Small and Large Firms over the Business Cycle*

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Abstract

Drawing from confidential firm-level data of US manufacturing firms, we provide new evidence on the cyclicality of small and large firms. We show that the cyclicality of sales and investment declines with firm size. The effect is primarily driven by differences between the top 0.5% of firms and the rest. Moreover, we show that, due to the skewness of sales and investment, the higher cyclicality of small firms has a negligible influence on the behavior of aggregates. We argue that the size asymmetry is unlikely to be driven by financial frictions given 1) the absence of statistically significant differences in the behavior of production inputs or debt in recessions, 2) the survival of the size effect after directly controlling for proxies of financial strength, and 3) the predictions of a simple financial frictions model, in which unconstrained (large) firms contract *more* in recessions than constrained (small) firms.

Keywords: Firm size, business cycles, financial accelerator

JEL Classification: E23, E32, G30

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1 Introduction

An important line of research in macroeconomics and corporate finance has sought to document cross-sectional differences in the response of firms to aggregate shocks. Following the work of Gertler and Gilchrist (1994), this literature has paid close attention to firm size. This focus was motivated by the idea that, since size may proxy for financial constraints, a higher sensitivity of small firms would provide evidence in favor of the “financial accelerator” — the view that financial frictions can amplify downturns.[1] However, largely because of data limitations, there remains vigorous debate about both the basic facts and their financial interpretation. More generally, relatively little is known about systematic differences in business-cycle sensitivities across firms.

In this paper, we bring new evidence to bear on these issues. We address three central questions. First, are small firms more cyclically sensitive than large firms, and if so, to what extent? Second, does this excess sensitivity substantially amplify aggregate fluctuations? Third, is this excess sensitivity a 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) to assemble a representative, quarterly panel of US manufacturing firms from 1977 to 2014. We then use this dataset to quantify the excess sensitivity of firms at the bottom of the size distribution, relate it to the behavior of aggregate quantities in our sample, and assess whether excess sensitivity is evidence of a financial amplification mechanism. To our knowledge, this paper is the first to use this firm-level data.

The firm-level microdata of the QFR carry several advantages relative to both the publicly released version of the QFR and alternative firm-level datasets. The publicly released QFR 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, as firms move across firm size categories (both in the long-run, and during recessions). The panel aspect of the firm-level data allows us to address this reclassification bias, by classifying firms on lagged size or other lagged observables. Additionally, given the skewness of the size distribution, it is unclear how well aggregated firm bins capture the behavior of the average or median firm within a size category. Finally, and most

[1] The view that financial frictions may be responsible for the excess sensitivity of small firms in recession is buttressed by an extensive corporate finance literature in which private and bank-dependent firms are often treated as being more financially constrained.Farre-Mensa and Ljungqvist (2016) provide an overview of measures of financial constraints commonly used in the corporate finance literature. Size is often used alone or as part of an index as a proxy for financial constraints - see Rajan and Zingales (1995) Almeida, Campello and Weisbach (2004), Whited and Wu (2006), and Hadlock and Pierce (2010).

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. Most importantly, Compustat is limited to publicly traded firms; its sample is not representative of the cross-section of US firms. By contrast, the QFR panel is constructed by Census to accurately reflect the cross-section of US manufacturing firms.[2] Having a representative sample of US firms matters not only when assessing the implications of excess sensitivity for aggregates, but also when linking it to financial constraints: Compustat indeed omits private, bank-dependent firms, precisely those the most likely to be financially constrained. Other advantages include the fact that firms report data at the quarterly frequency, disaggregate debt by source (banks, bond markets, commercial paper, and other sources of debt), and are instructed by Census to consolidate statements domestically, in contrast with Compustat where financial statements reflect global operations.

Using the QFR microdata, we find evidence in favor of the excess sensitivity of small firms. On average over the sample, we find that the difference between sales growth of the bottom 99% of firms and the top 1% of firms exhibits a strong contemporary correlation with GDP. Our baseline estimate is that a 1% drop in GDP is associated with a 2.6% drop in sales at the 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 large differences in the sales elasticity to GDP up to the 99.5th percentile. Though particular episodes differ, over the five recessions in our sample, 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.[3]

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, this 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.

However, despite its statistical significance, we show that the excess sensitivity of small firms is quantitatively too small to have an effect on the cyclical behavior of aggregates. Our data allows

[2] The QFR 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.

[3] Despite differences in methodology, which we discuss in detail, 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); in fact, we replicate their findings in the aggregated version of our data.

us to construct counterfactual paths for aggregate sales growth, inventory growth and investment under the alternative assumption that firm-level cyclical sensitivities are the same in the cross-section, and plot this counterfactual against realized aggregate sales growth. The difference between the two time series is difficult to detect. This finding is due to 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. Moreover, this concentration has been sharply rising over the last 30 years implying that the relative importance of small firms for the cyclicality of aggregates has, if anything, been declining. While the size differences in cyclical sensitivities are statistically significant, they are also not large enough to counterbalance this skewness.[4] To the extent that alternative monetary or fiscal policies could address this differential cyclicality, our results show 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 public 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, we provide three findings that cast doubt on whether the size difference is driven by a financial accelerator mechanism.

First, the measured cyclical behavior of both inputs (fixed capital and inventory) and debt issuance across size groups is not fully consistent with the typical narrative describing the financial accelerator. In particular, the cumulative decline in investment and inventories at large firms during recessions is smaller than, but not statistically distinguishable from, the decline at small firms. Furthermore, both small and large firms cut back on short-term borrowing during recessions, which is at odds with the financial accelerator 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 and whether it recently issued dividends. We show that none of these controls eliminates the size differential that we document; additionally, the quantitative magnitude of the size differential is almost unchanged (except when one controls for

[4] Our findings with respect to skewness echoes Gabaix (2011), but we nevertheless find that the average/typical firm behaves over the cycle in much the same way as the aggregates which are dominated by the behavior of the largest firm. In this sense, a "representative firm" does not appear to be a bad approximation for the purposes of understanding business cycles.

access to bond markets, in which case the size effect is magnified). At a minimum, these results suggests that the size asymmetry may be driven by nonfinancial factors.

Third, we show that the type of excess sensitivity we document in the data does not necessarily emerge from a benchmark model of financial frictions. Specifically, we study the effects of an aggregate, non-financial shock in a benchmark heterogeneous firm model of investment with financial frictions. We show that while, in this model, small firms are financially constrained, they also tend to be *less* responsive to aggregate shocks than large, unconstrained firms. The reason for this is that the shock affects not only the current net worth of firms, but also their optimal size. Unconstrained firms respond to the shock by adjusting to that optimal size; constrained firms are already below target, and do not adjust. Financial frictions thus operate in a manner similar to adjustment costs, thereby moderating the response of aggregates relative to a world without frictions. We argue that, despite its simplicity, the mechanisms present in the model we analyze are likely to generalize to richer environments.

We conclude by directly examining the recession behavior of firms sorted by financial strength instead of size. We use the same five financial strength indicators as described earlier: leverage, liquidity, bank dependence, access to public debt markets, and dividend issuance. Leverage, liquidity and bank dependence groups all display a behavior qualitatively consistent with the financial accelerator narrative; for example, inventories of bank-dependent firms fall somewhat more during the early stages of recessions. However, in all cases, the difference is not statistically or economically significant. Firms with access to public debt markets display, if anything, a higher sensitivity to recessions. Only the behavior of dividend-issuing firms is significantly different from that of non-dividend issuing firms. Overall, this exercise suggests that these simple proxies for financial strength do not tend to be associated with a higher degree of responsiveness during recessions.

It is worth emphasizing some limits to the scope of our findings. Our data does not allow us to measure employment; thus, we cannot assess the possibility that labor hoarding may differ across small and large firms during recessions. Second, we cannot rule out large excess sensitivity among non-manufacturing firms, which account for a substantial fraction of value added and employment.[5] Third, although a complete comparison is not possible from our data, the skewness of the real outcomes we measure — sales, inventory and fixed investment — is more pronounced than what existing estimates suggest for employment, thus magnifying the relative importance of large firms' cyclical behavior for aggregates in our sample.

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

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

of size asymmetries between small and large firms. Section 5 presents findings on whether the size differences we document are evidence of a financial accelerator. Section 6 concludes.

1.1 Related Literature

Our analysis most closely relates to a literature examining the business cycle fluctuations of small and large firms. This literature, beginning with Gertler and Gilchrist (1994), utilizes the public releases of the QFR data to examine the cyclicality of sales at small and large firms. Gertler and Gilchrist (1994) showed that small firms are more sensitive than large firms in response to monetary policy shocks, but, more recently, Chari, Christiano and Kehoe (2013) argue that this differential cyclicality does not hold across all recessions. Using the Gertler & Gilchrist methodology, Kudlyak and Sanchez (2016) show that large firms contract more than small firms in the Great Recession. We are able to replicate the findings of each of these papers using our data set and the Gertler & Gilchrist methodology for classifying large and small firms; we discuss in Section 3 the reason for differences in our results versus this literature.

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) and Mehrotra and Sergeyev (2016) consider the behavior of job flows and employment by firm size and age. Fort et al. (2013) 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.

A broad empirical literature has examined the role of disruptions to firm credit supply as a driver of particular recessions; much of this work uses firm size as a proxy for financial constraints. 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. In the Great Recession, Chodorow-Reich (2014) finds the largest effects of the credit shock due to Lehman Brothers bankruptcy at small and medium sized firms. Mian and Sufi (2014) use establishment size as a proxy for financing frictions in examining the effect of falling house prices on credit supply. Using a heterogenous firm dynamics model, Khan and Thomas (2013) show that a credit shock generates a sharper fall in employment at financial constrained firms consistent with the behavior of employment small and large firms 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.

We also relate to a literature that investigates the cyclicality of firm financing in aggregate and in the cross-section. 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 substitution 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.[6] 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.[7]

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 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

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

[7] 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.

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.[8] 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.[9]

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.[10] 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 sampling weights over this period.[11] These weights were also adjusted so that aggregate assets for

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

[9] 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 .

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

[11] 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.

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.[12] Less than 0.1% of firm-quarter observations have balance sheets for which the sum of liabilities and equity does not match reported assets within less than 0.01% suggesting that the data suffers from limited misreporting. 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.[13]

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.[14]

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 constitutes a representative sample of the population of US manufacturing firms, given that the sampling frame is drawn from IRS administrative data and response is mandatory. 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.

[12]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.

[13]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.

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

There are three other differences between Compustat and the QFR. First, the income and balance sheet data is reported at a quarterly frequency facilitating 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 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.[15] 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.[16]

2.4 Summary Statistics

Table 1 provides summary statistics on key real and financial characteristics for small and large manufacturing firms. These statistics are constructed by grouping 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.[17]

[Table 1 about here.]

Table 1, panel A 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

[15] 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.

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

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

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, Table 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.

Table 1, panel B provides key financial 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 classes providing no evidence that smaller firms 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 consistent with Gertler and Gilchrist (1994).

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.[18] Table 2 contains a more complete decomposition of firms' balance sheet by size groups. This decomposition shows that the higher share of intangible assets does not come at the expense of a lower share of tangible long-term assets among large firms, but rather a substantially lower fraction of short-term assets (receivables and inventory) relative to small firms. Thus, both on the liability and the asset side, large firms' maturity structure is longer than short firms'.

[Table 2 about here.]

It is worth emphasizing that, despite differences across size classes in various real and financial characteristics, there remains tremendous heterogeneity within size classes. Table 3 provides an approximate interquartile range for sales growth, leverage, and liquidity.[19] 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 remains substantial. It is

[18]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 measure of market value is readily available.

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

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 3 about here.]

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. Finally, within size classes, firms display substantial heterogeneity in capital structure and firm growth rates. 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 at small firms.

3.1 Measurement framework

Appendix A provides the formal details for the measurement framework 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 such as 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 aggregate implications of differences in average firm-level growth, are discussed in greater 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).[20] 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.

In our discussion, we use a one-year lag for size, and define small firms as those in the bottom 99% of book assets.[21] In the regression results, we report 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 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 $\hat{g}_t^{(\text{small})}$), and the top 1% (denoted by $\hat{g}_t^{(\text{large})}$).[22] 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

[20] 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).

[21] We adopt this classification because 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.

[22] 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.

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.]

Table 4 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:

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

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.[23] Excess sensitivity would be characterized by a statistically significant coefficients γ_j for one or several of the size groups; the first column of table 4 reveals that this is the case, so that the size effect does not simply reflect cyclical differences across industries.

The results of table 4 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

[23] 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.

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.

[Table 4 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).[24] 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.

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

[Figure 4 about here.]

The regression evidence, reported in Table 4, 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 smaller conditional elasticity to GDP growth.[25] 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.[26]

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 The behavior of small and large firms during recessions

The time series for the aggregate growth rates of small and large firms suggest that recessions are times when the excess sensitivity of small firms may be particularly pronounced. And indeed, much of the evidence on the excess sensitivity of small firms focuses on differential behavior around specific episodes, as opposed to average sensitivities to business cycles.

To summarize differences in the behavior of small and large firms around recessions, we compute the cumulative change in variables of interest in a 15-quarter window around the beginning of a recession. Let $g_{i,t}$ denote one of the outcome variables of interest (year-on-year sales growth, inventory growth); we estimate the model:

$$g_{i,t} = \alpha + \beta \mathbf{1}_{\{i \in \mathcal{S}_t\}} + \sum_{k=-4}^{10} \left(\alpha_k + \beta_k \mathbf{1}_{\{i \in \mathcal{S}_t\}} \right) \mathbf{1}_{\{t+k \in \mathcal{H}\}} \tag{3}$$

[25] 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.

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

where $\mathcal{S}_t$ is the set of small firms, defined as the bottom 99% of the lagged distribution of book assets, and $\mathcal{H}$ is one of four recession start dates: $\mathcal{H} = \{1981q3, 1990q3, 2001q1, 2007q4\}$. We then construct cumulative responses by size: $\{c_{\mathcal{L},k}\}_{k=-4}^{10}$ and $\{c_{\mathcal{S},k}\}_{k=-4}^{10}$ for large and small firms respectively:

$$c_{\mathcal{L},k} = \sum_{j=-4}^{k} (\alpha + \alpha_j) - \sum_{j=-4}^{0} (\alpha + \alpha_j) \,,$$

$$c_{\mathcal{S},k} = c_{\mathcal{L},k} + \sum_{j=-4}^{k} (\beta + \beta_j) - \sum_{j=-4}^{0} (\beta + \beta_j) \,,$$

as well as the associated standard errors. Note, in particular, that in order to avoid overlapping event windows, we only consider the second of the two recession start dates of the early 1980s. Figure (5) reports the cumulative path of sales, inventory and fixed capital and the associated +/-2 standard error bands.

[Figure 5 about here.]

The behavior of sales, reported in the left panel (5), is qualitatively consistent with the baseline regression: the cumulative drop in sales following the onset of the recession is substantially larger for the bottom 99% of firms, and the difference is statistically significant. Quantitatively, the differential response of sales during recessions is larger than implied by the baseline regressions: for example, over the first year of the recession, large firms' sales fall by 2.8%, while small firms' sales fall by 4.9%, a difference of approximately 2.1%. The average year-on-year decline in real GDP over the first year of recessions we consider, by contrast, is 1.0%; our baseline regression estimates would then suggest that the differential growth rate should be 0.6%, or only about 30% of the observed gap of 2.1%. There are two reasons for this difference. First, small firms tend to come slightly more frequently from the durable goods sector, which is more cyclically sensitive, in our data; the regression framework (3) does not account for industry effects.[27] The second reason for the difference between the baseline regression estimates and the event study analysis is that excess sensitivity of small firms' sales does seem to be stronger during recessions. An estimate of the baseline regression, restricted to the first two years after the onset of recessions, produces an excess sensitivity of 1.0, instead of the baseline estimate of 0.6.

The behavior of inventory investment and fixed investment is qualitatively consistent with the baseline regressions; however, the differences are not statistically different across size groups, except for the cumulative decline in large firms' inventory at long lags. Perhaps the most striking qualitative feature of investment behavior is that the decline of investment among large firms seem

[27] Alternatively, excess sensitivity in our baseline regression rises to about 0.85 if we do not control for industry composition.

to lag that of small firms by three to four quarters.[28] This lag is not visible in the sales response. Also in contrast to the sales response, the lack of statistical significance suggests that the excess sensitivity documented in the baseline regressions is driven by recoveries, rather than recessions. This is partly visible in Figure (5): the relative response of small firms' inventory at 10 and more quarters out is statistically different at that stage, when recoveries are already under way. In undisclosed results, we verify that restricting the sample to the onset of recessions indeed leads to insignificant estimates of excess sensitivity for inventory and fixed capital investment.

3.5 Robustness

We next briefly discuss 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.

Sample dates Table (5) 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 real GDP growth (yoy) 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 recessions 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.[29]

[Table 5 about here.]

Proxies for the state of the business cycle Table (6) 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 results using GDP growth. Inventory growth is a

[28] Aggregate fixed capital formation, in the QFR data, lags real GDP growth by three to four quarters as well: the contemporaneous correlation with year-on-year real GDP growth is 0.19, while the three-quarter lagged correlation is 0.59. This is consistent with the recession behavior documented in Figure (5), since, as discussed below, large firms account for between 80-90% of total fixed capital formation in the QFR data.

[29] These are also episodes of particularly extreme GDP growth; the fact that eliminating these observations from the sample reduces the precision of the estimate should perhaps not be surprising.

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 that for small firms. When excluding the 2007q4-2010q4 dates, the elasticity of the small-large firm difference with respect to IP growth again becomes 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 6 about here.]

3.6 Relationship with results in the literature

We close this section by discussing the relationship between our results and evidence on the cyclical behavior of small and large firms documented by two important contributions on the topic: Gertler and Gilchrist (1994) and Fort et al. (2013).

Gertler and Gilchrist (1994) — henceforth, GG — use the public releases of the QFR from 1958 to 1992 to document differences in the cyclicality of small and large firms. Both the evidence provided in the present paper, and the evidence in GG point toward the excess sensitivity of small firms. However, the size effect we find is more muted, and depends markedly on two specific episodes, the Great Recession and the recovery of the 1980s recessions.

Our approach and theirs differ in two main ways: the methodology, and the choice of dates. Appendix (C) discusses in detail methodological differences; empirically, the most important distinction between our approach and GG is in the choice of dates. GG focus on the behavior of small and large firms around the dates identified by Romer and Romer (1989) as monetary contractions, in the 1958-1992 sample; by contrast, we focus on recessions in the 1977-2014 sample.

In order to clarify the differences, figure (6) compares the cumulative change in sales of the top 1% and bottom 99% of firms, after a Romer and Romer (1989) date (left column), and after the beginning of a recession (right column). The top row replicates the GG methodology of size grouping using the aggregated version of our micro-data, while the bottom row defines size using the top 1% vs. bottom 99% used elsewhere in this paper. We use the five Romer and Romer (1989) dates provided by the updated evidence in Kudlyak and Sanchez (2016): 1978q3, 1979q4, 1988q4, 1994q2 and 2008q3.

Consistent with the results reported by GG, under either their methodology, or the top 1%/bottom 99% approach, sales display substantial excess sensitivity among small firms after a Romer and Romer (1989) date. However, after recessions start, evidence of excess sensitivity among small firms is weaker; in fact, under the GG methodology, large firms' sales appear to contract more. This result is driven entirely by the 2008q3 observation, and is consistent with the evidence of Chari, Christiano and Kehoe (2013) and Kudlyak and Sanchez (2016). The main difference is thus the focus of the GG analysis on monetary policy contractions, as opposed to our measurement of the average difference in cyclicality.[30]

[Figure 6 about here.]

Fort et al. (2013) examine the response of employment by both firm size and firm age over the business. The authors emphasize the small-young firms exhibit a stronger sensitivity to the business cycle relative to large-mature firms. The authors also emphasize that the business cycle behavior of firm employment depends crucially on firm age (as opposed to simply firm size). Our data set does not provide a measure for firm age, and it is difficult in generate to identify small-young firms given that smaller firms are only tracked for 8-12 quarters. Moreover, our dataset does not provide a measure of firm employment.

To construct a proxy for firm age, we identify firms starting in 1982 that appear for at least five years and strictly less than five years in the sample.[31] This procedure has a clear drawback - firms older than five years that are only sampled once will be correctly classified as old. With this caveat in mind, we find that the size effect remains within the subsample of mature firms; the size effect is slightly smaller but is not solely driven by firm age.

We also investigate the correlation between GDP growth and the differential growth rate of young-small firms versus mature-large firms in our sample. Using the age definition as above, we define large firms as firms in the top 5% of the size distribution, while small firms are those in the bottom 80%. Firms in the top 5% in 2012 have sales of $ 1.04 billion in our data set, while firms in the bottom 80% have sales of $ 2.95 million. Using the Statistics of US Business in 2012 that provide average sales by firm employment categories, these averages roughly correspond to firms with over 500 employees and firms with less than 20 employees in the manufacturing sector. Using these definitions, we find the the growth differential between young-small and mature-large has a positive correlation with GDP growth of the same magnitude as documented in Fort et al. (2013).[32]

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 relevant for aggregate fluctuations, and are these differences driven by a financial accelerator mechanism?

[30] Appendix C also compares the behavior of investment around recessions versus Romer and Romer (1989) dates using the quantile methodology, and shows in particular that investment of small firms contracts more around Romer and Romer (1989) dates; for inventory, this is consistent with the GG evidence.

[31] There are a nontrivial number of observations for small firms which are sampled in distinct periods; that is, a firm is sampled for 8-12 quarters and appears several years later resampled again for 8-12 quarters. We identify firms primarily off employer identification number (EIN). In this way, we can identify small-mature firms.

[32] Specifically, we follow the analysis in Table 1 of their paper.

4 Aggregate implications

4.1 A simple decomposition of aggregate growth

Appendix B shows that the growth rate of any aggregate variable of interest between quarters $t-4$ and t, denoted by G_t, can be decomposed as:

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

Here, $s_{t-4} = \frac{X_{t-4}^{(small)}}{X_{t-4}}$ is the initial fraction 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 in their group, and their subsequent growth.[33] These terms capture the idea that if firms that are initially large in their group also grow faster, then total growth will tend to outpace firm-level growth in that group (and vice-versa if initially large 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.

The decomposition (4) 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 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.

[33] Specifically, $\hat{cov}_t^{(\text{j})} = \sum_{i \in \mathcal{I}_t^{(\text{j})}} \left(w_{i,t-4} - \frac{1}{\#\mathcal{I}_t}\right)\left(g_{i,t} - \hat{g}_t^{(j)}\right)$, where j is small or large firms and 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. This term is a cross-sectional covariance up to a normalizing factor. Appendix B contains more details on the decomposition and its interpretation.

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 (4) also holds within each firm group, namely:

$$\begin{aligned} G_t^{(\text{small})} &= g_t^{(\text{small})} + \hat{cov}_t^{(\text{small})}, \\ G_t^{(\text{large})} &= g_t^{(\text{large})} + \hat{cov}_t^{(\text{large})}. \end{aligned} \tag{5}$$

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:

$$corr(G_t^{(\text{small})}, Y_t) = \frac{\sigma_{\hat{g}_t^{(\text{small})}}}{\sigma_{G_t^{(\text{small})}}} corr\left(\hat{g}_t^{(\text{small})}, Y_t\right) + \frac{\sigma_{\hat{cov}_t^{(\text{small})}}}{\sigma_{G_t^{(\text{small})}}} corr\left(\hat{cov}_t^{(\text{small})}, Y_t\right). \tag{6}$$

Here, σ_Z denote the standard deviation of variable Z. Equation (6) 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 7 about here.]

Table 7 reports the values of the different elements of the right-hand side of (6), 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 7, reflecting the rise in concentration.

[Figure 7 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 $\frac{\sigma_{\hat{cov}_t^{(\text{large})}}}{\sigma_{G_t^{(\text{large})}}} corr\left(\hat{cov}_t^{(\text{large})}, Y_t\right)$. This 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 (8) 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 distribution of assets. Two points about these time series are worth emphasizing.

[Figure 8 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 that smaller firms are less capital-intensive. Nevertheless, this skewness presents 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 35.6% in 1977q3 to 20.4% in 2014q1, while their share of assets falls from 25.6% to 9.0%; this decline is secular over the period 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 0.37 in the sample. While substantial cyclicality of the share could, in principle, offset its low average level and magnify the term $\Delta\hat{g}_t$, Figure (8) suggests 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:

$$G_t^{(1)} = G_t - s_{t-4}\left(\hat{g}_t^{(\text{small})} - \hat{g}_t^{(\text{large})}\right) \tag{7}$$

This time series nets out the contribution of firm-level growth differentials between the small and large firms — the second term of the decomposition (4). 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:

$$\begin{aligned} G_t^{(2)} &= G_t - s_{t-4}\left(\hat{g}_t^{(\text{small})} - \hat{g}_t^{(\text{large})}\right) \\ &\qquad - s_{t-4}\left(\hat{cov}_t^{(\text{small})} - \hat{cov}_t^{(\text{large})}\right) \\ &= G_t^{(large)}. \end{aligned} \tag{8}$$

We are interested in the differences in cyclicality between these aggregate time 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 8 about here.]

Table 8 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 this difference is not statistically significant. The economic interpretation of this difference is that, all other things equal, if the elasticity of small firms' sales growth were equal to that of large firms, aggregate sales' elasticity to GDP growth would only be only 5% smaller. 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: 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 8 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 8 indicates that both cyclical movements in the covariance term and cyclical variation in small firms' share, have a limited impact on the cyclical fluctuations in aggregate growth. Figure 9 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 visually indisguishable.

[Figure 9 about here.]

This section has shown that, while the excess sensitivity of small firms is economically and statistically significant, it is also of 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 captured by 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 mentioned in our introduction, the early financial accelerator literature emphasized a variety of mechanisms whereby recessions, including ones not originating in the financial sector, could be worsened due to the presence of financial frictions. In this section, we investigate whether the size asymmetry we have documented should be interpreted as evidence of such financial amplification. We show that during recessions, the difference in the behavior of inputs (fixed investment and inventory) and debt issuance across size groups is either statistically insignificant, or has the opposite sign to what the theory would predict. Additionally, when we estimate our baseline size regression augmented with a number of proxies for financial constraints, the size effects remains significant, and in most cases, is quantitatively unchanged. Finally, we show the idea that small firms should display excess sensitivity to aggregate fluctuations is not borne out in a benchmark model with heterogeneous firms and financial frictions. Overall, this evidence casts doubt on the view that the excess sensitivity of small firms is driven by financial frictions.

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. A firm may wish to borrow in a recession to avoid firing workers or liquidating assets, thereby smoothing production over the cycle. Thus, the authors argue that the financial accelerator should manifest itself as a faster contraction of sales and inventories at small vs. large firms during recessions; the same logic suggests that fixed investment rates should should fall more substantially among small firms during recessions. Additionally, issuance of debt, particularly short-term, should rise by more (or fall by less) among large firms. As Gertler and Gilchrist (1994) emphasize, the relative 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, such as Kashyap, Lamont and Stein (1994).

5.2 Production inputs and debt during recessions

The event study plots reported in Figure (3.4), in section 3, show that the behavior of inventory and fixed investment rates of small and large firms following the onset of a recession has some qualitative features that are consistent with the financial accelerator narrative: small firms' inventory and fixed investment respond more rapidly to the onset of the recession. However, the figure also shows that the investment responses are not statistically distinguishable across size groups.

[Figure 10 about here.]

In line with this evidence, figure 10 shows that the behavior of debt, particularly short-term debt and bank debt, are not consistent with the basic financial interpretation of the size effect. The cumulative decline in bank and short-term debt is initially more pronounced among large firms, though not statistically different; eventually, the reduction in debt actually becomes bigger among large firms. Here, short-term debt is measured as debt with maturity one year or less normalized by assets lagged four quarter, and bank debt is short and long-term bank loans normalized by assets lagged four quarters. The figure reports the cumulative average change at the firm level, where firms are classified as small or large based on their lagged asset value; the cumulative responses are constructed in the same way as in section 3.[34]

[Table 9 about here.]

Table 9 reproduces the size regressions from section 3, using debt to asset ratios instead of measures of real activity as left-hand side variable. These unconditional estimates of the cyclical sensitivity of debt by size provide complementary evidence to the recession graphs. 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. The point estimates for bank debt furthermore suggest that bank debt is acyclical among the top 0.5% of firms, and slightly procyclical among small firms, consistent with the slightly earlier decline in bank debt among small firms during the onset of recessions.

Overall, the bulk of this evidence does not line up with a financial view of the size effect: the decline in inventory and fixed investment occurs earlier on at small firms, but the difference is statistically indistinguishable from 0; additionally, the behavior of bank debt and short-term debt is also statistically indistinguishable between small and large firms during recessions.

[34] It is also difficult to observe sharp differences in the behavior of debt overall (the left panel of Figure 10); the financial accelerator mechanism, however, focuses for the most part on bank financing and short-term debt financing.

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:

$$
\begin{aligned}
g_{i,t} &= \alpha + \beta \log\left(\tfrac{GDP_t}{GDP_{t-4}}\right) + \sum_{j\in\{(90,99),(99,99.5),(99.5,100)\}} \left(\gamma_j + \delta_j \log\left(\frac{GDP_t}{GDP_{t-4}}\right)\right) \mathbf{1}_{\left\{i\in\mathcal{I}_t^{(j)}\right\}} \\
&\quad + \sum_{k\in\mathcal{K}} \left(\zeta_k + \eta_k \log\left(\frac{GDP_t}{GDP_{t-4}}\right)\right) \mathbf{1}_{\left\{i\in\mathcal{F}_t^{(k)}\right\}} \qquad (9) \\
&\quad + (\mathit{Industry\ controls}) + \epsilon_{i,t}.
\end{aligned}
$$

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.[35] In contrast to the baseline regression, $k \in \mathcal{K}$ now indexes groups of our measures of financial strength. We consider five different measures of financial strength: bank-dependence, leverage, liquidity, access to public debt markets, and dividend issuance.

[Table 10 about here.]

Column (1) in Table 10 controls for the degree of bank-dependence in the size regression. Our measure of bank dependence is the share of bank debt in total debt, and this 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%).

Column (2) in Table 10 controls for leverage. 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.[36]

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

[36] We use fixed thresholds given the absence of a time trend in leverage.

Column (3) controls for 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.[37]

Column (4) controls for access to public debt markets. Specifically, we classify a firm-quarter observation as having access to public debt markets if the same firm has ever reported some positive liability in either commercial paper or long-term bonds. Because it relies only on responses from the long-form survey, this variable is most informative for the largest firms (it is equal to zero for firms receiving the short-firm survey). As documented by Faulkender and Petersen (2005), even among publicly traded firms, only a minority have access to public debt market, so that there is meaningful variation in this measure among small firms.

Finally, column (5) controls for dividend issuance. A firm-quarter observation is classified as a dividend issuer if it issued dividends one year prior to the quarter of observation. About half of firm-quarter observations in the regression sample are dividend issuers.

For bank-dependence, leverage, liquidity, and dividend issuance, the coefficients on GDP interacted with size class — particularly the top 0.5% — remain significant, and in magnitude, similar to the baseline regression after controlling for the financial constraint proxy. The exception is market access, but the change in the size coefficient is inconsistent with the financial accelerator view. One would expect firms with market access to have a lower degree of sensitivity to the business cycle, and therefore the size effect to fall (or equivalently, the gap between the sensitivity of small and large firms to business cycles) once one controls for market access. Instead, we find that it rises, suggesting that firms with access to public debt markets are, if anything, more cyclically sensitive than other large firms. This result appears again in section 5.5; it may be due to firms with more cyclical investment opportunities chosing to tap bond markets at the beginning of recoveries.

In any case, the main message of Table 10 is that the excess sensitivity of small firms survives, and is in fact almost unchanged, after including controlling for other proxies for financial constraints.

5.4 Excess sensitivity in a stylized model of frictional investment

We next ask to what extent size asymmetries should emerge in response to aggregate shocks in a heterogeneous-firm model of investment with financial frictions. We contrast a frictionless version of the model to a version in which external financing is costly. The frictionless model is homothetic: firms' responses to aggregate shocks are independent of their size. We show, however, that the introduction of financing frictions need not produce the type of size-related excess sensitivity we observe in the data.

[37]There is a rise in the cash to asset ratio for the median firm in the QFR dataset, starting around 2005. The top quartile of the cash to asset distribution, however, is fairly stable over time, rising only slightly toward the end of the sample.

Model description The model is set in discrete time. Firms maximize the present discounted value of future payouts to equityholders, and use the constant discount rate $\frac{1}{1+r}$. The problem of a surviving firm, indexed by i, in period t, is:

$$\begin{aligned} V(k_{i,t};a_{i,t},x_t) &= \max_{k_{i,t+1}} \quad p_{i,t} + \frac{1}{1+r}\mathbb{E}_t\left[\eta k_{i,t+1} + (1-\eta)V(k_{i,t+1};a_{i,t+1},x_{t+1})\right] \\ \text{s.t.} \quad p_{i,t} &= (a_{i,t}x_t)^{1-\zeta}k_{i,t}^{\zeta} - (k_{i,t+1}-(1-\delta)k_{i,t}) \\ [\lambda_{i,t}] \quad p_{i,t} &\geq 0 \end{aligned}$$

Here, $k_{i,t}$ are the firm's assets in place. The firm's operating profits are given by $\pi_{i,t} = (a_{i,t}x_t)^{1-\zeta}k_{i,t}^{\zeta}$, with $0 < \zeta < 1$ denoting the curvature of the profit function with respect to assets; x_t is an aggregate shock, and $a_{i,t}$ is an idiosyncratic shock (which is identically distributed across firms, and independent from x_t). Appendix (D) provides two possible derivations for this profit function (a model with decreasing returns in production, and a model with an imperfectly competitive goods market), and the associated definitions of $a_{i,t}$ and $x_{i,t}$ in terms of idiosyncratic and aggregate variables. In particular, x_t captures aggregate changes in wages, demand or productivity; it is not a financial shock.

There are two financial frictions in this environment. The first is that payouts to equityholders (dividends) must be positive, that is, $p_{i,t} \geq 0$. The frictionless model is one where, by contrast, payouts to equityholders can take any sign, without affecting their marginal benefit (or cost): $p_{i,t} \gtreqless 0$. The second is that firms are not allowed to borrow. In the model with frictions, firms are therefore completely internally financed. The shadow value of internal funds is $\nu_{i,t} = 1 + \lambda_{i,t}$; a firm is constrained, if and only if, $\nu_{i,t} > 1$. This stark assumption of pure internal financing is a useful benchmark, which we reconsider in potential extensions below.

Finally, with probability η, a surviving firm exogenously exits after production and investment. In this case, its capital stock is sold, and equityholders receive the proceeds as payout. In order to focus the analysis on intensive margin responses, we assume that replacement of each exiting firm occurs at a exogenously determined level of assets, k_e, and with $a_{i,t}$ drawn from the ergodic distribution of the idiosyncratic shock.

The response to an aggregate shock So as to clarify the effects of aggregate shocks in this model, we focus on the case in which there are no differences in idiosyncratic productivities across firms: $a_{i,t} = 1, \forall i, t$. In a stationary steady-state, the frictionless model has the simple solution:

$$k_{i,t+1} = k^* \equiv \left(\frac{\zeta}{r+\delta}\right)^{\frac{1}{1-\zeta}} x, \quad \forall i, t. \tag{10}$$

In particular, all surviving firms have the same size. By contrast, in the stationary steady-state of the model with financial frictions, size is given by:

$$k_{i,t+1} = \begin{cases} x^{1-\zeta} k_{i,t}^{\zeta} + (1-\delta) k_{i,t} & \text{if } k_{i,t} \leq \underline{k} \\ k^* & \text{if } k_{i,t} > \underline{k} \end{cases} \tag{11}$$

where $\underline{k}$, the unconstrained threshold, is the unique solution to: $k^* = x^{1-\zeta}\underline{k}^{\zeta} + (1-\delta)\underline{k}$. So long as $k_e < \underline{k}$, the steady-state also features a cross-section of firms of different sizes: firms are born small relative to their desired size k^*, must save to reach it, and might be thwarted by the exit shock.

[Figure 11 about here.]

In such an environment, what are the cross-sectional implications of an aggregate shock? Figure 11 reports the perfect foresight response of output to a temporary decline in x_t, starting from the steady-state described by (11).[38] In the model with frictions, the most responsive firms are the largest ones — there is excess sensitivity, but it has the opposite sign as in the data.

The aggregate shock has two effects: it lowers all firms' net worth $n_{i,t} = x_t^{1-\zeta} k_{i,t}^{\zeta} + (1-\delta)k_{i,t}$; and it reduces the optimal unconstrained size of firms,

$$k^*_{t+1} = \left(\frac{\zeta}{r+\delta}\right)^{\frac{1}{1-\zeta}} x_{t+1}.$$

When the shock hits the economy, initially unconstrained firms (those with $k_{i,0} \geq \underline{k}$) find themselves with financial slack: even though their net worth falls, it still remains above the new unconstrained threshold $\underline{k}_0$ such that $k_1^* = x_0^{1-\zeta}\underline{k}_0^{\zeta} + (1-\delta)\underline{k}_0$.[39] These firms respond by paying out excess cash, and shrinking to $k_{i,1} = k_1^*$. By contrast, most constrained firms start from a point where $k_{i,0} < \underline{k}_0$. That is, these firms are below their optimal size *even after* the aggregate shock. These firms' responses then only reflect the net worth effect, and not the optimal size effect; their investment rates do not fall as sharply, and, relative to trend, their sales also do not decline as much. The financial friction therefore works like an adjustment cost, and moderates the response of quantities. As a result, aggregate sales and investment are also less responsive than in the model without frictions, as evidenced by the aggregate impulse responses of the top panel of Figure 11.

Generality This simple model is meant to illustrate that financial frictions need not generate excess sensitivity of small firms to aggregate shocks. Despite the simplicity of the environment, we believe that this lesson is likely to extend to a broad class of models.[40]

[38] The calibration of the model is described in appendix (D); in particular, the choice of the exogenous exit rate and the entry size imply that in steady-state, 1% of firms are unconstrained.

[39] Optimal size moves one for one with the aggregate shock, whereas decreasing returns imply that net worth moves less than one-for-one.

[40] We note that our simple model shares the same fundamental financial frictions as the recent models of Khan and Thomas (2013), Gopinath et al. (2015), Chaney et al. (2015) and Alfaro, Bloom and Lin (2016), when the collateral

One worry is that this result would cease to hold if external financing through debt and equity were modeled more precisely. One can very easily allow for equity issuance in the simple framework above, by replacing $p_{i,t}$ by $\Phi_E(p_{i,t})$, where:

$$\Phi_E(x) \quad = \begin{cases} (1+\gamma_e)x & \text{if} \quad x \leq 0 \\ x & \text{if} \quad x \geq 0 \end{cases}$$

The frictionless model is then $\gamma_e = 0$, while the model without external financing is $\gamma_e = +\infty$. Relaxing the assumption of no debt financing would require taking a stance on the cost and benefits of debt issuance for unconstrained firms. However, either extension would result in slacker constraints for small firms, bringing the response of investment closer to (but no larger than) the frictionless optimum. Other effects (countercyclical liquidation, or changes in the external financing premium) might further amplify the response of constrained firms; the large responsiveness of unconstrained firms would nevertheless remain.

A second worry is the assumption of uniform productivities: *all* cross-sectional size heterogeneity arises because of financial frictions. The polar case is $a_{i,t} = a_i \ \forall(i,t)$. In that case, some small firms (those with low a_i, but high net worth) will be unconstrained; these firms' response to an aggregate shock will be similar to that of the large, unconstrained firms in the model with equal productivities. The gap between the response of small and large firms would therefore be narrower; changing its sign would furthermore require the distribution of a_i and the entry size k_e to be such that, on average, large firms tend to be more constrained than small ones. The central intuition that constrained firms are less responsive to aggregate shocks, not more, would still hold.

A last worry is that we have abstracted from general equilibrium considerations. In particular, the model does not incorporate potential feedback through changes in the price of capital goods, which might help undo the relative strength of the net worth and the optimal size effects. First, the optimal size would depend negatively on asset prices; procyclical asset prices might thus be a force pushing unconstrained firms toward higher investment. Second, the net worth effect would be stronger, as the price of depreciated capital falls.

Overall, the fundamental mechanics of the simple model we described — and in particular, the net worth and optimal size effects — are likely to survive in more complex settings, with the implication that excess sensitivity of small firms should not be interpreted as a manifestation of financial frictions.

constraint parameter is set to 0. The pattern of firms unable to obtain external funds, and forced to save their way to an optimal size, is the same; they are also present in microfounded models of debt issuance, such as Cooley and Quadrini (2001), Hennessy and Whited (2007), and Gilchrist, Sim and Zakrajšek (2014).

5.5 Non-size evidence of a financial accelerator

The regression results we have discussed so far present, at best, mixed evidence in favor the financial accelerator mechanism. We conclude this section by documenting whether firms respond heterogeneously to recessions when conditioning directly on balance sheet characteristics, instead of size. Specifically, we provide event study plots comparing the evolution firm sales, inventories, and tangible investment around recessions, separating firms in groups of leverage, liquidity, bank-dependence, access to bond markets, and dividend issuance.

[Figure 12 about here.]

Figure 12 depicts the evolution of firms sales, inventories, and fixed capital comparing zero leverage firms (which account for roughly 20% of firm-quarter observations), and firms with positive leverage; we classify firms based on their four-quarter lagged debt to asset ratio.[41] As the plots show, the evolution of sales and investment at the two groups of firms is largely indistinguishable during recessions. The same holds true for liquidity: when sorting firms into low liquidity (firms with a cash to asset ratio of less than 0.2) and high liquidity (firms with a cash to asset ratio of greater than 0.2), we also find largely indistinguishable cumulative responses of sales, inventories, and investment.

The last row of Figure 12 sorts firms into bank-dependent and non-bank-dependent. The former are defined as firms with more than 90% of debt in the form of bank loans four quarters past. While bank dependent firms do qualitatively experience a sharper contraction in their sales and investment than non-bank dependent firms, the differences are, again, not statistically significant. Overall, these findings would appear to be inconsistent with a financial accelerator mechanism. In particular, the leverage results are inconsistent with Bernanke, Gertler and Gilchrist (1999), where the external finance premium is monotonically increasing with firm leverage. Under the financial accelerator mechanism, higher leverage firms should experience increases in the cost of external financing during recessions, leading to a faster decline in factor inputs and production relative to firms that do not rely on external financing. By contrast, the evidence provided above suggests that there is no sharp difference in the behavior of higher-leverage firms during recessions.

[Figure 13 about here.]

Figure 13 provides the event study plots for firms sorted on public debt market access (top row) and dividend issuance (bottom row). Firms with a history of accessing public debt markets contract their sales and inventories *faster* than firms with no history of market access. The financial

[41] Because of constraints on the amount of data disclosed, firms had to be split into two groups, instead of the three groups used in the unconditional regression results of table . Results for leverage, liquidity and bank dependence are however qualitatively consistent when constructed for more disaggregated groups.

accelerator mechanism would predict the opposite, as firms with access to bond markets should better be able to smooth sales and inventories over the business cycle. Moreover, the point estimates suggest that investment falls faster at firms without market access, but that the difference is not statistically significant. By contrast, firms sorted on dividend issuance do display statistically significant differences for inventory and investments in recessions: firms that issed dividends also reduce inventories and investment more gradually than firms that did not. This suggests that, during recessions, dividend issuance may be the most robust indicator of financial constraints.

Overall, these findings provide only weak evidence for the presence of a financial accelerator. Standard measures of balance sheet strength do not predict excess sensitivity for financially weaker firms in recessions; market access seems to be associated with a magnified sensitivity to recessions. Dividend issuance appears somewhat more promising, with non-dividend issuing firms cutting inputs faster in recessions than dividend issuing firms. Further research is needed to determine to what extend dividend issuance is a good proxy for financial constraints as opposed to future investment opportunities.

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:

$$\mathcal{I}_t(x) \quad \equiv \{ \quad i \quad \text{s.t.} \quad x_{i,t-4} > 0 \quad \text{and} \quad x_{i,t} > 0 \quad \} \tag{12}$$

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:

$$\begin{aligned} \mathcal{I}_t^{(\text{small})} &= \mathcal{I}_t^{(0,99)}, \\ \mathcal{I}_t^{(\text{large})} &= \mathcal{I}_t^{(99,100)} = \mathcal{I}_t \setminus \mathcal{I}_t^{(0,99)}. \end{aligned} \tag{13}$$

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

$$g_{i,t}(x) = \begin{cases} \log\left(\frac{x_{i,t}}{x_{i,t-4}}\right) & \text{if} \quad x \in \{\text{sales}, \text{inventory}, \text{NPPE stock}, \text{assets}\} \\ \frac{nppe_{i,t} - nppe_{i,t-4} + dep_{i,t-4,t}}{nppe_{i,t-4}} & \text{if} \quad x = \text{fixed investment}. \end{cases} \tag{14}$$

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:

$$\begin{aligned} \hat{g}_t^{(k_1,k_2)}(x) &\equiv \frac{1}{\mathcal{Z}_{t-4}^{(k_1,k_2)}} \sum_{i \in \mathcal{I}_t^{(k_1,k_2)}} z_{i,t-4}\, g_{i,t}(x) \\ Z_{t-4}^{(k_1,k_2)} &\equiv \sum_{i \in \mathcal{I}_t^{(k_1,k_2)}} z_{i,t-4}. \end{aligned} \tag{15}$$

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 (15). 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 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.[42] For some variable of interest $x \in \{\text{sales}, \text{inventory}, \text{NPPE stock}, \text{assets}\}$, and for some quarter t, define:

$$\begin{aligned} X_t &= \sum_{i \in \mathcal{I}_t} x_{i,t}, & X_{t-4} &= \sum_{i \in \mathcal{I}_t} x_{i,t-4}, & G_t &= \frac{X_t}{X_{t-4}}, \\ X_t^{(\text{small})} &= \sum_{i \in \mathcal{I}_t^{(\text{small})}} x_{i,t}, & X_{t-4}^{(\text{small})} &= \sum_{i \in \mathcal{I}_t^{(\text{small})}} x_{i,t-4}, & G_{t-4}^{(\text{small})} &= \frac{X_t^{(\text{small})}}{X_{t-4}^{(\text{small})}}, \\ X_t^{(\text{large})} &= \sum_{i \in \mathcal{I}_t^{(\text{large})}} x_{i,t}, & X_{t-4}^{(\text{large})} &= \sum_{i \in \mathcal{I}_t^{(\text{large})}} x_{i,t-4}, & G_{t-4}^{(\text{large})} &= \frac{X_t^{(\text{large})}}{X_{t-4}^{(\text{large})}}. \end{aligned} \tag{16}$$

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

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

[42] 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.

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:

$$\begin{aligned} g_{i,t} &= \frac{x_{i,t}}{x_{i,t-4}} \\ w_{i,t-4} &= \begin{cases} \frac{x_{i,t-4}}{X_{t-4}^{\text{(small)}}} & \text{if } i \in \mathcal{I}_t^{(small)} \\ \frac{x_{i,t-4}}{X_{t-4}^{\text{(large)}}} & \text{if } i \in \mathcal{I}_t^{(large)} \end{cases} \end{aligned} \tag{17}$$

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:

$$G_t^{(small)} = \hat{g}_t^{\text{(small)}} + c\hat{o}v_t^{\text{(small)}}, \tag{18}$$

where:

$$\begin{aligned} \hat{g}_t^{(small)} &= \frac{1}{\#\mathcal{I}_t^{\text{(small)}}} \sum_{i \in \mathcal{I}_t} g_{i,t} \\ c\hat{o}v_t^{\text{(small)}} &= \sum_{i \in \mathcal{I}_t^{\text{(small)}}} \left(w_{i,t-4} - \frac{1}{\#\mathcal{I}_t} \right) \left(g_{i,t} - \hat{g}_t^{(small)} \right). \end{aligned} \tag{19}$$

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:

$$\begin{aligned} G_t &= s_{t-4} G_t^{\text{(small)}} + (1 - s_{t-4}) G_t^{\text{(large)}} \\ &= G_t^{\text{(large)}} + s_{t-4} \left(G_t^{\text{(small)}} - G_t^{\text{(large)}} \right). \end{aligned} \tag{20}$$

Combining the two equations, we obtain the decomposition:

$$\begin{aligned} G_t &= \hat{g}_t^{\text{(large)}} \\ &+ s_{t-4} \left(\hat{g}_t^{\text{(small)}} - \hat{g}_t^{\text{(large)}} \right) \\ &+ c\hat{o}v_t, \end{aligned} \tag{21}$$

where the covariance term $c\hat{o}v_t$ is given by:

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

C Details on the comparison to Gertler and Gilchrist (1994)

C.1 The methodology of Gertler and Gilchrist (1994)

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:

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

The growth rate of large firms is defined analogously, using the cumulative sum of sales over the remaining bins of asset size. In our implementations of the GG methodology, we use four-quarter lagged growth rates, in order to remove seasonality in our data. Moreover, consistent with GG, we de-mean the small and large growth series before computing cumulative growth rates.

C.2 Differences between the GG methodology and our approach

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 7, 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. 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 8, 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 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.

C.3 Romer-Romer dates vs. recession dates for inventory and investment

[Figure 14 about here.]

Figure (14) reports the cumulative response of inventory and fixed capital after a recession start (bottom row) and a Romer-Romer date (top row). Both sets of cumulative changes are constructed using the bottom 99%/top 1% classification of firms. Consistent with the evidence for sales provided in the main text, Romer-Romer dates are characterized by a higher sensitivity of investment at small firms. Around recessions, the excess sensitivity of small firms is less visible, in particular for inventory.

D Model details

D.1 The profit function

The profit function function is assumed to be given by:

$$\pi_{i,t} = (a_{i,t}x_t)^{1-\zeta}\, k_{i,t}^{\zeta}, \quad \zeta \in [0, 1[\tag{22}$$

The following two models provide background for this formulation of the profit function, as well an explicit formulation for the aggregate and idiosyncratic shocks $a_{i,t}$ and x_t.

Decreasing returns in production The firm choses labor input to solve:

$$\begin{aligned} \pi_{i,t} &= \max_{l_{i,t}} \quad y_{i,t} - w_t l_{i,t} \\ &\text{s.t.} \qquad y_{i,t} \leq z_{i,t}\,(k_{i,t})^{\alpha\zeta}\,(h_t l_{i,t})^{1-\alpha} \quad [mc_{i,t}] \end{aligned} \tag{23}$$

where $1-\alpha \in [0, 1]$ is labor's share of revenue, $\zeta \in [0, 1]$ is the degree of decreasing returns to scale, $z_{i,t}$ is idiosyncratic productivity, and $y_{i,t}$ is aggregate productivity. Here, w_t is the aggregate real wage, h_t is labor-augmenting productivity, and $z_{i,t}$ is firm-specific total factor productivity. The solution is:

$$\pi_{i,t} = (a_{i,t}x_t)^{1-\zeta}\, k_{i,t}^{\zeta} \tag{24}$$

$$s_{i,t} = \frac{1}{\alpha}\pi_{i,t} \tag{25}$$

$$l_{i,t} = \frac{1-\alpha}{\alpha}\frac{\pi_{i,t}}{w_t} \tag{26}$$

$$a_{i,t} \equiv z_{i,t}^{\frac{1}{\alpha(1-\zeta)}} \tag{27}$$

$$x_t \equiv \left(\alpha^{\alpha}(1-\alpha)^{1-\alpha}\right)^{\frac{1}{\alpha(1-\zeta)}} \left(\frac{h_t}{w_t}\right)^{\frac{1-\alpha}{\alpha(1-\zeta)}} \tag{28}$$

Imperfect competition The firm choses labor input and the relative price of its variety to solve:

$$\begin{aligned} \pi_{i,t} &= \max_{l_{i,t},p_{i,t}} \quad p_{i,t}\left(p_{i,t}^{-(\epsilon+1)}\left(\omega_{i,t}d_t\right)\right) - w_t l_{i,t} \\ &\text{s.t.} \qquad p_{i,t}^{-(\epsilon+1)}\left(\omega_{i,t}d_t\right) \leq \left(k_{i,t}\right)^{\alpha}\left(h_t l_{i,t}\right)^{1-\alpha} \quad [mc_{i,t}] \end{aligned} \tag{29}$$

Here, d_t represents aggregate demand, and $\omega_{i,t}$ represents a firm-specific demand shifter, and other variables are defined as above. The labor share is:

$$\frac{\zeta}{\zeta+\alpha(1-\zeta)}(1-\alpha),$$

where the curvature parameter ζ is given by:

$$\zeta \equiv \frac{\alpha\epsilon}{1+\alpha\epsilon} \in [0,1]\,.$$

The case $\zeta = 1$ (or $\epsilon = +\infty$) corresponds to perfect competition. The solution is:

$$\pi_{i,t} = (a_{i,t}x_t)^{1-\zeta}\, k_{i,t}^{\zeta} \tag{30}$$

$$s_{i,t} = (\zeta + \alpha(1-\zeta))\frac{1}{\alpha}\pi_{i,t} \tag{31}$$

$$l_{i,t} = \zeta\frac{1-\alpha}{\alpha}\frac{\pi_{i,t}}{w_t} \tag{32}$$

$$a_{i,t} \equiv \omega_{i,t} \tag{33}$$

$$x_t \equiv \left(\left(1+\alpha\frac{1-\zeta}{\zeta}\right)^{-\left(1+\alpha\frac{1-\zeta}{\zeta}\right)}\left(\frac{\alpha}{\zeta}\right)^{\frac{\alpha}{\zeta}}(1-\alpha)^{1-\alpha}\right)^{\frac{\zeta}{\alpha(1-\zeta)}}\left(\frac{w_t}{h_t}\right)^{-\frac{1-\alpha}{\alpha}\frac{\zeta}{1-\zeta}} d_t \tag{34}$$

D.2 Calibration of the model with homogeneous productivities

The steady-state of the model with homogeneous producitivities has seven parameters: the curvature of the profit function, ζ, the rate of depreciation of capital, δ, the risk-free rate, r, the exit rate η, the entry size k_e, and the steady-state value of the exogenous processes x and a.

We set $\zeta = 0.7$, in the range of the estimates in Hennessy and Whited (2007); furthermore, we use $\delta = \frac{0.065}{4}$ and $r = \frac{0.015}{4}$, since the calibration of the model is quarterly. Additionally, we normalize $a = 1$ and set:

$$x = \left(\frac{\zeta}{\delta + r}\right)^{-\frac{1}{1-\zeta}},$$

This normalization implies that the steady-state size of unconstrained firms satisfies $\log(k^*) = 0$.

Given a value for the entry size k_e such that $k_e < \bar{k}$, there exists a unique integer $N \geq 2$ such that:

$$\mathbf{n}^{N-1}(k_e) < k^* \quad , \quad \mathbf{n}^N(k_e) \geq k^*,$$

where $\mathbf{n}(k) \equiv x^{1-\zeta}k^{\zeta} + (1-\delta)k$, and $\mathbf{n}^j(.)$ is the j-th iterate of $\mathbf{n}$. The stationary distribution is then a discrete distribution $\{\mu_j\}_{j=0}^N$, with $\sum_{j=0}^N \mu_j = 1$, supported on $N+1$ points $\{k_j\}_{j=0}^N$, where:

$$k_j = \begin{cases} \mathbf{n}^j(k_e) & \text{if } 0 \leq j \leq N-1 \\ k^* & \text{if } j = N \end{cases} \tag{35}$$

Given the exit rate η, and a mass of entering firms M, the distribution is given by:

$$\mu_j = \begin{cases} (1-\eta)^j M & \text{if } 0 \leq j \leq N-1 \\ \frac{(1-\eta)^N}{\eta} M & \text{if } j = N \end{cases} \tag{36}$$

We normalize $M = \frac{1}{\eta}$, so that the total mass of firms is 1 in steady-state. We then pick the entry size k_e to be $k_e = (0.0008)k^*$, similar to the $p20/p99$ ratio of book assets in the QFR. Given that $\log(k^*) = 0$, this requires $\log(k_e) = \log(0.0008)$. Given this choice of k_e, $N(k_e)$ is determined; given the calibration above, we have $N = 146$. We then pick η so that, in steady-state, 1% of firms are unconstrained: $\frac{(1-\eta)^N}{\eta} = 0.01$. This choice allows us to think of the size-conditional impulse response reported in the main text as also reflecting the behavior of constrained and unconstrained firms. Given all other parameters, matching this target requires $\eta = 0.042$. This exit rate is somewhat higher than what is observed among the firms of the balanced QFR panel. With a lower curvature of the profit function, however, it is straightforward to obtain lower implied exit rates through this procedure; moreover, the qualitative implications of the model are independent of the particular value chosen for η.

List of Figures

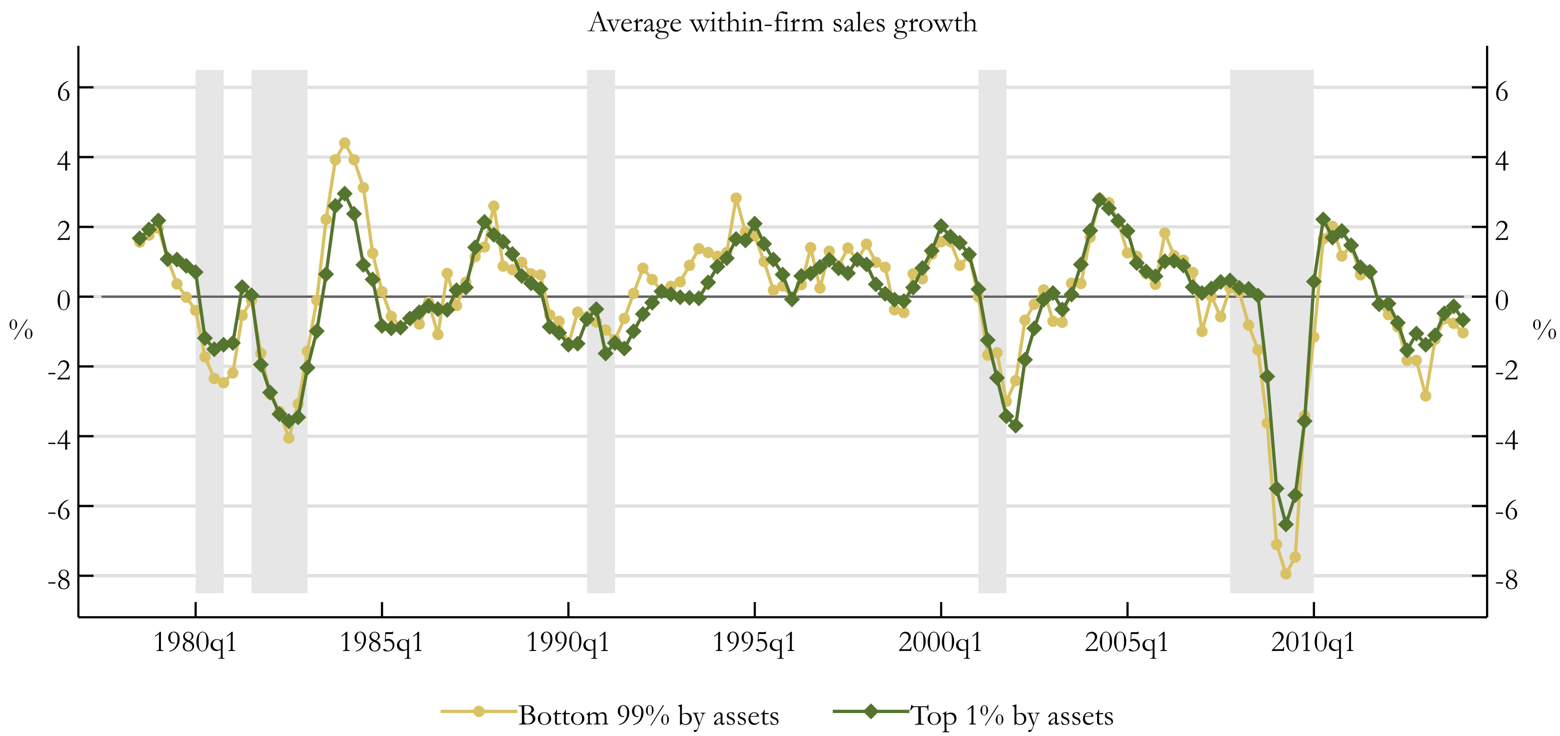

Figure 1: Average firm-level growth rate of sales of small (yellow, round markers) and large (green, diamond markers) firms. Small firms are those belonging to the bottom 99% of the one-year lagged distribution of book assets, while large firms are those belonging to the top 1% of the one-year lagged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

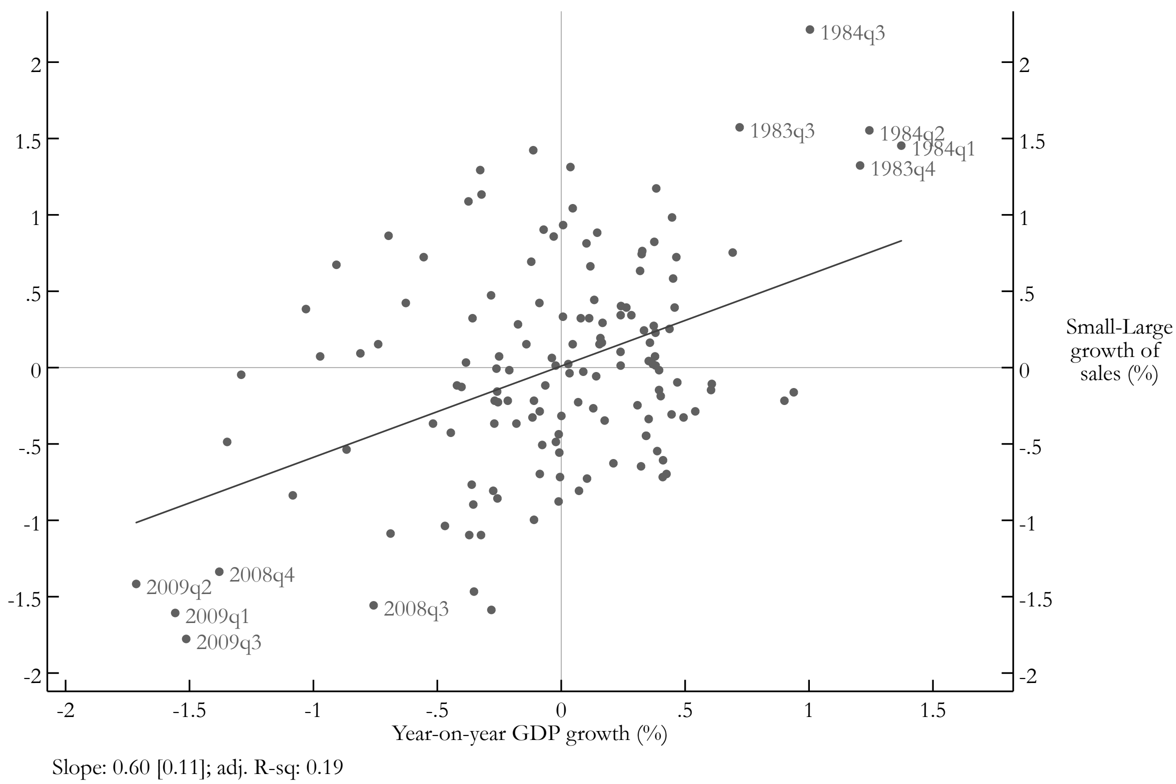

Figure 2: Difference between average growth rate of sales $\hat{g}_t^{(small)}(\text{sales}) - \hat{g}_t^{(large)}(\text{sales})$ (vertical axis) and year-on-year GDP growth (horizontal axis). Both series are demeaned. White standard errors in brackets.

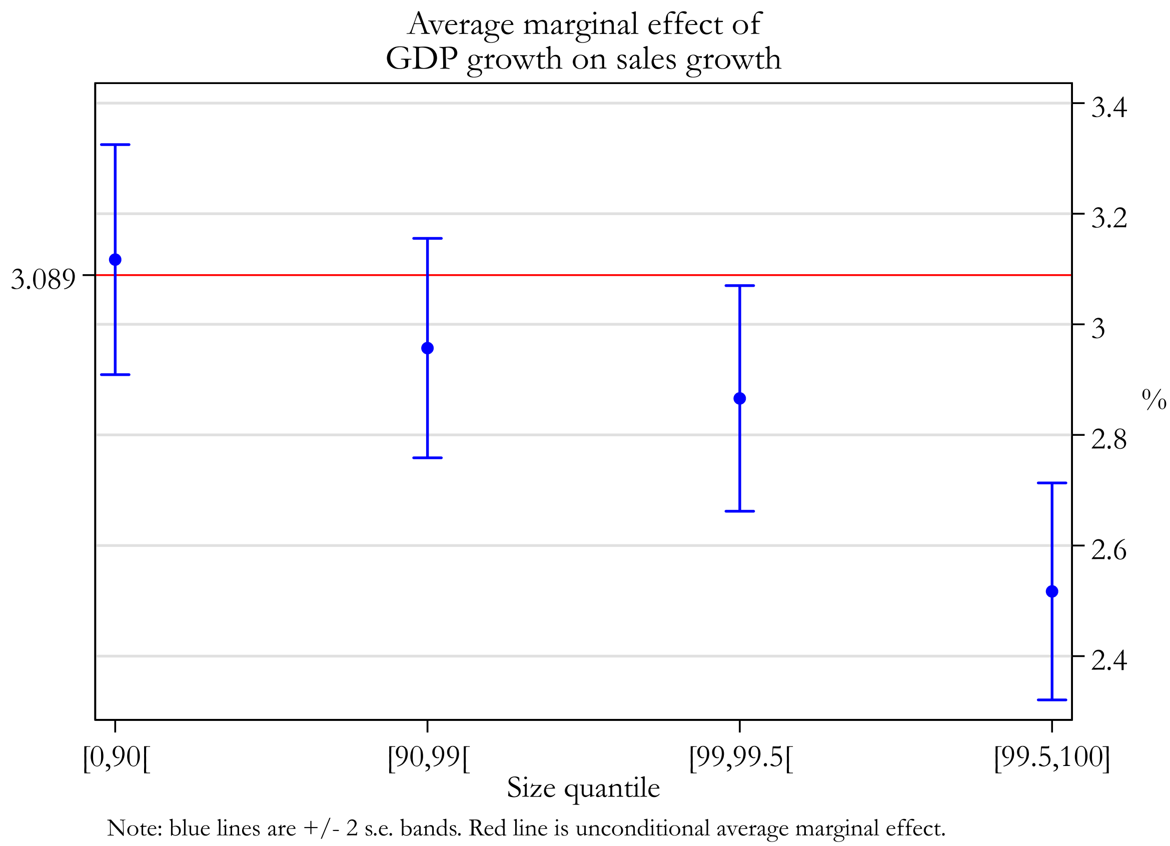

Figure 3: Marginal effects of GDP growth on sales growth, by size group (blue boxplots), and unconditionally (red line). The marginal effects are computed using estimates of model (2).

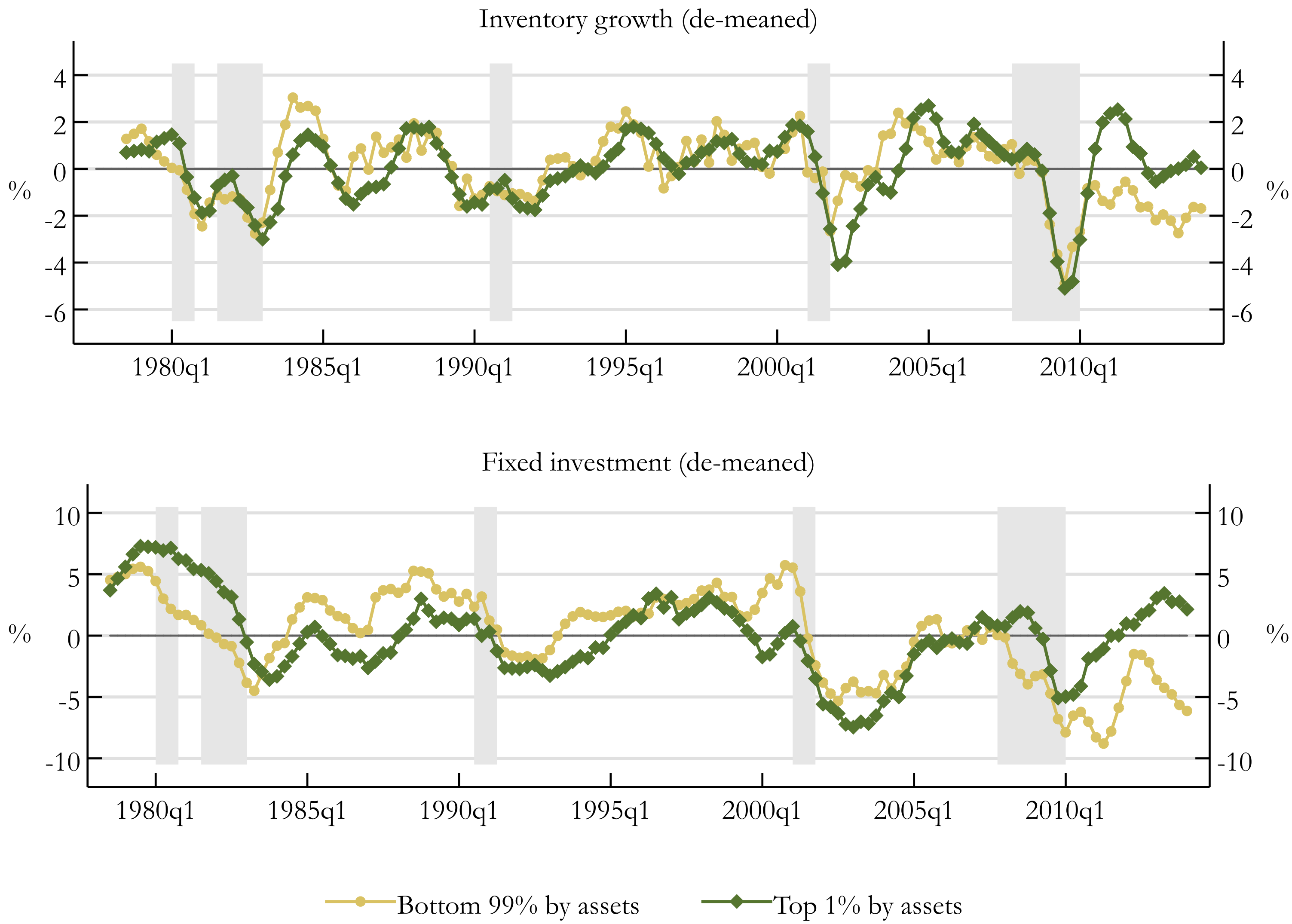

Figure 4: Average firm-level growth rate of small (yellow, round markers) and large (green, diamond markers) firms; top: inventory growth rate; bottom: fixed investment rate. Small firms are those belonging to the bottom 99% of the one-year lagged distribution of book assets, while large firms are those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

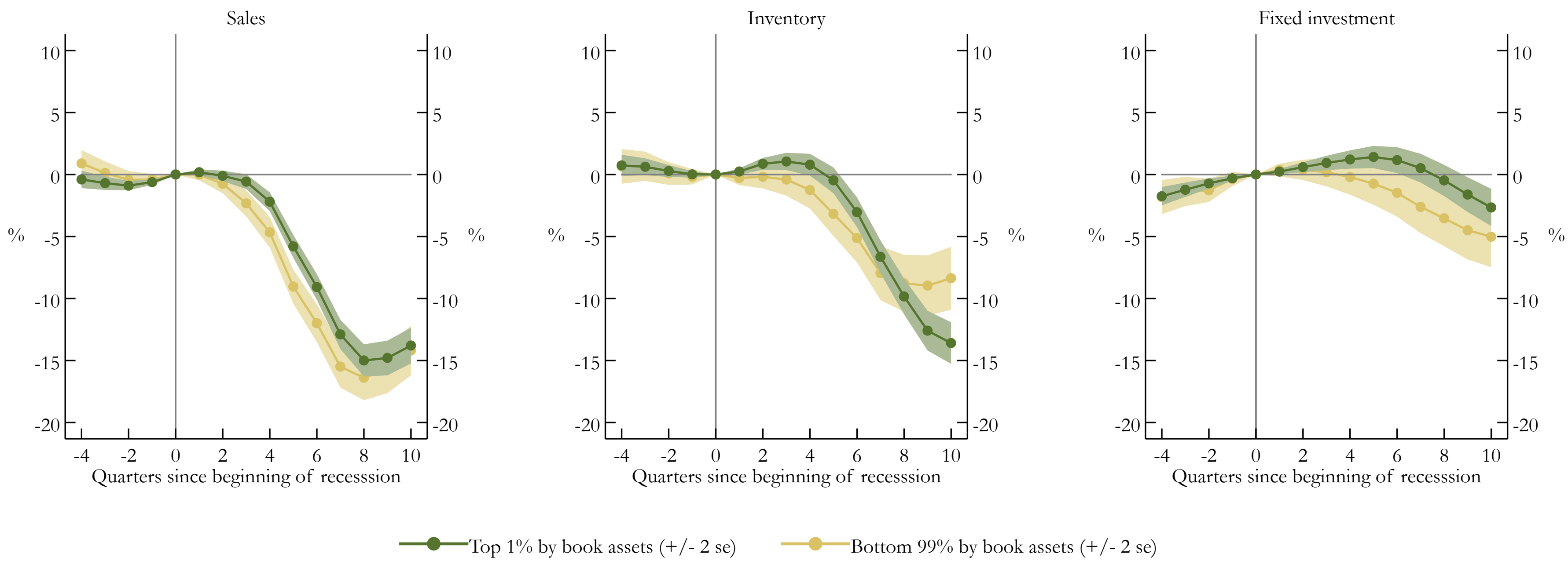

Figure 5: The behavior of sales, inventory and fixed capital after the start of a recession. Each graph reports the cumulative change in a variable of interest after the beginning of a recession; see section (3.4) for details on the estimation. Shaded areas are +/- 2 standard error bands. Top row: sales, inventory and fixed investment. In the regression framework, sales and inventory growth rates are computed year-on-year and expressed at the quarterly frequency; the investment rate is also computed year-on-year and expressed at the quarterly frequency. Bottom row: total debt to assets ratio, bank debt to asset ratio and short-term debt to asset ratio. The change in each debt ratio is computed year-on-year, normalizing by one-year lagged assets, and expressed at the quarterly frequency. Recession start dates are 1981q3, 1990q3, 2001q1, and 2007q4.

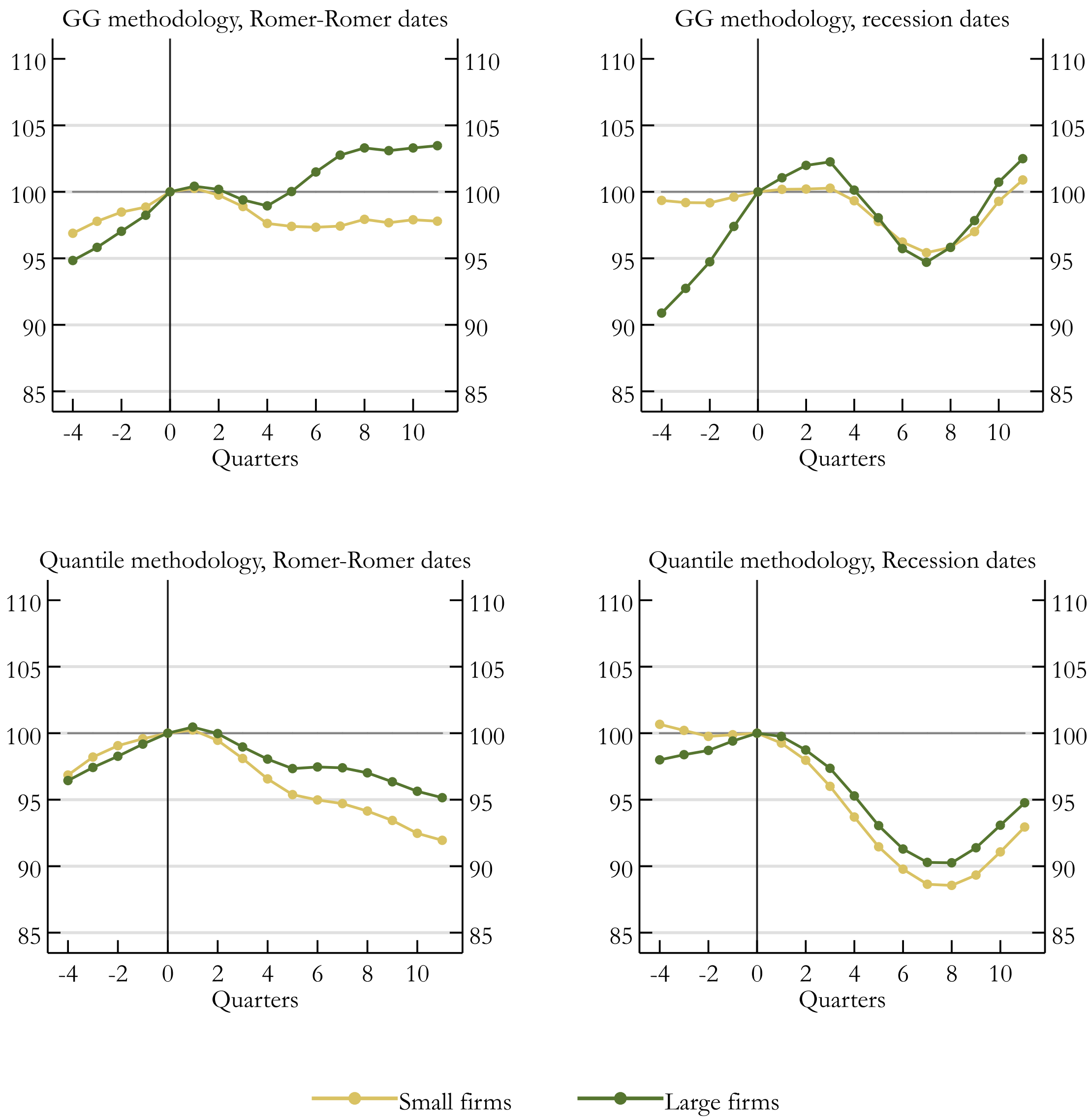

Figure 6: Cumulative changes in sales after a Romer and Romer date (left column) and after a recession start date (right column). The top row uses the Gertler and Gilchrist (1994) methodology to construct small and large firms groups; the methodology is described in appendix (C). The bottom row uses the bottom 99%/top 1% classification adopted elsewhere in the present paper. Cumulative changes are computed using the average growth rate time series for each size group, after removing the unconditional mean. Romer-Romer dates are 1978q3, 1979q4, 1988q4, 1994q2 and 2008q3. Recession start dates are 1981q3, 1990q3, 2001q1, and 2007q4.

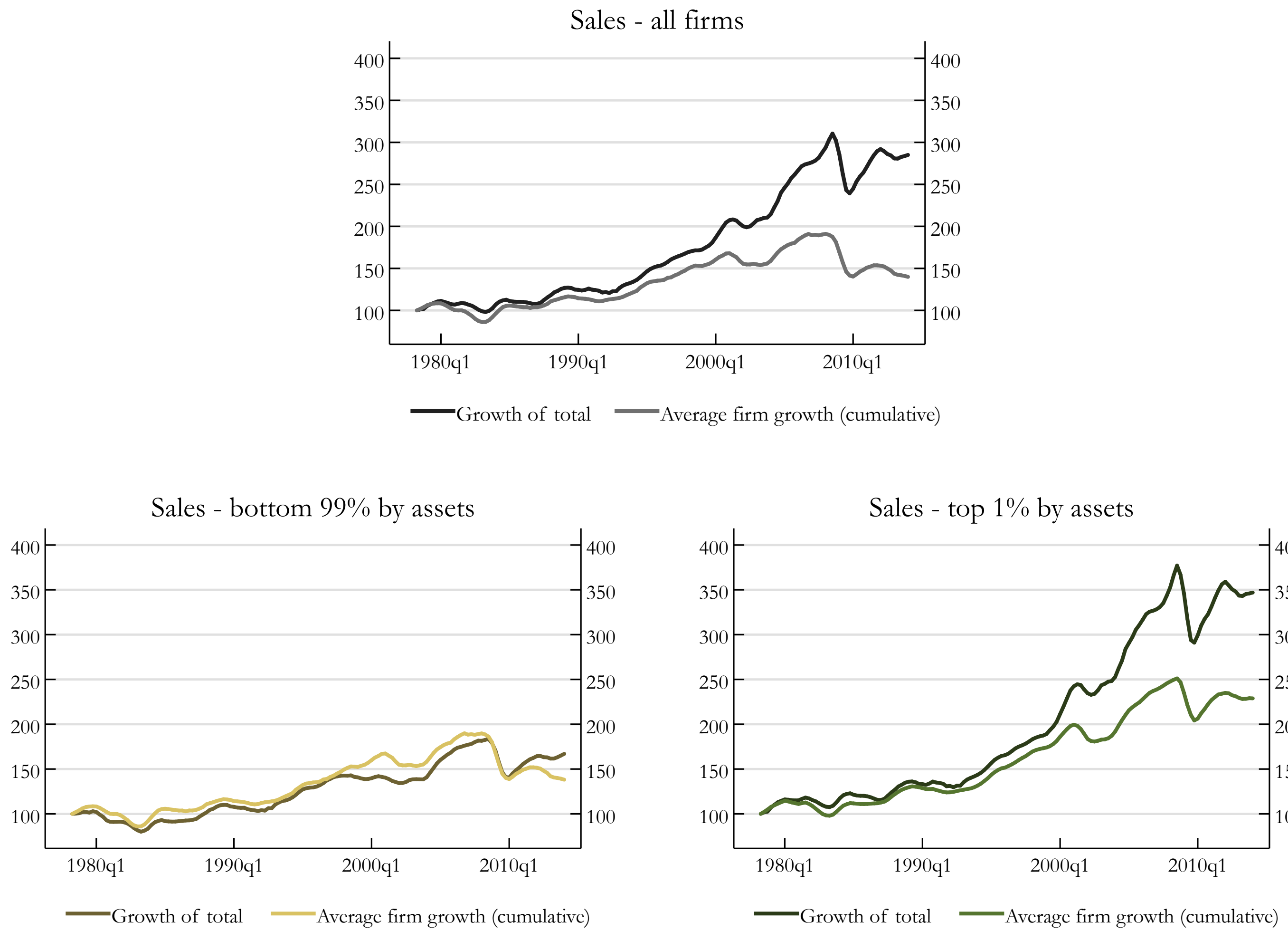

Figure 7: Aggregate sales and average within-firm cumualtive growth rate of sales. Each panel reports total annual sales (the cumulative value of $\hat{G}_t$), and the cumulative average growth rate of sales (the cumulative value of $\hat{g}_t$), for a different group of firms. All series are normalized to 100 in 1978q1.

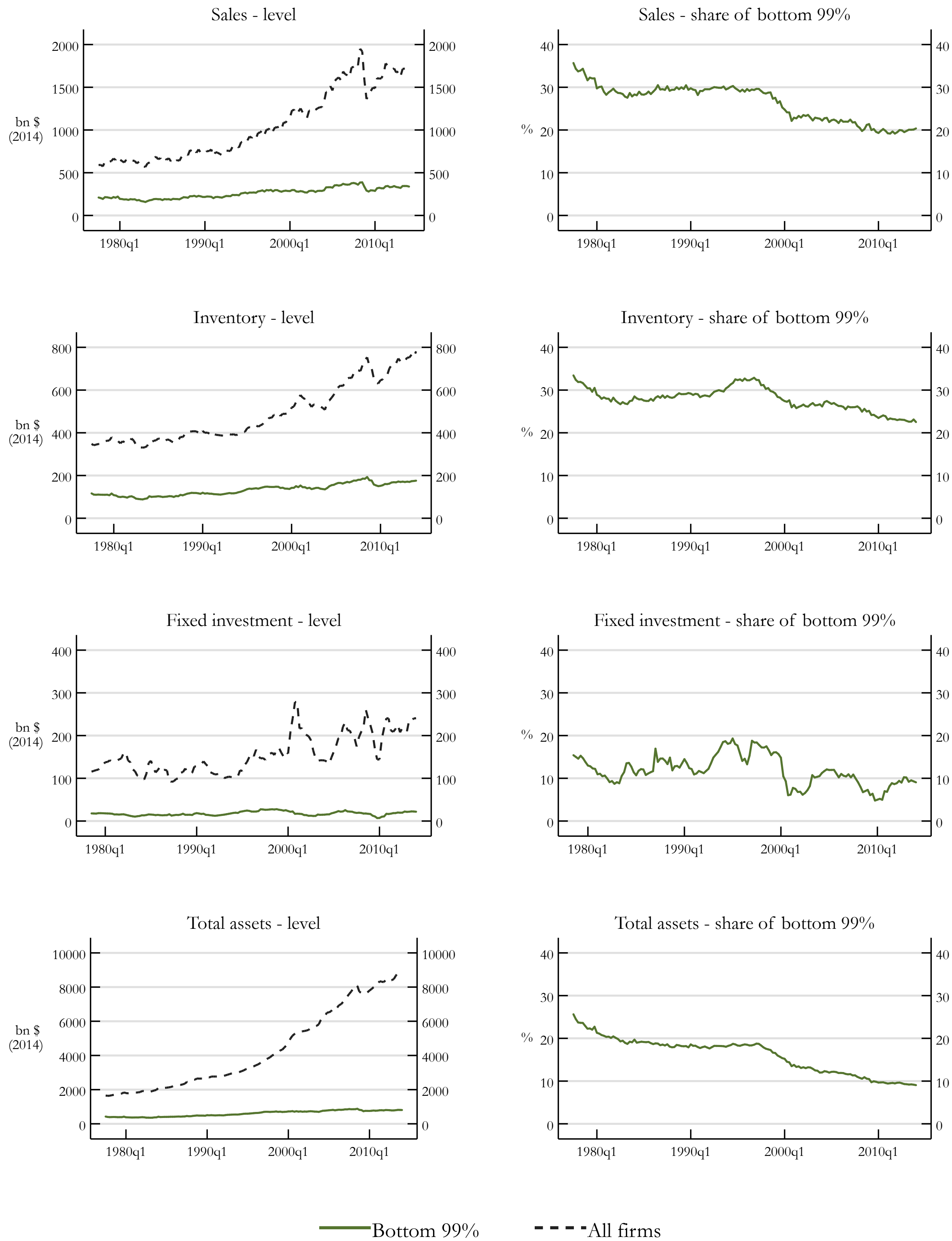

Figure 8: Concentration of sales, inventory, fixed investment, and total assets in the US manufacturing sector. The left column reports total nominal values for the bottom 99% and top 1% of firms by size. All series are deflated by the BEA price index for manufacturing, normalized to 1 in 2009q1; the 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).

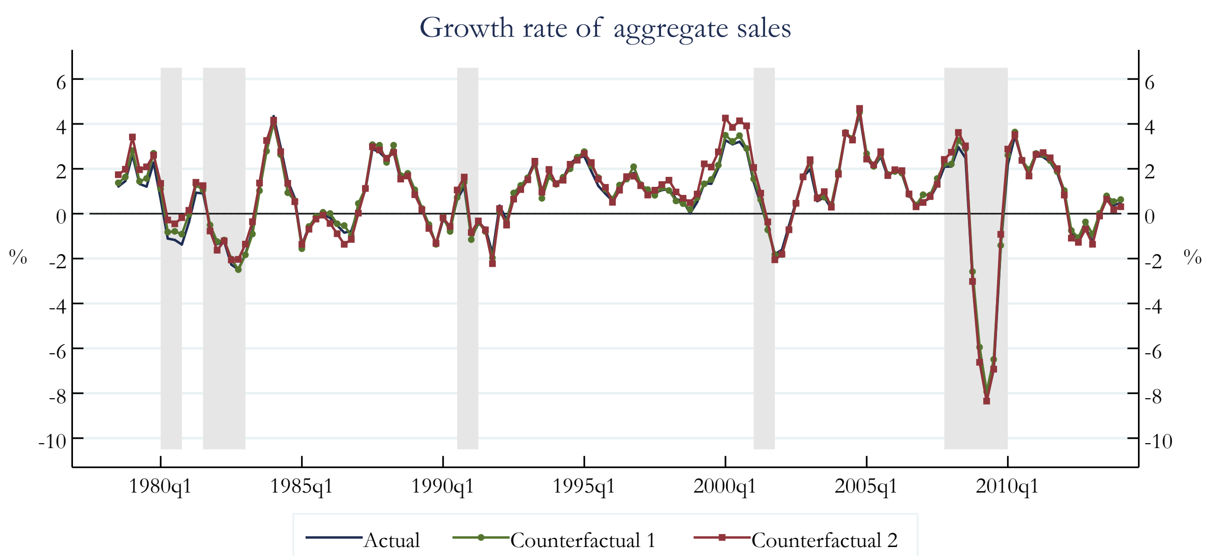

Figure 9: Aggregate growth rate of sales G_t (solid blue line), counterfactual growth rate 1 $G_t^{(1)}$, and counterfactual growth rate 2 $G_t^{(2)}$.

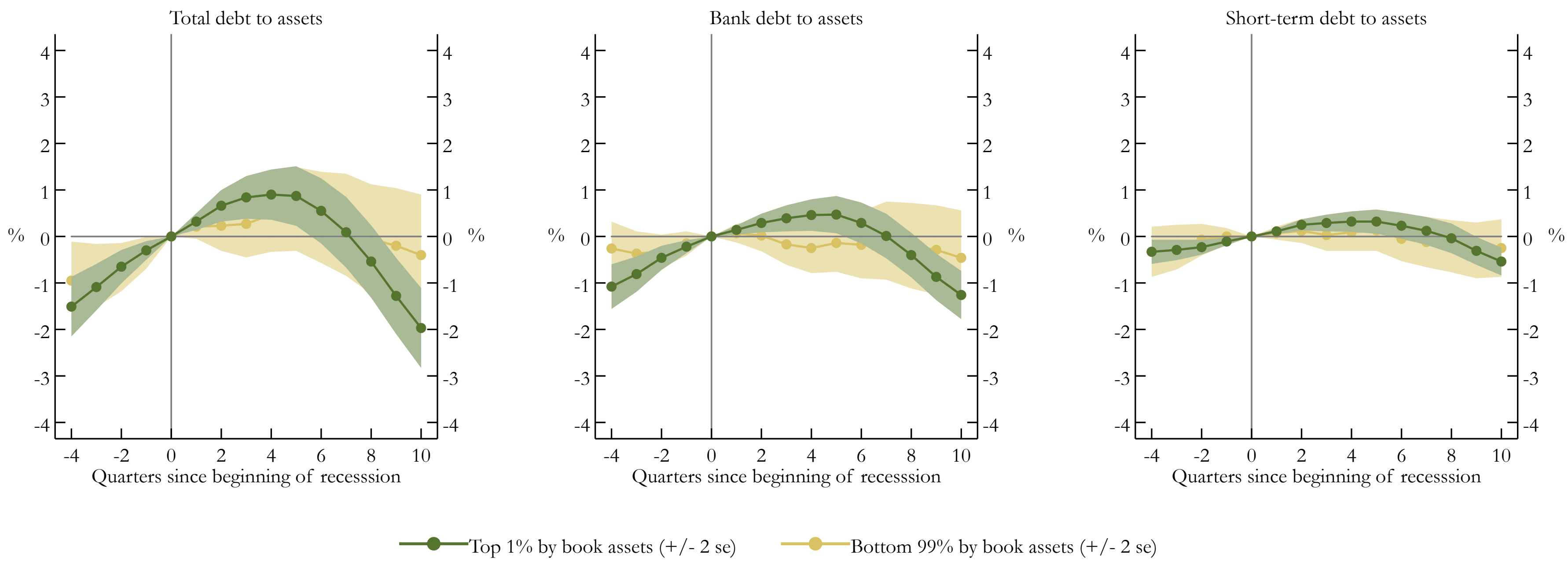

Figure 10: The behavior of debt overall, bank debt, and short-term debt after the start of a recession. Each panel reports changes relative to quarter 0 (the recession start date), computed using the cumulative sum of average growth rate of each size group. Growth rates at the firm-level are computed 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.

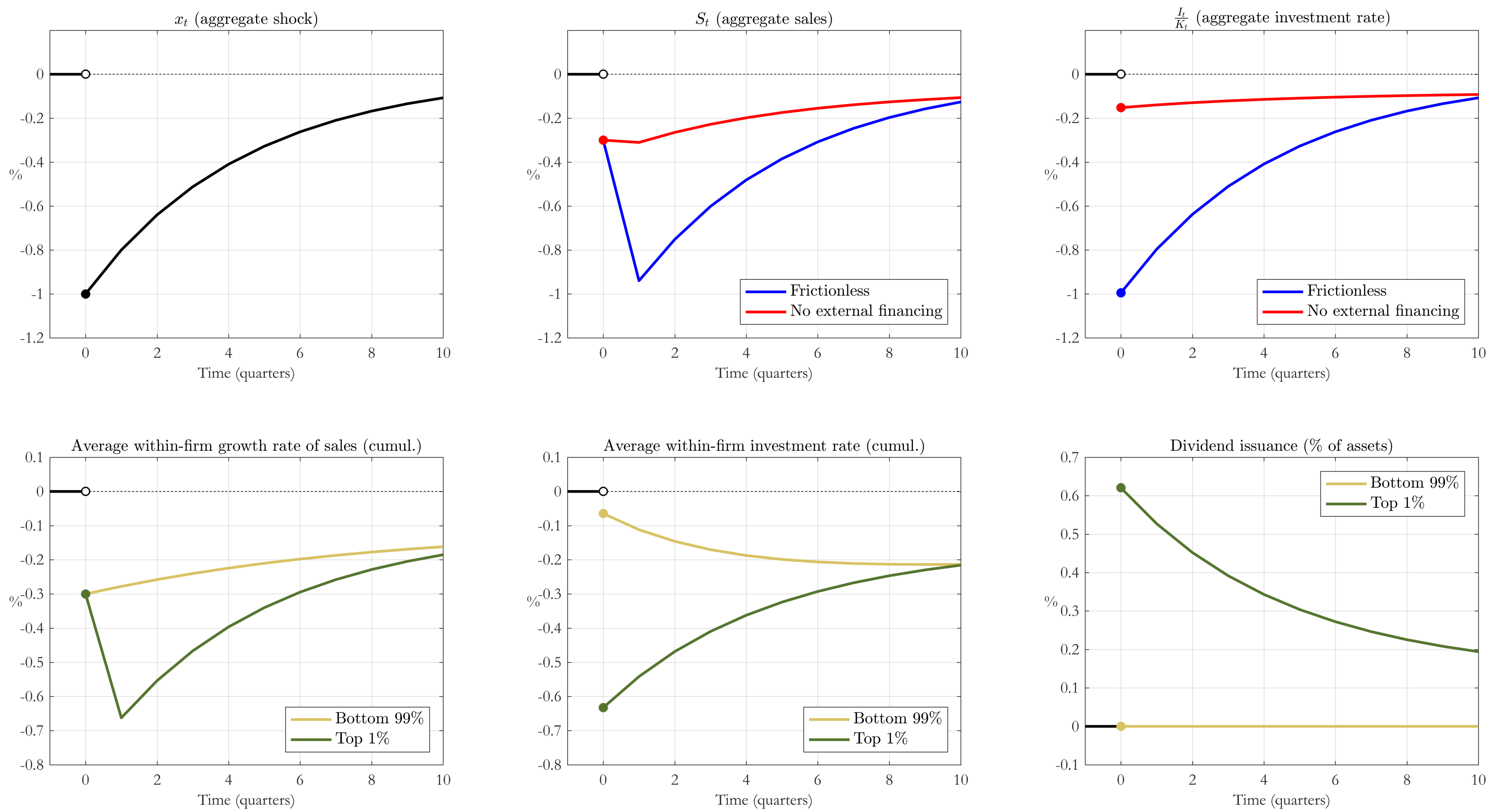

Figure 11: The response of two versions of the simple model of section 5.4 to a temporary decline in the aggregate factor x_t. The top row compares reports the path of x_t, and the behavior of aggregate sales $S_t = \int_i s_{i,t} d\mu_t(i)$ and the aggregate investment rate $\frac{I_t}{K_t} = \frac{\int_i i_{i,t} d\mu_t(i)}{\int_i k_{i,t} d\mu_t(i)}$, in the frictionless version of the model (blue line) and in the version with financial frictions (red line). The bottom row reports impulse responses in the model with financial frictions: the fraction of constrained firms, and the size-conditional responses of sales growth and investment. The green lines correspond to firms in the top 1% of the one-quarter lagged distribution of book assets, and the yellow lines correspond to firms in the bottom 99%.

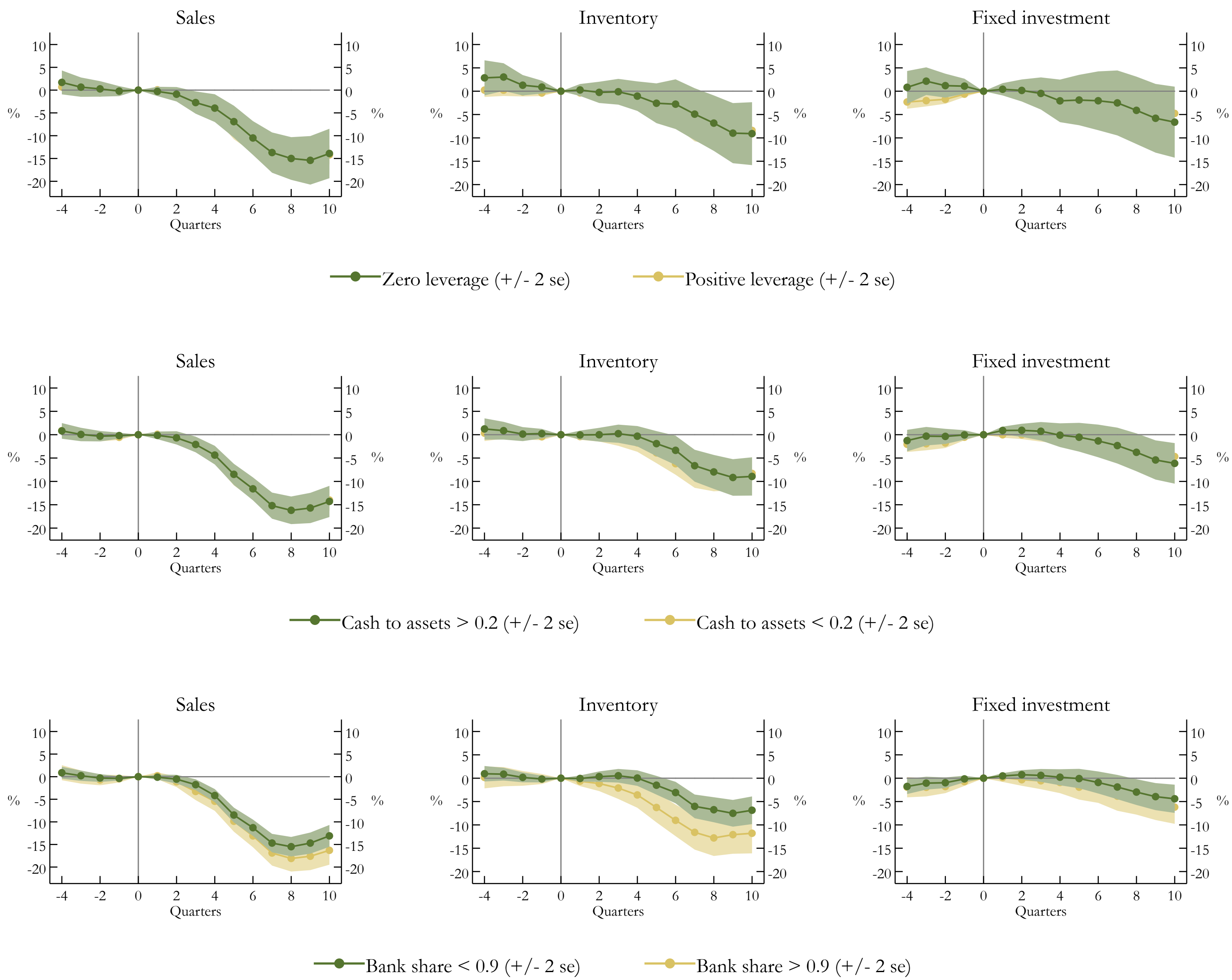

Figure 12: Sales, inventory and fixed capital after the start of a recession, across firms sorted by leverage, liquidity and bank dependence. Each graph reports the cumulative change in a variable of interest after the beginning of a recession; see section (3.4) for details on the estimation. Shaded areas are +/- 2 standard error bands. Variable definitions are given in appendix (A). Top row: firms sorted based on lagged leveraged; middle row: firms sort based on lagged cash-to-asset ratio; bottom row: firms sorted on bank dependence.

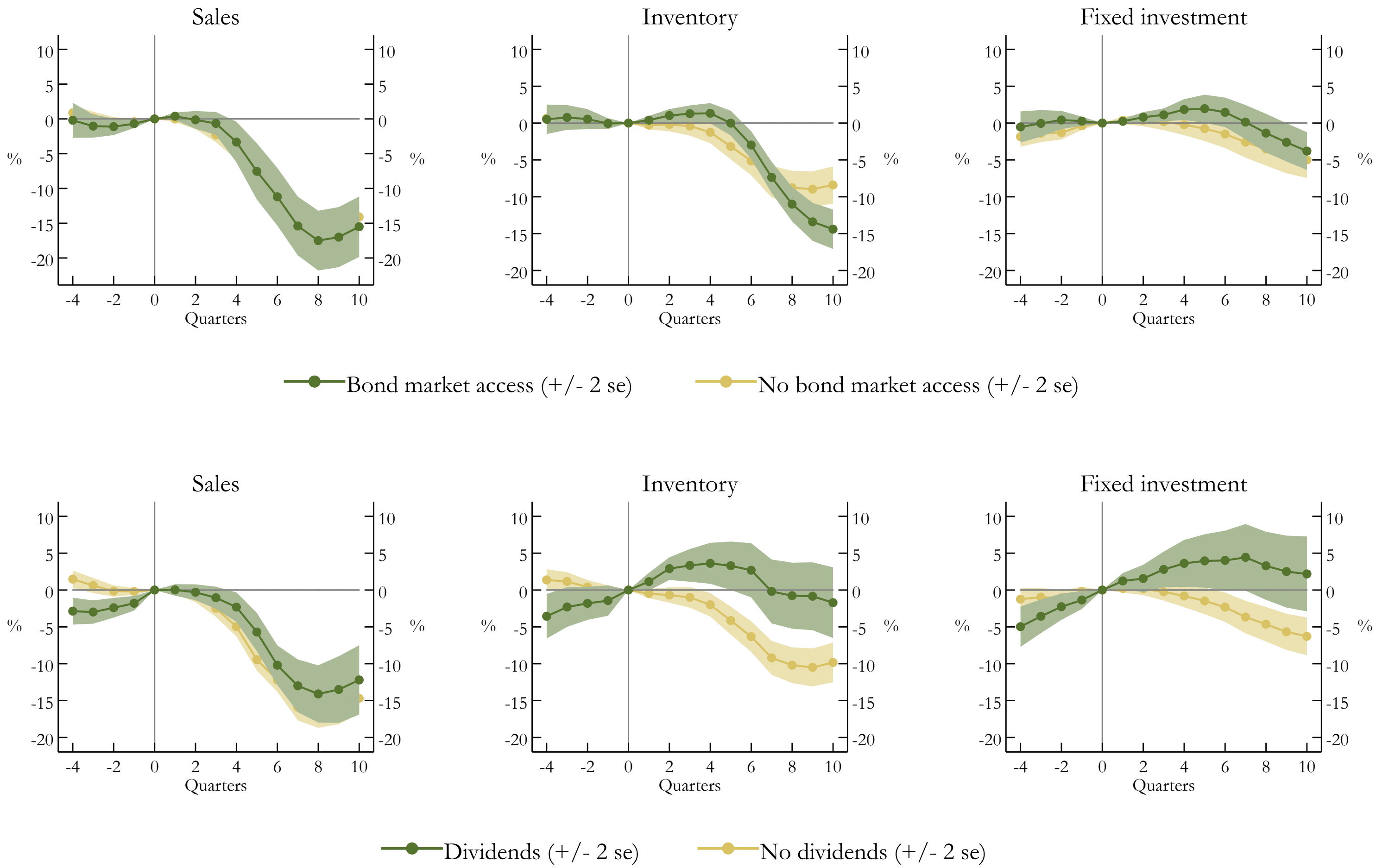

Figure 13: Sales, inventory and fixed capital after the start of a recession, across firms sorted by market access and dividend issuance. Each graph reports the cumulative change in a variable of interest after the beginning of a recession; see section (3.4) for details on the estimation. Shaded areas are +/- 2 standard error bands. Variable definitions are given in appendix (A). Top row: firms sorted based on lagged access to bond market; bottom row: firms sort based on lagged dividend issuance.

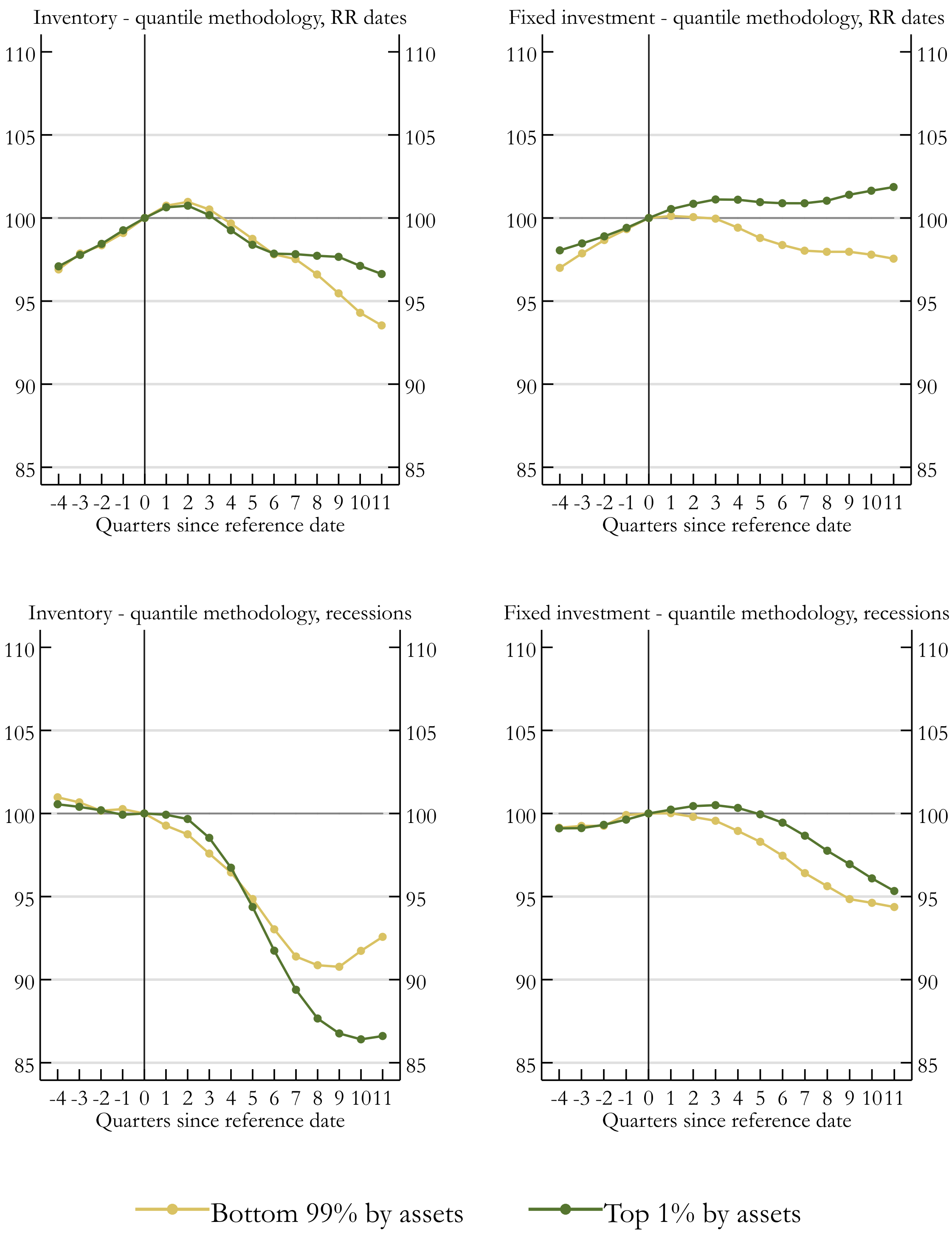

Figure 14: Cumulative changes in inventory and fixed capital after a Romer and Romer date (top row) and after a recession start date (bottom row). Cumulative changes are computed using the average growth rate time series for each size group, after removing the unconditional mean. Romer-Romer dates are 1978q3, 1979q4, 1988q4, 1994q2 and 2008q3. Recession start dates are 1981q3, 1990q3, 2001q1, and 2007q4.

List of Tables

Panel A: size and growth

Size group	*0-90th*	*90-99th*	*99-99.5th*	*>99.5th*
Assets ($ mil.)	$2.0	$48.8	$626.0	$6766.3
Sales ($ mil., quarterly)	$1.2	$18.8	$181.1	$1420.8
Sales growth (year-on-year)	0.19%	4.58%	4.34%	4.08%
Investment rate (year-on-year)	26.50%	24.91%	21.89%	20.36%

Panel B: financial characteristics

Size group	*0-90th*	*90-99th*	*99-99.5th*	*>99.5th*
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
Zero leverage (% of tot. firm-quarter obs.)	20%	13%	8%	3%
Negative book equity (% of tot. firm-quarter obs.)	5%	<1%	<1%	<1%
Bank dependent (% of tot. firm-quarter obs.)	26%	29%	20%	10%

Table 1: Real and financial firm characteristics, by size group. 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*
Assets				
Financial assets, incl. cash	0.149	0.099	0.074	0.055
Short-term assets				
Receivables	0.284	0.229	0.165	0.124
Inventory	0.218	0.241	0.172	0.130
Other	0.040	0.037	0.042	0.041
Long-term assets				
Net property, plant and equipment	0.269	0.288	0.289	0.287
Other, incl. intangibles	0.050	0.106	0.259	0.362
Liabilities				
Debt				
Due in 1 year or less				
Bank debt	0.083	0.083	0.032	0.016
Non-bank debt	0.035	0.019	0.019	0.028
Due in more than 1 year				
Bank debt	0.107	0.111	0.110	0.072
Non-bank debt	0.123	0.079	0.141	0.179
Trade payables	0.156	0.123	0.085	0.071
Other, incl. capital leases	0.099	0.121	0.187	0.233
Equity	0.393	0.463	0.426	0.416

Table 2: Average balance sheet, by size group. All numbers are expressed as fraction of total book assets. Fractions may not add up to 1 due to rounding. Financial assets are the sum of cash and deposits, treasury and federal agency securities, and all other financial assets. Other short-term assets include pre-paid expenses and income taxes receivable. Non-bank debt inculdes commercial paper, bonds, and other short- and long-term notes. Other liabilities include tax liabilities and capital leases. Definitions of the variables in terms of QFR items from survey forms 300, 201, and 200 are available upon the authors on request. 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	-26.27%	-16.59%	-12.66%	-10.97%
Sales growth	0.19%	4.58%	4.34%	4.08%
Sales growth, > p75	26.77%	25.83%	21.41%	19.19%
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 3: 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 confidentiality.

	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 4: 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 $\frac{nppe_{i,t} - nppe_{i,t-4} + dep_{i,t-4,t}}{nppe_{i,t-4}}$, 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 5: 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 6: 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
$\frac{\sigma_{\hat{cov}_t}}{\sigma_{G_t}}$	0.54	0.45	0.41
$corr(\hat{cov}_t, Y_t)$	−0.32	−0.05	−0.15

Table 7: 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 β	Counterfactual 1 $\beta^{(1)}$	Counterfactual 2 $\beta^{(2)}$
Sales	2.293 (0.342)	2.154 (0.342)	2.270 (0.366)
Inventory	0.919 (0.226)	0.719 (0.250)	0.770 (0.226)
Fixed investment	0.584 (0.145)	0.569 (0.151)	0.569 (0.148)
Total assets	0.876 (0.121)	0.787 (0.129)	0.838 (0.119)
Observations	143	143	143

Table 8: 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	≈ 460000	≈ 460000	≈ 460000	≈ 460000
nr. firms	≈ 60000	≈ 60000	≈ 60000	≈ 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 9: 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	(1)	(2)	(3)	(4)	(5)
$[90, 99] \times$ GDP growth	-0.160	-0.189	-0.195	-0.162	-0.193	-0.176
$[99, 99.5] \times$ GDP growth	-0.251^{*}	-0.257^{*}	-0.321^{**}	-0.282^{*}	-0.490^{***}	-0.247
$[99.5, 100] \times$ GDP growth	-0.600^{***}	-0.563^{***}	-0.675^{***}	-0.640^{***}	-1.097^{***}	-0.594^{***}
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^{**}	
Dividend issuance $\times$ GDP growth						0.087
N	≈ 460000	≈ 460000	≈ 460000	≈ 460000	≈ 460000	≈ 460000
nr. firms	≈ 60000	≈ 60000	≈ 60000	≈ 60000	≈ 60000	≈ 60000
adj. R^2	0.025	0.025	0.025	0.025	0.025	0.025
industry controls	yes	yes	yes	yes	yes	yes
s.e. clustering	firm-level	firm-level	firm-level	firm-level	firm-level	firm-level

Table 10: Estimate of regression of the regression model (9) for sales growth on firm size and proxies for financial constraints. 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 proxy for financial constraints. Standard errors clustered at the firm level. $*$, $**$ and $***$ indicate 10%, 5% and 1% significance levels, respectively with p-values reported in parentheses.