates by size groups, and is thus potentially affected by reclassification. The within-firm version of this plot (as in the bottom row of Figure 5, will be added in a future revision of this paper.

**Sample dates** Table (4) reports estimates of simple OLS regressions of the average difference in within-firm growth rates, $\hat{g}_t^{(\text{small})} - \hat{g}_t^{(\text{large})}$, on year-on-year real GDP growth, for different subsamples of the data: all dates excluding the early 1980's recession (1981q3-1984q3); all dates excluding the Great Recession (2007q4-2010q4); all dates excluding both; pre-1992; and post-1992. For all three variables and most subsamples, the estimates of the slope coefficients are significant at the 1% level. Moreover, the coefficients have a similar magnitude as the baseline, suggesting that the estimates of the excess sensitivity of small firms obtained in the full sample are robust and fairly stable over the complete sample period. One exception to this finding is the specification that excludes both the 1981q3-1984q3 and 2007q4-2010q4 for sales. Both the recovery from the early 1980's recession, and the Great Recession itself, are influential observations for sales, in line with the impression conveyed by the scatterplot of Figure 2. They are also episodes of particularly high GDP growth in absolute value, albeit with different signs; the fact that eliminating these observations from the sample reduces the precision of the estimate should therefore perhaps not be surprising.

[Table 4 about here.]

**Proxies for the state of the business cycle** Table (5) reports the same simple OLS regressions using three alternative proxies for the state of the business cycle: industrial production growth for all sectors; industrial production growth for the manufacturing sector; and the change in the unemployment rate. The magnitudes of the estimated elasticities are not comparable across business-cycle indicators, but for sales and investment, the results are statistically significant at the 1% level and qualitatively consistent with the evidence obtained using real GDP growth. Inventory growth is a clear outlier: the estimated slope coefficients for industrial production and the change in civilian unemployment rate are not significant. This partly reflects the Great Recession and its aftermath, during which large firms' inventory re-stocking was far sharper than small firms': when excluding the 2007q4-2010q4 dates, the elasticity of the small-large firm difference with respect to industrial production growth becomes again significant. Nevertheless, this suggests that the evidence on the excess sensitivity of inventory growth depends to a larger extent on the exact proxy used for the state of the business cycle.

[Table 5 about here.]

This section has established that small firms tend to exhibit a higher degree of sensitivity of sales growth, inventory growth and investment to aggregate conditions that large firms. Quantitatively, a 1% point fall in GDP is associated with a 3.1% point drop in sales among the bottom 99% of firms, but only a 2.5% fall among the top 1%; the differences in elasticities are larger for inventory and fixed investment. The remainder of the paper asks two questions: are these differences important for aggregate fluctuations, and are these differences driven by a financial accelerator mechanism?

# 4 Aggregate implications

## 4.1 A simple decomposition of aggregate growth

Appendix C shows that the growth rate of the aggregate value of any variable of interest (say, sales) between quarters $t-4$ and $t$, denoted by $G_t$, can be decomposed as:

$$\begin{aligned} G_t &= \hat{g}_t^{(\text{large})} \\ &+ s_{t-4}\left(\hat{g}_t^{(\text{small})} - \hat{g}_t^{(\text{large})}\right) \\ &+ \hat{cov}_t. \end{aligned} \tag{3}$$

Where,

$$s_{t-4} = \frac{X_{t-4}^{(small)}}{X_{t-4}}$$

is the initial fraction of the total value of $x$ accounted for by small firms, and $\hat{g}_t^{(small)}$ and $\hat{g}_t^{(large)}$ are the cross-sectional average growth rates considered in the previous section. The term $\hat{cov}_t$ is itself a weighted average of two terms:

$$\hat{cov}_t = \hat{cov}_t^{(\text{large})} + s_{t-4}\left(\hat{cov}_t^{(\text{small})} - \hat{cov}_t^{(\text{large})}\right).$$

Each of the two terms $\hat{cov}_t^{(\text{small})}$ and $\hat{cov}_t^{(\text{large})}$ can be interpreted as cross-sectional covariances between firms' initial shares of their group's total, and their subsequent growth.[26] These terms capture the idea that if firms that are initially important in their group also grow faster, then total growth will tend to outpace firm-level growth in that group (and vice-versa if initially important firms grow more slowly). In principle, differences in the covariance terms between small and large firms may also by relevant for understand the contribution of small firms to fluctuations in aggregate growth. Note that this decomposition is only correct if the set of firms entering aggregate sales is held constant from $t$ to $t-4$; thus, it should be thought of as a decomposition of growth of *surviving* firms and does not reflect any effect of entry or exit.[27]

The decomposition (3) attributes aggregate growth in the variable of interest to three different sources: firm-level growth of large firms, $\hat{g}_t^{(\text{large})}$; differential firm-level growth between small and

[26] Specifically, for small firms, $\hat{cov}_t^{(\text{small})} = \sum_{i \in \mathcal{I}_t^{(\text{small})}} \left(w_{i,t-4} - \frac{1}{\#\mathcal{I}_t}\right)\left(g_{i,t} - \hat{g}_t^{(small)}\right)$, where $w_{i,t-4}$ is the four-quarter lagged share of the total value of the variable of interest accounted for by firm $i$; $\hat{cov}_t^{(large)}$ is defined similarly. This term is a cross-sectional covariance up to a normalizing factor. Appendix C contains more details on the decomposition and its interpretation.

[27] An additional issue with the decomposition is that it is exact in the population of surviving firms; however, we estimate it using a weighted representative sample of firms. Change in the weighting of observations across time periods can complicate the interpretation of the decomposition. The decomposition (3) could in principle be extended to estimate the bias implied by both focusing on surviving firms and using sample weights. However, this requires supplementary data disclosure; future versions of the paper will include these robustness exercises.

large firms, $\Delta\hat{g}_t \equiv \hat{g}_t^{(\text{small})} - \hat{g}_t^{(\text{large})}$; and a term capturing the covariance between initial size and growth, $\hat{cov}_t$. It clarifies the intuitive fact that, in order to matter, the growth differential $\Delta\hat{g}_t$ must be large relative to small firms' initial share, $s_{t-4}$. Additionally, the decomposition indicates that business-cycle variation in $\hat{cov}_t$ could offset the effect of firm-level growth on aggregates. The relationship between firm-level and aggregate growth thus depends on the properties of $s_{t-4}$ and $\hat{cov}_t$ in the data.

### 4.2 The covariance between initial size and growth

In order to clarify the contribution of the term $\hat{cov}_t$ to business-cycle variation in $G_t$, it is useful to note that the analogous decomposition to (3) also holds within each firm group, namely:

$$\begin{aligned} G_t^{(\text{small})} &= g_t^{(\text{small})} + \hat{cov}_t^{(\text{small})}, \\ G_t^{(\text{large})} &= g_t^{(\text{large})} + \hat{cov}_t^{(\text{large})}. \end{aligned} \tag{4}$$

Let $Y_t$ be a business-cycle indicator; for instance, $Y_t \equiv \log\left(\frac{GDP_t}{GDP_{t-4}}\right)$. We can then write the correlation between $G_t^{(\text{small})}$ and $Y_t$ as:

$$corr(G_t^{(\text{small})}, Y_t) = \frac{\sigma_{\hat{g}_t^{(\text{small})}}}{\sigma_{G_t^{(\text{small})}}} corr\left(\hat{g}_t^{(\text{small})}, Y_t\right) + \frac{\sigma_{\hat{cov}_t^{(\text{small})}}}{\sigma_{G_t^{(\text{small})}}} corr\left(\hat{cov}_t^{(\text{small})}, Y_t\right). \tag{5}$$

Here, $\sigma_Z$ denote the standard deviation of variable $Z$. Equation (5) breaks down the correlation between $G_t$ and $Y_t$ into a component originating from firm-level growth, and a component originating from the covariance term. Of course, the same holds for large firms, and for firms overall.

[Table 6 about here.]

Table 6 reports the values of the different elements of the right-hand side of (5), when the variable of interest is sales. It shows that the covariance terms - whether it be for small firms, large firms or all firms - have a limited (although non-zero) contribution to business-cycle variation in aggregate growth. Of course, these terms are non-zero on average; in fact, their sample means are 0.13, 0.29 and 0.23 for small, large and all firms, respectively. The large *average* difference in the covariance term between small and large firms has a substantial effect on trends. Namely, for small firms, cumulative average firm-level growth tracks fairly closely the path of aggregates; by contrast, for large firms, cumulative firm-level growth falls far short of the trend in aggregates, as documented in Figure 8.

[Figure 8 about here.]

But both the correlation to GDP growth of these covariance terms, and their standard deviation relative to aggregate sales growth $G_t$, are substantially smaller than for the cross-sectional average

firm-level growth rates. For example, for large firms, the correlation between aggregate sales growth and GDP growth is 0.62 in the sample; this can be broken down into a contribution of $0.64 = 0.83 \times 0.77$, coming from the term $\frac{\sigma_{\hat{g}_t^{(\text{large})}}}{\sigma_{G_t^{(\text{large})}}} corr\left(\hat{g}_t^{(\text{large})}, Y_t\right)$, and $-0.02 = 0.45 \times (-0.05)$, coming from the term $\frac{\sigma_{\hat{cov}_t^{(\text{large})}}}{\sigma_{G_t^{(\text{large})}}} corr\left(\hat{cov}_t^{(\text{large})}, Y_t\right)$. These simple decomposition thus suggest that, up to first order, business-cycle variation in the covariance terms contribute little to aggregate growth; instead, average firm-level growth is the dominant factor.

### 4.3 The relative importance of small firms

Figure (9) reports the level (left column) and the share (right column) of total sales, inventory, fixed investment, and total assets of the bottom 99% of firms by size. The right column, in particular, corresponds to the time-series $s_t$ defined above. As previously, size groups are defined relative to the one-year lagged empirical distribution of assets. Two points about these time series are worth emphasizing.

[Figure 9 about here.]

First, the relative importance of the bottom 99% is, on average, small. Their average share of total sales, inventory, fixed investment, and total assets, are, respectively, 26.4%, 27.8%, 11.8% and 16.0% in this sample. The particularly low share for assets reflects the extreme degree of skewness of the firm size distribution; by contrast, the fact that the share of sales is higher is consistent with the fact, documented in section 2, that smaller firms are less capital-intensive. Nevertheless, this is a first hurdle for the excess sensitivity of small firms to substantially affect aggregates.

Second, movements in the average shares seem dominated by a long-term downward trend, not business-cycle variation. The share of sales of the bottom 99% falls from from 35.6% in 1977q3 to 20.4% in 2014q1, while their share of assets falls from 25.6% to 9.0%; this decline is gradual, with an acceleration around the 2000's. This is not to say that cyclical movements in small firms' shares are completely absent: for instance, the raw correlation $corr\left(s_{t-4}, \log\left(\frac{GDP_t}{GDP_{t-4}}\right)\right)$ is approximately equal to 0.37 in the sample. While a substantial cyclicality of the share could, in principle, offset its low average level and magnify the term $\Delta\hat{g}_t$, the time series of Figure (9) suggest that this unlikely to be the case in the data.

The discussion of the link between firm-level and aggregate growth in the data can be summarized as follows: business cycle variation in aggregate growth is primarily driven by firm-level growth, not by the residual covariance term; but the relative importance of small firms for aggregates is likely too limited for the excess sensitivity of small firms to have an impact on aggregate growth. The next section focuses on quantifying more precisely these points by constructing counterfactual paths for aggregate growth and analyzing their business cycle behavior.

### 4.4 Counterfactuals

In order to quantify the importance of the small/large firm differential for the cyclical behavior of aggregate growth in our sample, we start by constructing the counterfactual time series:

$$G_t^{(1)} = G_t - s_{t-4}\left(\hat{g}_t^{(\text{small})} - \hat{g}_t^{(\text{large})}\right) \tag{6}$$

This time series nets out the contribution of firm-level growth differentials between the small and large firms — the second term of the decomposition (3). One could also net out differentials in the covariance terms; the counterfactual time series obtained would then simply be the aggregate growth rate among large firms:

$$\begin{aligned} G_t^{(2)} &= G_t - s_{t-4}\left(\hat{g}_t^{(\text{small})} - \hat{g}_t^{(\text{large})}\right) \\ &\quad - s_{t-4}\left(\hat{cov}_t^{(\text{small})} - \hat{cov}_t^{(\text{large})}\right) \\ &= G_t^{(large)}. \end{aligned} \tag{7}$$

We are interested in the differences in cyclicality between these aggregate times series. As in the previous section, our simple metric for cyclicality are the estimates of the slope term in an OLS regression of $G_t$, $G_t^{(1)}$, and $G_t^{(2)}$ on the annual log-change in real GDP.

[Table 7 about here.]

Table 7 reports the estimated slopes of the actual and counterfactual aggregate growth series for sales, inventory, fixed investment, and total assets. For sales (first line), the actual and counterfactual elasticities are close: the point estimates differ by approximately 13 basis points, and the difference is not statistically significant. The economic interpretation of this difference is that, all other things equal, if the average elasticity of small firms' sales growth were equal to that of large firms, aggregate sales' elasticity to GDP growth would only be 0.13 points smaller — from a baseline of approximately 2.30. The second counterfactual series is even closer, indicating that cyclical variation in the difference between the covariance terms between small and large firms is, if anything, dampening aggregate fluctuations. The same conclusion holds for inventory; and it holds, in even stronger terms, for investment and for total assets. This is perhaps unsurprising, given the high degree of concentration documented previously.

Note that the results are consistent with a simple rule of thumb, according to which the aggregate impact of small firms' excess sensitivity is equal to the product of the typical share of the small firms, multiplied by the excess sensitivity of small firms. For sales, for example, the results of the previous section indicate that the difference in elasticities to GDP growth between small and large firms (the excess sensitivity of small firms) is approximately 0.6. The results reported in Figure 9 indicate small firms' share is, on average, approximately 25%. The product of the two is: $0.6 \times 0.25 = 15$ bps, or approximately the difference between the estimated and counterfactual

elasticities (13 bps). The fact that this rule of thumb delivers approximately the same result as the computation reported in Table 7 indicates that both cyclical movements in the covariance term $C_t$, and cyclical variation in small firms' share, $s_t$, have a limited impact on the cyclical fluctuations in aggregate growth. Figure 10 drives home this last point, by reporting the three time series $G_t$, $G_t^{(1)}$ and $G_t^{(2)}$ for sales. The three overlap, and are hard to distinguish visually.

[Figure 10 about here.]

### 4.5 Relationship to Gertler and Gilchrist (1994)

We close this section by discussing briefly the relationship between our results and the difference in the cyclical behavior of small and large firms documented by Gertler and Gilchrist (1994) — henceforth, GG. Both our evidence and theirs points toward the excess sensitivity of small firms. However, there are a number of differences between our approach and theirs. We highlight the three main ones below. While in principle, all three could affect the conclusions, we argue that, in the data, only one seems important: the choice of dates (monetary contractions versus recessions).

**Firm-level vs. aggregate growth** The first difference with GG is that, whereas that paper focuses on total growth of small and large firms, we have primarily focused on average firm-level growth for each group. As discussed in Section 4.2, the two are equal up to a covariance term that captures the relationship between initial size and subsequent growth. And, as documented in table 6, from an accounting standpoint, the correlation between GDP growth and the aggregate growth rate of sales of both small and large firms is mostly accounted for by the correlation of within-firm growth, and not by the covariance term. Another way to put this is that the correlation between aggregate growth rates $G_t$, $G_t^{(\text{small})}$ and $G_t^{(\text{large})}$ and their firm-level counterparts $\hat{g}_t$, $\hat{g}_t^{(\text{small})}$ and $\hat{g}_t^{(\text{large})}$ are very high (the sample correlations are 0.91, 0.86 and 0.90, respectively). We thus think it unlikely that the focus on firm-level growth, as opposed to aggregates, would lead us to substantially different conclusions.

**Definition of size groups** The second difference between this paper and GG has to do with the definition of small and large firms. Because of the format of the public version of the QFR data, which only discloses total sales by bins of nominal book assets, GG construct a "synthetic" small and a "synthetic" large firm. In their definition, small firms account, by construction, for 30% of total nominal sales in any particular quarter.[28] By contrast, our approach is to define size groups in terms of the (one-year lagged) position of the firm in the distribution of nominal book assets. As emphasized by Figure 9, in the earlier part of our sample, the share of sales the bottom 99% of firms is close to 30%. Thus, our and their method should group results in approximately similar

[28] Appendix D contains a precise description of their methodology.

groupings of firms for that sample period. In the latter parts of the sample, however, given the decline in the share of the bottom 99%, the GG method would have led to a definition of small firms reaching higher in the size distribution. Given that the evidence reported in the previous section suggests that sensitivity to GDP growth slopes downward with size, adopting the GG classification would likely have led us to estimate a lower magnitude of the excess sensitivity of small firms.

**Dates** The third and most important difference with GG is the difference in both the sampling period, and the dates on which the analysis focuses. Their approach is to focus on the consequences of exogenous monetary contractions. In order to implement this approach, they construct wormplots (analogous to those reported in Figures 5, 6 and 7) around the dates identified by Romer and Romer (1989) as monetary contractions.

[Figure 11 about here.]

Figure 11 reports these wormplots in our sample, using the five Romer and Romer dates in our sample, as provided by the updated evidence in Kudlyak and Sanchez (2016): 1978q3, 1979q4, 1988q4, 1994q2 and 2008q3. The resulting wormplots differ from those reported in Section 3.4 in some key respects. In particular, the sales of small firms display significantly more excess sensitivity than after recession starts. This is consistent with the evidence provided by Gertler and Gilchrist (1994) despite the fact that our samples do not overlap substantially. More broadly, our view is that the particular dates which one uses to assess excess sensitivity matter greatly for the conclusions, especially when there are relatively few such dates in the sample. This is why we prefer to focus on the regression approach discussed in Section 3.

This section has shown that, while the excess sensitivity of small firms is economically and statistically significant, it is also of very limited relevance for the behavior of aggregates in our sample. This is primarily because the relative importance of the bottom 99% is small and declining in the data, and secondarily because the difference between aggregate and firm-level growth - a residual which captures the covariance between initial size and growth - displays very little cyclical variation, so that firm-level and aggregate growth closely track each other. We next turn to investigating whether the excess sensitivity of small firms is driven by a financial accelerator mechanism.

## 5 Financial origins of excess sensitivity

As we mentioned in our literature review, the early financial accelerator literature emphasized a variety of mechanisms whereby recessions could be worsened due to tightening financial constraints. In this section, we investigate the degree to which the size asymmetry we have documented is consistent with a financial accelerator mechanism. Overall, the behavior of small and large firms in

recessions is consistent with the financial accelerator, but when we condition directly on proxies for financial constraints in our event study plots and regressions, the size effect remains and coefficients on our proxies for financial constraints are often insignificant and/or enter with the wrong sign. Moreover, evidence specific the Great Recession is quite weak; in particular, zero-leverage firms behave no differently from firms with positive leverage, a surprising finding given the perceived importance of disruptions to the supply of credit in this recession.

### 5.1 Basic predictions of the financial accelerator

The basic empirical regularities underlying the financial accelerator model are laid out succinctly in Gertler and Gilchrist (1994). The authors use the QFR public releases to argue that size serves as a proxy for financial constraints given that small firms are more likely to be bank-dependent and less likely to have access to public debt and equity markets. The basic mechanism posited is that bank-dependent and private firms are unable to borrow in a recession (or do so at higher costs) than large firms. A firm may wish to borrow in a recession to avoid firing workers and maintain investment/finance inventory investment so as to smooth production over the cycle. Thus, the authors argue that the financial accelerator should manifest itself as a faster contraction of sales and inventories at financially constrained vs. unconstrained firms. Likewise, investment rates should be less cyclical and firms with capital market access should increase short-term debt holding. As Gertler and Gilchrist (1994) emphasize, the behavior of sales, inventories, and short-term debt around the Romer and Romer dates are consistent with the predictions of the financial accelerator. The same basic predictions have been emphasized in contemporaneous work like Kashyap, Lamont and Stein (1994).

### 5.2 The behavior of debt

As shown in Section 4, on recession dates, sales growth, inventory growth, and tangible investment rates all decrease faster at small firms relative to large firms. The behavior of these series is consistent with the presence of a financial accelerator. However, as Figure 12 shows, the behavior of short-term debt is not; short-term debt falls on recession dates at both small and large firms. Here, short-term debt is measured as debt with maturity one year or less. The figure reports the cumulative average change, normalized by one-year lagged assets at the firm level. The time-series show that the cumulative decline of short-term debt is, if anything, slightly larger at large firms in the quarters following the start of a recession.[29]

[Figure 12 about here.]

[29] It is also difficult to observe sharp differences in the behavior of debt overall and of bank debt (the left and middle panels of Figure 12); the financial accelerator mechanism, however, focuses for the most part on short-term financing.

Table 8, which reproduces the size regressions from earlier and include short-term debt as an additional left-hand side variable provides the same conclusion as the worm plots. Short-term debt (as a fraction of lagged assets) does not display any size asymmetry and the point estimates suggest that short-term debt is procyclical at both large and small firms. The absence of a size asymmetry and the procyclicality of short-term debt at the largest firms is inconsistent with the financial accelerator interpretation.

[Table 8 about here.]

### 5.3 Size and other proxies for financial constraints

An advantage of using the QFR data is the ability to condition on firm-specific measures of leverage, liquidity, and bank-dependence that may better proxy for underlying access to financing in recessions than size does. We classify firms into leverage, liquidity, bank-dependence, and debt market access classes and examine in a regression framework whether these financial indicators eliminate the size effect, as well as whether, on their own, they provide evidence consistent with the narrative underlying the financial accelerator. In particular, we estimate the following horse-race regressions:

$$\begin{aligned} g_{i,t} &= \alpha + \beta \log\left(\tfrac{GDP_t}{GDP_{t-4}}\right) \\ &+ \sum_{j\in\{(90,99),(99,99.5),(99.5,100)\}} \left(\gamma_j + \delta_j \log\left(\frac{GDP_t}{GDP_{t-4}}\right)\right) \mathbf{1}_{i\in\mathcal{I}_t^{(j)}} \\ &+ \sum_{k\in\mathcal{K}} \left(\zeta_k + \eta_k \log\left(\frac{GDP_t}{GDP_{t-4}}\right)\right) \mathbf{1}_{i\in\mathcal{F}_t^{(k)}} \\ &+ (\textit{Industry controls}) + \epsilon_{i,t}. \end{aligned} \tag{8}$$

In this regression framework, the size controls are identical to the baseline estimation of section 3: size groups are defined using lagged firm size, and results for 90-99th percentile, 99th to 99.5th percentile, and top 0.5% are reported relative to the baseline 0-90% group. As before, we also include indicators for durable and non-durable manufacturing.[30] In contrast to the baseline regression, $k \in \mathcal{K}$ now indexes groups of our measures of financial strength. We consider four different measures of financial strength: bank-dependence, leverage, liquidity, and access to public debt markets.

[Table 9 about here.]

The second column in Table 9 adds a control for the degree of bank-dependence to the size regression. Our measure of bank dependence is the share of bank debt in total debt, and this

[30] Our results hold when controlling for NAICS 3-digit industries.

variable has a bimodal distribution, with some firms nearly fully reliant on bank debt and some firms (including zero leverage firms) have no reliance on bank debt. We sort firm into low bank dependence firms (with a bank share of less than 10%), intermediate bank dependence firms (between 10% and 90%), and high bank dependence firms (over 90%). The coefficients on GDP interacted with size class - particularly the top 0.5% remain significant and similar to the baseline regression. However, the coefficient on bank-dependence is insignificant and enters with the wrong sign.

The third column in Table 9 provides estimates of the joint effect of size and leverage and sales growth. We split the sample into four bins: firms with zero debt, firms with a debt to asset ratio of less than 15%, firms with a debt to asset ratio of between 15% and 50%, and firms with debt to asset ratio over 50%. Firms with leverage less than 15% approximately account for the bottom quarter of the leverage distribution, while firms above 50% account for approximately the top quarter.[31] As coefficients on GDP growth interacted with firm size class show, the top 0.5% remain less sensitive to the cycle than the bottom 90%. Moreover, we find evidence that zero leverage and low leverage firms are less cyclically sensitive in comparison to middle and high leverage firms. The fact that lower leverage firms are less cyclically sensitive is consistent with the financial accelerator mechanism. Indeed, in Bernanke, Gertler and Gilchrist (1999), the external finance premium is proportional to the leverage ratio - increases in firm leverage due to a fall in firm equity or decrease in the value of firm assets raises the cost of external financing, decreasing production.

In the fourth column, we consider the joint effect of size and liquidity. We consider three liquidity classes: a low cash to asset ratio of less than 1%, an intermediate cash to asset ratio of 1% to 20%, and a high level of cash to assets above 20%. As with leverage, we choose fixed thresholds that approximate the bottom and top quartiles. The size effect remains with the point estimates similar to the baseline size regression; the low sensitivity is concentrated at the top 0.5%. However, like the indicator for bank dependence, higher liquidity firms do not exhibit a statistically significant difference in sensitivity relative to lower liquidity firms and the sign on the coefficient for the most liquid firms goes in the wrong direction.

Finally, in the last column, we introduce a dummy variable that indicates whether a firm has ever had some positive level of non-bank debt. That is, we classify a firm as having access to public debt markets if the firm ever records some positive liability for non-bank debt (either short-term commercial paper or long-term corporate debt). Because it relies only on responses from the long-form survey, this variable is most informative for the largest firms. The coefficient on market access interacted with GDP is positive and significant while the coefficients on firm size become more negative and significant. Effectively, since most of the variation in the market access measure is coming among firms in the top 1% of the size distribution, this measure indicates that, among large firms, those without market access are less cyclically sensitive than those with market access.

[31] We use fixed thresholds given the absence of a time trend in leverage and mitigating reclassification bias over the cycle.

This sign on market access along with the resulting changes in the coefficient on size are inconsistent with the financial accelerator view. That is, one would expect firms with market access to have a lower degree of sensitivity to the business cycle. Our findings are consistent with a nonfinancial interpretation - larger firms are less cyclical simply because the investment opportunities of these firms are less cyclical due to their position in the firm lifecycle. These firms have lower degrees of leverage and less market access simply because financing is not needed for growth. This asymmetry due to investment opportunities would also explain our leverage findings.

In any case, as table 9 shows, the excess sensitivity of small firms survives after including various proxies for financial constraints. While this does not rule out that the size effect reflects underlying financial frictions, the fact that size generally appears more significant than measures of financing constraints and the coefficients remain stable across specifications, supports the view that size is reflecting nonfinancial factors.

It is conceivable that size proxies for firm age, and that firm age is a better proxy for financing constraints in comparison to leverage, liquidity, etc. Given that small firms are sampled for only eight quarters, we cannot do much with the existing survey to proxy for age. However, it may be possible to combine other Census data sets to find a firm age measure. We also plan to restrict the sample to those firms that are continuously sample (i.e. firms with over $250 million in assets), and investigate whether the size effect holds in this subsample. The presence of a size effect in this set of mature, older firms would be suggestive that the size effect is distinct from firm age.

### 5.4 Zero Leverage Firms

The regression results we have discussed so far present, at best, mixed evidence in favor the financial accelerator mechanism. Instead of focusing on whether the size asymmetry is financial or nonfinancial in origin, we next document whether firms respond heterogeneously to recessions when conditioning directly on balance sheet characteristics. In particular, we consider differences between firms with zero leverage and firms with positive leverage.

[Figure 13 about here.]

Figure 13 below depicts wormplots for sales, inventory and fixed capital for zero leverage firms and positive leverage firms separately. In the top row, the wormplots are constructed using cumulative average firm growth; in the bottom row, they are constructed using within-firm changes relative to recession start date. Leverage groups are defined using one-year lagged leverage in the top row, and initial leverage (as of the recession start date) in the bottom row.

As is clear from the figures, zero leverage firms and positive leverage firms' sales behave very similarly on average across recessions. There is little evidence of a pretrend in either the all recessions wormplot or the Great Recession wormplot. For inventory or fixed investment, the

message is analogous: zero leverage and positive leverage firms experience very similar contractions. Figure 14 reports the same wormplots as 13, but only for 2008q3. Indeed, if anything, during the Great Recession, sales and investment at zero leverage firms contracts faster, on average, than at firms with positive leverage.

[Figure 14 about here.]

These findings would appear to be inconsistent with a financial accelerator mechanism. As noted, in Bernanke, Gertler and Gilchrist (1999), the external finance premium is monotonically increasing with firm leverage. Under the financial accelerator mechanism, these positive and higher leverage firms should experience increases in the cost of external financing, leading to a faster decline in factor inputs and production. It stands to reasons that these mechanisms would have been considerably stronger in the Great Recession given the disruption to the banking system and the supply of credit to firms. The evidence provided above suggests that this was not the case among the manufacturing firms surveyed in the QFR.

## 6 Conclusion

This paper has brought new evidence to bear on the question of whether, and why, cross-sectional differences in exposure to business cycles might be related to firm size. This evidence, though limited to the manufacturing sector, has the advantage of covering a representative sample of the population of US firms, at the quarterly frequency, over a period spanning the last 5 recessions. Moreover, this evidence allows one to directly link real decisions of firms to their financial strength, which the literature on firm dynamics and business cycles has argued is a key determinant of heterogeneous responses to aggregate conditions.

We find strong evidence that smaller firms tend to be more sensitive to aggregate conditions than large firms, consistent with previous literature. Our point estimate suggests that a 1% drop in GDP is associated with a 2.5% contraction in sales for firms in the top 1% of the size distribution, but a 3.1% contraction for firms in the bottom 99%.

Our evidence however casts doubt on the commonly accepted interpretations of this finding. First, we show that the effect is at least as much about expansions as it is about recessions, and furthermore, that it is mostly accounted for by the top 0.5%, with the rest of firms in the distribution having statistically indistinguishable sensitivities. Second, the degree of concentration of sales and investment is dramatic; by the latter parts of the sample, for instance, the top 0.5% of firms account for about 75% of sales. As a result, the excess sensitivity of smaller firms is insufficient to substantially affect the volatility of aggregates; we estimate that, absent excess sensitivity, the elasticity of aggregate sales to GDP growth in our sample would only be about 0.15 points smaller, from a baseline of 2.30.

Finally, we provide preliminary evidence that this excess sensitivity cannot easily be accounted for by financial factors: the behavior of debt (in particular short-term debt) during recessions does not significantly differ among small firms; controlling for rough proxies for financial constraints does not eliminate our estimated size effect; and, perhaps most surprisingly, firm groups conditioning directly on these proxies (in particular, on whether a firm has zero leverage at the onset of a recession) does not exhibit a substantial difference in cyclical sensitivity either.

These results suggest two potential directions to further test the hypothesis that the excess sensitivity of small firms is financial in nature. First, while it is notoriously difficult to measure financial constraints — we acknowledge that the proxies we use in this paper evidently suffer from a number of concerns about endogeneity —, the broader question of whether small firms are more financially constrained could be explored in more detail using this data; differential exposure in the timing of either tax or banking reforms is a potential avenue of research. Second, the evidence provided here could be interpreted from the standpoint of a structural model with heterogeneous firms and financial frictions. We leave these issues — and the broader question of the extent to which the financial accelerator contributes to amplifying business cycles — to future research.

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# A Measurement framework

For clarity, the following paragraphs provide the details of the way in which we construct the size classification and growth measures used in section 3.

**Sample selection** Let $i$ index firms and $t$ index quarters. Let $x \in X$ index variables of interest; in the analysis, we use $X = \{\text{sales}, \text{inventory}, \text{NPPE stock}, \text{assets}\}$. Let:

$$\mathcal{I}_t(x) \equiv \{ \quad i \quad \text{s.t.} \quad x_{i,t-4} > 0 \quad \text{and} \quad x_{i,t} > 0 \quad \} \tag{9}$$

We restrict attention to firms with strictly positive values of the variables of interest so as to compute log growth rates (see below). In order to be able to construct a consistent sample across variables of interest, we only consider firms $i \in \mathcal{I}_t$, where:

$$\mathcal{I}_t \equiv \bigcap_{x \in X} \mathcal{I}_t(x).$$

**Size classification** Let $a_{i,t}$ denote book assets. For every quarter $t$, we compute a set of percentiles,

$$\mathcal{P}_t = \left\{ \bar{a}_t^{(k)} \right\}_{k \in K},$$

where $K \subset [0, 100]$, $\bar{a}_t^{(0)} = 0$ and $\bar{a}_t^{(k)} = +\infty$. These percentiles are computed using the distribution of book assets of *all* firms, not only those firms $i \in \mathcal{I}_t$. Moreover, these percentiles are obtained using the Census-provided cross-sectional sampling weights $z_{i,t}$. We then define:

$$\mathcal{I}_t^{(k_1,k_2)} = \left\{ \quad i \in \mathcal{I}_t \quad \text{s.t.} \quad a_{i,t-4} \in \left[ \bar{a}_{t-4}^{(k_1)}, \bar{a}_{t-4}^{(k_2)} \right[ \quad \right\}.$$

In the case of the simple sample split between bottom 99% and top 1%, the small and large firms groups are defined as:

$$\begin{array}{ll} \mathcal{I}_t^{(\text{small})} & = \mathcal{I}_t^{(0,99)}, \\ \mathcal{I}_t^{(\text{large})} & = \mathcal{I}_t^{(99,100)} = \mathcal{I}_t \setminus \mathcal{I}_t^{(0,99)}. \end{array} \tag{10}$$

**Growth rates** For any $i \in \mathcal{I}_t$, we define growth rates as:

$$g_{i,t}(x) = \begin{cases} \log\left(\frac{x_{i,t}}{x_{i,t-4}}\right) & \text{if} \quad x \in \{\text{sales}, \text{inventory}, \text{NPPE stock}, \text{assets}\} \\ \frac{nppe_{i,t} - nppe_{i,t-4} + dep_{i,t-4,t}}{nppe_{i,t-4}} & \text{if} \quad x = \text{fixed investment}. \end{cases} \tag{11}$$

We focus on log growth-rates because they are easier to use in the decomposition of aggregate growth into firm-level growth rate discussed in section 4. Annual differences (instead of quarterly differences) are the main specification both because they are consistent with the size classification

(which is based on one-year lags, so as to adequately capture initial size), and because they neutralize the issue of seasonal variation in the variables of interest. Cross-sectional averages of growth rates are then defined as:

$$\begin{aligned} \hat{g}_t^{(k_1,k_2)}(x) &\equiv \frac{1}{Z_{t-4}^{(k_1,k_2)}} \sum_{i \in \mathcal{I}_t^{(k_1,k_2)}} z_{i,t-4} g_{i,t}(x) \\ Z_{t-4}^{(k_1,k_2)} &\equiv \sum_{i \in \mathcal{I}_t^{(k_1,k_2)}} z_{i,t-4}. \end{aligned} \tag{12}$$

and $z_{i,t-4}$ are the Census-provided cross-sectional sampling weights. Throughout, we analyze cross-sectional average time-series after de-meaning them (since the focus in not on long-term trends, but rather on the cyclicality of growth); we do not use any further detrending or filtering.

**Robustness** Our results for sales, inventory, the stock of net property, plant and equipment are robust to using half-growth rates of the form $2\frac{x_{i,t}-x_{i,t-4}}{x_{i,t}+x_{i,t-4}}$. Qualitatively and quantitatively, results do not change substantially whether one uses the one-year lagged or current weights in computing average growth rates of the form (12). Since the sample is titled toward larger firms, carrying the analysis using unweighted data ($z_{i,t} = 1, \forall(i,t)$) leads to qualitatively identical results, but somewhat smaller magnitudes.

# B Variable definitions for wormplots

The time series in the top panels of figure 5 are constructed as follows: for $x \in X$, and for a particular date $t_0$, define:

$$l_{t,t_0}(x)^{(\text{small})} = 100 \times \begin{cases} \prod_{k=0}^{t-t_0} \left(1 + \hat{g}_{t_0+k}(x)^{(\text{small})}\right) & \text{if } t \geq t_0 \\ \left(\prod_{k=0}^{t-t_0} \left(1 + \hat{g}_{t_0+k}(x)^{(\text{small})}\right)\right)^{-1} & \text{if } t \leq t_0 \end{cases} \tag{13}$$

where $\hat{g}_t(x)^{(\text{small})}$ is defined as in section 3.1; define the cumulative path of large firms similarly.

For the bottom panels, we start by defining a set of firms $\mathcal{I}_{t_0}$:

$$\mathcal{J}_{t_0} = \left\{ i \quad \text{s.t. } a_{i,t} \leq \bar{a}_{t-4}^{(99)} \quad \text{and} \quad \forall m \leq k \leq M, \quad x_{i,t+k} > 0 \quad , \quad x \in X \quad \right\},$$

where $m < 0$ and $M > 0$ is the window chosen. We define this set of firm for each date $t_0$ of interest. We then report:

$$m_{t,t_0}(x)^{(\text{small})} = 100 \times \frac{1}{Z_{t_0}^{(small)}} \sum_{i \in \mathcal{I}_{t_0}} z_{i,t_0} \frac{x_{i,t}}{x_{i,t_0}},$$

and a similar time series for the set of large firms. In the definition, $Z_{t_0}^{(small)} \equiv \sum_{i \in \mathcal{I}_{t_0}} z_{i,t_0}$ is defined using the Census-provided cross-sectional sampling weight, as in (12. These definition effectively

amount to creating size groups based on the $t_0$-quantile of the size distribution to which the firm belongs.

In both cases, we use the stock of net property, plant and equipment, as opposed to our constructed flow of investment in net property, plant and equipment, in this exercise, because the flow measure can be negative for certain firms during recessions. This makes reporting relative levels difficult.

# C Decompositions of aggregate growth

Assume that all observations are equally weighted, that is:

$$z_{i,t} = 1 \quad \forall (i,t).$$

Let $\mathcal{I}_t^{(\text{small})} \subset \mathcal{I}_t$ denote the set of indexes of small firms, and $\mathcal{I}_t^{(\text{large})} = \mathcal{I}_t \setminus \mathcal{I}_t^{(\text{small})}$ be the set of large firms.[32] For some variable of interest $x \in \{\text{sales}, \text{inventory}, \text{NPPE stock}, \text{assets}\}$, and for some quarter $t$, define:

$$\begin{array}{llllll} X_t & = \sum_{i \in \mathcal{I}_t} x_{i,t}, & X_{t-4} & = \sum_{i \in \mathcal{I}_t} x_{i,t-4}, & G_t & = \frac{X_t}{X_{t-4}}, \\ X_t^{(\text{small})} & = \sum_{i \in \mathcal{I}_t^{(\text{small})}} x_{i,t}, & X_{t-4}^{(\text{small})} & = \sum_{i \in \mathcal{I}_t^{(\text{small})}} x_{i,t-4}, & G_{t-4}^{(\text{small})} & = \frac{X_t^{(\text{small})}}{X_{t-4}^{(\text{small})}}, \\ X_t^{(\text{large})} & = \sum_{i \in \mathcal{I}_t^{(\text{large})}} x_{i,t}, & X_{t-4}^{(\text{large})} & = \sum_{i \in \mathcal{I}_t^{(\text{large})}} x_{i,t-4}, & G_{t-4}^{(\text{large})} & = \frac{X_t^{(\text{large})}}{X_{t-4}^{(\text{large})}}. \end{array} \tag{14}$$

These are simply totals for all firms and by group, along with their growth rates. Let:

$$s_{t-4} = \frac{X_{t-4}^{(\text{small})}}{X_{t-4}}$$

be the initial fraction of the aggregate value of $x$ accounted for by small firms. Define the following firm-level growth rates and shares by:

$$\begin{array}{lll} g_{i,t} & = & \frac{x_{i,t}}{x_{i,t-4}} \\ w_{i,t-4} & = & \begin{cases} \frac{x_{i,t-4}}{X_{t-4}^{(\text{small})}} & \text{if } i \in \mathcal{I}_t^{(small)} \\ \frac{x_{i,t-4}}{X_{t-4}^{(\text{large})}} & \text{if } i \in \mathcal{I}_t^{(large)} \end{cases} \end{array} \tag{15}$$

First, note that the total growth of $x$ for small firms (the growth rate $G_{t-4}^{(\text{small})}$ defined above) can be decomposed as:

$$G_t^{(small)} = \hat{g}_t^{(\text{small})} + c\hat{o}v_t^{(\text{small})}, \tag{16}$$

[32] See appendix A for a formal definition of the size classification. Here, we refer to an arbitrary size classification, so long as it constitutes a partition of $\mathcal{I}_t$; in the counterfactuals that are reported next, we will focus on partition between the bottom 99% and top 1% by lagged book assets.

where:

$$\begin{aligned} \hat{g}_t^{(small)} &= \frac{1}{\#\mathcal{I}_t^{(\text{small})}} \sum_{i \in \mathcal{I}_t} g_{i,t} \\ \hat{cov}_t^{(\text{small})} &= \sum_{i \in \mathcal{I}_t^{(\text{small})}} \left( w_{i,t-4} - \frac{1}{\#\mathcal{I}_t} \right) \left( g_{i,t} - \hat{g}_t^{(small)} \right). \end{aligned} \tag{17}$$

The first term in this decomposition, $\hat{g}_t^{(\text{small})}$, is the cross-sectional average growth rate of the variable $x$. (Up to a constant and up to the approximation $log(x) \approx x-1$ for $x$ close to 1, this is the same variable as reported, for instance, in figure 1 for sales.) The second term can be interpreted as an (un-normalized) covariance, since $\frac{1}{\#\mathcal{I}_t^{(\text{small})}} = \frac{1}{\#\mathcal{I}_t^{(\text{small})}} \sum_{i \in \mathcal{I}_t^{(\text{small})}} w_{i,t-4}$. It captures the dependence between initial size (as proxied by the initial share of total size, $w_{i,t-4}$) and subsequent growth (as measured by $g_{i,t}$). Note that this decomposition is exact in any subset of $\mathcal{I}_t$; it holds for large firms as well, for example. Second, note that since $X_t = X_t^{(small)} + X_t^{(large)}$ and $X_{t-4} = X_{t-4}^{(small)} + X_{t-4}^{(large)}$, the following simple shift-share decomposition holds:

$$\begin{aligned} G_t &= s_{t-4} G_t^{(\text{small})} + (1 - s_{t-4}) G_t^{(\text{large})} \\ &= G_t^{(\text{large})} + s_{t-4} \left( G_t^{(\text{small})} - G_t^{(\text{large})} \right). \end{aligned} \tag{18}$$

Combining the two equations, we obtain the decomposition:

$$\begin{aligned} G_t &= \hat{g}_t^{(\text{large})} \\ &+ s_{t-4} \left( \hat{g}_t^{(\text{small})} - \hat{g}_t^{(\text{large})} \right) \\ &+ \hat{cov}_t, \end{aligned} \tag{19}$$

where the covariance term $\hat{cov}_t$ is given by:

$$\hat{cov}_t = \hat{cov}_t^{(\text{large})} + s_{t-4} \left( \hat{cov}_t^{(\text{small})} - \hat{cov}_t^{(\text{large})} \right).$$

# D The methodology of Gertler and Gilchrist (1994) for constructing small and large firm groups

The methodology of Gertler and Gilchrist (1994) is as follows. Let $x$ denote nominal assets, let $\left\{x^{(1)}, ..., x^{(n)}\right\}$ denote the QFR's nominal asset bins' cutoffs, and let $y$ denote nominal sales. For each quarter $t$, define $\underline{x}_t$ by:

$$\underline{x}_t = \max \left\{ x \in \left\{x^{(1)}, ..., x^{(n)}\right\} \Big/ \frac{\sum_{x_{i,t} \leq x} y_{i,t}}{Y_t} \leq 0.3 \right\}$$

Furthermore, let $\underline{x}_t^+$ be the cutoff immediately above $\underline{x}_t$ in the list $\left\{x^{(1)}, ..., x^{(n)}\right\}$. Compute the weight $w_t$ such that:

$$w_t \frac{\sum_{x_{i,t} \leq \underline{x}_t} y_{i,t}}{Y_t} + (1 - w_t) \frac{\sum_{x_{i,t} \leq \underline{x}_t^+} y_{i,t}}{Y_t} = 0.3$$

The growth rate of small firms' sales between time $t-1$ and $t$ is then defined as:

$$G_t^{(small,GG)} = w_t \frac{\sum_{\{i/x_{i,t} \leq \underline{x}_t\}} y_{i,t}}{\sum_{\{i/x_{i,t-1} \leq \underline{x}_t\}} y_{i,t-1}} + (1-w_t) \frac{\sum_{\left\{i/x_{i,t} \leq \underline{x}_t^+\right\}} y_{i,t}}{\sum_{\left\{i/x_{i,t-1} \leq \underline{x}_t^+\right\}} y_{i,t-1}}.$$

The growth rate of large firms is defined analogously, using the cumulative sum of sales over the remaining bins of asset size.

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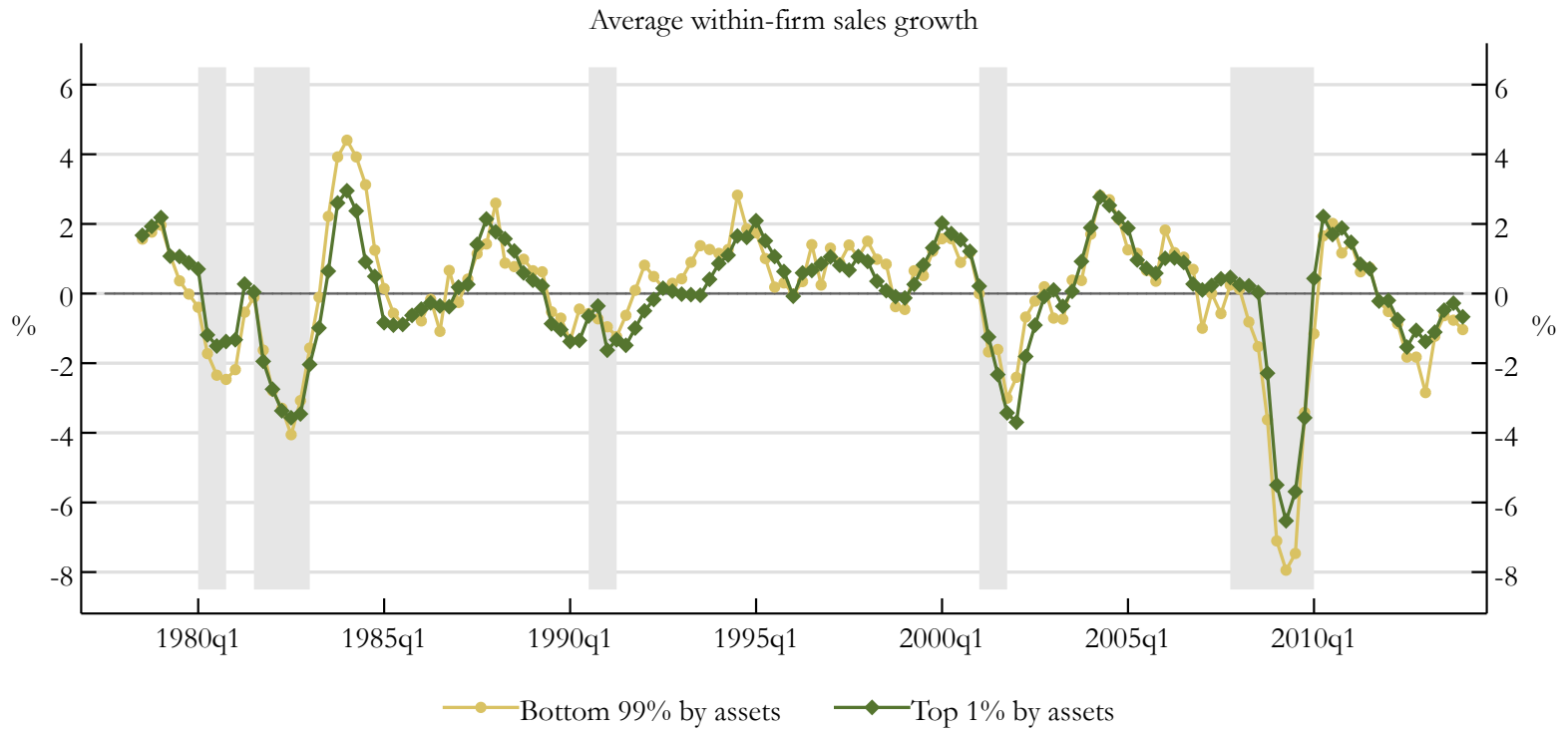



**Figure 1:** Average firm-level growth rate of sales of small (yellow, round markers) and large (green, diamond markers) firms. Small firms are those belonging to the bottom 99% of the one-year lagged distribution of book assets, while large firms are those belonging to the top 1% of the one-year lagged distribution of book assets. See appendix A for details on the construction of size groups and growth rates. Times series are demeaned.

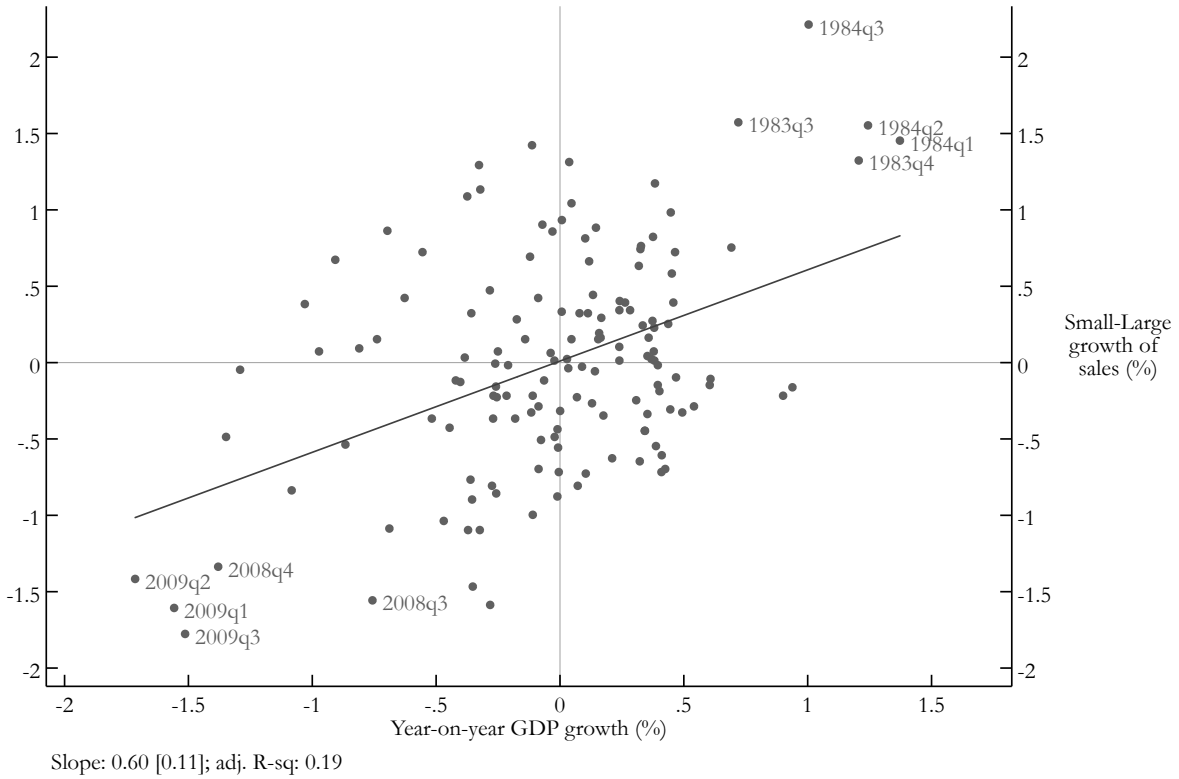
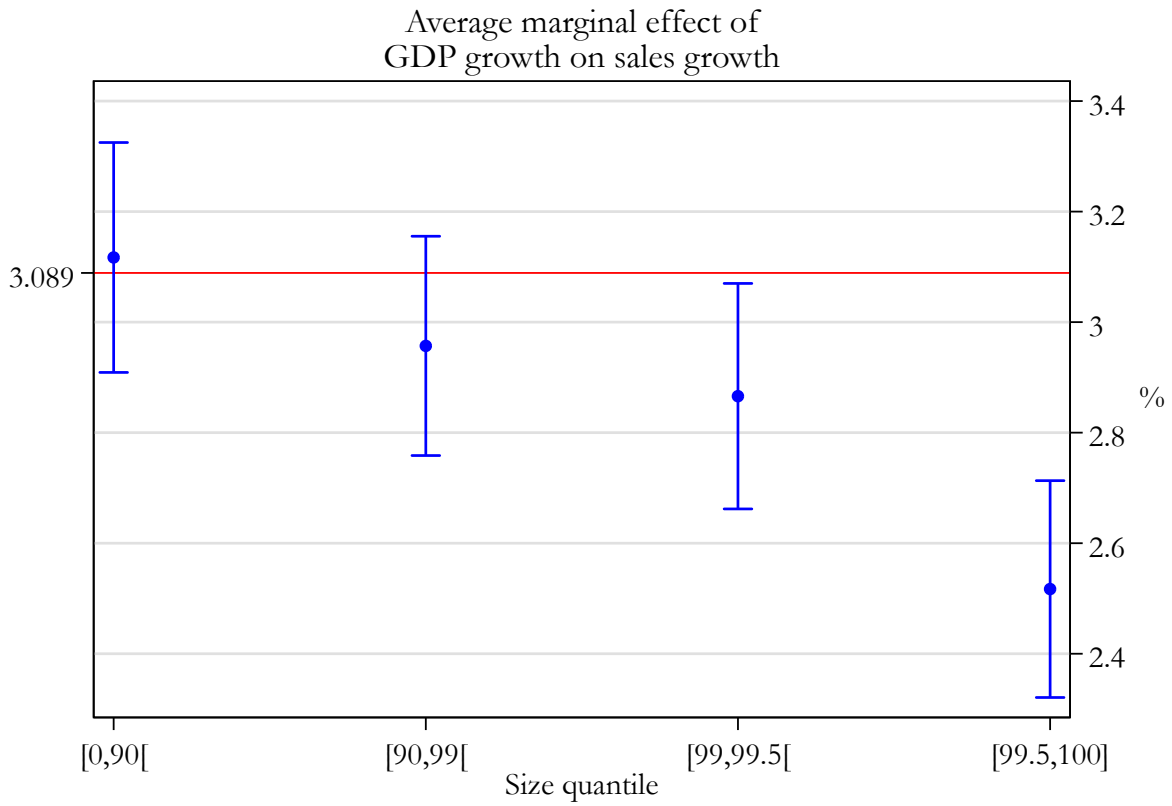



**Figure 2:** Difference between average growth rate of sales $\hat{g}_t^{(small)}(\text{sales}) - \hat{g}_t^{(large)}(\text{sales})$ (vertical axis) and year-on-year GDP growth (horizontal axis). Both series are demeaned. White standard errors in brackets.




Note: blue lines are +/- 2 s.e. bands. Red line is unconditional average marginal effect.

**Figure 3:** Marginal effects of GDP growth on sales growth, by size group (blue boxplots), and unconditionally (red line). The marginal effects are computed using estimates of model (2).

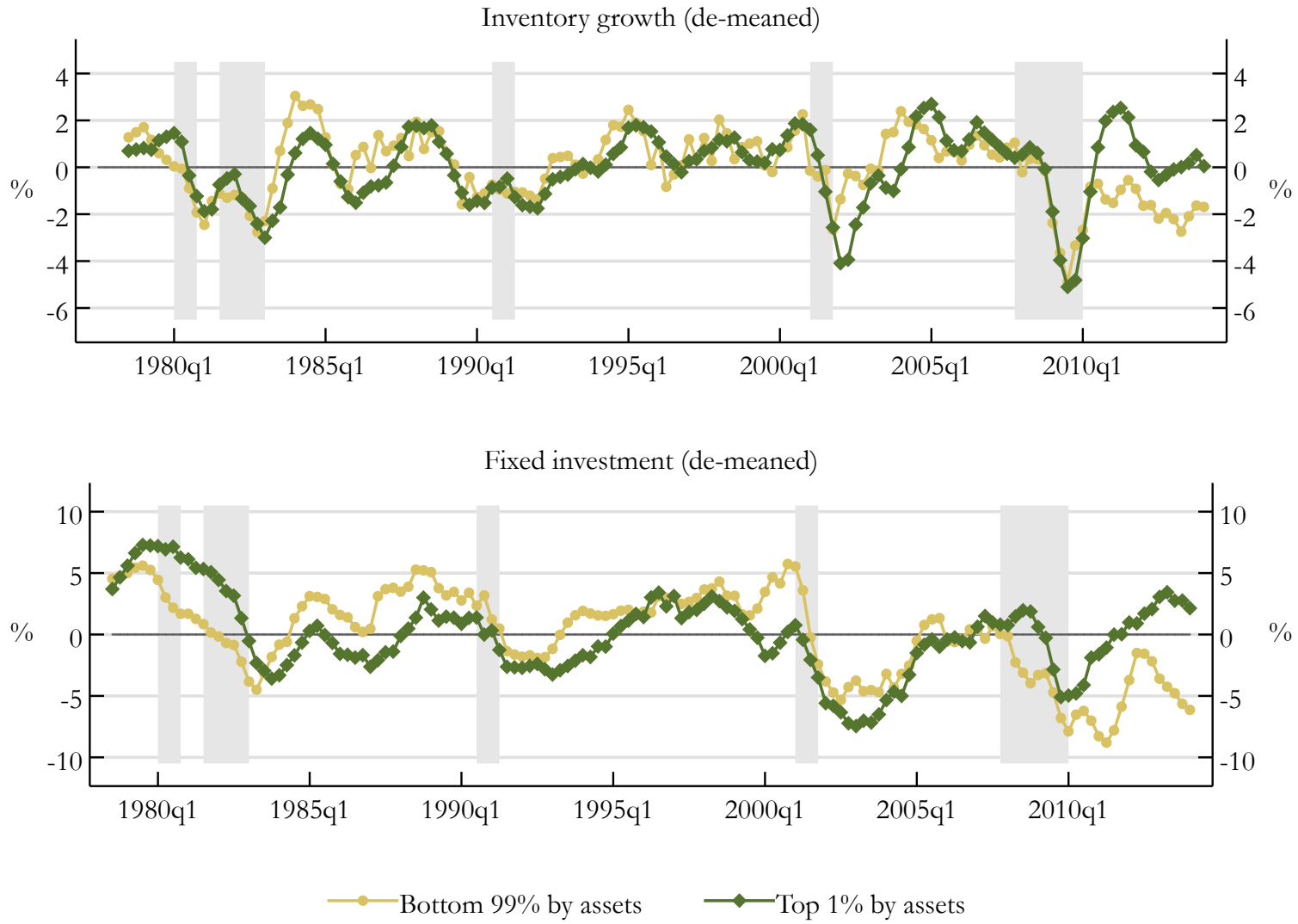



**Figure 4:** Average firm-level growth rate of small (yellow, round markers) and large (green, diamond markers) firms; top: inventory growth rate; bottom: fixed investment rate. Small firms are those belonging to the bottom 99% of the one-year lagged distribution of book assets, while large firms are those belonging to the top 1%. See Appendix A for details on the construction of size groups and growth rates. All series are demeaned.

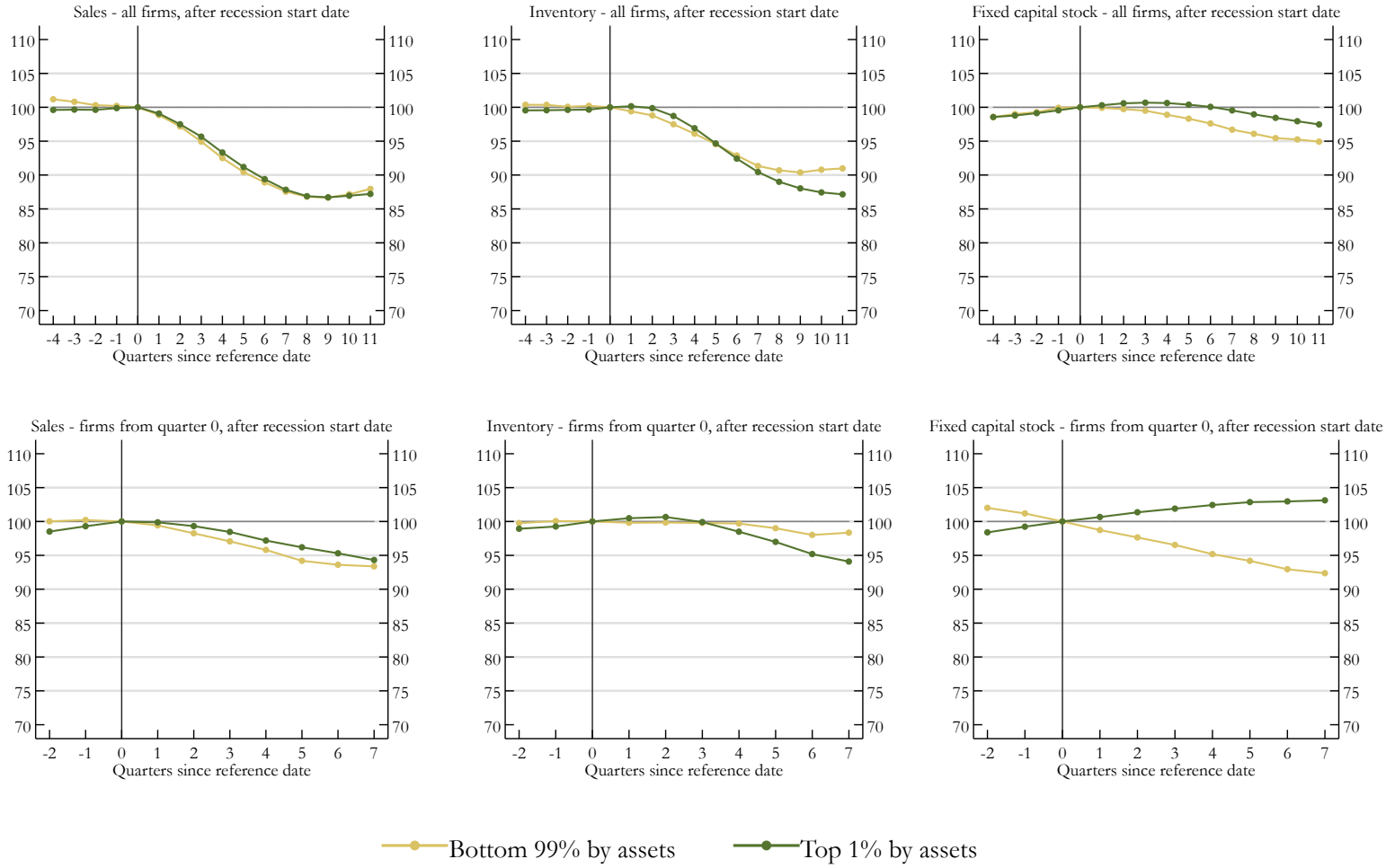



**Figure 5:** The behavior of sales, inventory and fixed capital after the start of a recession. The top panel reports levels relative to quarter 0 (the recession start date), computed using the average growth rate time series for each size group. The bottom panel reports levels relative to quarter 0 computed within firm, using the set of firms continuously sampled in a 10-quarter window around the recession date. Appendix B provides details on the construction of the time series.

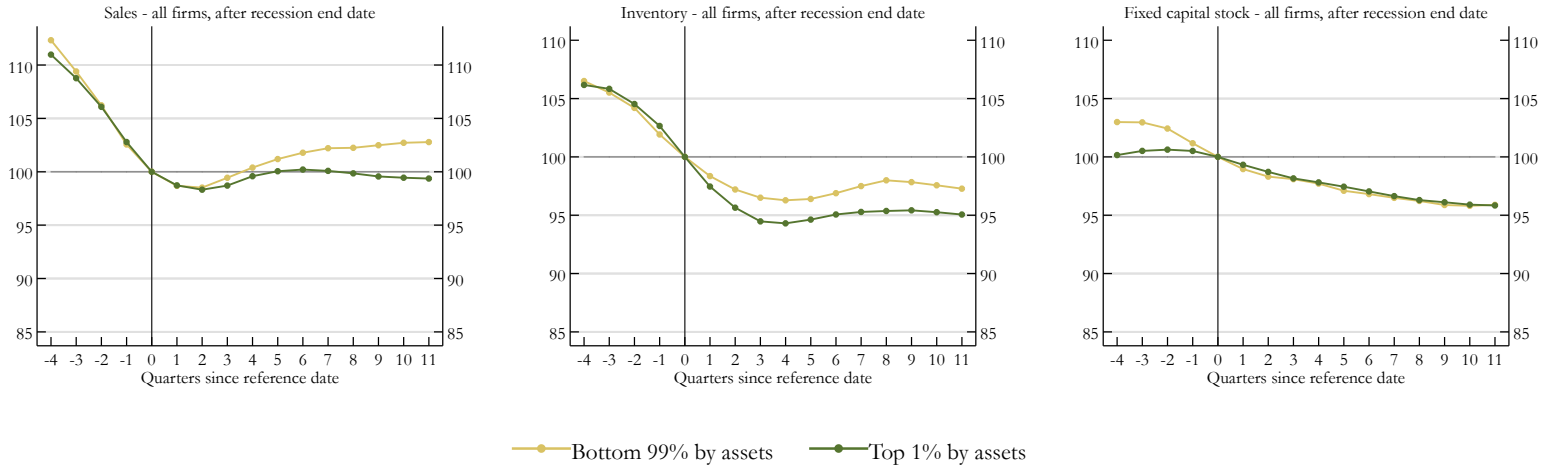



**Figure 6:** The behavior of sales, inventory and fixed capital after the end of a recession. The top panel reports levels relative to quarter 0 (the recession end date), computed using the average growth rate time series for each size group. The bottom panel reports levels relative to quarter 0 computed within firm, using the set of firms continuously sampled in a 10-quarter window around the recession date. Appendix B provides details on the construction of the time series.

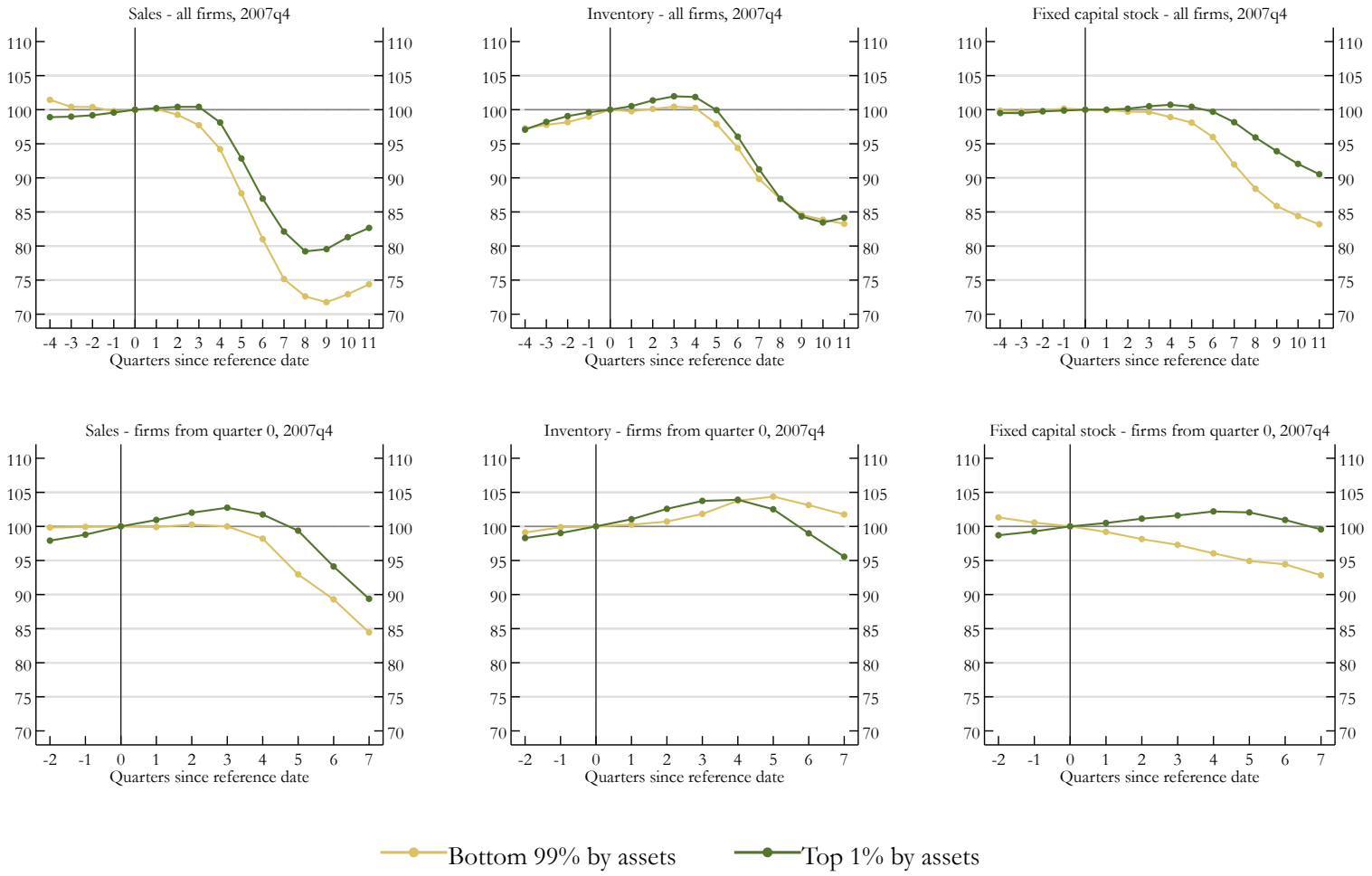



**Figure 7:** The behavior of sales, inventory and fixed capital around 2007q4. The top panel reports levels relative to quarter 0, computed using the average growth rate time series for each size group. The bottom panel reports levels relative to quarter 0 computed within firm, using the set of firms continuously sampled in a 10-quarter window around the recession date. Appendix XX: a.x provides details on the construction of the time series.

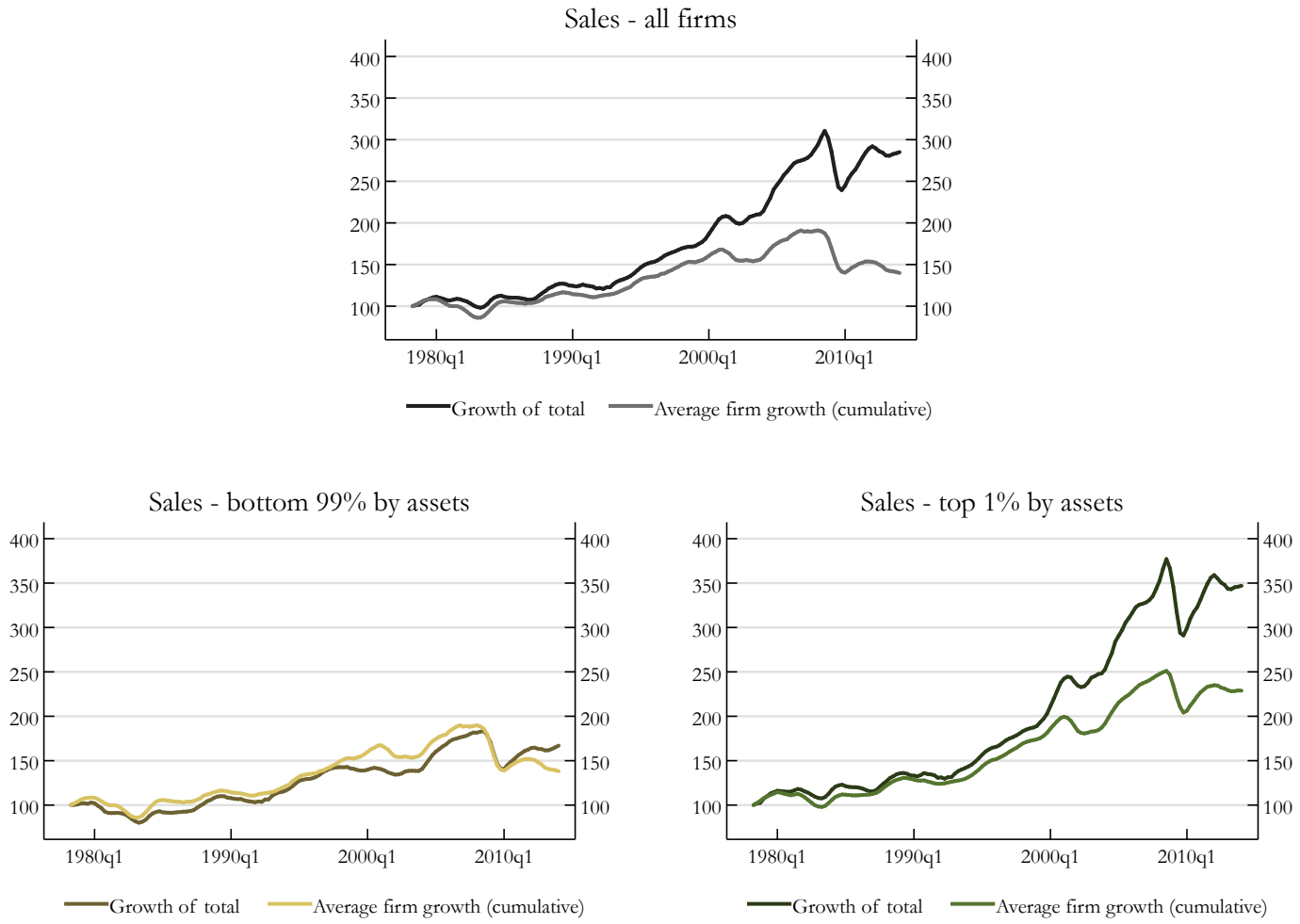



**Figure 8:** Aggregate sales and average within-firm cumualtive growth rate of sales. Each panel reports total annual sales (the cumulative value of $\hat{G}_t$), and the cumulative average growth rate of sales (the cumulative value of $\hat{g}_t$), for a different group of firms. All series are normalized to 100 in 1978q1.

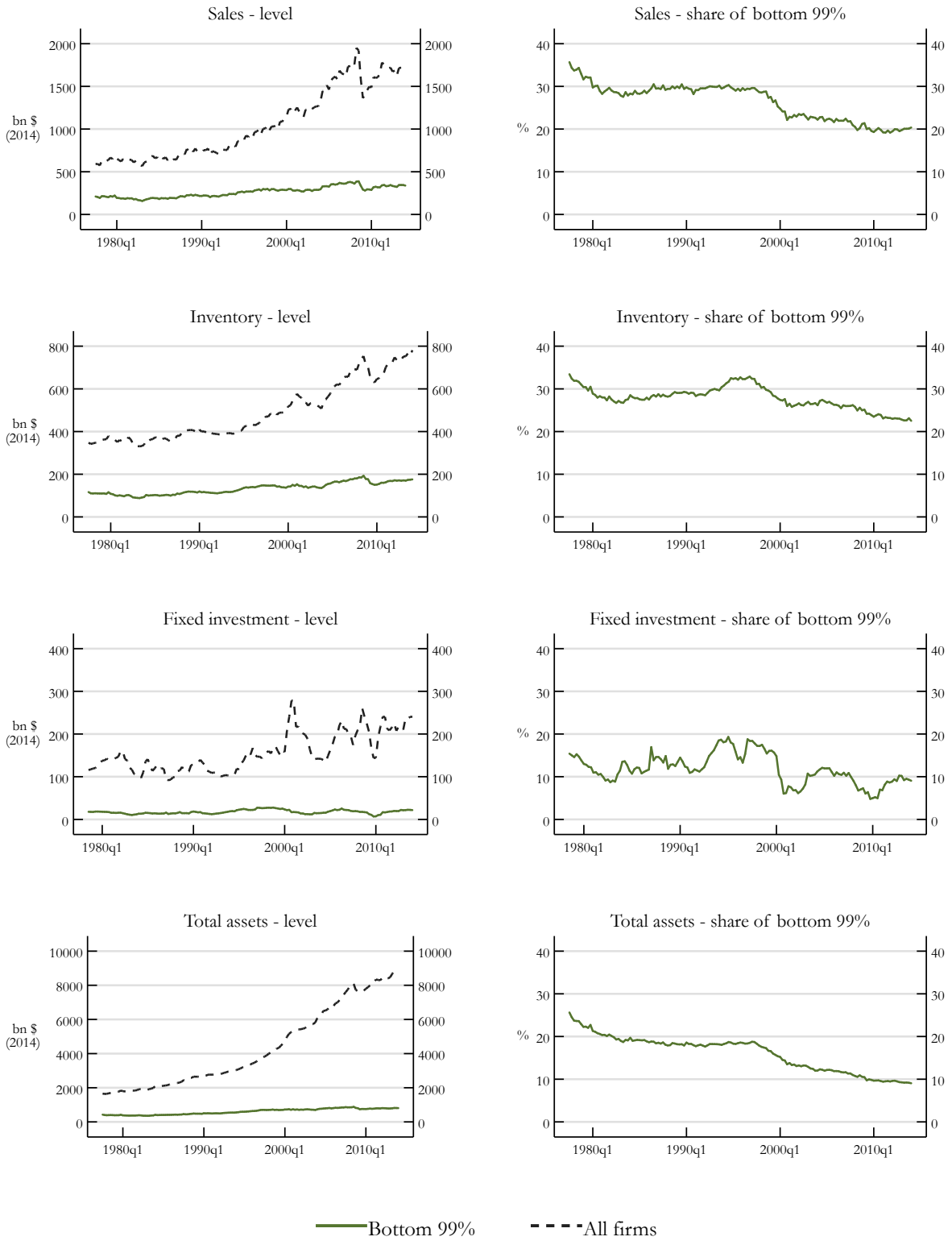



**Figure 9:** Concentration of sales, inventory, fixed investment, and total assets in the US manufacturing sector. The left column reports total nominal values for the bottom 99% and top 1% of firms by size. All series are deflated by the BEA price index for manufacturing, normalized to 1 in 2009q1; the series is available at http://bea.gov/industry/gdpbyind_data.htm. Series are unfiltered. The right column reports the share of the bottom 99% (the ratio of the corresponding graph in the left column).




**Figure 10:** Aggregate growth rate of sales $G_t$ (solid blue line), counterfactual growth rate 1 $G_t^{(1)}$, and counterfactual growth rate 2 $G_t^{(2)}$.

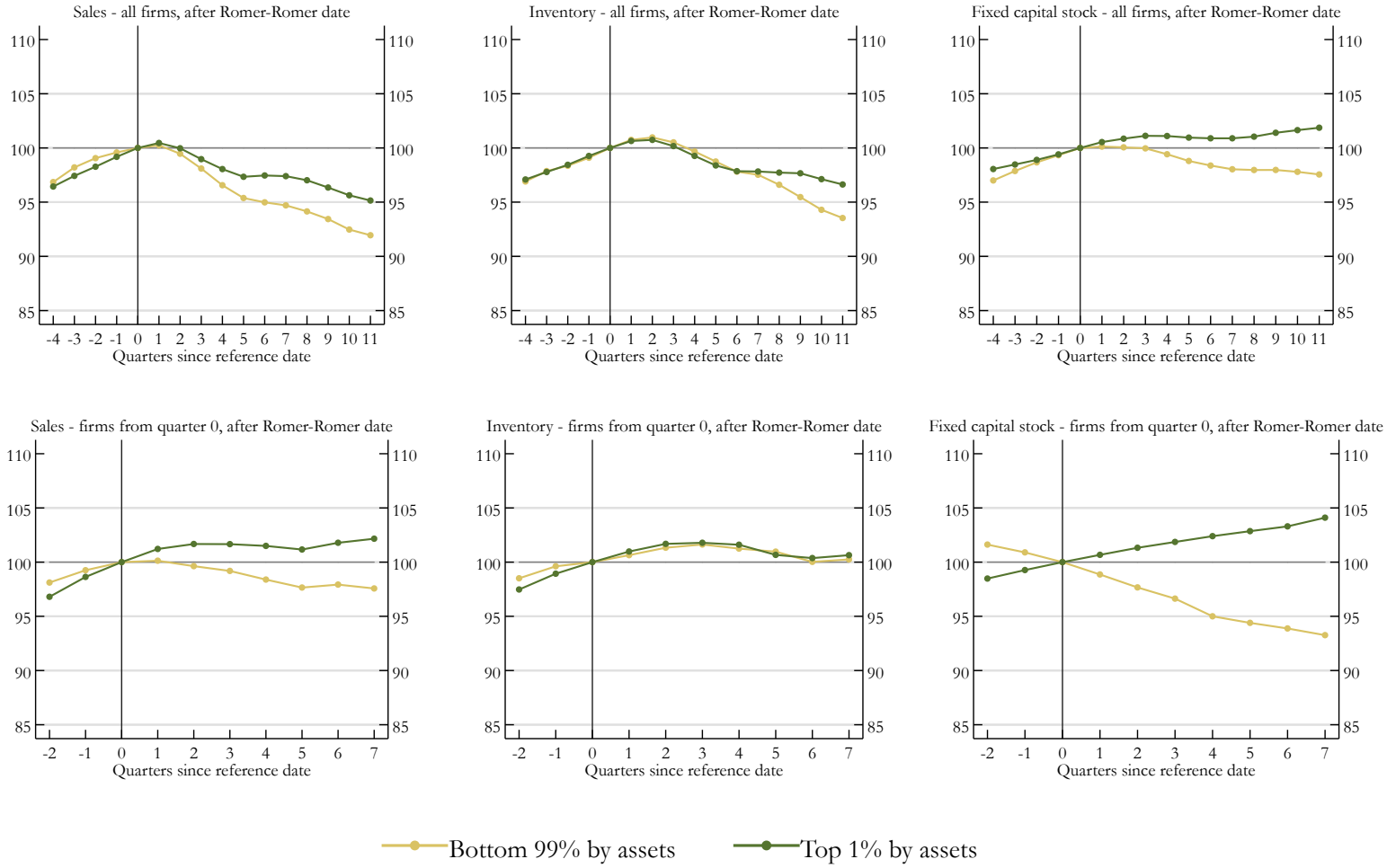



**Figure 11:** The behavior of sales, inventory and fixed capital after a Romer and Romer date. The top panel reports levels relative to quarter 0 (the monetary contraction date), computed using the average growth rate time series for each size group. The bottom panel reports levels relative to quarter 0 computed within firm, using the set of firms continuously sampled in a 10-quarter window around the recession date. Appendix B provides details on the construction of the time series.

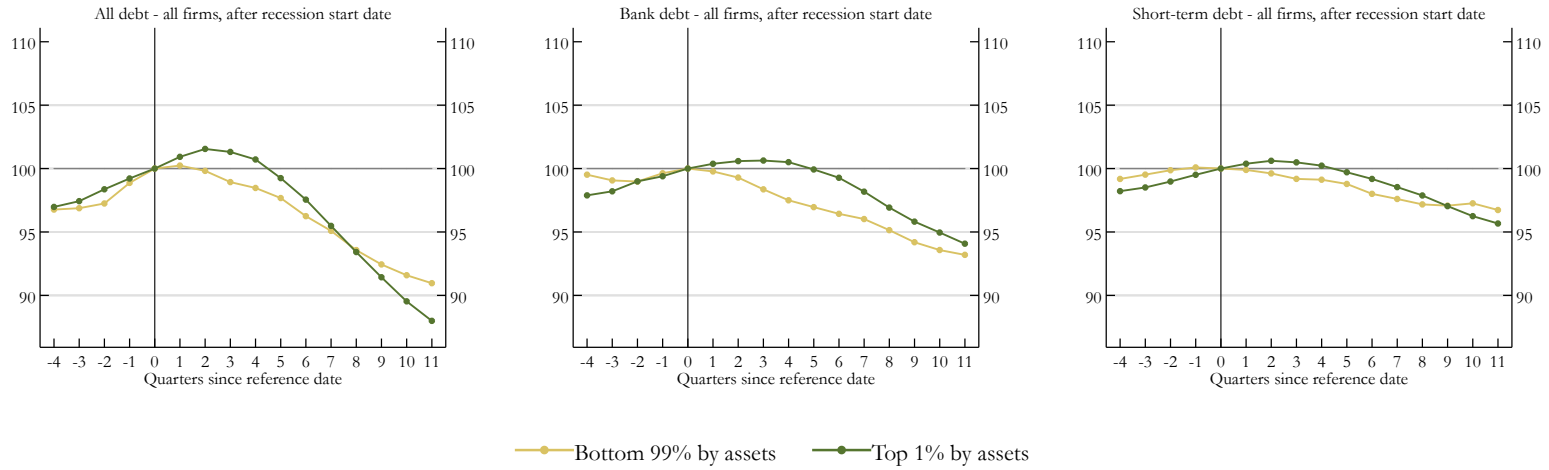



**Figure 12:** The behavior of debt overall, bank debt, and short-term debt after the start of a recession. Each panel reports changes relative to quarter 0 (the recession start date), computed using the cumulative sum of average growth rate of each size group. Growth rates at the firm-level are computed as $\frac{x_{i,t}-x_{i,t-4}}{assets_{i,t-4}}$, where $x \in \{\text{all debt}, \text{bank debt}, \text{short-term debt}\}$. Size groups are defined with a four-quarter lag, as detailed in appendix B.

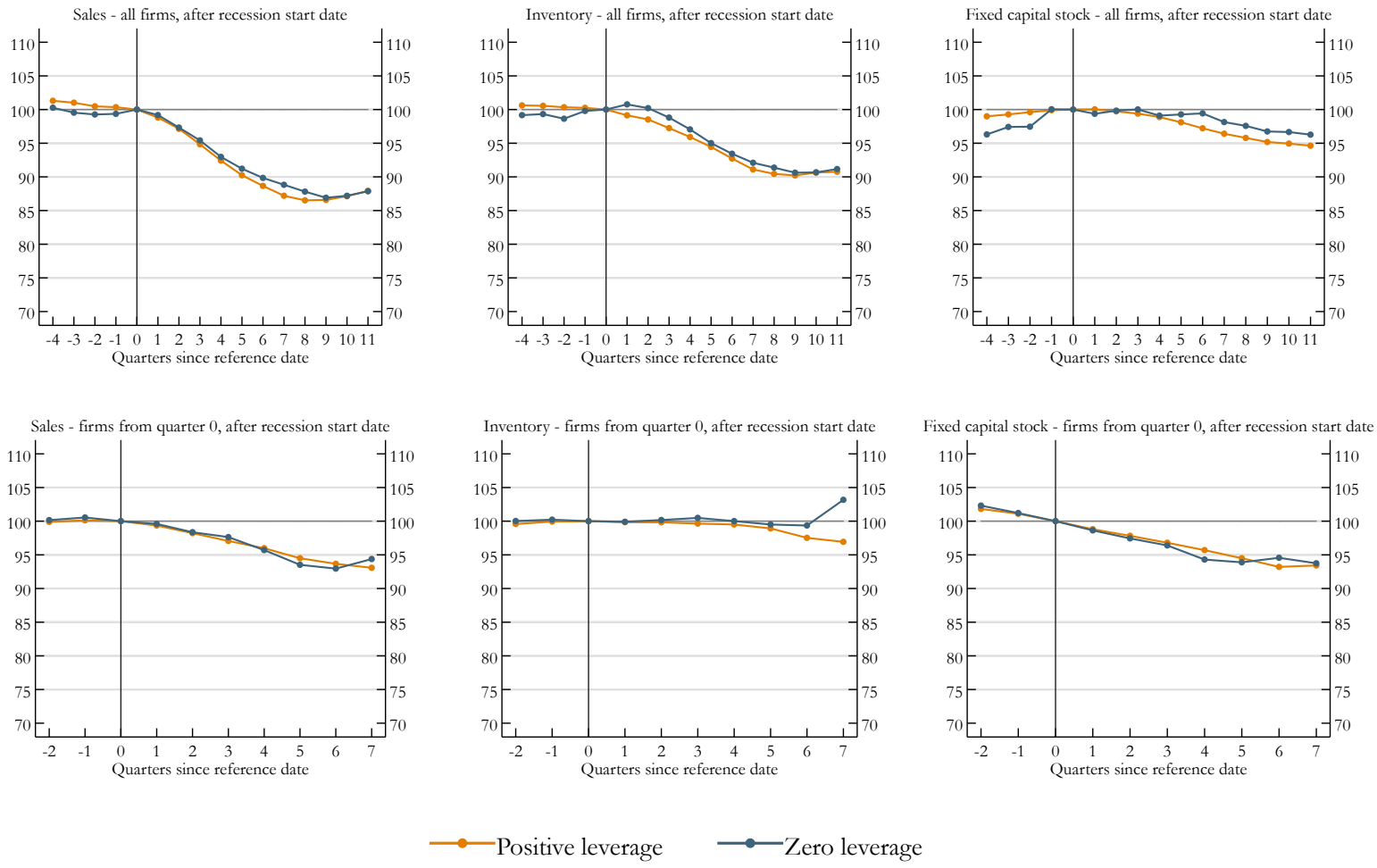



**Figure 13:** The behavior of sales, inventory and fixed capital after the start of a recession: zero-leverage and positive leverage firms. The top panel reports levels relative to quarter 0 (the recession start date), computed using the average growth rate time series for each leverage group. The bottom panel reports levels relative to quarter 0 computed within firm, using the set of firms continuously sampled in a 10-quarter window around the recession date. In the top row, firms are classified according to their one-year lagged leverage ratio. In the bottom row, firms are classified according to their quarter 0 leverage.

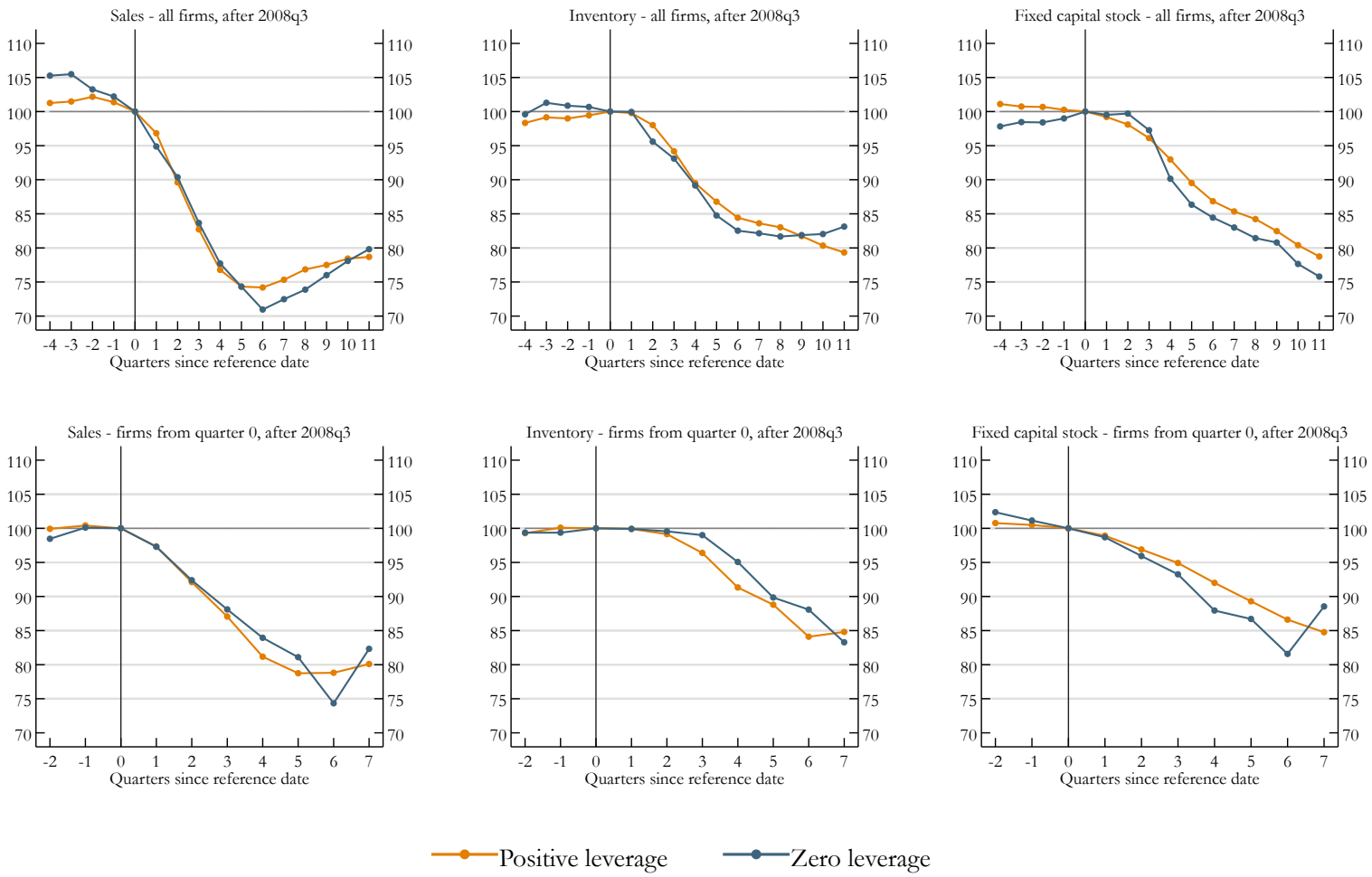



**Figure 14:** The behavior of sales, inventory and fixed capital after 2008q3: zero-leverage and positive leverage firms. The top panel reports levels relative to 2008q3, computed using the average growth rate time series for each leverage group. The bottom panel reports levels relative to 2008q3 computed within firm, using the set of firms continuously sampled in a 10-quarter window around the recession date. In the top row, firms are classified according to their one-year lagged leverage ratio. In the bottom row, firms are classified according to their leverage in 2008q3.

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| *Size group* | *0-90th* | *90-99th* | *99-99.5th* | *> 99.5th* |
|---|---|---|---|---|
| Assets ($ mil.) | $2.0 | $48.8 | $626.0 | $6766.3 |
| Sales ($ mil.) | $1.2 | $18.8 | $181.1 | $1420.8 |
| Sales growth (annual) | 1.97% | 6.07% | 5.08% | 5.51% |
| Investment rate (annual) | 26.7% | 25.1% | 22.1% | 20.5% |
| Debt to asset ratio | 0.35 | 0.29 | 0.30 | 0.28 |
| Cash to asset ratio | 0.15 | 0.10 | 0.07 | 0.06 |
| Short-term debt (fraction of total debt) | 0.33 | 0.33 | 0.20 | 0.18 |
| Bank debt (fraction of total debt) | 0.48 | 0.57 | 0.43 | 0.28 |
| Trade credit (fraction of total liabilities) | 0.32 | 0.27 | 0.17 | 0.13 |
| Intangible assets (fraction of total assets) | 0.05 | 0.11 | 0.26 | 0.36 |

**Table 1:** Assets and sales are averages from 1977q1 to 2014q1 within category expressed in real 2009 dollars; values are deflated using the price index for value added in manufacturing, available from the Bureau of Economic Analysis at http://bea.gov/industry/gdpbyind_data.htm. All other variables are ratios as described in the main text. See Appendix A for details on the construction of size groups.

| *Size group* | *0-90th* | *90-99th* | *99-99.5th* | *> 99.5th* |
|---|---|---|---|---|
| Sales growth, < p25 | -41.3% | -28.1% | -21.5% | -18.9% |
| Sales growth | 1.97% | 6.07% | 5.08% | 5.51% |
| Sales growth, > p75 | 16.5% | 17.5% | 15.1% | 13.7% |
| | | | | |
| Leverage, < p25 | 0.00 | 0.01 | 0.04 | 0.07 |
| Leverage | 0.35 | 0.29 | 0.30 | 0.28 |
| Leverage, > p75 | 0.47 | 0.39 | 0.39 | 0.36 |
| | | | | |
| Liquidity, < p25 | 0.00 | 0.00 | 0.00 | 0.00 |
| Liquidity | 0.15 | 0.10 | 0.07 | 0.06 |
| Liquidity, > p75 | 0.20 | 0.13 | 0.10 | 0.07 |

**Table 2:** Approximate inter-quartile ranges for selected variables, by firm size group. All variables are averages from 1977q1 to 2014q1 within size group. Leverage is defined as the ratio of debt to assets, while liquidity is defined as the ratio of cash to assets. See Appendix A for details on the construction of the size groups. Exact percentiles are not reported in order to preserve data confindentiality.

| | Sales | Inventory | Fixed investment |
|---|---|---|---|
| GDP growth | $3.700^{***}$ | $2.065^{***}$ | $0.912^{***}$ |
| | (0.000) | (0.000) | (0.000) |
| $[90, 99] \times$ GDP growth | $-0.160$ | $-0.107$ | $-0.299^{*}$ |
| | (0.260) | (0.538) | (0.057) |
| $[99, 99.5] \times$ GDP growth | $-0.251^{*}$ | $-0.299^{*}$ | $-0.687^{***}$ |
| | (0.080) | (0.097) | (0.000) |
| $[99.5, 100] \times$ GDP growth | $-0.600^{***}$ | $-0.730^{***}$ | $-1.257^{***}$ |
| | (0.000) | (0.000) | (0.000) |
| $N$ | $\approx 460000$ | $\approx 460000$ | $\approx 460000$ |
| nr. firms | $\approx 60000$ | $\approx 60000$ | $\approx 60000$ |
| adj. $R^2$ | 0.025 | 0.006 | 0.003 |
| industry controls | yes | yes | yes |
| s.e. clustering | firm-level | firm-level | firm-level |

**Table 3:** Estimate of regression of the baseline model (2) for sales growth, inventory growth, and the fixed investment rate. See Appendix A for details on the construction of the dependent variable and size groups. The investment rate is computed as $\frac{ppe_{i,t} - ppe_{i,t-4} + dep_{i,t-4,t}}{ppe_{i,t-4}}$, where $dep_{i,t-4,t}$ is cumulative reported depreciation between $t-4$ and $t$. All values are deflated by the quarterly manufacturing price index. $*$, $**$ and $***$ indicate 10%, 5% and 1% significance levels, respectively with p-values reported in parentheses.

| *Sample* | Sales | Inventory | Fixed investment | nr. of obs |
|---|---|---|---|---|
| All dates | 0.597 | 0.701 | 0.781 | 143 |
| | (0.113) | (0.160) | (0.098) | |
| Excl. 1981q3-1984q3 | 0.531 | 0.539 | 0.842 | 130 |
| | (0.127) | (0.186) | (0.131) | |
| Excl. 2007q4-2010q4 | 0.410 | 1.004 | 0.706 | 130 |
| | (0.135) | (0.183) | (0.094) | |
| Excl. 1981q3-1984q3 | 0.197 | 0.996 | 0.736 | 117 |
| and 2007q4-2010q4 | (0.155) | (0.264) | (0.142) | |
| post-1992q1 | 0.699 | 0.878 | 0.526 | 89 |
| | (0.129) | (0.131) | (0.098) | |
| pre-1992q1 | 0.488 | 0.423 | 1.146 | 54 |
| | (0.155) | (0.257) | (0.175) | |

**Table 4:** Excess sensitivity of small firms in different sub-samples. Each line reports the estimates of the slope in a simple OLS regression of $\hat{g}_t^{(\text{small})}(x) - \hat{g}_t^{(\text{large})}(x)$ on $\log\left(\frac{GDP_t}{GDP_{t-4}}\right)$, as defined in section 3.1. Columns correspond to sales, inventory, and the fixed investment rate. White standard error in parentheses.

| *Proxy for aggregate conditions* | Sales | Inventory | Fixed investment |
|---|---|---|---|
| Real GDP growth | 0.597 | 0.701 | 0.781 |
| | (0.113) | (0.160) | (0.098) |
| Industrial production growth | 0.247 | 0.053 | 0.396 |
| | (0.057) | (0.077) | (0.056) |
| Industrial production growth (manufacturing) | 0.229 | 0.098 | 0.341 |
| | (0.044) | (0.066) | (0.050) |
| Change in civilian unemployment rate | −0.232 | 0.077 | −0.299 |
| | (0.065) | (0.098) | (0.056) |

**Table 5:** Excess sensitivity of small firms using different proxies for the state of the business cycle. Each line reports the estimates of the slope in a simple OLS regression of $\hat{g}_t^{(\text{small})} - \hat{g}_t^{(\text{large})}$ on $\log\left(\frac{GDP_t}{GDP_{t-4}}\right)$, as defined in section 3.1. Columns correspond to sales, inventory, and the fixed investment rate. White standard error in parentheses. The time series used are the year-on-year growth rate of real GDP (FRED series GDPC1); the year-on-year growth rate of the total index for manufacturing production (FRED series IPB50001SQ); the year-on-year growth rate of the index for industrial manufacturing production (FRED series IPGMFSQ); and the year-on-year change in the civilian unemployment rate (FRED series UNRATE).

| | Small firms | Large firms | All firms |
|---|---|---|---|
| $corr(G_t, Y_t)$ | 0.68 | 0.62 | 0.65 |
| $\frac{\sigma_{\hat{g}_t}}{\sigma_{G_t}}$ | 1.02 | 0.83 | 0.89 |
| $corr(\hat{g}_t, Y_t)$ | 0.84 | 0.77 | 0.80 |
| $\frac{\sigma_{c\hat{o}v_t}}{\sigma_{G_t}}$ | 0.54 | 0.45 | 0.41 |
| $corr(c\hat{o}v_t, Y_t)$ | $-0.32$ | $-0.05$ | $-0.15$ |

**Table 6:** Decomposition of the correlations of aggregate sales growth among all firms, small firms, and large firms, to GDP growth. See section 4.2 for details on the decomposition.

| | Actual $\beta$ | Counterfactual 1 $\beta^{(1)}$ | Counterfactual 2 $\beta^{(2)}$ |
|---|---|---|---|
| Sales | 2.293 | 2.154 | 2.270 |
| | (0.342) | (0.342) | (0.366) |
| Inventory | 0.919 | 0.719 | 0.770 |
| | (0.226) | (0.250) | (0.226) |
| Fixed investment | 0.584 | 0.569 | 0.569 |
| | (0.145) | (0.151) | (0.148) |
| Total assets | 0.876 | 0.787 | 0.838 |
| | (0.121) | (0.129) | (0.119) |
| Observations | 143 | 143 | 143 |

**Table 7:** Cyclical sensitivities of aggregate sales, inventory, fixed investment, and total assets. Each line reports the estimated slope in regressions of the form $G_t = \alpha + \beta \log\left(\frac{GDP_t}{GDP_{t-4}}\right) + \epsilon_t$, where $G_t$ is an aggregate growth rate of sales, inventory, fixed investment, or total assets. The first column uses the actual time series $G_t$; the second column, the counterfactual time series $G_t^{(1)}$; and the third column, the counterfactual time series $G_t^{(2)}$. Heteroskedasticity robust standard errors in parentheses.

| | sales | total debt | bank debt | short-term debt |
|---|---|---|---|---|
| GDP growth | $3.700^{***}$ | $0.3386^{***}$ | $0.2661^{***}$ | $0.089^{**}$ |
| | (0.000) | (0.000) | (0.000) | (0.034) |
| $[90, 99] \times$ GDP growth | $-0.160$ | $0.1361^{*}$ | 0.0697 | 0.060 |
| | (0.260) | (0.095) | (0.277) | (0.170) |
| $[99, 99.5] \times$ GDP growth | $-0.251^{*}$ | 0.0756 | $-0.054$ | $-0.025$ |
| | (0.080) | (0.469) | (0.452) | (0.560) |
| $[99.5, 100] \times$ GDP growth | $-0.600^{***}$ | $-0.3010^{***}$ | $-0.3131^{***}$ | $-0.048$ |
| | (0.000) | (0.000) | (0.000) | (0.240) |
| $N$ | $\approx 460000$ | $\approx 460000$ | $\approx 460000$ | $\approx 460000$ |
| nr. firms | $\approx 60000$ | $\approx 60000$ | $\approx 60000$ | $\approx 60000$ |
| adj. $R^2$ | $< 0.025$ | 0.001 | 0.001 | $< 0.001$ |
| industry controls | yes | yes | yes | yes |
| s.e. clustering | firm-level | firm-level | firm-level | firm-level |

**Table 8:** Estimate of regression of the baseline model (2) for sales growth, total debt, bank debt, and short-term debt growth. See Appendix A for details on the construction of the dependent variable and size groups. The growth rate debt, bank debt and short-term debt is computed as $\frac{debt_{i,t} - debt_{i,t-4}}{assets_{i,t-4}}$. Standard errors clustered at the firm level. All values are deflated by the quarterly manufacturing price index. $*$, $**$ and $***$ indicate 10%, 5% and 1% significance levels, respectively with p-values reported in parentheses.

| | Baseline | Bank dep. | Leverage | Liquidity | Mkt. access |
|---|---|---|---|---|---|
| $[90, 99] \times$ GDP growth | $-0.160$ | $-0.189$ | $-0.195$ | $-0.162$ | $-0.193$ |
| $[99, 99.5] \times$ GDP growth | $-0.251^{*}$ | $-0.257^{*}$ | $-0.321^{**}$ | $-0.282^{*}$ | $-0.490^{***}$ |
| $[99.5, 100] \times$ GDP growth | $-0.600^{***}$ | $-0.563^{***}$ | $-0.675^{***}$ | $-0.640^{***}$ | $-1.097^{***}$ |
| Bank share [0.10,0.90] $\times$ GDP growth | | 0.300 | | | |
| Bank share $< 0.10 \times$ GDP growth | | $-0.315$ | | | |
| Leverage [0.15,0.50] $\times$ GDP growth | | | $-0.126$ | | |
| Leverage (0,0.15] $\times$ GDP growth | | | $-0.474^{*}$ | | |
| Leverage $= 0 \times$ GDP growth | | | $-0.630^{**}$ | | |
| Liquidity [0.01,0.20] $\times$ GDP growth | | | | 0.228 | |
| Liquidity $> 0.20 \times$ GDP growth | | | | $-0.101$ | |
| Market access $\times$ GDP growth | | | | | $0.826^{**}$ |
| $N$ | $\approx 460000$ | $\approx 460000$ | $\approx 460000$ | $\approx 460000$ | $\approx 460000$ |
| nr. firms | $\approx 60000$ | $\approx 60000$ | $\approx 60000$ | $\approx 60000$ | $\approx 60000$ |
| adj. $R^2$ | 0.025 | 0.025 | 0.025 | 0.025 | 0.025 |
| industry controls | yes | yes | yes | yes | yes |
| s.e. clustering | firm-level | firm-level | firm-level | firm-level | firm-level |

**Table 9:** Estimate of regression of the regression model (8) for sales growth on firm size and financial constraint group. Each column is a separate regression. See Appendix A for details on the construction of the dependent variable and size groups. See text for description of each financial constraint group. Standard errors clustered at the firm level. $*$, $**$ and $***$ indicate 10%, 5% and 1% significance levels, respectively with p-values reported in parentheses.