

Small and Large Firms Over the Business Cycle*

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Abstract

This paper uses new confidential Census data to revisit the relationship between firm size, cyclicalities, and financial frictions. First, we find that large firms (the top 1% by size) are less cyclically sensitive than the rest. Second, high and rising concentration implies that the higher cyclicalities of the bottom 99% of firms only has a limited impact on aggregate fluctuations. Third, differences in cyclicalities are not simply explained by financial frictions, and in fact appear largely unrelated to proxies for financial strength. Industry variation instead suggests that large firms have less cyclical customer bases, in particular due to export exposure.

Keywords: Firm size, business cycles, financial accelerator.

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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 greater sensitivity of small firms to the cycle would provide evidence in favor of the “financial accelerator” — the view that financial frictions can amplify the response of the economy to aggregate shocks, even those non-financial in nature.¹ However, largely because of data limitations, vigorous debate remains as to 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 questions. First, are small firms more cyclically sensitive than large firms and if so, to what extent? Second, what would happen to aggregate fluctuations if the sensitivity of small firms matches that of large firms? Third, is this greater sensitivity a manifestation of differences in access to finance?

Our new evidence comes from the confidential microdata underlying the US Census Bureau’s Quarterly Financial Report (QFR), a survey that collects income statements and balance sheets of manufacturing, retail and wholesale trade firms. We use these micro records to assemble a representative, quarterly panel of US manufacturing firms from 1977 to 2014. The resulting dataset is made up of approximately 900000 observations on 80000 different firms. We use this dataset to quantify the greater sensitivity of firms at the bottom of the size distribution, relate it to the behavior of aggregate quantities in our sample, and assess whether it is evidence of a financial amplification mechanism.

To our knowledge, this paper is the first to use this firm-level data in its panel format. The primary advantage of the QFR is that it provides balance-sheet and income-statement data for smaller, private firms. This is the group of firms that, a priori, one might expect to be the most financially constrained, but for which financial data is typically unavailable in public-use datasets. The QFR firm-level data is released to the public as aggregates by firm size categories, but an important advantage of the firm-level data is that controls can be introduced for financial factors that may be correlated with firm size and could better account for any measured higher sensitivity of small firms. Additionally, the QFR panel is constructed by Census to accurately reflect the size distribution of US manufacturing firms, allowing us to analyze how differences in cyclicity by firm size translate into aggregate fluctuations.²

Using the QFR microdata, we find evidence of greater cyclical sensitivity among small firms.

¹The view that financial frictions may be responsible for the greater sensitivity of small firms to recessions 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 \(2010\)](#).

²We discuss the relationship between the QFR data and other data sources on financial statements in Section 2.3.

On average over the sample, the difference between sales growth of the bottom 99% of firms and the top 1% of firms (by book assets) exhibits a strong contemporaneous correlation with GDP. Our baseline estimate is that a 1% drop in GDP is associated with a 2.5% 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 disaggregate firms into finer-size quantiles. Though particular episodes differ, over the five recessions in our sample, sales at small firms contract more than sales at large firms.

Interestingly, the size effect is concentrated at the very top of the distribution — the top 0.5% of firms; the variation in sales elasticity to GDP outside of the top 0.5% is small and statistically insignificant. In and of itself, the wide range of firm size with no measurable size differences in cyclicalities suggests that financial factors may not account for the size effect. Firm size in our data ranges from less than \$200K in assets for the smallest firms to \$750 million (real 2009 dollars) in assets for firms in the 99th percentile; it is not obvious that financial frictions should be similarly severe over this wide a range of firm size. An advantage of our dataset is that it allows us to document this relatively flat elasticity profile across a wide range of firm size.

The greater 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.

We then show that the greater sensitivity of the bottom 99% of firms, although statistically significant, is in general too small in magnitude to have an effect on the cyclical behavior of aggregates. Our data allows 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; the data also allows us to plot this counterfactual against realized aggregate sales growth. The difference between the two time series is difficult to detect. This finding is mainly due to the extreme skewness of the distribution of sales and investment in the cross-section. For instance, the top 1% 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 rising over the last 30 years, implying that the relative importance of small firms for the cyclicalities of aggregates has, if anything, been declining. Size-driven differences in cyclical sensitivities are too small to counterbalance this skewness.³ To the extent that alternative monetary or fiscal policies could address this differential cyclicalities, those policies would have little effect on aggregate fluctuations.

Our findings verifying the greater cyclicalities of small firms beg the question of whether these differences in cyclicalities are driven by a financial accelerator mechanism. [Gertler and Gilchrist \(1994\)](#) argued that size may serve as a proxy for the degree of financial constraints, given that

³This gradual rise in concentration mirrors the findings of [Autor et al. \(2017\)](#). Our findings with respect to skewness also echo [Gabaix \(2011\)](#), but we nevertheless find that the “median” firm behaves over the cycle in much the same way as the aggregates, which themselves are dominated by the behavior of the very largest firms.

small firms exhibit greater bank dependence, cannot issue debt publicly, and face a higher degree of idiosyncratic risk. We verify that it is indeed the case that small firms differ from large firms along these dimensions.⁴ However, we provide three findings that cast doubt on whether the size effect is evidence of a financial accelerator mechanism.

First, 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. We also run triple-interaction regressions, where firm size categories are interacted with measures of financial strength. Effectively, we double sort firms by size and a proxy of financial strength. We find the size effect remains present within both the “constrained” and “unconstrained” group, and that its magnitude is largely unchanged. An advantage of our dataset is the ability to condition on balance sheet variables at the firm level. Ex-ante, one would have expected these variables to explain at least some of the size effect; the fact that they do not is surprising and is a first indication that the size effect may not be a manifestation of financial frictions.

Second, to address the possibility that size is simply a better proxy for financing constraints than other balance sheet variables, we look for additional testable predictions of the view that the size effect reflects financial frictions. A typical prediction of financial accelerator mechanisms is that the supply of credit to financially constrained firms should be more cyclically sensitive. In turn, net external financial flows (and in particular, net debt flows) should display a higher responsiveness to aggregate conditions among financially constrained firms.⁵ We test this prediction using a simple event study framework around the recession start dates in our sample. Whereas we document a statistically significant difference in the response of sales and investment across size groups, we find no such difference in the response of debt. Total debt, bank debt and, particularly, short-term debt all behave very similarly among small and large firms.

Third, we construct the size-dependent responses of investment and debt flows to identified monetary policy shocks. Arguably, the financial accelerator mechanism may be more acute in response to monetary policy shocks as they affect firms’ cost of capital more directly. Indeed, consistent with the results of [Gertler and Gilchrist \(1994\)](#), we find that sales at small firms contract more than sales at large firms around the [Romer and Romer \(1989\)](#) dates that appear in our sample.⁶

Our sample only has three Romer and Romer dates. So we use an alternative method to gauge

⁴These average differences in capital structure *across* size groups is, however, dwarfed by heterogeneity in capital structure *within* each size group.

⁵We illustrate this mechanism in a model in which firms differ by size, and firm size is a perfect proxy for financial frictions; the model is described and analyzed in Appendix [G](#).

⁶Our results, however, differ in their quantitative implications, particularly so in the second part of the sample after 1990. We discuss our replication of their analysis in Section 4.6 and in Appendix [I](#) and explain the differences in magnitudes we uncover.

the effects of monetary policy. Specifically, we project firm-level responses of sales and investment on the identified monetary policy shock series of [Romer and Romer \(2004\)](#) — extended by [Wieland and Yang \(2016\)](#) up to 2007 —, using a method analogous to [Jordà \(2005\)](#). Results from this approach that are qualitatively consistent, with small firms more responsive to the shock, but lack statistical significance for most dependent variables, with the notable exception of inventories. Additionally, we find no evidence that bank debt or short-term debt contract faster at small versus large firms after monetary policy shocks. Overall, neither the regression evidence, nor the behavior of debt, nor the difference in responsiveness to monetary policy shocks provides strong support in favor of the view that the size effect is a reflection of financial constraints.

Given the absence of compelling evidence in favor of financial amplification, we also search for non-financial explanations for the size effect. Here, we find some limited evidence in favor of demand-driven explanations: that small firms are more cyclically sensitive because their customer base is more cyclically sensitive than that of large firms. We show that, within 3-digit manufacturing industries, the magnitude of the size effect is correlated with export exposure and downstream diversification. In the first case, industries that have greater export exposure (as measured by exports as a share of total output) exhibit a larger size effect. To the extent that the largest firms are exporters and international business cycles are imperfectly correlated with the US business cycle, demand at the largest firms in high-export industries is buffered relative to industries with less export exposure. In the second case, downstream diversification is quantified by a Herfindahl index that measures how broadly an industry’s production is used across the economy. Under the assumption that the largest firms within 3-digit industries with a high Herfindahl are the firms selling across industries, then these firms may be better insulated. This evidence is consistent with (although only suggestive of) a non-financial explanation for the size effect.

Though not in the main body of the paper, we also examine in [Appendix J](#) 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 significantly 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. In [Section 4](#), we use firm counts in our data to estimate that the top 1% of firms in our sample have at least 2500 employees. Based on this cutoff, using Business Dynamics Statistics data, firms with fewer than 2500 employees in manufacturing account

for a substantial share of employment (over 50%). Therefore, if the differential sales elasticity we find carries over to employment, small firms may be more relevant for employment fluctuations. Likewise, we cannot rule out a large size effect among non-manufacturing firms, which account for a substantial fraction of business-cycle fluctuations in value added and employment.⁷

It is worth reflecting on what implications our findings have for the importance of financial friction more broadly. First, our results are silent about the importance of financial frictions for firm growth and innovation in the medium and long-run. Second, given the structure of the QFR, our data cannot say anything about the importance of financial frictions for entry, which may be a channel through which recessions have a long-run scarring effect (see, for example, [Siemer \(2013\)](#), [Moreira \(2016\)](#), and [Alon et al. \(2018\)](#)). Third, to the extent that our main size measure (book assets) proxies for pledgeable assets of the firm, our findings suggest that the relatively simple collateral constraints used in standard macroeconomic models of the financial accelerator may not find strong support in the data. However, they do not rule out other models of financial amplification — in particular, those where borrowing capacity may not be limited by assets in place or net worth but instead by future cash flows. Recent work by [Lian and Ma \(2017\)](#) and [Chodorow-Reich and Falato \(2017\)](#) may be more promising in thinking about the channels through which financial constraints operate in practice. We think the QFR can be useful in testing these alternative views of the effect of financing frictions on aggregate fluctuations.

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 and in recessions. Section 4 analyzes the aggregate implications 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, including the effect of identified monetary policy shocks. 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 \(1994\)](#), uses the public releases of the QFR data to examine the cyclicalities of sales at small and large firms. [Gertler and Gilchrist \(1994\)](#) showed that small firms are more responsive than large firms to monetary policy shocks, but, more recently, [Chari, Christiano and Kehoe \(2013\)](#) argue that this differential cyclicalities does not hold across all recessions. Using the Gertler & Gilchrist methodology, [Kudlyak and Sanchez \(2017\)](#) 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 and Appendix I the reason for differences in our results versus this literature.

⁷It is worth noting that even if the difference between small and large firms may be relevant for employment fluctuations in manufacturing, we find no evidence that financing is more cyclical at these firms, as would be predicted in a financial frictions model with employment along the lines of the model outlined in Appendix G.

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 has 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 firms while also finding evidence of a separate size asymmetry. Recent work by Ottonello and Winberry (2017) shows that low leverage firms respond more strongly to monetary policy shocks than high leverage firms among Compustat firms.

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 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 heterogeneous firm dynamics model, Khan and Thomas (2013) show that a credit shock generates a sharper fall in employment at financially constrained firms, consistent with the behavior of employment at small and large firms in the Great Recession.

It is worth noting that this literature has typically focused on the effect of identified credit shocks or monetary policy shocks in examining the real effects of a financial disruption. Gertler and Gilchrist (1994) use Romer and Romer dates, Chodorow-Reich (2014) and Buera and Karimakar (2017) use linkages between banks and firms, and Bergman, Iyer and Thakor (2015) use temperature shocks in the farming sector to trace the effects of a disruption to credit. Although we also examine monetary policy shocks, the advantage of our data set is that it is representative of the manufacturing sector. The QFR survey is indeed designed to encompass the cross-section of all manufacturing firms. This feature allows us to investigate how cross-sectional differences in the response to shocks in the population of all US firms. This makes the external validity of our results easier to assess, and it also allows us to quantify how heterogeneous responses to shocks translate to aggregate fluctuations.

Our paper also relates to a literature that studies the cyclicity of firm financing in aggregate and in the cross-section. Jermann and Quadrini (2012) investigates the cyclicity of overall corporate debt and equity, while Covas and Den Haan (2011) argues that the cyclicity of equity financing differs with firm size. Begenau and Salomao (2015) analyze the cyclicity of financing in Compustat data and consider implications in a quantitative firm dynamics model, while Crouzet (2017) 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. In contrast to these papers, our data set captures the cyclicity 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 whole-sale and retail trade firms. Surveyed firms are required to report an income and balance sheet statement each quarter. Data collected by the QFR is used by the 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.⁸

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 or 1120-S) 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, whereas 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 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 that 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 that 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.⁹ 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.¹⁰

⁸The 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.

⁹The QFR short and long forms are available at <http://www.census.gov/econ/qfr/forms.html>.

¹⁰To be more precise, the QFR uses post-stratification sampling weights, which are adjusted to reflect potential

2.2 Data construction

The micro files of the QFR required substantial initial work in order to construct a usable panel data set.¹¹ This is because, in comparison to other Census datasets like the Longitudinal Business Database, the QFR microdata has almost never been used by researchers and, to our knowledge, not at all since the move to the NAICS classification, in 2000.¹² 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.¹³ These weights were also adjusted so that aggregate assets for manufacturing firms match assets as publicly reported by the Census Bureau. Between 1977 and 1994, and post 2000, we find that, using the Census Bureau’s sampling weights, aggregate sales and assets match the publicly available releases.

In addition to linking the firm observations across quarters and imputing sampling weights, we also drop miscoded observations and keep only firms with strictly positive assets and balance sheet data that balances correctly. 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%. Additionally, financial statements are consistent over time (net income equals change in retained earning plus dividend payments) for more than 98% of observations, and less than 0.7% of observations have a zero change in sales in consecutive quarters. This suggests that the data suffers from limited misreporting, either from reporting errors or from repeated reporting of stale data. 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.¹⁴

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.

¹¹An 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, 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.

¹²The only instance of the use of the QFR microdata of which we are aware is [Bernanke, Gertler and Gilchrist \(1996\)](#), who use the pre-2000 microdata to compare firm-level to aggregate growth in sales. They do not attempt to exploit the panel dimension of the data, as we do here.

¹³Aggregates 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>.

¹⁴Currently, we have not analyzed the non-manufacturing part of the data set, since firms with less than \$50

In this paper, we focus on three 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 four quarters prior to the observation date, 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-on-year growth rates eliminates approximately half of the observations.¹⁵ Finally, in section 5.3, where we construct the cumulative responses to identified monetary policy shocks, we focus on the subsample of firms-quarter observations for which we have complete data for the 8 subsequent quarters, so as to construct firm-level responses in the two years following the shock. Given the sample structure, this choice of window allows us to retain small firms in the analysis.

2.3 Relationship other data sources

The QFR data set has some advantages relative to Compustat, which is the primary firm-level data set in use. The primary advantage is that the QFR provides a representative sample of the population of US manufacturing firms; the sampling frame is drawn from IRS administrative data and response is mandatory.¹⁶ In particular, it includes private, smaller, bank-dependent firms that constitute the typical firm in the population. Because these firms are those most likely to suffer from frictions arising from limited access to capital markets, the QFR is a particularly attractive data set for the questions we investigate.

Relative to Compustat, 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. As an input into the national accounts, the QFR attempts to more accurately measure activity within the US. The QFR data provides somewhat more detailed information on firm assets and liabilities than what is typically available in Compustat. For example, 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.¹⁷ Section 2.4 provides a comparison of key summary statistics between the sample used in this paper and the Compustat manufacturing segment.

Aside from Compustat, alternative US data sets for small firms include the Survey of Small Business Finances, Orbis (Dinlersoz et al., 2018), and Sageworks (Asker, Farre-Mensa and Ljungqvist, 2011). The most important difference between the QFR and these datasets is that it provides the

million in assets are not sampled, but we plan to do so in future work.

¹⁵The growth rate sample is more than half the full sample due to the presence of large, continually sampled (long-form) firms.

¹⁶Given our focus, one possible concern is that the QFR is *not* representative of the growth rate distribution in manufacturing. In future work, we plan on linking the QFR to the Dun and Bradstreet business database with information on firm employment. This database could be used to reweight the QFR to match the growth rate distribution in the manufacturing segment of Dun and Bradstreet.

¹⁷The 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.

longer time horizon and higher frequency of observation needed to analyze cross-sectional differences in the business-cycle behavior of firms.

2.4 Summary Statistics

Table 5 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 quantile groups, 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 2009q1.¹⁸

Summary statistics by size group Table 5, 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 annually. By contrast, firms within the bottom 90% of the size distribution have just \$2 million in assets and \$1.2 million in sales. Investment also displays a high degree of skewness but, as Table 5 shows, investment rates are comparable across size classes so that differences in investment intensity do not account for the skewness in investment. Finally, note that sales growth is substantially faster at the largest manufacturing firms over this period leading to a marked increase in concentration over the past 35 years.

Table 5, 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. However, we do find that smaller firms are more reliant on short-term debt and bank debt (as a share of total debt) and hold more on trade credit than larger firms.

One clear difference between large and small firms — particularly among the largest 0.5% of firms — is the intangible asset share. Firms in the survey report separately property, plant, and equipment (tangible assets) from other long-term assets. A high share of intangible assets likely reflects the accumulation of goodwill due to past acquisitions, so that the sharp increase in intangible asset share across size classes underscores the importance of acquisitions for growth at the very largest firms.¹⁹

Between vs. within size group variation It is worth emphasizing that, despite differences across size classes in various real and financial characteristics, there remains tremendous heterogeneity *within* size classes. Table 10 provides an approximate interquartile range for sales growth,

¹⁸The series is available at http://bea.gov/industry/gdpbyind_data.htm.

¹⁹Even 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 contains only book value of assets; for most firms in our sample, which are private, no measure of market value is readily available.

leverage, and liquidity.²⁰ 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 also worth noting that a substantial fraction of firms have zero leverage; these zero-leverage firms tend to be concentrated in the bottom 90% of the size distribution.

Comparison with Compustat Table 5 also reports summary statistics for firms in the Compustat manufacturing segment.²¹ Panel A shows that the average size of a Compustat manufacturing firm is close to, but lower than, the average size of QFR firms in the top 1% of the cross-sectional distribution of assets (which is approximately \$3696m). Quarterly sales are also somewhat lower (\$502.2m vs. \$801m in the top 1% of the QFR), though that figure includes foreign sales for Compustat firms. Finally, capital structure for Compustat firms is similar to that of the top 1% firms in the QFR.

3 The cyclical sensitivity of small firms

This section measures the extent to which small firms display greater cyclical sensitivity than large firms. By “greater cyclical sensitivity”, we mean that a worsening in aggregate conditions is associated with systematically bigger declines in sales and investment among small firms than among large firms.

3.1 Measurement framework

Appendix A describes in detail the sample selection, the size groupings, and the measures of firm-level growth which we use throughout this section. Three features of this measurement framework are worth noting. First, we measure the sensitivity of *firm-level* growth to aggregate conditions. We thus sort on size at the firm level, and fully control for industry effects (and, in later sections, for firm-level differences in capital structure). This is distinct from previous work on the QFR data, which was limited to measuring the growth of aggregates by nominal size bins due to the formatting of the public releases of the QFR. The connection between firm-level and aggregate growth is 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, as in the public QFR releases. Classifying firms by their *lagged* position in the size distribution helps alleviate the cyclical effects of reclassification bias emphasized in Moscarini

²⁰Due to data disclosure restrictions, we provide averages above and below the median within size classes, rather than the exact 25th and 75th percentiles.

²¹Details on the construction of the sample and the definition of balance sheet ratios in terms of Compustat variables is reported in appendix E.1.

and Postel-Vinay (2012).²² 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.

Third, in our baseline estimates, we measure growth among the sample of *surviving* firms. In particular, we do not take into account the effect of differences in the cyclical sensitivities of the rate of entry and exit of small and large firms. Our baseline results should thus be thought of as capturing the intensive margin differences between small and large firms. We discuss the impact of entry and exit on our estimates in Section 3.3.

3.2 Results

Sales Figure 1 shows the time series for the average growth rate of sales of two size groups: the bottom 99% (denoted by $\hat{g}_t^{(small)}$) and the top 1% (denoted by $\hat{g}_t^{(large)}$). Each series is the year-on-year equal-weighted average growth rate of sales among firms belonging to each of the two size groups one year prior.²³

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 periods that stand out the most 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 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 bivariate simple OLS between the two series is 0.60, with a Newey-West standard error of 0.20 (allowing for up to 8 lags). The economic interpretation of this coefficient is that, for every percentage point decline in GDP, sales decline, on average, by 0.6% more among small firms than they do among large firms.²⁴

Table 4 reports estimates of the semi-elasticity of firm-level growth to GDP growth and confirms

²²If firms tend to cross the threshold from small to large during expansions, measures of the relative growth rate of large firms using their ex-post size will be biased upward.

²³The specific definition of the time series reported for the small firm group is given in equation (13) of Appendix A, for the interquartile range $(k_1, k_2) = (0, 99)$. The large firm group corresponds to $(k_1, k_2) = (99, 100)$. 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. Section 3.3 further discusses results using alternative deflators.

²⁴This correlation is robust to alternative measures of the business cycle: growth rate of overall industrial production or manufacturing IP or the change in the unemployment rate. This correlation also holds for subsamples before and after 1992 and excluding either the Volcker recovery or the Great Recession. However, the correlation becomes insignificant if both the Volcker recovery and the Great Recession are excluded.

the visual impressions conveyed by Figure 2. The model estimated is:

$$g_{i,t} = \sum_{j \in \mathcal{J}} (\alpha_j + \beta_j \Delta GDP_t) \mathbf{1}_{i \in \mathcal{I}_t^{(j)}} + \sum_{l \in \mathcal{L}} (\gamma_l + \delta_l \Delta GDP_t) \mathbf{1}_{i \in \mathcal{L}} + \epsilon_{i,t}. \quad (1)$$

Here, i identifies a firm and t identifies a quarter. The dependent variable, $g_{i,t}$, is the year-on-year log change in sales. The set $\mathcal{I}_t^{(j)}$ is a size group; for instance, firms below the 90th percentile of the distribution of book assets four quarters ago.²⁵ Additionally, $\Delta GDP_t = \log \left(\frac{GDP_t}{GDP_{t-4}} \right)$ is the year-on-year growth rate of GDP, and $\mathcal{L}$ is a set of industry dummies.²⁶ 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.

The first column of Table 4 reports estimates of the difference $\beta_j - \beta_{(0,90)}$, for the size groups $j \in \{(90, 99), (99, 99.5), (99.5, 100)\}$. For these three size groups, the difference is negative, consistent with the view that small firms are more sensitive to aggregate fluctuations. The size effect thus does not simply reflect cyclical differences across industries. The results of Table 4 also reveal that the cross-sectional differences in cyclical sensitivity are most notable among the top 0.5%, which represents approximately 500 firms in each quarter. The point estimates of cyclical sensitivity decrease for the largest three size quintiles, but the difference relative to the 0-90% group is only statistically significant for the largest size group. 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.

Figure 3 conveys a similar message but reports estimates of the absolute cyclical sensitivity of each size group. Specifically, it plots the average marginal effect of ΔGDP_t at the mean, for each size group (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 is substantially larger than the cross-group difference. This fact will be important in Section 4 when we consider the aggregate implications for sales of the cross-group difference in elasticities.

Investment The time series for inventory growth and investment in fixed assets reported in Figure 4 also displays 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). 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

²⁵See appendix A for a formal definition of the size groups.

²⁶The baseline regression results are reported by classifying firms into durable and non-durable industries. Results are unchanged when using NAICS 3-digit industries. Section 3.3 further discusses results under alternative industry classifications. Section 5 reports the size effect within NAICS 3-digit industries.

mixed message. In particular, in the aftermath of the Great Recession, inventories at large firms 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.²⁷

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 (1) when the dependent variable is either inventory growth (second column) or the fixed investment rate (third column). Consistent with the behavior of sales, inventory growth of the top 0.5% of firms has a significantly smaller conditional elasticity to GDP growth.²⁸ The economic magnitude of the effect is large: For the bottom 90%, the average marginal effect of a 1% drop in GDP is a 1.9% drop in inventory, about double the effect for the top 0.5%.

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. In terms of economic magnitudes, a 1% drop in GDP is associated with a 0.9% drop in investment among the (0, 99) group, relative to a baseline investment rate of approximately 26.0%. Among the (99, 100) group, the investment drop is more muted: 0.15%, relative to a baseline investment rate of approximately 21%. 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.

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.

3.3 Robustness

Alternative specifications In the main regression specification, equation 1, sales are deflated using a common value-added price deflator for all firms in manufacturing. We use this deflator because, to our knowledge, at the quarterly frequency, there are no price deflators for output either at the manufacturing sector level or at more disaggregated levels within manufacturing. However, at the annual frequency, the BEA GDP by industry tables provide such indices. Table 5 in appendix compares estimates of the size effect in the Compustat quarterly sample when using different deflators. The top panel contains estimates for the same sample period as in the QFR, 1977q1-2014q1. Column (1) reports results from the specification of equation 1, using the same

²⁷This lag structure also accounts for the fact that the contemporaneous correlation of GDP growth and investment is not significantly positive among the largest firms in the QFR sample, as documented in Table 4. Appendix E discusses this lag in more detail and shows that it is also present in both the annual and the quarterly Compustat data.

²⁸As 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.

quarterly value-added deflator as in that specification. The results of column (1) indicate a size effect in Compustat, though it is substantially smaller in magnitude than in the QFR, consistent with the fact there is less size variation in Compustat than in the QFR. Column (2) reports results from a specification that uses a manufacturing-wide deflator, but for gross output instead of value-added. Column (3) reports results from a specification that uses a separate annual gross output deflator for BEA subsector in manufacturing (the BEA subsectors in manufacturing correspond approximately to 3 digit NAICS industries). Estimates of the size effect in columns (1)-(3) are all very close in magnitude. Finally, column (4) reports results from estimating a specification with industry-quarter fixed effects (instead of controlling for industry effects and their interaction with GDP growth, as is done in columns (1)-(3) and in Table 4). The results of that specification are also very close in magnitude to those of specifications (1)-(3). Overall, these results indicate that estimates of the size effect in manufacturing are not sensitive to the choice of deflators nor to the way differences in cyclicity across industries are controlled for.²⁹

Entry and exit Our baseline results focus on the sample of surviving firms. This is primarily because the variables explaining non-response are not continuously available prior to 2000, so that we cannot confidently distinguish between true exits, corporate re-organizations, and non-response prior to that date. We re-estimated the size effect in the sample of all firms-quarter observations *including* unanticipated non-responses, which account for approximately 3.5% of observations, and using the Davis, Haltiwanger and Schuh (1996) bounded growth rates in order to include exiting firms.³⁰ Although the point estimate for the size effect is higher including exit, it is not statistically different from the estimate excluding imputed exit (but still using the bounded growth rates). This result is driven by the fact that in this data, the imputed exit rate among the bottom 99% group is not substantially more volatile at business cycle frequencies than among the top 1% group.

Entry is poorly measured in the QFR data, because firms must have filed tax returns for at least one year in order to be included in the sample. Nevertheless, other data sources indicate that, in manufacturing, the contribution of entry and exit to overall employment growth is fairly limited. Figure 5 shows employment growth at all firms and at continuing firms excluding those with initial size below than 10 employees (this restriction is made because we estimate that the QFR does not sample firms below 10 employees; however, the graph is unchanged when including all firms). As can be seen, the differences are negligible (the correlation is equal to 0.997), indicating that employment fluctuations at continuing firms are not substantially different than overall employment fluctuations. Effectively, entry and exit do not appear to make an outsize contribution to employment fluctuations in manufacturing.³¹

²⁹A complementary question is whether our finding of a size effect for sales extends to value-added, as the two may have different cyclical properties. Appendix B discusses this question; we thank an anonymous referee for raising this point.

³⁰Appendix F contains a comparison of our baseline results on the continuing firm sample, which use log-growth rates, to those obtained using the Davis, Haltiwanger and Schuh (1996) growth rates. Key findings, and in particular the magnitude of the size effects, are unchanged using these instead of log-growth rates.

³¹This statement should not be construed to claim that entry is not important; some subset of new firms are

Firm size and firm age Fort et al. (2013) argue that the business cycle behavior of firm employment depends crucially on firm age (as opposed to simply firm size). Our data set does not have an indicator for firm age. To proxy for firm age in the QFR, we group firms (starting in 1982) into those that first appeared at least five years ago in the sample and the rest. We then re-estimate the size effect in the sample of firms at least five years of age. 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. This procedure has a clear drawback — firms older than five years that are only sampled once will be incorrectly classified as young. Subject to this caveat, we find that the size effect survives within the subsample of mature firms and is approximately 80% in magnitude of what it is in the overall sample. This suggests that the size effect may be related to age but is not solely driven by young firms (i.e. still appears for mature firms).

4 Aggregate implications

This section explores whether the greater sensitivity of small firms is an important contributor to aggregate fluctuations. In order to answer this question, we provide a simple decomposition of aggregate growth into components originating from firm-level growth in different size groups. This decomposition highlights the role of the greater sensitivity of small firms and allows us to compute counterfactuals that quantify its contribution to aggregate fluctuations.

4.1 A simple decomposition

At first glance, it seems that to answer the question of this section, one may want to use the following simple rule of thumb: the impact of small firms' greater sensitivity is equal to the product of the typical share of total sales of small firms, multiplied by the difference in the cyclicity of small firms' sales. The results of the previous section indicate that the difference in elasticities to GDP growth between small and large firms is approximately 0.6. Assuming (for now) that small firms' share is, on average, 50%, one would obtain a contribution of $0.6 \times 0.50 = 30$ bps. This number would then have to be compared to the elasticity of aggregate sales to GDP, to get a sense of the contribution of the greater sensitivity of small firms to aggregate fluctuations.

This simple rule of thumb turns out to be incomplete, at least in theory. Appendix C shows that the growth rate G_t of any aggregate variable of interest (for instance, sales) between quarters $t - 4$ and t , among continuing firms, can be decomposed as:

$$G_t = \hat{g}_t^{(\text{large})} + s_{t-4} \left(\hat{g}_t^{(\text{small})} - \hat{g}_t^{(\text{large})} \right) + \text{cov}_t. \quad (2)$$

Here, $s_{t-4} = \frac{X_{t-4}^{(\text{small})}}{X_{t-4}}$ is the initial fraction of the aggregate accounted for by small firms, and $\hat{g}_t^{(\text{small})}$

successful, and these firms will be sampled or will be surveyed with certainty once sufficiently large.

and $\hat{g}_t^{(large)}$ are the cross-sectional average growth rates considered in the previous section.³² The term $\hat{g}_t^{(large)} + s_{t-4} \left(\hat{g}_t^{(small)} - \hat{g}_t^{(large)} \right)$ represents average firm-level growth; the contribution of the product $s_{t-4} \left(\hat{g}_t^{(small)} - \hat{g}_t^{(large)} \right)$ to cyclical movements in G_t is what the simple rule of thumb described above would capture.

The decomposition (2) however highlights the presence of another term, $\hat{c}ov_t$. The term $\hat{c}ov_t$ is itself a weighted average of two terms:

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

Each of the two terms $\hat{c}ov_t^{(small)}$ and $\hat{c}ov_t^{(large)}$ can be interpreted as the (group-specific) cross-sectional covariance between firms' initial size and their subsequent growth.³³ These terms capture the intuition that if firms that are initially large also grow faster, then aggregate growth, G_t , will tend to outpace average firm-level growth, $\hat{g}_t^{(large)} + s_{t-4} \left(\hat{g}_t^{(small)} - \hat{g}_t^{(large)} \right)$. In principle, the behavior of these covariance terms may affect how one quantifies the contribution of the greater sensitivity of small firms to aggregate fluctuations. However, as the results below suggest, empirically this issue turns out to be small, and the cyclical fluctuations in aggregate growth tend to be dominated by fluctuations in average firm-level average, the term $\hat{g}_t^{(large)} + s_{t-4} \left(\hat{g}_t^{(small)} - \hat{g}_t^{(large)} \right)$.³⁴

4.2 Quantifying the contribution of the greater sensitivity of small firms

We can use the decomposition (2) to form the following, counterfactual growth rate of aggregate sales:

$$G_t^{(1)} = G_t - s_{t-4} \left(\hat{g}_t^{(small)} - \hat{g}_t^{(large)} \right). \quad (3)$$

This time series nets out the contribution of the greater sensitivity in *average* growth rates among small firms — the second term of the decomposition (2). Additionally, one can net out the contribution of differences in the covariance terms in decomposition (2):

$$\begin{aligned} G_t^{(2)} &= G_t - s_{t-4} \left(\hat{g}_t^{(small)} - \hat{g}_t^{(large)} \right) - s_{t-4} \left(\hat{c}ov_t^{(small)} - \hat{c}ov_t^{(large)} \right) \\ &= G_t^{(large)}, \end{aligned} \quad (4)$$

thus simply obtaining the aggregate growth rate of sales among large firms.

One way to quantify the contribution of the greater sensitivity of small firms is then to com-

³²This section analyzes a decomposition for the same log growth rates as discussed in the previous section, up to the approximation $\log(1+x) \approx x$. Appendix F derives a similar decomposition for the commonly used growth rates $\tilde{g}_{i,t} = \frac{x_{i,t} - x_{i,t-4}}{\frac{1}{2}(x_{i,t-4} + x_{i,t})}$, introduced by Davis, Haltiwanger and Schuh (1996). The appendix reproduces the same decomposition using these growth rates and shows that all the results of this section are unchanged.

³³Specifically, $\hat{c}ov_t^{(j)} = \sum_{i \in \mathcal{I}_t^{(j)}} \left(w_{i,t-4} - \frac{1}{\#\mathcal{I}_t} \right) \left(g_{i,t} - \hat{g}_t^{(j)} \right)$, 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.

³⁴Appendix D contains a precise decomposition of the contribution of the covariance terms to the cyclical fluctuations in aggregate growth and shows that it is small, whether one looks at small firms only, large firms only, or all firms jointly.

pare the comovement between a business-cycle indicator and the actual growth rate of aggregate sales, G_t , to the comovement between the same business cycle indicator and either one the two counterfactual growth rates $G_t^{(1)}$ and $G_t^{(2)}$. We do this by computing 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 6 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. Given the magnitude of the elasticity of aggregate sales to GDP growth (about 2.2), 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 about 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.

Why are the actual aggregate growth rates, and the counterfactual growth rates that eliminate the contribution of the greater sensitivity of small firms, so close to one another? Primarily, this is due to the fact that the share of sales and investment of small firms, s_{t-4} , is very low *relative to* the difference in cyclicalities between small and large firms, i.e. the term $\left(\hat{g}_t^{(\text{small})} - \hat{g}_t^{(\text{large})}\right)$. Figure 7 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 of Figure 7, in particular, corresponds to the time series s_t defined above. Two points about these time series are worth emphasizing.

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 greater 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 $\text{corr}(s_{t-4}, \Delta GDP_t)$ is approximately 0.37 in the sample. Although substantial cyclicalities of the share could, in principle, offset its low average level and magnify the term $\left(\hat{g}_t^{(\text{small})} - \hat{g}_t^{(\text{large})}\right)$, Figure 7 suggests that this unlikely to be the case in the data.

Going back to the initial discussion of the section, the simple rule of thumb turns out to deliver an answer that are approximately correct. The results reported in Figure 7 indicate small firms' share is, on average, approximately 25%. The product of this with the differences in cyclicalities

documented in the previous section 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 6 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.³⁵

It is important to insist on two aspects this result. First, the decomposition (2) is only correct if the set of firms entering aggregate sales is held constant from t to $t - 4$ (as is done in all the calculations of this section). Thus, the results of this section quantify the contribution of the greater sensitivity of small firms to the intensive margin of business-cycle fluctuations in aggregate sales and investment; they are silent about the extensive margin (the business-cycle fluctuations driven by entry and exit).³⁶ Second, these results are still consistent with the view that small firms contribute to aggregate fluctuations more than their share of sales, inventory, or investment would suggest. That is indeed necessarily the case, given the fact that their share is roughly stable (at business-cycle frequencies) and that they display more sensitivity to cycles than large firms do — that is, given that the term $(\hat{g}_t^{(\text{small})} - \hat{g}_t^{(\text{large})})$ is procyclical. The point of the analysis is simply to state that the *additional* fluctuations in aggregate sales that are due to this term are small relative to the overall business cycle volatility of aggregates.

4.3 An alternative decomposition

The following, complementary approach can be used to evaluate the relative contribution of small and large firms to aggregate fluctuations.³⁷ In general, aggregate growth G_t can be decomposed as:

$$\begin{aligned}
G_t &= s_{t-4}G_t^{(\text{small})} + (1 - s_{t-4})G_t^{(\text{large})} \\
&= \underbrace{s_{t-4}\bar{G}^{(\text{small})} + (1 - s_{t-4})G_t^{(\text{large})}}_{\equiv \tilde{G}_t^{\text{large}}} + \underbrace{s_{t-4}G_t^{(\text{small})} + (1 - s_{t-4})\bar{G}^{(\text{large})}}_{\equiv \tilde{G}_t^{\text{small}}} - \underbrace{(s_{t-4}\bar{G}^{(\text{small})} + (1 - s_{t-4})\bar{G}^{(\text{large})})}_{\equiv -R_t} \\
&= \tilde{G}_t^{\text{large}} + \tilde{G}_t^{\text{small}} + R_t.
\end{aligned} \tag{5}$$

This decomposition separates aggregate (or total) growth into three terms. The first one, $\tilde{G}_t^{\text{large}}$, is equal to the total growth rate that would obtain, if total growth among small firms had no cyclical component (that is, were set equal to its sample mean, denoted here by $\bar{G}^{\text{small}}$). This term thus captures the contribution of large firms to business cycle fluctuations in aggregates. The second term represents the symmetric term, for small firms. The third term is a reallocation component:

³⁵Figure 6 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 indistinguishable.

³⁶See section 3.3 for a discussion of the effects of exit on our estimates. Additionally, our decomposition does not capture the potential long-run effects that declining entry during recessions may have on aggregate growth; see, for instance, Moreira (2016).

³⁷This decomposition is similar to the Shimer (2012) decomposition of fluctuations in the unemployment rate between changes in job finding rates and changes in employment exit rates. We thank an anonymous referee for suggesting to apply this decomposition to the question of this paper.

it represents the fluctuations in aggregates that would arise if only small firms' share, s_{t-4} , were to fluctuate over the cycle (while growth rates in each size group stayed equal to their sample mean).

Table 7 contains results from a variance decomposition based on equation (5). Each line reports the respective contribution of the terms $\tilde{G}_t^{\text{large}}$, $\tilde{G}_t^{\text{small}}$ and R_t to the variance of G_t (that is, the covariance of the term with G_t , divided by the variance of G_t). Consistent with the previous discussion, the last column shows that the contribution of the reallocation term R_t to fluctuations in sector-wide totals is negligible. Additionally, the first and second columns show that it is large firms that account for the bulk of the variance in the growth of total sales, inventory, fixed investment, and assets. Large firms' contribution to the variance in aggregate growth rates ranges from 70% to 90%, approximately in line with the averages shares reported in figure 7. This result supports the view that the greater sensitivity of small firms is not large enough to significantly amplify their contribution to aggregate fluctuations, above and beyond what their average shares of sales, inventory or investment would predict.

4.4 Employment

Although we have shown that the contribution of the greater sensitivity of small firms to aggregate fluctuations in sales, inventories, and investment is small, we are unable to offer a similar calculation for employment given that firms do not report employment in this survey.³⁸ However, we can estimate the employment threshold for large firms using data from the Census Bureau's Business Dynamics Statistics. There are roughly 1000 firms in the top 1% of our sample. In the BDS, the top 1000 firms in 2014 correspond to those firms with over 2500 employees. Likewise, given that firms are only sampled if their assets exceed \$250K, we estimate that firms with less than 10 employees are not sampled. In 2014, firms with over 2500 employees account for 43% of manufacturing employment (only counting firms with at least 10 employees), compared to approximately 80% for sales, 76% for inventory and 90% for investment (see figure 7). Thus, the degree of skewness in employment is considerably less than that of sales, inventories, and investment.

Thus, to the extent that small and large firms differ in their elasticity of employment growth to GDP, these differences are more likely to be relevant for overall employment fluctuations in manufacturing. In Figure 8, we use BDS data to compute employment growth rates in manufacturing for all firms (with at least 10 employees), and for firms with more than 2500 employees. The two series are positively correlation, but the degree of correlation is weaker than for the actual and counterfactual (excluding small firms) total sales growth series reported in Figure 6.

It is worth noting that the top 1% of manufacturing firms also exhibit very different trends in employment growth from small manufacturing firms. Since 1980, the share of manufacturing employment at firms with 2500 employees has been falling over time (from about 55% to 43% in the early 1980s) with average employment growth of -1.97% from 1978-2014. By contrast, small firms (1-499 employees) and medium size firms (500-2499 employees) have employment growth rates of

³⁸In principle, the QFR could be linked to other Census datasets on employment such as the LBD, but current IRS and Census Bureau restrictions on the QFR do not allow this merging.

-0.60% and -0.51% respectively. The contraction of employment at the largest firms coupled with the high average sales growth at the top firms (discussed in Section 2) implies a large decrease in labor share in manufacturing. This is consistent with the evidence in Kehrig and Vincent (2017) who document reallocation of activity towards the most productive manufacturing firms which have simultaneously decreased their labor share.

5 The financial origins of the cyclicity of small firms

As mentioned in the 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 effect we have documented should be interpreted as evidence of such financial amplification. We start by including various proxies for balance sheet strength in our size regressions; we find that the size effect remains significant and, in most cases, is quantitatively unchanged. However, it is possible that size is simply a better proxy for financial constraints. An additional prediction of typical financial amplification models is that small (or constrained) firms should also exhibit more cyclical financing flows than large (or unconstrained) firms. However, we show that this prediction is not borne out in the data. Finally, while the financial accelerator mechanism should, in principle, operate regardless of the underlying source of aggregate fluctuations, it may nevertheless be more potent following shocks that directly affect firms' cost of capital. In order to test this hypothesis, we explore the relative responsiveness of small firms to identified shocks to monetary policy. We find that, while the sales and investment of small firms tends to contract more than those of large firms in response to an exogenous monetary tightening, the difference is not statistically significant.

5.1 The size effect and other proxies for financial constraints

We start by examining how estimates of the size effect vary when controlling for observable financial characteristics at the firm level. We start by estimating the following “horse-race” regressions:

$$\begin{aligned}
g_{i,t} = & \sum_{j \in \mathcal{J}} (\alpha_j + \beta_j \Delta GDP_t) \mathbf{1}_{\{i \in \mathcal{I}_t^{(j)}\}} + \sum_{l \in \mathcal{L}} (\gamma_l + \delta_l \Delta GDP_t) \mathbf{1}_{\{i \in \mathcal{L}\}} \\
& + \sum_{k \in \mathcal{K}} (\zeta_k + \eta_k \Delta GDP_t) \mathbf{1}_{\{i \in \mathcal{F}_t^{(k)}\}} + \epsilon_{i,t}.
\end{aligned} \tag{6}$$

In these regressions, the size controls are identical to the baseline estimation of Section 3; size groups, indexed by j , 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.³⁹ 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

³⁹Our results hold when controlling for NAICS 3-digit industries.

markets, and dividend issuance. Though these balance sheet variables are endogenous (along with firm size), we view these regressions as a useful test as to whether financial factors can explain the size effect.

Column (1) in Table 16 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. 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) 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.

Column (3) controls for liquidity. We consider three liquidity classes: cash to asset ratio of less than 1%; cash to asset ratio between 1% and 20%; cash to asset ratio above 20%. As with leverage, we choose fixed thresholds that approximate the bottom and top quartiles.⁴⁰

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-form survey). As documented by Faulkender and Petersen (2005), even among publicly traded firms, only a minority have access to public debt markets, so that there is meaningful variation in this measure among large firms.

Finally, column (5) controls for dividend issuance. A firm-quarter observation is classified as a dividend issuer if it issued dividends in the 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. Thus, none of these controls changes the estimates of the size effect. 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 in magnitude 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 Appendix J, where we estimate cyclical sensitivities by groups of proxies for financial strength; it may be due to firms with more cyclical investment opportunities choosing to tap bond markets at the beginning

⁴⁰The cash to asset ratio for the median firm in the QFR dataset rises 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. We use fixed thresholds for leverage given the absence of a time trend.

of recoveries.

In any case, the main message of Table 16 is that the greater sensitivity of small firms survives, and is in fact almost unchanged (or even amplified) after controlling for the five simple proxies for financial constraints.⁴¹ In Appendix H, we present the results from triple interaction regressions where we investigate whether the size effect differs after binning firms by financial strength (as proxied by the five ratios considered in Table 16). We find that differences in the size effect between the financially strong and weak bins is neither uniform in terms of sign nor statistically significant.

5.2 The behavior of debt

The findings of the previous section may be driven by the fact that size is a superior proxy for financial constraints. A central idea financial accelerator mechanism is that the supply of external funds (typically, debt) to constrained firms should be more cyclical. A more cyclical supply of funds, in turn, should translate to a higher responsiveness of net borrowing to expansions and recessions among constrained firms. Appendix G illustrates this mechanism with a simple model where firm size is, by construction, a perfect indicator of financial constraints. A key prediction of the model is that greater cyclicity of investment among small firms, if it is driven by financial constraints, should also translate into greater sensitivity of debt issuance.

In order to compare this prediction to the data, 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, etc.); we estimate the model:

$$g_{i,t} = \alpha + \beta \mathbf{1}_{\{i \in \mathcal{I}_t^{(0,99)}\}} + \sum_{k=-4}^{10} \left(\alpha_k + \beta_k \mathbf{1}_{\{i \in \mathcal{I}_t^{(0,99)}\}} \right) \mathbf{1}_{\{t+k \in \mathcal{H}\}} + \epsilon_{i,t} \quad (7)$$

where $i \in \mathcal{I}_t^{(0,99)}$ 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:

$$\begin{aligned} c_{\mathcal{L},k} &= \sum_{j=-4}^k (\alpha + \alpha_j) - \sum_{j=-4}^0 (\alpha + \alpha_j), \\ c_{\mathcal{S},k} &= c_{\mathcal{L},k} + \sum_{j=-4}^k (\beta + \beta_j) - \sum_{j=-4}^0 (\beta + \beta_j), \end{aligned}$$

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.

⁴¹Fort et al. (2013) argues that firm age is a better measure of financial constraints than firm size. We used a rough proxy for firm age in 3 (counting years in sample). However as noted earlier, in future work, we plan to link the QFR to the Dun and Bradstreet business database to obtain a more reliable and precise measure of firm age.

Figure 9 reports the cumulative path of sales, inventory and fixed capital and the associated ± 2 standard error bands. The behavior of sales 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. The behavior of inventory investment and fixed investment is also 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 to lag that of small firms by three to four quarters.⁴² This lag is not visible in the sales response.⁴³ Figure 10 repeats this exercise for cumulative changes in total debt, bank debt and short-term debt. Here, short-term debt is measured as debt with maturity one year or less normalized by assets lagged four quarters, and bank debt is short and long-term bank loans normalized by assets lagged four quarters.

These figures suggest that there is little difference in the cyclical behavior of debt financing at small and large firms. The left panel of Figure 10 shows that it is difficult to observe sharp differences in the behavior of debt overall. Given that the behavior of overall debt may mask significant movements in important components of debt, we also display the response of bank debt and short-term debt. 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. The response of short-term debt among small firms is particularly, and strikingly, difficult to separate from that of large firms. Given that large firm debt contracts more than small firm debt at longer horizons, even assuming the 95th percentile responses does not deliver an economically large difference in the debt stock. For the total debt to asset ratio, small firms contract at most approximately 1.25% at 10 quarters while large firms lowest estimated response is approximately 1% - a difference of only 25 basis points (the average debt to asset ratio is 30%).

5.3 The greater sensitivity of small firms to monetary policy shocks

So far, we have presented evidence on the elasticity of firm sales to the US business cycle by firm size. One concern with these unconditional correlations is that they may mask important differences across firm size in the response to particular types of macroeconomic shocks. That is, some part of business cycle fluctuations may be driven by shocks that have a uniform effect across firm size while other shocks exhibit stronger effects across firm size. In particular, Gertler and Gilchrist (1994)

⁴²Aggregate 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 9, since, as discussed below, large firms account for between 80-90% of total fixed capital formation in the QFR data.

⁴³Also in contrast to the sales response, the lack of statistical significance suggests that the greater sensitivity documented in the baseline regressions is driven by recoveries, rather than recessions. This is partly visible in Figure 9: 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 greater sensitivity for inventory and fixed capital investment.

focus on the response of small and large firms after monetary policy shocks as identified in [Romer and Romer \(1989\)](#). Arguably, monetary policy shocks impact the cost of external borrowing more directly, inducing countercyclical fluctuations in borrowing costs.⁴⁴ In turn, these episodes may provide a better test of the financial accelerator mechanism.

Estimation framework To gauge the effect of monetary policy shocks, we examine the response of sales by firm size groups to the monetary shock series constructed in [Romer and Romer \(2004\)](#) and updated by [Wieland and Yang \(2016\)](#). We construct the responses by firm size group using a projection method analogous to [Jordà \(2005\)](#). Our specification is:

$$\begin{aligned} \Delta y_{i,t,t+h} = & \sum_{j \in \mathcal{J}} \left(\alpha_j^{(h)} + \beta_j^{(h)} rr_{t-1,t} + \phi_j^{(h)}(L) X_t \right) \mathbf{1}_{\{i \in \mathcal{I}_t^{(j)}\}} + \sum_{l \in \mathcal{L}} \left(\gamma_l^{(h)} + \delta_l^{(h)} rr_{t-1,t} \right) \mathbf{1}_{\{i \in \mathcal{L}\}} \\ & + \sum_{j \in \mathcal{J}} \sum_{q=1}^4 \left(\mathbf{1}_{\{i \in \mathcal{I}_t^{(j)}\}} \times \mathbf{1}_{\{\mathbf{q}(t)=q\}} \right) s_{j,q}^{(h)} + \epsilon_{i,t,h} \end{aligned} \quad (8)$$

Here, y is the log of sales (or other variable of interest), i indexes the firm, t is the quarterly date, h is horizon, $\mathcal{J}$ are size groups, $rr_{t-1,t}$ is the shock, $\mathcal{L}$ is industries, $\mathbf{q}(t)$ is the quarter (1 through 4) associated with date t , and X_t is a set of macroeconomic controls. We classify firms into two size groups, the (0,99) and the (99,100) groups. Our macro controls include unemployment, CPI, commodity prices, and the Fed funds rate allowing for two lags. Our industry groups are the durable and non-durable sectors.⁴⁵ The primary coefficient of interest is $\beta_j^{(h)}$, which is the response of sales in size group j at horizon h to the monetary policy shock $rr_{t-1,t}$.

As discussed in [Romer and Romer \(2004\)](#), the monetary policy shock is measured using the deviation of the implemented Fed funds rate from internal forecasts prior to the meeting date. The updated time series time series is monthly from 1969m1 to 2007m12. The sample stops thereafter because of the binding zero lower bound. We aggregate this time series to the quarterly frequency by taking the cumulative sum of the shock for each quarter, and using the end-of-quarter monthly value. We then use the quarterly time series from 1977q3 to 2007q4; our projection estimates thus exclude the response to monetary policy shocks that occurred during or after the Great Recession. In response to a 1 percentage point innovation to the shock, similar projection methods using aggregate data indicate that the Federal Funds rate increases by 1.9 percentage points on impact, and mean-reverts back to zero within the first three quarters. The response of aggregate variables is strong and persistent: the trough in the response of industrial production is -1.1% (four quarters out) and the peak response of unemployment is a 0.35 percentage points (also four quarters out). The response of the CPI is slightly weaker, although it eventually declines by -0.5% two years out.⁴⁶

⁴⁴The financial accelerator mechanism works through balance sheet effects where a fall in the price of capital goods reduces firm net worth and raises borrowing costs. Various credit channels of monetary policy (the bank lending channel, bank credit channel, and net worth channel) each emphasize how changes in monetary policy transmit to firms by raising the cost of borrowing.

⁴⁵Results are qualitatively unchanged when using NAICS 3-digit sub-sectors instead.

⁴⁶Results for Jorda projections using aggregate data are available from the authors upon request. Note that an alternative approach would be to use the series identified using high-frequency variation in Fed Funds futures around

Results for sales and investment Figure 11 shows the response of sales, inventory investment, and fixed investment to the Romer and Romer shock series. Sales growth falls somewhat faster at small firms relative to large firms, consistent with our findings for the elasticity of firm sales growth with respect to the business cycle. However, the difference between sales growth at the top 1% and the bottom 99% is not statistically significant for most quarters. The evidence for a size effect is stronger for inventory growth, with small firms’ inventory contracting while large firms’ inventory continues to expand after the shock. In this case, the difference between the small and large firms is statistically significant. Investment rates, like sales growth, are more sensitive at small firms, but the difference is again not statistically significant.

The small size effect we document stands in contrast to Gertler and Gilchrist (1994) who find substantial differences between small and large firms after Romer and Romer dates. In Appendix I, we replicate their findings for the three Romer and Romer dates that overlap between their sample and our sample. As we discuss, the main source of differences appears to be the sample; when we look at responses including the two additional dates of 1994q2 and 2008q3, which have been suggested as additional dates of monetary policy shocks by Kudlyak and Sanchez (2017), we find a much smaller difference between small and large firms. Other methodological differences discussed at length in Appendix I are largely irrelevant.

Overall, the effect of monetary policy shocks is qualitatively consistent with the view that small firms are more sensitive, but the differences across size groups are not statistically significant for sales or investment. To avoid attrition bias (since small firms are sampled for 8 quarters), we estimated the Jorda specification in firm-level data up to a horizon of only 8 quarters. To obtain a longer horizon, we also estimated a specification analogous to (8) using cumulative average growth within firm-size classes instead of firm-level growth; these projections amount to pooling firm-level data by size class before estimating the effect of monetary policy shocks. Our findings are essentially unchanged.

Results for debt issuance The financial accelerator mechanism largely relies on differential balance sheet responses across firms. To the extent that size helps capture this mechanism, one should therefore expect to find a differential response in net external financing, and in particular debt flows, in response to the identified shock. We therefore estimate the specification (8) using three additional dependent variables: the ratio of total debt to assets, the ratio of bank debt to assets, and the ratio of short-term debt to assets. In effect, this estimation traces out the response of firm borrowing to an identified monetary policy shock.

Figure 12 shows the cumulative change in each of these debt ratios after a exogenous tightening monetary policy announcement dates, as in Bernanke and Kuttner (2005), Gürkaynak, Sack and Swanson (2005) and Gertler and Karadi (2015). The time series for these shocks is only available from 1990m1 onwards, but does cover the Great Recession period. The results from such an analysis, also available from the authors upon request, are qualitatively consistent with those obtained using the Romer-Romer shocks, in that point estimates indicate that small firms display greater sensitivity, but are not statistically significant. However, one drawback of using these shocks is that, in a Jorda projection framework, they lead to an expansionary response of aggregates, as pointed out by Ramey (2016). This is also true in our firm-level data, where innovations to the shock series are associated with overall increases in sales, inventories and, to a lesser extent, investment.

in monetary policy. In the case of total debt and bank debt, the point estimates show that net debt flows to small firms fall somewhat more than net debt flows to large firms at most horizons, but the difference between small and large firms is not significant. In the case of short-term debt, the response of large firms exceeds that of small firms at all horizons though, again, the difference is insignificant. The point estimates show that the differential response of debt is largest for total debt to assets; however, even at the 95th percentile, the differential effect is 75 basis points. If in response to a 1% monetary policy shock, large firms left kept their debt to asset ratio at 30% (approximately the average level in our data set), then small firms debt to asset ratio would fall to 29.25% indicated that the differential effect is also economically small. In comparison to the evidence at recession dates, the greater sensitivity of debt is even harder to discern, bolstering our conclusion that the size effect does not reflect the effect of financial frictions. As in Section 3, we can also estimate impulse responses over longer time horizons by taking average debt growth by firm size classes and then applying the Jorda method. We can also use an alternative series of monetary policy shocks from [Gertler and Karadi \(2015\)](#). In both cases, the point estimates are either inconsistent with the prediction that small firms are subject to tighter borrowing constraints after monetary policy shocks or the differences between small and large firms' responses are statistically insignificant.

5.4 Alternative explanations for the size effect

We next investigate alternative explanations for the size effect by exploiting variation in the size effect across 3-digit manufacturing industries. The size effect survives within 3-digit industries, but displays substantial heterogeneity and is attenuated or reversed in some of the smaller subindustries. First, we find no correlation between the size effect at the three digit level and a measure of external financial dependence based on [Kaplan and Zingales \(1997\)](#).⁴⁷ The absence of any correlation strengthens our view that the size effect is not driven by financial frictions.

We explore two alternative, non-financial hypotheses for the size effect: international exposure and downstream diversification. Using BEA input-output tables, we construct a measure of export intensity, total exports divided by gross output.⁴⁸ We find a positive correlation between the size effect and export intensity; industries with a high export share exhibit a stronger differences in the cyclicalities between large and small firms. This correlation is consistent with a demand-driven hypothesis: Large firms (which are more likely to be firms that export) are less exposed to the US business cycle, and to the extent that business cycles across countries are imperfectly correlated, these firms are relatively insulated from fluctuations in US GDP. The left panel of Figure 13 plots the correlation between the size effect and export exposure.

Export growth (yoy, quarterly frequency) has a correlation coefficient of 0.38 with GDP growth (yoy, quarterly frequency). Assuming that small firms have no export exposure, a simple back-of-the-envelope calculation suggests that a firm with 100% export exposure would have an elasticity

⁴⁷Specifically, we use the values for NAICS industries in Appendix Table A2 in [Duygan-Bump, Levkov and Montoriol-Garriga \(2015\)](#).

⁴⁸We compute this measure every five years from 2000 to 2015 and take averages over this period.

to GDP of $0.38 \times 3.1 = 1.18$. If the elasticity to GDP scales down linearly with the degree of export exposure, firms with 40% exports should have a relative response of -0.77 . In the data in Figure 13, the regression line shows that 40% export exposure is associated with a size effect of -1.16 ; thus the export channel explains about 2/3 of the size effect documented. However, to make this case more definitively in the QFR, a firm-level measure of exports would be needed.

We can test the hypothesis that the size effect is due to differences in the cyclical sensitivity of the customer base of small and large firms in another way. We examine the correlation of a measure of downstream diversification with the size effect at the 3-digit level. Our measure of downstream diversification is a Herfindahl index using the share of industry X's gross output used by industry Y. A high value of the Herfindahl indicates low diversification — industries that supply relatively little to other industries as inputs. We find a modest negative correlation between the Herfindahl index and the size effect; those industries that are more diversified exhibit a greater difference between large and small firms. The right panel of 13 plots the correlation between our diversification measure and the size effect across 3-digit NAICS.

The correlation is further strengthened if NAICS 336 (motor vehicles), which is an outlier in concentration, is dropped. This correlation is consistent with the hypothesis that differences in the cyclical sensitivity of demand between small and large firms may be responsible for the size effect. The implicit assumption is that large firms may be able to serve customers from more industries — and particularly so if they belong to sectors that have a large degree of downstream diversification. Although these findings are clearly limited, they suggest that differences in the cyclical sensitivity of their customer base contribute to the higher cyclical sensitivity of small firms — a mechanism that is distinct from financial frictions.

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 has the advantage of covering a representative sample of the population of US manufacturing firms at high frequency for an extensive time, a period spanning the last 5 recessions. Moreover, in contrast to other Census datasets, 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 with a 3.1% contraction for firms in the bottom 99%.

Our evidence, however, casts doubt on the commonly accepted interpretations of this finding. We show that the effect is mostly accounted for by the top 0.5%, with the rest of firms in the distribution having statistically indistinguishable sensitivities. Additionally, the degree of concen-

tration 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 greater sensitivity of smaller firms is insufficient to substantially affect the volatility of aggregates; we estimate that, absent the greater sensitivity of small firms, the elasticity of aggregate sales to GDP growth in our sample would only be about 0.15 points, smaller relative to a baseline of 2.20.

Most important, we provide evidence that this greater sensitivity of small firms cannot easily be accounted for by financial factors: controlling for proxies for financial constraints does not change estimates of the size effect, and the behavior of debt (in particular short-term debt) during recessions does not significantly differ between small and large firms. We also show that, in response to identified monetary policy shocks, we find only limited and statistically insignificant evidence of greater sensitivity of sales, investment or debt financing at small firms.

Our decision to focus, in this paper, on differences across firm size and their relation to financial frictions is motivated partly by the extensive use of firm size in the business cycle/macro literature on this topic. This focus is also justified by the fact that relative to other datasets, the QFR is has superior information about the financial behavior of small and private firms. However, it would be natural to disregard firm size and focus solely on other indicators of financial strength, such as leverage or bank-dependence. Appendix J compares the behavior in sales and investment in firms sorted solely by proxies for financial strength. With the exception of sorting on dividend issuance, most other proxies of financial strength show little power in predicting heterogeneous responses of firms to recessions.

The results of this paper suggest two potential directions to further test the hypothesis that the greater sensitivity of small firms is financial in nature. First, although it is notoriously difficult to measure financial constraints, 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 results on sorts of firms by groups of financial strength (leverage, liquidity, dividend issuance) reported here could be interpreted from the standpoint of a more detailed structural model than the one considered in this paper. We leave these issues to future research.

References

- Almeida, Heitor, Murillo Campello, and Michael S. Weisbach.** 2004. “The Cash Flow Sensitivity of Cash.” *Journal of Finance*, 59(4): 1777–1804.
- Alon, Titan, David Berger, Robert Dent, and Benjamin Pugsley.** 2018. “Older and Slower: The Startup Deficit’s Lasting Effects on Aggregate Productivity Growth.” *Journal of Monetary Economics*, 93(S): 68–85.
- Asker, John, Joan Farre-Mensa, and Alexander Ljungqvist.** 2011. “Comparing the Investment Behavior of Public and Private Firms.” National Bureau of Economic Research.
- Autor, David, David Dorn, Lawrence F. Katz, Christina Patterson, and John Van Reenen.** 2017. “Concentrating on the Fall of the Labor Share.” *American Economic Review*, 107(5): 180–185.
- Begenau, Juliane, and Juliana Salomao.** 2015. “Firm Financing over the Business Cycle.” Mimeo. University of Minnesota.
- Bergman, Nittai K., Rajkamal Iyer, and Richard T. Thakor.** 2015. “Financial Accelerator at Work: Evidence from Corn Fields.” National Bureau of Economic Research.
- Bernanke, Ben S., and Alan S. Blinder.** 1992. “The Federal Funds Rate and the Channels of Monetary Transmission.” *American Economic Review*, 82(4): 901–921.
- Bernanke, Ben S., and Kenneth N. Kuttner.** 2005. “What Explains the Stock Market’s Reaction to Federal Reserve Policy?” *Journal of Finance*, 60(3): 1221–1257.
- Bernanke, Ben S., Cara S. Lown, and Benjamin M. Friedman.** 1991. “The Credit Crunch.” *Brookings Papers on Economic Activity*, 21(2): 205–247.
- Bernanke, Ben S., Mark Gertler, and Simon Gilchrist.** 1996. “The Flight to Quality and the Financial Accelerator.” *Review of Economics and Statistics*, 78(1): 1–15.
- Buera, Francisco J., and Sudipto Karmakar.** 2017. “Real Effects of Financial Distress: The Role of Heterogeneity.” Mimeo. Federal Reserve Bank of Chicago.
- Chari, V.V., Lawrence Christiano, and Patrick Kehoe.** 2013. “The Behavior of Large and Small Firms Over the Business Cycle.” Mimeo. University of Minnesota.
- Chodorow-Reich, Gabriel.** 2014. “The Employment Effects of Credit Market Disruptions: Firm-Level Evidence from the 2008-2009 Financial Crisis.” *Quarterly Journal of Economics*, 129(1): 1–59.
- Chodorow-Reich, Gabriel, and Antonio Falato.** 2017. “The Loan Covenant Channel: How Bank Health Transmits to the Real Economy.” Mimeo. Harvard University.

- Covas, Francisco, and Wouter J. Den Haan.** 2011. “The Cyclical Behavior of Debt and Equity Finance.” *American Economic Review*, 101(2): 877–899.
- Crouzet, Nicolas.** 2017. “Aggregate Implications of Corporate Debt Choices.” *Forthcoming, Review of Economic Studies*.
- Davis, Steven J., John Haltiwanger, and Scott Schuh.** 1996. “Small Business and Job Creation: Dissecting the myth and Reassessing the Facts.” *Small Business Economics*, 8(4): 297–315.
- Dinlersoz, Emin, Sebnem Kalemli-Ozcan, Henry Hyatt, and Veronika Penciakova.** 2018. “Leverage over the Life Cycle and Implications for Firm Growth and Shock Responsiveness.” Mimeo. University of Maryland.
- Duygan-Bump, Burcu, Alexey Levkov, and Judit Montoriol-Garriga.** 2015. “Financing Constraints and Unemployment: Evidence from the Great Recession.” *Journal of Monetary Economics*, 75: 89–105.
- Farre-Mensa, Joan, and Alexander Ljungqvist.** 2016. “Do Measures of Financial Constraints Measure Financial Constraints?” *Review of Financial Studies*, 29(2): 271–308.
- Faulkender, Michael, and Mitchell A. Petersen.** 2005. “Does the Source of Capital Affect Capital Structure?” *Review of Financial Studies*, 19(1): 45–79.
- Fort, Teresa C., John Haltiwanger, Ron S. Jarmin, and Javier Miranda.** 2013. “How Firms Respond to Business Cycles: The Role of Firm Age and Firm Size.” *IMF Economic Review*, 61(3): 520–559.
- Gabaix, Xavier.** 2011. “The Granular Origins of Aggregate Fluctuations.” *Econometrica*, 79(3): 733–772.
- Gertler, Mark, and Peter Karadi.** 2015. “Monetary Policy Surprises, Credit Costs, and Economic Activity.” *American Economic Journal: Macroeconomics*, 7(1): 44–76.
- Gertler, Mark, and Simon Gilchrist.** 1994. “Monetary Policy, Business Cycles, and the Behavior of Small Manufacturing Firms.” *Quarterly Journal of Economics*, 109(2): 309–340.
- Gürkaynak, Refet S., Brian Sack, and Eric Swanson.** 2005. “The Sensitivity of Long-term Interest Rates to Economic News: Evidence and Implications for Macroeconomic Models.” *American Economic Review*, 95(1): 425–436.
- Hadlock, Charles J., and Joshua R. Pierce.** 2010. “New Evidence on Measuring Financial Constraints: Moving Beyond the KZ Index.” *Review of Financial Studies*, 23(5): 1909–1940.
- Jermann, Urban, and Vincenzo Quadrini.** 2012. “Macroeconomic Effects of Financial Shocks.” *American Economic Review*, 102(1): 238–271.

- Jordà, Òscar.** 2005. “Estimation and Inference of Impulse Responses Local Projections.” *American Economic Review*, 95(1): 161–182.
- Kaplan, Steven N., and Luigi Zingales.** 1997. “Do Investment-Cash Flow Sensitivities Provide Useful Measures of Financing Constraints?” *Quarterly Journal of Economics*, 112(1): 169–215.
- Kashyap, Anil K., Owen A. Lamont, and Jeremy C. Stein.** 1994. “Credit Conditions and the Cyclical Behavior of Inventories.” *Quarterly Journal of Economics*, 109(3): 565–592.
- Kehrig, Matthias, and Nicolas Vincent.** 2017. “Growing Productivity without Growing Wages: The Micro-Level Anatomy of the Aggregate Labor Share Decline.” Mimeo. Duke University.
- Khan, Aubhik, and Julia K. Thomas.** 2013. “Credit Shocks and Aggregate Fluctuations in an Economy with Production Heterogeneity.” *Journal of Political Economy*, 121(6): 1055–1107.
- Kudlyak, Marianna, and Juan M. Sanchez.** 2017. “Revisiting Gertler-Gilchrist Evidence on the Behavior of Small and Large Firms.” *Journal of Economic Dynamics and Control*, 77: 48–69.
- Lian, Chen, and Yueran Ma.** 2017. “Anatomy of Corporate Borrowing Constraints.” Mimeo. University of Chicago.
- Mehrotra, Neil R., and Dmitriy Sergeyev.** 2016. “Financial Shocks and Job Flows.” Mimeo. Brown University.
- Mian, Atif, and Amir Sufi.** 2014. “What Explains the 2007-2009 Drop in Employment?” *Econometrica*, 82(6): 2197–2223.
- Moreira, Sara.** 2016. “Firm dynamics, persistent effects of entry conditions, and business cycles.” Mimeo. Northwestern University.
- Moscarini, Giuseppe, and Fabien Postel-Vinay.** 2012. “The Contribution of Large and Small Employers to Job Creation in Times of High and Low Unemployment.” *American Economic Review*, 102(6): 2509–2539.
- Ottonello, Pablo, and Thomas Winberry.** 2017. “Financial Heterogeneity and the Investment Channel of Monetary Policy.” Mimeo. University of Chicago.
- Rajan, Raghuram G., and Luigi Zingales.** 1995. “What Do We Know about Capital Structure? Some Evidence from International Data.” *Journal of Finance*, 50(5): 1421–1460.
- Ramey, Valerie A.** 2016. “Macroeconomic Shocks and Their Propagation.” *Handbook of Macroeconomics*, 2: 71–162.
- Romer, Christina D., and David H. Romer.** 1989. “Does Monetary Policy Matter? A New Test in the Spirit of Friedman and Schwartz.” *NBER Macroeconomics Annual*, 4: 121–170.

- Romer, Christina D, and David H Romer.** 2004. “A New Measure of Monetary Shocks: Derivation and Implications.” *American Economic Review*, 1055–1084.
- Sharpe, Steven A.** 1994. “Financial Market Imperfections, Firm Leverage, and the Cyclicalities of Employment.” *American Economic Review*, 84(4): 1060–1074.
- Shimer, Robert.** 2012. “Reassessing the ins and outs of unemployment.” *Review of Economic Dynamics*, 15(2): 127–148.
- Shourideh, Ali, and Ariel Zetlin-Jones.** 2012. “External Financing and the Role of Financial Frictions over the Business Cycle: Measurement and Theory.” Mimeo. University of Pennsylvania.
- Siemer, Michael.** 2013. “Firm Entry and Employment Dynamics in the Great Recession.” Mimeo. Boston University.
- Whited, Toni M., and Guojun Wu.** 2006. “Financial Constraints Risk.” *Review of Financial Studies*, 19(2): 531–559.
- Wieland, Johannes F, and Mu-Jeung Yang.** 2016. “Financial Dampening.” National Bureau of Economic Research.

Panel A: size and growth

<i>Size group</i>	<i>0-90th</i>	<i>90-99th</i>	<i>99-99.5th</i>	<i>>99.5th</i>	Compustat
Assets (\$ mil.)	\$2.0	\$48.8	\$626.0	\$6766.3	\$1797.1
Sales (\$ mil., quarterly)	\$1.2	\$18.8	\$181.1	\$1420.8	\$446.4
Sales growth (year-on-year)	0.19%	4.58%	4.34%	4.08%	7.33%
Investment rate (year-on-year)	26.50%	24.91%	21.89%	20.36%	26.73%

Panel B: financial characteristics

<i>Size group</i>	<i>0-90th</i>	<i>90-99th</i>	<i>99-99.5th</i>	<i>>99.5th</i>	Compustat
Debt to asset ratio	0.35	0.29	0.30	0.28	0.28
Cash to asset ratio	0.15	0.10	0.07	0.06	0.13
Net leverage	0.20	0.19	0.23	0.22	0.15
Short-term debt (fraction of total debt)	0.33	0.33	0.20	0.18	0.16
Bank debt (fraction of total debt)	0.48	0.57	0.43	0.28	n.a.
Trade credit (fraction of total liabilities)	0.32	0.27	0.17	0.13	0.20
Intangible assets (fraction of total assets)	0.05	0.11	0.26	0.36	0.19
Zero leverage (% of tot. firm-quarter obs.)	20%	13%	8%	3%	4.8%
Negative book equity (% of tot. firm-quarter obs.)	5%	<1%	<1%	<1%	1.7%
Bank dependent (% of tot. firm-quarter obs.)	26%	29%	20%	10%	n.a.

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. "Bank dependent" indicates that more than 90% of the firm's outstanding debt is bank debt (firms with no debt are not classified as bank dependent). The data for the Compustat analysis is drawn from the Compustat annual files; for a description of the Compustat sample used, see appendix E. Annual Compustat sales are divided by 4 to obtain a quarterly value. Size groups are quantiles of the cross-sectional distribution of book assets in a given quarter; see Appendix A for more details on their construction.

<i>Size group</i>	<i>0-90th</i>	<i>90-99th</i>	<i>99-99.5th</i>	<i>> 99.5th</i>
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 includes 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. Size groups are quantiles of the cross-sectional distribution of book assets in a given quarter; see Appendix A for more details on their construction.

<i>Size group</i>	<i>0-90th</i>	<i>90-99th</i>	<i>99-99.5th</i>	<i>> 99.5th</i>
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. Exact percentiles are not reported in order to preserve data confidentiality. Size groups are quantiles of the cross-sectional distribution of book assets in a given quarter; see Appendix A for more details on their construction.

	Sales	Inventory	Fixed investment
GDP growth	3.700*** (1.045)	2.065*** (0.583)	0.912*** (0.258)
[90, 99] $\times$ GDP growth	−0.160 (0.142)	−0.107 (0.174)	−0.299* (0.157)
[99, 99.5] $\times$ GDP growth	−0.251* (0.143)	−0.299* (0.180)	−0.687*** (0.194)
[99.5, 100] $\times$ GDP growth	−0.600*** (0.169)	−0.730*** (0.206)	−1.257*** (0.355)
N	≈ 460000	≈ 460000	≈ 460000
nr. firms	≈ 60000	≈ 60000	≈ 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: Regression of sales growth, inventory growth, and fixed investment rates on GDP growth. Each line reports the estimated semi-elasticity of the variable of interest with respect to GDP growth for a size group relative to firms in the smallest size group (the 0 – 90th interquantile range). Size groups are defined with respect to the one-year lagged cross-sectional distribution of book assets; see Appendix A for more details on the construction of these groups. All specifications contain an indicator for durable/non-durable industries, and the interaction of this indicator with GDP growth. 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 standard errors reported in parentheses.

Outcome variable: sales growth (log)				
Compustat quarterly, manufacturing sector, 1977q4-2014q1				
	(1)	(2)	(3)	(4)
25-50% $\times$ GDP growth	-0.18 (0.511)	-0.20 (0.458)	-0.20 (0.479)	-0.22 (0.430)
50-75% $\times$ GDP growth	-0.09 (0.746)	-0.10 (0.691)	-0.10 (0.707)	-0.12 (0.657)
75-100% $\times$ GDP growth	-0.25 (0.318)	-0.27 (0.268)	-0.26 (0.294)	-0.28 (0.248)
Observations	238421	238421	238421	238421
Firms	6079	6079	6079	6079
Deflator type	Value-added	Output	Output	Output
Deflator level	Manufacturing	Manufacturing	BEA subsectors	BEA subsectors
Industry $\times$ GDP growth control	Yes	Yes	Yes	No
Industry-quarter effects	No	No	No	Yes

p-values in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5: The size effect in the quarterly manufacturing sample in Compustat. The table shows results for the sample from 1977q1 to 2014q1 (the same dates for which the QFR is available). Reported are the semi-elasticities of sales growth to GDP growth for the top three quartiles of the size distribution, relative to the bottom quartile of the size distribution. Size is defined as the one-year lagged value of book assets. Industries are defined as the BEA sub-sectors for manufacturing, which approximately correspond to NAICS 3-digit groups. Specification (1) reports results from a specification identical to the main specification, equation 1. Specification (2) deflates sales by an output (instead of value-added) deflator, identical across manufacturing industries. Specification (3) deflates sales by output deflators specific to each BEA sub-sector. Finally, specification (4) adds for industry-quarter fixed effects instead of controlling for industry effects and their interaction with GDP growth. Standard errors are clustered at the firm level in all specifications.

	Actual	Counterfactual 1	Counterfactual 2
	β	$\beta^{(1)}$	$\beta^{(2)}$
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 6: Cyclical sensitivities of aggregate sales, inventory, fixed investment, and total assets. Each line reports the estimated slope in regressions of the form $Z_t = \alpha + \beta \log \left(\frac{GDP_t}{GDP_{t-4}} \right) + \epsilon_t$. The first column reports results for $Z_t = G_t$, where G_t is the actual aggregate growth rate. The second column uses $Z_t = G_t^{(1)}$, where $G_t^{(1)}$ is a counterfactual aggregate growth rate series in which we have assumed that the average firm-level growth rate of small and large firms is equal (so that small firms do not have greater average sensitivity to business cycles than large firms). The third column uses $Z_t = G_t^{(2)}$, where $G_t^{(2)}$ is another counterfactual time series in which we have also assumed that the covariance between initial size and subsequent growth is also the same between small and large firms. Heteroskedasticity robust standard errors in parentheses.

	$\tilde{G}_t^{\text{large}}$	$\tilde{G}_t^{\text{small}}$	R_t
Sales	0.792	0.207	0.001
Inventory	0.723	0.276	0.001
Fixed investment	0.963	0.035	0.002
Total assets	0.924	0.071	0.005
Observations	143	143	143

Table 7: Variance decomposition for total sales, total inventory investment, total fixed investment, and total assets. Each column shows the contribution of a different term ($\tilde{G}_t^{\text{large}}$, $\tilde{G}_t^{\text{small}}$ or R_t) to the variance of G_t , i.e. the covariance between G_t and the term, divided by the variance of G_t (or alternatively, the coefficient in a single-variable OLS regression of the term on G_t).

	Baseline	(1)	(2)	(3)	(4)	(5)
$[90, 99] \times \text{GDP growth}$	-0.160	-0.189	-0.195	-0.162	-0.193	-0.176
$[99, 99.5] \times \text{GDP growth}$	-0.251*	-0.257*	-0.321**	-0.282*	-0.490***	-0.247
$[99.5, 100] \times \text{GDP growth}$	-0.600***	-0.563***	-0.675***	-0.640***	-1.097***	-0.594***
Bank share $[0.10, 0.90] \times \text{GDP growth}$		0.300				
Bank share $< 0.10 \times \text{GDP growth}$		-0.315				
Leverage $[0.15, 0.50] \times \text{GDP growth}$			-0.126			
Leverage $(0, 0.15] \times \text{GDP growth}$			-0.474*			
Leverage $= 0 \times \text{GDP growth}$			-0.630**			
Liquidity $[0.01, 0.20] \times \text{GDP growth}$				0.228		
Liquidity $> 0.20 \times \text{GDP growth}$				-0.101		
Market access $\times \text{GDP growth}$					0.826**	
Dividend issuance $\times \text{GDP growth}$						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 8: Regression of sales growth on firm size and proxies for financial constraints (model 6). Each column is a separate regression. All coefficients are the semi-elasticity with respect to GDP growth, relative to a baseline group. For size, the baseline group is the $[0, 90]$ group. For the bank share, the reference group is the group of firms with more than 90% of bank debt, as a fraction of total debt. For leverage, the reference group is the group of firms with a ratio of debt to assets above 50%. For liquidity, the reference group is the group of firms with a cash to asset ratio below 1%. For market access, the reference group is the group of firms that have never issued a bond or commercial paper in the past. For dividend issuance, the reference group is the group of firms that have not issued dividends in the past year. Standard errors clustered at the firm level. *, ** and *** indicate 10%, 5% and 1% significance levels, respectively with p-values reported in parentheses.



Figure 1: Average firm-level growth rate of sales of small (yellow, round markers) and large (green, diamond markers) firms. Times series are demeaned before plotting. 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 more details on the construction of size groups.

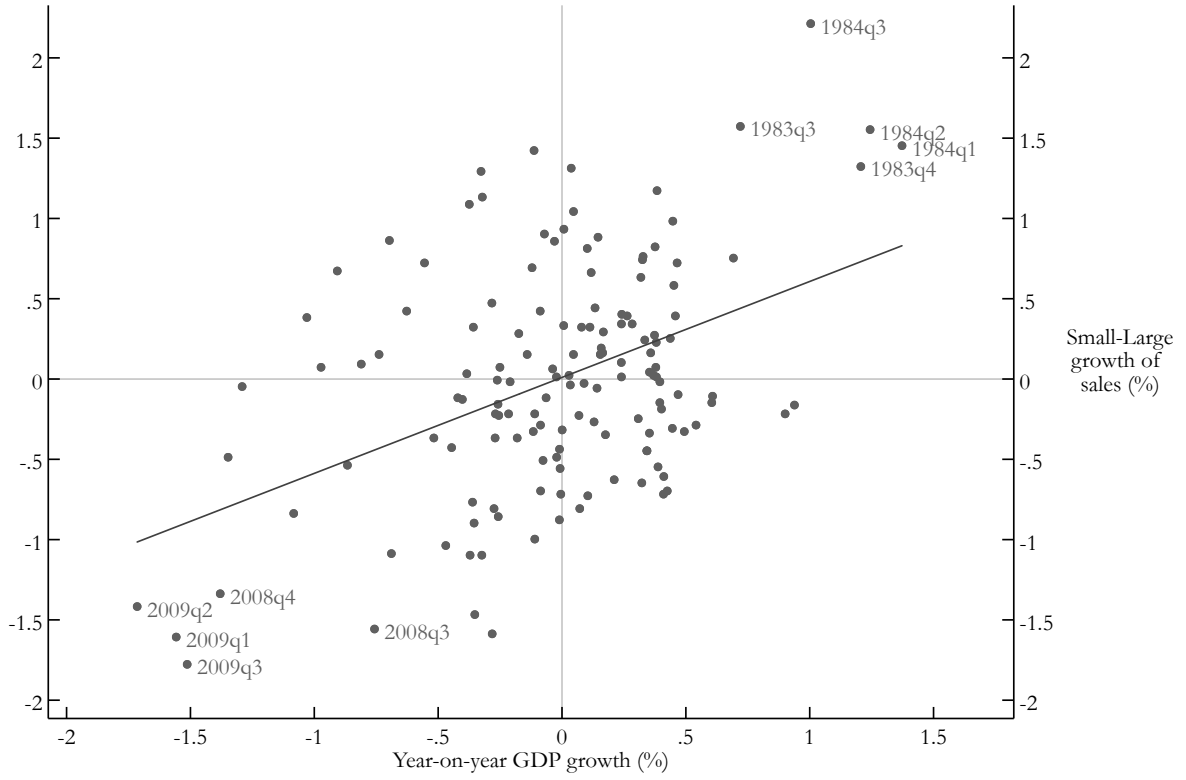
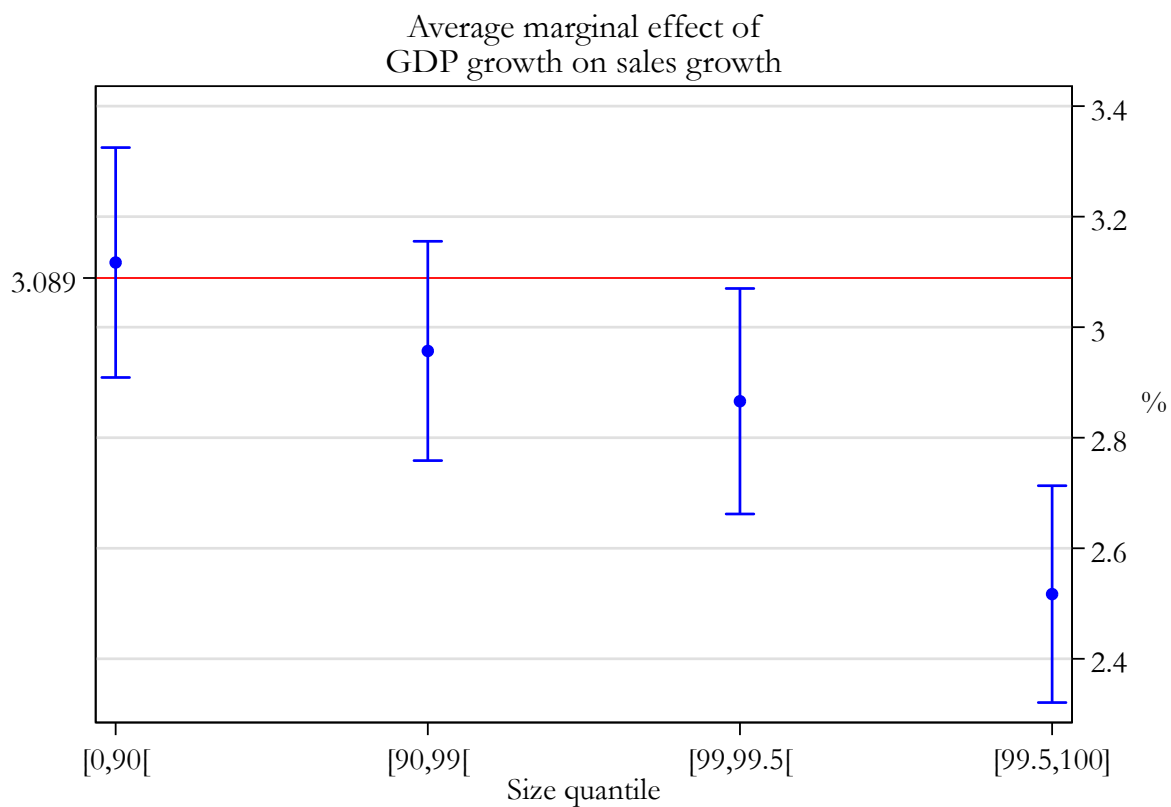


Figure 2: Difference between average growth rates of sales $\hat{g}_t^{(small)}(\text{sales}) - \hat{g}_t^{(large)}(\text{sales})$ (vertical axis) and year-on-year GDP growth (horizontal axis). Both series are demeaned. The OLS regression line has a slope of 0.60, with Newey-West standard error (allowing up to 8 lags) of 0.20.



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

Figure 3: Marginal effects of GDP growth on sales growth, by size group (blue boxplots), and unconditionally (red line). The marginal effects are computed using estimates of model (1), whose estimation results are reported in table 4.

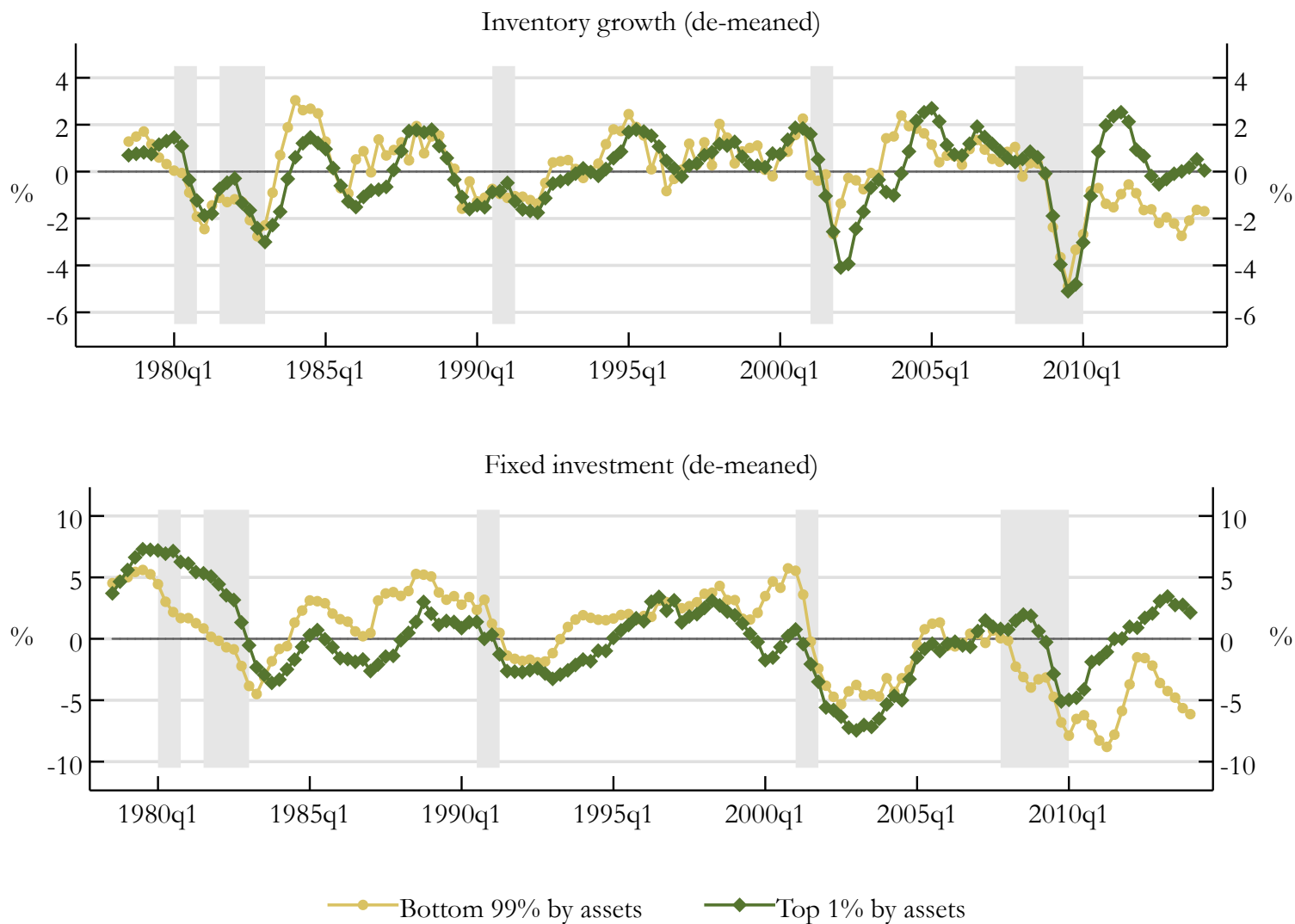


Figure 4: Average firm-level growth rate of small (yellow, round markers) and large (green, diamond markers) firms; top: inventory growth rate; bottom: fixed investment rate. All series are demeaned before plotting. Small firms are those belonging to the bottom 99% of the one-year lagged distribution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

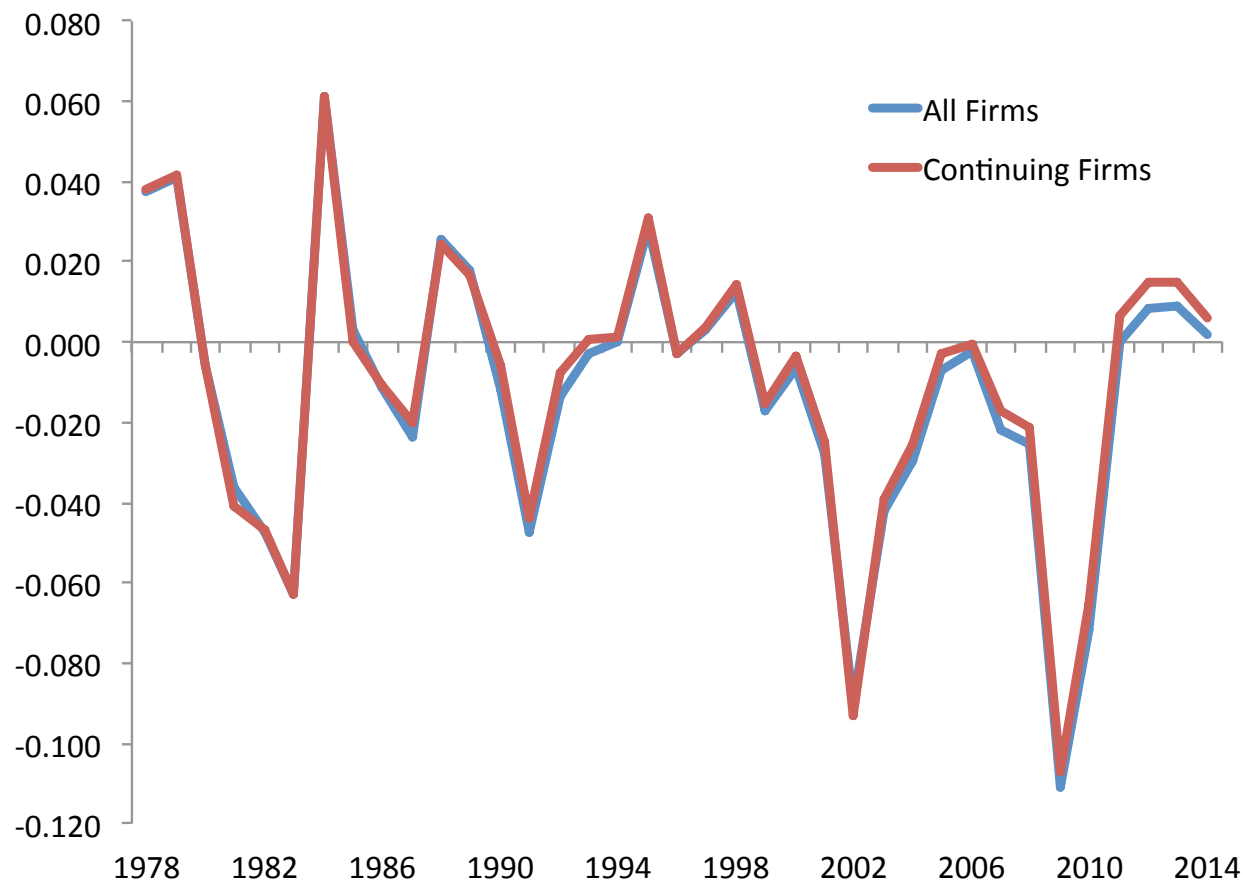


Figure 5: The blue line is employment growth at firms with initial firm size of 10 employees or more in manufacturing from the Business Dynamics Statistics (BDS) from 1978-2014. The red line is employment growth at continuing firms with initial firms size of 10 employees or more in manufacturing. Employment growth at continuing firms is defined as the change in employment less net entry (entry - exits). Entry and exit are restricted to firms over 10 employees. BDS data by industry and initial firm size available from https://www.census.gov/ces/dataproducts/bds/data_firm.html.

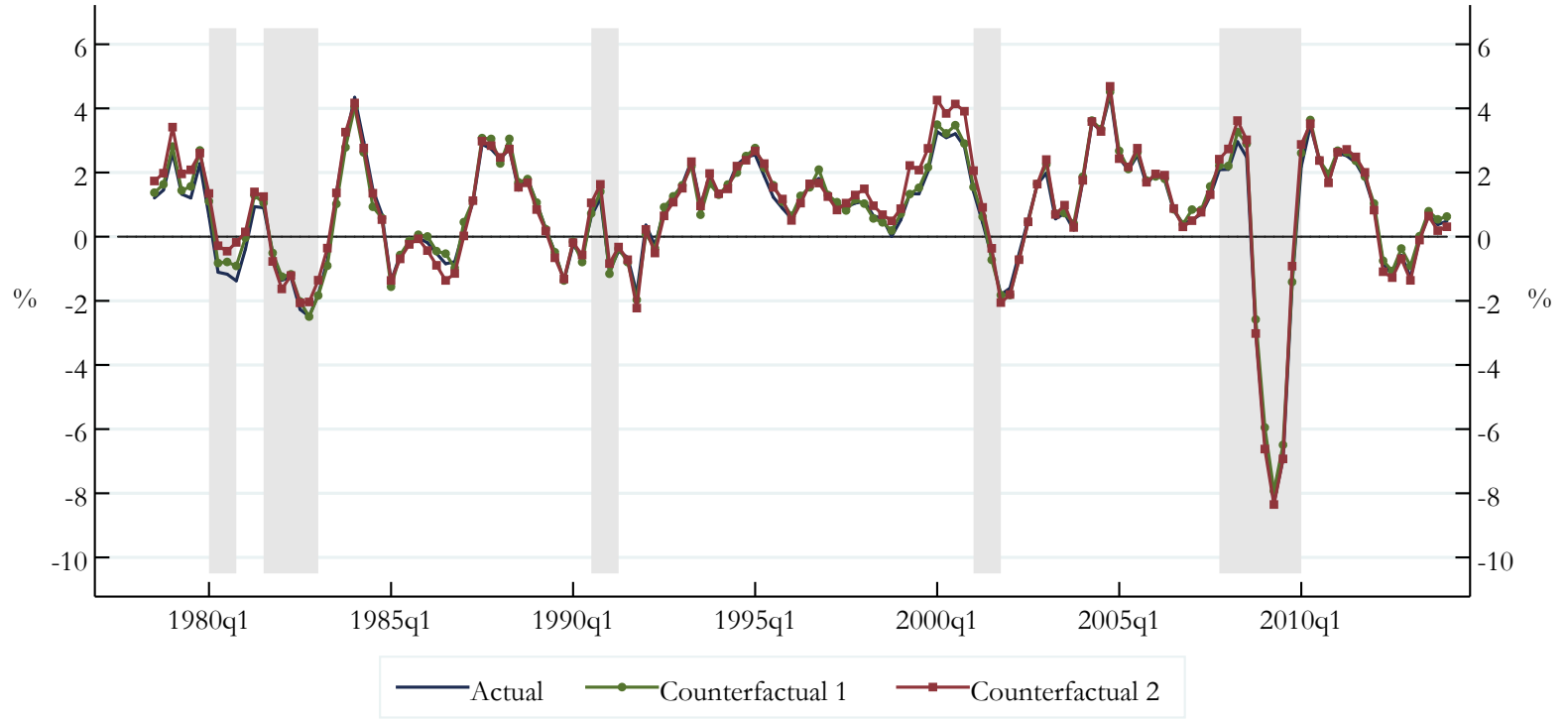


Figure 6: Aggregate growth rate of sales G_t (solid blue line); counterfactual growth rate $G_t^{(1)}$ (circled green line), which assumes that the average firm-level growth rate of small and large firms is equal; and counterfactual growth rate 2 $G_t^{(2)}$ (squared red line), which also assumes that the covariance between size and growth is the same between small and large firms.

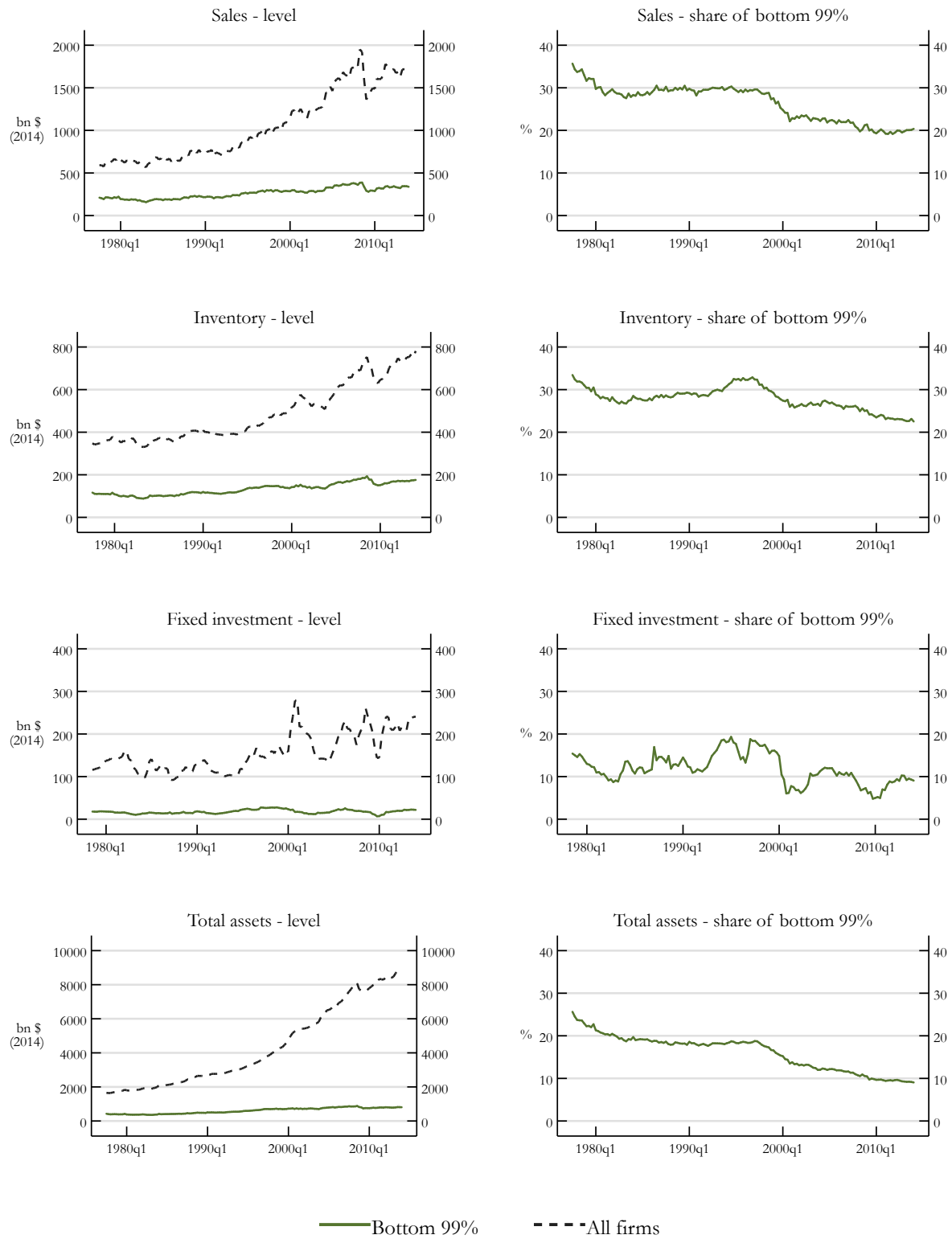


Figure 7: Concentration of sales, inventory, fixed investment, and total assets in the US manufacturing sector. The left column reports total nominal values for the bottom 99% and top 1% of firms by size. All series are deflated by the BEA price index for manufacturing, normalized to 1 in 2009q1; the series is available at http://bea.gov/industry/gdpbyind_data.htm. Series are unfiltered. The right column reports the share of the bottom 99% by size (the ratio of the corresponding graph in the left column). Size is defined in reference to the current cross-sectional distribution of book assets.

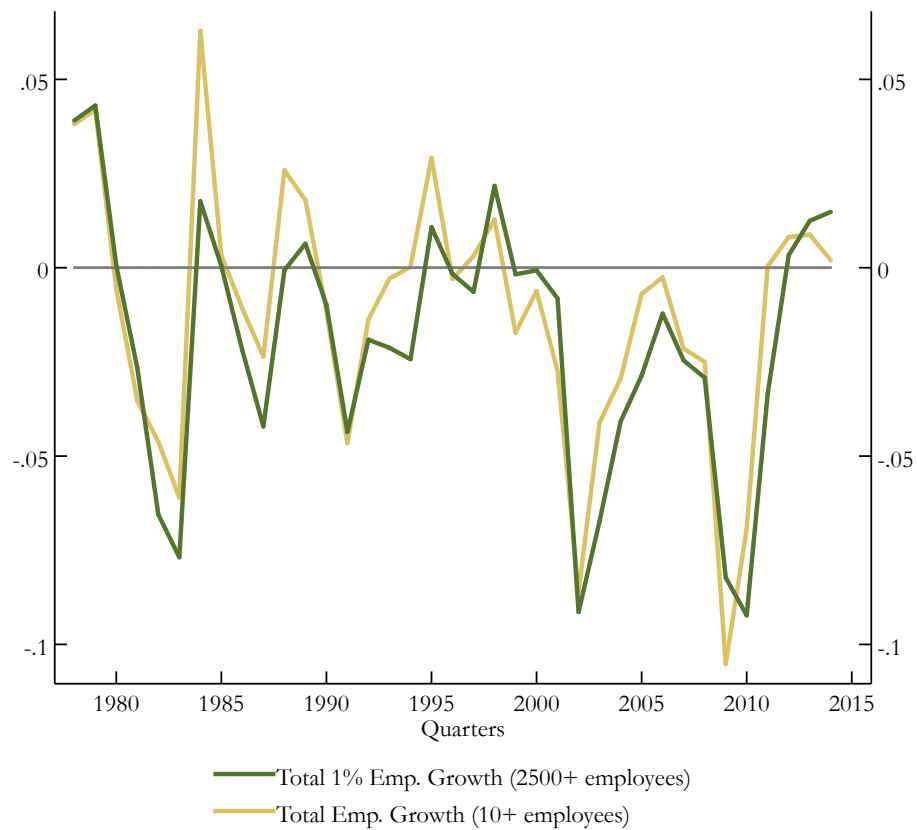


Figure 8: The green line displays annual employment growth for the estimated top 1% of manufacturing firms. The yellow line displays annual employment growth for all manufacturing firms with over 10 employees (our estimate of the portion of manufacturing employment captured in our data set).

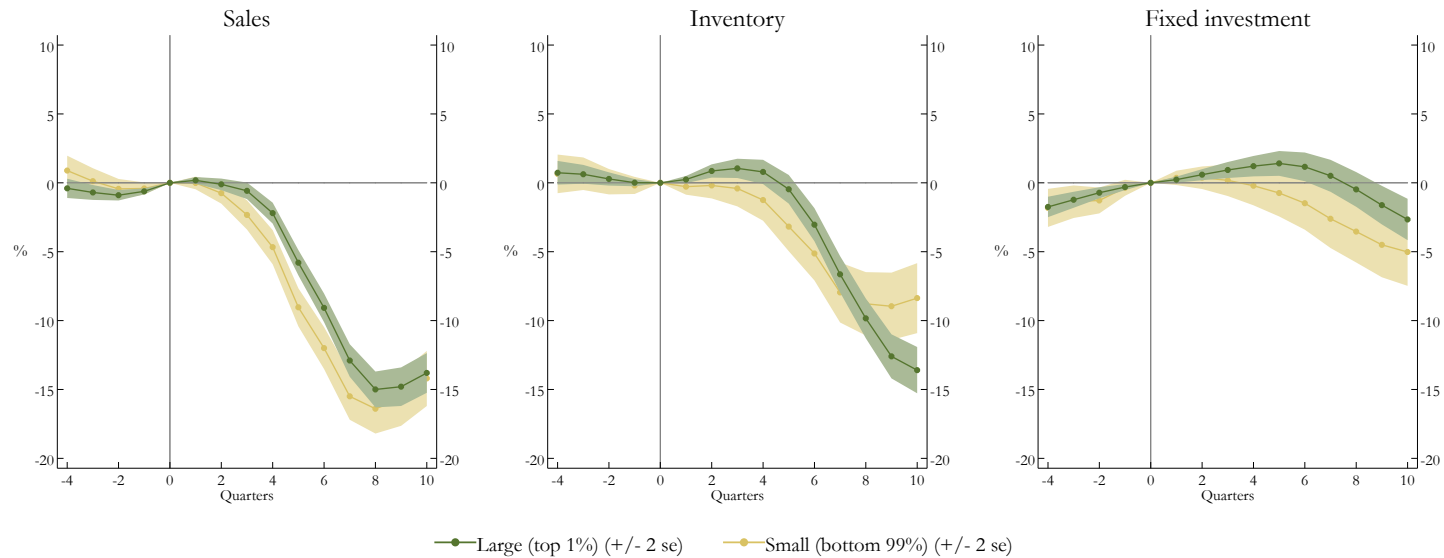


Figure 9: The behavior of sales, inventory and fixed capital after the start of a recession. Each graph reports the cumulative change in a variable of interest after the beginning of a recession. Shaded areas are ± 2 standard error bands. All growth rates are computed year-on-year and expressed at the quarterly frequency. Recession start dates are 1981q3, 1990q3, 2001q1, and 2007q4. See section 5.2 for more details.

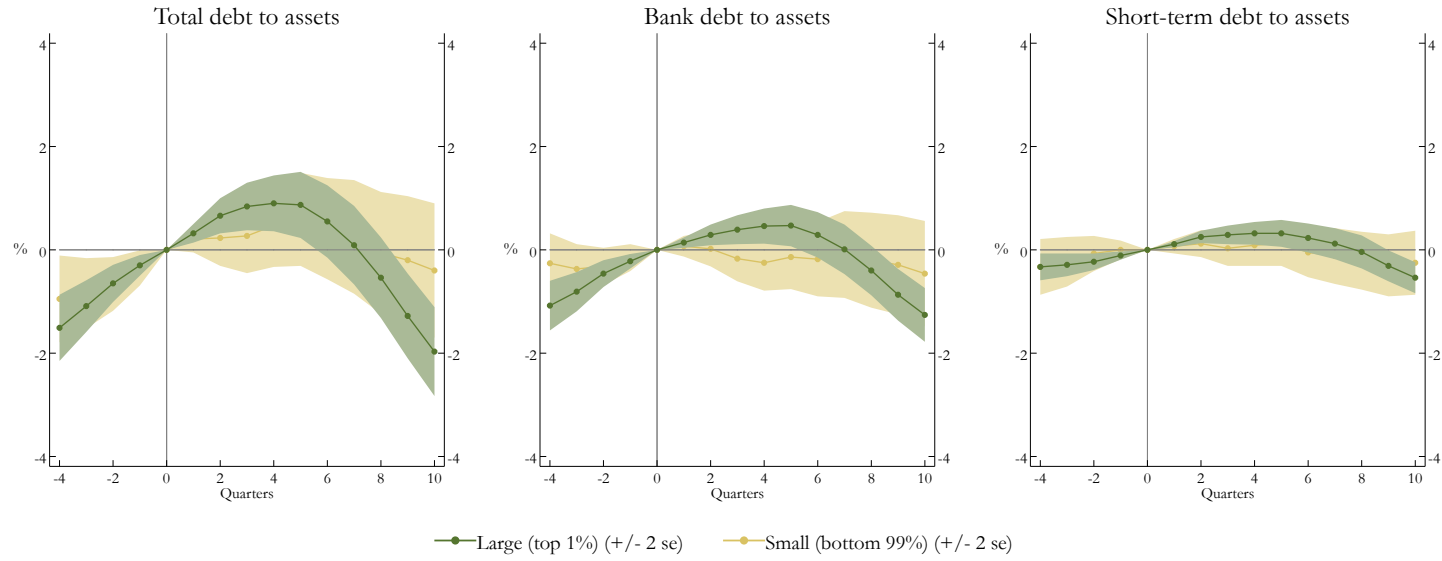


Figure 10: The behavior of debt overall, bank debt, and short-term debt after the start of a recession. Each panel reports changes relative to quarter 0 (the recession start date), computed using the cumulative sum of average growth rate of each size group. Growth rates at the firm-level are computed as $\frac{x_{i,t} - x_{i,t-4}}{assets_{i,t-4}}$, where $x \in \{\text{all debt, bank debt, short-term debt}\}$. Size groups are defined with a four-quarter lag.

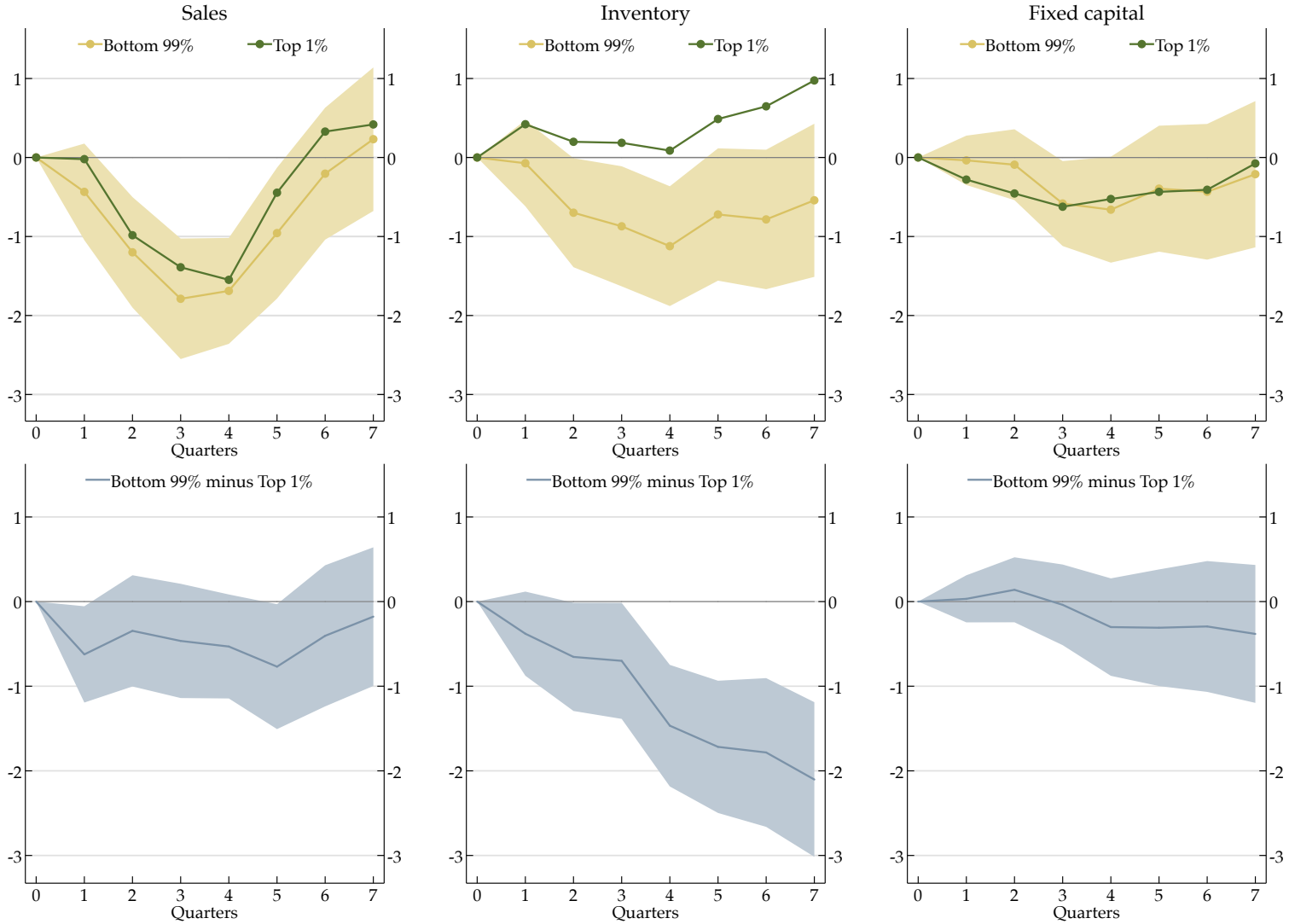


Figure 11: Firm-level response of sales, inventory and fixed capital to an innovation to the [Romer and Romer \(2004\)](#) shock. The estimated specification is model 8. The top row of graphs reports the average marginal effect at the mean of a one percentage point increase in $rr_{t-1,t}$, for the bottom 99% and top 1% size group. The yellow shaded area is the 95% confidence interval; standard errors are clustered at the firm-level and heteroskedasticity-robust. The bottom row of graphs reports the difference in the OLS coefficients $\beta_{(0,99)}^{(h)} - \hat{\beta}_{(99,100)}^{(h)}$, along with its 95% confidence interval. Data is from 1977q3 to 2007q4.

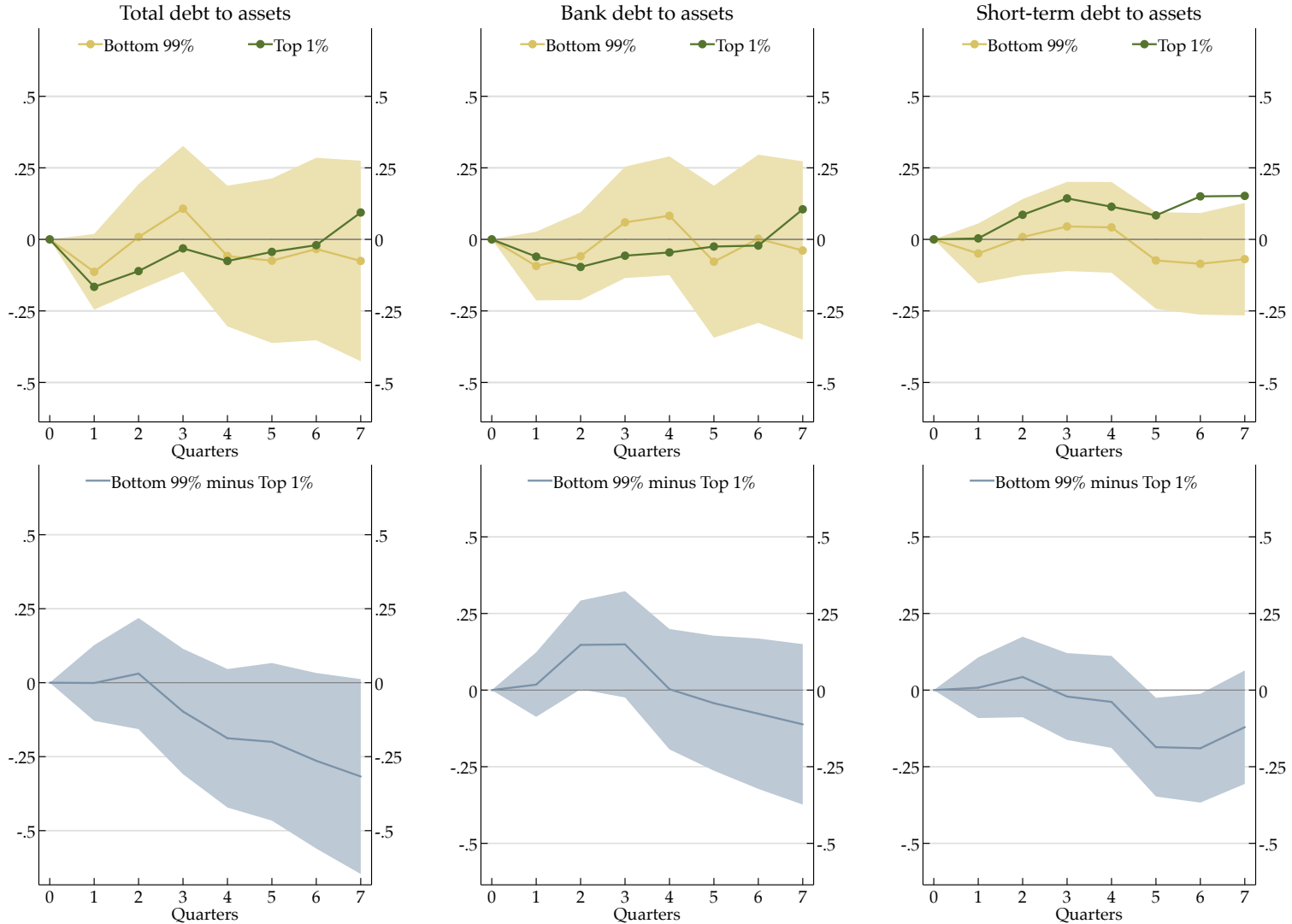


Figure 12: Firm-level response of the ratios of total debt, bank debt and short-term debt to assets to an innovation to the [Romer and Romer \(2004\)](#) shock. The estimated specification is model 8. The top row of graphs reports the average marginal effect at the mean of a one percentage point increase in $rr_{t-1,t}$, for the bottom 99% and top 1% size group. The yellow shaded area is the 95% confidence interval; standard errors are clustered at the firm-level and heteroskedasticity-robust. The bottom row of graphs reports the difference in the OLS coefficients $\beta_{(0,99)}^{(h)} - \hat{\beta}_{(99,100)}^{(h)}$, along with its 95% confidence interval. Data is from 1977q3 to 2007q4.

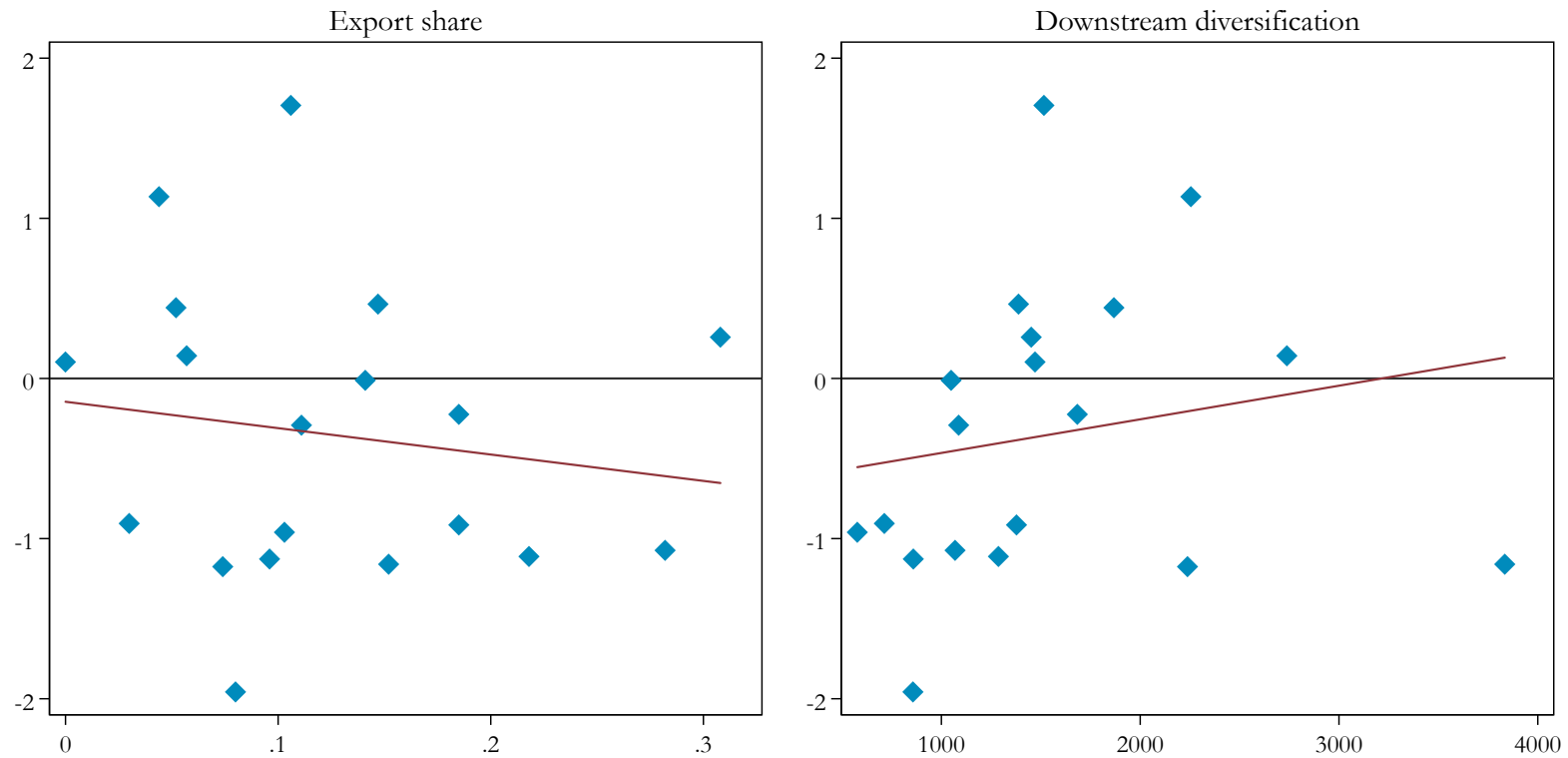


Figure 13: The left-hand panel shows a scatterplot of the size effect by 3-digit industry (y-axis) against the measure of export exposure by 3-digit industry. The size effect is the difference between the elasticity of the top 1% to US GDP growth and the elasticity of the bottom 99% within 3-digit industry. A more negative number indicates that larger firms within a given industry are less sensitive than smaller firms in that industry. Export exposure is measured as total exports divided by total gross output. The right-hand panel shows a scatterplot of the size effect against downstream diversification. Downstream diversification is measured as a Herfindahl index as the share industry X's gross output used by industry Y.

Appendices

A Measurement framework

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 $X = \{\text{sales, inventory, NPPE stock, assets}\}$. Let:

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

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

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

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

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

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

$$\mathcal{I}_t^{(k_1, k_2)} = \left\{ i \in \mathcal{I}_t \text{ s.t. } a_{i,t-4} \in \left[\bar{a}_{t-4}^{(k_1)}, \bar{a}_{t-4}^{(k_2)} \right[\right\}. \quad (10)$$

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

$$\begin{aligned} \mathcal{I}_t^{(\text{small})} &= \mathcal{I}_t^{(0, 99)}, \\ \mathcal{I}_t^{(\text{large})} &= \mathcal{I}_t^{(99, 100)} = \mathcal{I}_t \setminus \mathcal{I}_t^{(0, 99)}. \end{aligned} \quad (11)$$

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

$$g_{i,t}(x) = \begin{cases} \log \left(\frac{x_{i,t}}{x_{i,t-4}} \right) & \text{if } x \in \{\text{sales, inventory, NPPE stock, assets}\} \\ \frac{nppe_{i,t} - nppe_{i,t-4} + dep_{i,t-4,t}}{nppe_{i,t-4}} & \text{if } x = \text{fixed investment.} \end{cases} \quad (12)$$

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

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

$$\begin{aligned}\hat{g}_t^{(k_1, k_2)}(x) &\equiv \frac{1}{Z_{t-4}^{(k_1, k_2)}} \sum_{i \in \mathcal{I}_t^{(k_1, k_2)}} z_{i, t-4} g_{i, t}(x) \\ Z_{t-4}^{(k_1, k_2)} &\equiv \sum_{i \in \mathcal{I}_t^{(k_1, k_2)}} z_{i, t-4}.\end{aligned}\tag{13}$$

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 is not on long-term trends, but rather on the cyclical nature 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 (13). Since the sample is tilted 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 Sales and value added

The income statements which firms report to the QFR do not contain sufficient data to measure value added, and so our analysis focuses on sales as one of the main firm-level outcomes. A natural question, however, is whether the relative cyclical nature of sales is also informative about the relative cyclical nature of value added. Industry-level data indicate that the cyclical properties of value added may substantially differ from those of sales in certain sub-sectors of manufacturing. Table 9 reports the correlation between value added and output growth (at the annual frequency) in 18 BEA sub-industries of manufacturing between 1977 and 2014. (In the BEA’s measures, output growth differs is the closest proxy for revenue or sales growth, and differs primarily because of inventory changes.) This correlation is lower than 0.3 for 2 out of 18 industries, Oil & Gas and Furniture and Related Products, which together accounted for 6.8 percent of nominal value added in manufacturing in 2001. In these industries, the differences between the behavior of output and sales can be large: for instance, in the Oil & Gas industry, the 2007-2009 decline in gross output was 4.7%, but value added in that industry increased, by 3.2%. Table 10 shows estimates of the size effect, when dropping firms which belong to BEA subsectors where the correlation between real output growth and real sales growth is low, as reported in table 9. The results are reported when dropping the 2, 5 or 8 sectors with the lowest correlation between real output growth and real value added growth. In the first case, the results are unchanged. In the latter two cases, the size effect is weaker in the 50%-75% size group, but remains comparable to its baseline estimate in the two other size groups.

These results indicate that, in sectors where total value added growth and total output growth have similar cyclical properties, there is still a size effect for sales in the Compustat manufacturing sample. This is only suggestive evidence that the size effect for sales may translate to a size effect for value added; we recognize that direct measures of the cyclical behavior of value added across firm size groups would be needed to fully answer the question.

C Decompositions of aggregate growth

Assume that all observations are equally weighted, that is:

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

Let $\mathcal{I}_t^{(\text{small})} \subset \mathcal{I}_t$ denote the set of indexes of small firms, and $\mathcal{I}_t^{(\text{large})} = \mathcal{I}_t \setminus \mathcal{I}_t^{(\text{small})}$ be the set of large firms.⁴⁹ For some variable of interest $x \in \{\text{sales, inventory, NPPE stock, assets}\}$, and for some quarter t , define:

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

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

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

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

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

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

$$G_t^{(\text{small})} = \hat{g}_t^{(\text{small})} + \hat{c} \hat{v}_t^{(\text{small})}, \quad (16)$$

⁴⁹See appendix A for a formal definition of the size classification. Here, we refer to an arbitrary size classification, so long as it constitutes a partition of $\mathcal{I}_t$; in the counterfactuals that are reported next, we will focus on partition between the bottom 99% and top 1% by lagged book assets.

where:

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

The first term in this decomposition, $\hat{g}_t^{(small)}$, 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 $\frac{1}{\#\mathcal{I}_t^{(small)}} = \frac{1}{\#\mathcal{I}_t} \sum_{i \in \mathcal{I}_t^{(small)}} w_{i,t-4}$. 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:

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

Combining the two equations, we obtain the decomposition:

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

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

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

D The contribution of the covariance terms to the cyclicity of aggregate growth

In order to clarify the contribution of the term $\hat{c}ov_t$ to business-cycle variation in G_t , it is useful to note that the analogous decomposition to (2) also holds within each firm group, namely:

$$\begin{aligned}G_t^{(small)} &= g_t^{(small)} + \hat{c}ov_t^{(small)}, \\ G_t^{(large)} &= g_t^{(large)} + \hat{c}ov_t^{(large)}.\end{aligned}\tag{20}$$

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

$$\text{corr}(G_t^{(\text{small})}, Y_t) = \frac{\sigma_{\hat{g}_t^{(\text{small})}}}{\sigma_{G_t^{(\text{small})}}} \text{corr}(\hat{g}_t^{(\text{small})}, Y_t) + \frac{\sigma_{\hat{c}ov_t^{(\text{small})}}}{\sigma_{G_t^{(\text{small})}}} \text{corr}(\hat{c}ov_t^{(\text{small})}, Y_t). \quad (21)$$

Here, σ_Z denote the standard deviation of variable Z . Equation (21) breaks down the correlation between $G_t^{(\text{small})}$ 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 11 reports the values of the different elements of the right-hand side of (21), 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, within the small firm group, cumulative average firm-level growth tracks fairly closely the path of total sales. By contrast, for large firms, cumulative average firm-level growth falls far short of the trend in total sales, as documented in Figure 14.

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 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 $\frac{\sigma_{\hat{g}_t^{(\text{large})}}}{\sigma_{G_t^{(\text{large})}}} \text{corr}(\hat{g}_t^{(\text{large})}, Y_t)$, and $-0.02 = 0.45 \times (-0.05)$, coming from the term $\frac{\sigma_{\hat{c}ov_t^{(\text{large})}}}{\sigma_{G_t^{(\text{large})}}} \text{corr}(\hat{c}ov_t^{(\text{large})}, Y_t)$. 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.

E The cyclicity of investment rates

In the QFR data, two cyclical properties of firm-level investment stand out. First, the contemporaneous correlation of firm-level investment with GDP growth, after controlling for industry effects, is slightly negative among the top 0.5% of firms, as reported in Table 4. Second, during recessions, the decline in investment among the top 1% of firms lags that of the bottom 99% of firms by 2-4 quarters, as indicated by the right panel of Figure 11. This appendix argues that the lag structure in investment among the largest firms can also be documented in two analogous data sources: the manufacturing segments of the annual and quarterly versions of Compustat.⁵⁰

⁵⁰Replication code for this exercise is available from the authors upon request.

E.1 Data construction and summary statistics

Annual data Our source for the annual version of Compustat is the monthly update of the Fundamentals Annual file.⁵¹ In order to obtain up-to-date industry identifiers, we merge this file with the Company file; whenever the 3-digit NAICS historical code is missing, we fill it with the next most recent available observation, using the Company file NAICS as the last (year 2017) NAICS observation.

In order to facilitate comparison with the QFR results, we focus on the following measure of investment:

$$ik_{i,t} = \frac{k_{i,t} - k_{i,t-1} + dep_{i,t}}{k_{i,t-1}}.$$

Here, $k_{i,t}$ is the stock of net property, plant and equipment reported on the balance sheet of firm i in year t , and $dep_{i,t}$ is depreciation reported in the firm's year t income statement.⁵² Both $k_{i,t}$ and $dep_{i,t}$ are deflated using the BEA price index for manufacturing, as in the main text; the results also hold when using the BEA's 3-digit NAICS annual price indices to deflate nominal values. We keep firm-year observations in sample if (a) t is between 1977 and 2014; (b) the firm-year observation is incorporated in the US (variable `fic` from the company file equal to "USA"); (c) the 3-digit NAICS code is between 311 and 339 in sample; (b) $k_{i,t}$ is non-missing and weakly larger than 1m\$; (c) $dep_{i,t}$ is non-missing and weakly positive.

Each year, we create four size groups, corresponding to the four quartiles of the sample distribution of book assets. The average size of firms in each group over the 1977-2014 sample is reported in Table 12, after deflating book assets by the manufacturing price index. As in the main text, firms are then grouped according to their one-year lagged position in the firm size distribution. Relative to the overall sample, the regression sample is the subset of firm-year observations such that the firm is also present in sample one year prior; (b) total depreciation $dep_{i,t}$, in nominal terms, is weakly smaller than the one-year lagged stock of net property, plant and equipment. This latter criterion helps filter very large positive observation of $ik_{i,t}$. The resulting annual sample has 72363 firm-year observations.

Quarterly data We follow a similar procedure to construct the quarterly sample.⁵³ The fundamentals quarterly file does not contain NAICS 3-digit identifiers. Whenever possible, we use the 3D-NAICS identifier at the annual frequency, as described above; otherwise, we use the identifier from the company files. As in the QFR data, we construct year-on-year investment rates at the quarterly frequency for each firm: $ik_{i,t}^q = \frac{k_{i,t}^q - k_{i,t-4}^q + dep_{i,t-4,t}}{k_{i,t-4}^q}$. Here, t now denotes a quarter; $k_{i,t}^q$ denotes the net stock of property, plant and equipment (variable `ppentq`) deflated by the price

⁵¹We use the latest version of the `funda` file, available on WRDS at: [/wrds/comp/sasdata/nam/funda.sas7bdat](#). We use only firm-year observations with strictly positive assets (variable `at`) and which satisfy the four standard screens INDL for industry format, STD for data format, D for population source and C for consolidation. The company file we use is the latest version available at: [/wrds/comp/sasdata/nam/company/company.sas7bdat](#).

⁵²We use fiscal year, variable `fyear`, to date our observations; replacing by the calendar year which most overlaps the firm's fiscal year does not change our results.

⁵³We use the latest version of the `fundq` file, available on WRDS at: [/wrds/comp/sasdata/nam/fundq.sas7bdat](#).

index for manufacturing; we interpolate the annual time series in order to obtain quarterly data. The variable $dep_{i,t-4,t}$ denotes *total* depreciation over the preceding year, which we compute by taking the sum of reported depreciation in the four quarters up to and including quarter t . As in the annual data, we only keep observations for which $dep_{i,t-4,t} \geq k_{i,t-4}^q$ in nominal terms. Finally, we keep only observations with fiscal years between 1984 and 2014, since little data is available at the quarterly frequency prior to 1984. The resulting quarterly sample has 186784 firm-quarter observations.

Summary statistics Table 12 reports summary statistics for the average size and the average investment rate in the three different samples. QFR firms in the size-groups 1-2 (corresponding to the bottom 99% of the QFR distribution of book assets) are substantially smaller, on average, than firms in the bottom two size groups of the Compustat samples (the bottom 50% of the Compustat distribution of book assets). However, firms in group 4 (the top 0.5% of firms in QFR, and the top 25% of firms in Compustat) have comparable sizes (approximately 7bn\$ on average). Measured investment rate among smaller firms (groups 1-3) are somewhat lower in the QFR than they are in Compustat; however, for the top size group, they have the same average magnitude. This suggests that the top quartile of Compustat firms represents relatively well the top 0.5% of firms in the QFR, those with a differential investment behavior.

Additionally, table 2 reports summary statistics for the entirety of the Compustat sample. These statistics are computed using the annual data. The balance sheet ratios reported are defined as follows in terms of Compustat variables: the debt to asset ratio is $\frac{dlc+dltt}{at}$; cash to asset ratio is $\frac{che}{at}$; net leverage is the difference between the debt and the cash to asset ratios; the short-term debt ratio is $\frac{np}{dlc+dltt}$; the trade credit ratio is $\frac{ap}{lt}$, where lt is the total of lct , $dltt$, $txditc$ and lo (replacing individually missing variables, if at least one of the four is not missing); the intangible share is $\frac{intan}{at-act}$; zero leverage firms are those such that the debt to asset ratio is below 0.01; and negative equity firms are those such that the variable teq is not missing and negative.

E.2 The cyclical properties of investment

We first document unconditional estimates of the cyclicity of investment across size groups in Compustat data sources, and compare them to the QFR estimates. We use the same framework as in the main text, described in equation (1), in order to quantify this cyclicity; in particular, we use year-on-year GDP growth as our proxy for the state of the business cycle, and we control for durable/non-durable industry effects and their interaction with the year-on-year GDP growth. (The results are unchanged when controlling for 3D-NAICS effects in the same way). Table 13 reports the results, along with the estimates of the coefficients in the QFR data, which are identical to those reported in Table 4.

In both the quarterly and the annual Compustat, the baseline coefficient has the same magnitude and the opposite sign as the coefficient for the largest size group, group 4. In both cases, one cannot

reject that the sum of the two coefficients is equal to 0.⁵⁴ The baseline industry group corresponding to the coefficient reported in the first line of Table 13 are firms in the durable sector; however, estimates of the average marginal effect of GDP growth on investment (not reported) convey the same message. In annual data, the point estimate for the average marginal effect is 0.066, with a 95% confidence interval of $[-0.118; 0.245]$; in quarterly data, those numbers are -0.057 and $[-0.297, 0.182]$. Thus, in Compustat data as well as in QFR data, investment at the largest firms does not display a significantly positive correlation with contemporaneous GDP growth.

We next turn to the question of whether investment declines among large firms also display a lag in Compustat data. We estimate the same simple event study response for investment as the one described in section 5.2 of the main text, using the Compustat quarterly sample. In order to focus on the lag among the largest firms in the data, we trace out the cumulative investment rates of the top size group — groups 3 and 4 from Table 13 — and the bottom size group — groups 1 and 2 from Table 13. Figure 15 reports the results. As in the QFR data, investment lags the start of the recession: the peak of the cumulative investment rate occurs three quarters after the start of the recession in both size groups. Moreover, there is a sharper slowdown in the investment rate among the bottom size group (the cumulative investment rate is between quarters 0, when the recession starts, and 3 is smaller in the bottom size groups than in the top size groups). The difference in lags between the top and the bottom size groups is less visible than in the QFR data. The fact that the typical size of firms in the bottom size groups is substantially larger in the QFR than in Compustat may explain this discrepancy.

Overall, these findings indicate that Compustat data shares the two salient features of the QFR investment rates — the fact that the very largest firms do not display a positive contemporaneous correlation with GDP growth, and the fact that investment declines seems to lag the beginning of recessions.

F Decomposition of aggregate growth using DHS growth rates

This section replicates the decomposition results of section 4 using an alternative set of measures of growth at the firm level: the bounded growth rates introduced by Davis, Haltiwanger and Schuh (1996) (henceforth DHS). For any variable x , these growth rates are given by:

$$\tilde{g}_{i,t} = \frac{x_{i,t} - x_{i,t-4}}{\frac{1}{2}(x_{i,t} + x_{i,t-4})} \in [-2, 2].$$

These growth rates are a second-order accurate approximation to the standard growth rate $\frac{x_{i,t}}{x_{i,t-4}} - 1$ in a neighborhood of 1; furthermore, they are bounded, and moments of the distribution of these growth rates are therefore not too sensitive to outliers.

Using the same steps as outlined in appendix C, it is straightforward to verify that the following

⁵⁴The t-statistic for the tests are -0.24 in annual data and 1.41 in quarterly data, respectively.

decomposition holds exactly:

$$\tilde{G}_t = \hat{g}_t^{(large)} + \tilde{s}_{t-4}(\hat{g}_t^{(large)} - \hat{g}_t^{(small)}) + \hat{cov}_t^{(large)} + \tilde{s}_{t-4}(\hat{cov}_t^{(large)} - \hat{cov}_t^{(small)}),$$

where:

$$\begin{aligned}\tilde{G}_t &= \frac{X_t - X_{t-4}}{\frac{1}{2}(X_t + X_{t-4})} \\ \tilde{s}_{t-4} &= \frac{X_t^{(small)} + X_t^{(large)}}{X_t + X_{t-4}} \\ \hat{g}_t^{(small)} &= \frac{1}{\#\mathcal{I}_t^{(small)}} \sum_{i \in \mathcal{I}_t} \tilde{g}_{i,t} \\ \hat{cov}_t^{(small)} &= \sum_{i \in \mathcal{I}_t^{(small)}} \left(\tilde{w}_{i,t-4} - \frac{1}{\#\mathcal{I}_t} \right) (\tilde{g}_{i,t} - \hat{g}_t^{(small)}),\end{aligned}$$

and $\hat{g}_t^{(large)}$, $\hat{cov}_t^{(large)}$ are similarly defined. In this decomposition, the weights appearing in the covariance terms are given by:

$$\tilde{w}_{i,t} = \frac{x_{i,t} + x_{i,t-4}}{\sum_{i \in \mathcal{I}_t} x_{i,t} + x_{i,t-4}}.$$

Thus, they capture not the initial size of the firm relative to other firms initially in the same size group, but its average size over the period between $t - 4$ and t , relative to the average size of firms initially in the same size group.

When we apply this decomposition to the same sample as in section 4, the two key results of the analysis using log growth rates still hold. First, the covariance terms in the decomposition account for a very small fraction of the overall correlation between aggregate growth and GDP growth; the lion's share of that correlation, instead, comes from the cross-sectional average components, $\hat{g}_t^{(small)}$ and $\hat{g}_t^{(large)}$. Table 14 makes this point; its contents are almost identical to those of Table 14 in the main text. Second, estimated elasticities of counterfactual time series for aggregate growth attempting to remove either the “greater sensitivity” or the cyclicity of small firms overall are very close to the actual elasticities of time series for aggregate growth. Table 15 reports these results; again, they are almost identical to the results from the same exercise conducted using log growth rates, and reported in Table 6 in the main text. The reason for the similarity between these results is simple: these two growth rates are very highly correlated at the firm level, in the sample of continuing firms used throughout in the main text. The results of section 4 thus do not critically depend on the use of log growth-rates for the construction of the decomposition of aggregate growth.

G A simple model where size and financial constraints coincide

G.1 Overview of the model and the results

The baseline model 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:

$$\begin{aligned} \mathbf{V}_t(k_{i,t}) &= \max_{k_{i,t+1}} \eta n_{i,t} + (1-\eta) \left(n_{i,t} - k_{i,t+1} + \frac{1}{1+r} \mathbf{V}_{t+1}(k_{i,t+1}) \right) \\ \text{s.t.} \quad n_{i,t} &= z_t k_{i,t}^\zeta + (1-\delta)k_{i,t} \\ [\lambda_{i,t}] \quad 0 &\leq n_{i,t} - k_{i,t+1} \end{aligned}$$

Here, $k_{i,t}$ are the firm's assets in place. The firm's operating profits are given by $\pi_{i,t} = z_t k_{i,t}^\zeta$, with $0 < \zeta < 1$ denoting the curvature of the profit function with respect to assets and z_t is an aggregate shock, which may capture aggregate changes in productivity, demand, or the cost of inputs.⁵⁵ Finally, $n_{i,t}$ is the firm's net worth, which is equal to the sum of its operating profits and the depreciated value of its capital stock.

There are two financial frictions in this environment. The first is that payouts to equityholders must be positive: $n_{i,t} \geq k_{i,t}$. The frictionless model is one where, by contrast, payouts to equityholders can take any sign without affecting their marginal benefit (or cost): $n_{i,t} \geq k_{i,t}$. The second is that firms are not allowed to borrow. Firms are therefore completely internally financed. Note that another way to express the financial constraint is that $\pi_{i,t} \geq i_{i,t} = k_{i,t+1} - (1-\delta)k_{i,t}$, so that operating profits must fully cover investment in each period. The shadow value of internal funds is $\nu_{i,t} = 1 + \lambda_{i,t}$; a firm is constrained, if and only if, $\nu_{i,t} > 1$. The stark assumption of pure internal financing is a useful benchmark that we later relax.

Finally, with probability η , a surviving firm exogenously exits at the beginning of the period. In this case, equityholders receive the firm's net worth as a 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 .

In stationary equilibrium ($z_t = z$ for all t), the frictionless model has the simple solution:

$$k_{i,t+1} = k^* \equiv \left(\frac{\zeta z}{r + \delta} \right)^{\frac{1}{1-\zeta}}, \quad \forall i, t. \quad (22)$$

At this value for $k_{i,t+1}$, the expected discounted marginal product of capital is equal to 1. In the frictionless model, all surviving firms have the same size. By contrast, in stationary equilibrium,

⁵⁵The curvature in the profit function may originate either in decreasing returns in production or in monopoly power. Depending on which specific microfoundation for the profit function is chosen, z_t will be given by a specific combination of aggregate productivity, the real wage rate, and aggregate demand for the industry's product.

the solution to the model with frictions is:

$$k_{i,t+1} = \begin{cases} n_{i,t} & \text{if } n_{i,t} < k^* \\ k^* & \text{if } n_{i,t} \geq k^* \end{cases}. \quad (23)$$

So long as $n_e = zk_e^\zeta + (1 - \delta)k_e < k^*$, the stationary equilibrium also features a cross-section of firms of different sizes: firms are born small relative to their desired capital stock k^* , must save to reach it, and may fail to reach their optimal size due to the exogenous exit shock. (Details and proofs are reported in section G.2 below.)

The effects of an aggregate shock We consider the perfect foresight response of the model to a shock to z_t . Specifically, we assume that at time $t = -1$, $z_t = z$, and that the model is in its stationary equilibrium. Moreover, at time 0, firms learn that the future path of z_t , for $t \geq 0$, will be $z_t = z \exp(-\rho^t \epsilon)$, where $\epsilon > 0$ is a shock to productivity, and ρ is the persistence of the shock. This exercise is meant to approximate the response of the economy to a mean-reverting decline in productivity. The top panel of figure 16 shows the perfect foresight response of output to a temporary decline in z_t , starting from the steady-state described by (23).⁵⁶ In the model with frictions, the most responsive firms are the largest ones — there are differences in cyclicality across firms of different sizes, but of the opposite sign as in the data.

Why are large firms more sensitive? The aggregate shock has two effects: it lowers all firms' net worth $n_{i,t} = z_t k_{i,t}^\zeta + (1 - \delta)k_{i,t}$; but it also reduces the optimal unconstrained size of firms,

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

When the shock hits the economy, initially unconstrained firms (those with $n_{i,0} \geq k^*$) find themselves with financial slack: even though their net worth falls, it still remains above the new unconstrained threshold, $\underline{n}_1 = k_1^*$. As a result, 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 $n_{i,0} < \underline{n}_1 = k_1^*$. That is, these firms are below their optimal size *even after* the aggregate shock. These firms' responses then only reflect changes in net worth. Because net worth is a linear function of the aggregate shock, whereas the optimal size is a convex function of the aggregate shock, the optimal size response tends to be larger than the net worth response.⁵⁷ Financial frictions, in this case, work like an adjustment cost, moderating the response of quantities.

⁵⁶The calibration of the model is described in section G.2 below; in particular, the choice of the exogenous exit rate and the entry size imply that in steady-state, 1% of firms are unconstrained. The path of the shock is $z_t = z \exp(-\rho^t \epsilon)z$; in all figures, we use $\rho = 0.8$ and $\epsilon = 0.01$.

⁵⁷Below we show that a necessary condition for the response of net worth to be smaller than the response of the optimal investment target is that $\frac{\rho}{1-\zeta} \geq \frac{r+d}{\zeta}$. This condition is met in our calibration; it will be satisfied so long as the aggregate shock is not too transitory. It is clear that a purely transitory shock ($\rho = 0$) would only have a net worth effect and hence only cause constrained firms to respond.

Adding pro-cyclical external financing The previous example shows that restricted access to external finance alone is not sufficient to generate a size effect. We next add debt financing to the model and allow the borrowing constraint to be a function of both the firm's net worth and, crucially, of the aggregate shock. The firm's objective is now:

$$\begin{aligned}
\mathbf{V}_t(k_{i,t}, b_{i,t}) &= \max_{k_{i,t+1}, b_{i,t+1}} \eta n_{i,t} + (1 - \eta) \left(n_{i,t} - k_{i,t+1} + b_{i,t+1} + \frac{1}{1+r} \mathbf{V}_{t+1}(k_{i,t+1}, b_{i,t+1}) \right) \\
n_{i,t} &= z_t k_{i,t}^\zeta + (1 - \delta) k_{i,t} - (1 + r) b_{i,t} \\
\text{s.t.} \quad b_{i,t+1} &\leq \mathbf{b}(n_{i,t}; z_t) \\
n_{i,t} + b_{i,t+1} &\geq k_{i,t+1}
\end{aligned}$$

where $\mathbf{b}(\cdot, \cdot)$ — the borrowing constraint — is a function of both the firm's net worth and the aggregate shock z_t . As before, firms cannot raise equity (i.e. issue negative dividends).⁵⁸

The solution to the firm's problem is similar to the case with no borrowing; the details and proofs are reported in section G.3 below. Firms with high levels of net worth invest at the optimal level k_{t+1}^* , while firms with insufficient net worth are either partially or fully constrained. Partially or fully constrained firms do not issue any dividends. Fully constrained firms utilize all their borrowing capacity; that is, $k_{i,t+1} = n_{i,t} + \mathbf{b}(n_{i,t}, x_{t+1})$. Partially constrained firms invest at the currently optimal level, but pay zero dividends. There need not be partially constrained firms in equilibrium; the situation only occurs when fundamentals are such that firms may be constrained tomorrow, for example if z_t is rising sharply over time.⁵⁹

As before, we construct the response to a one-time unanticipated and mean-reverting decline in z_t and compare the responses of small and large firms. The bottom panel of Figure 16 displays the sales, investment, dividend issuance, and debt financing response of small and large firms. These responses are constructed under the assumption that the borrowing constraint is sufficiently elastic with respect to the aggregate shock so as to generate greater sensitivity of investment among small firms.⁶⁰ Under this assumption, small firms will cut back on investment faster, and subsequently experience larger declines in sales than large firms. It is straightforward to understand why a highly procyclical borrowing constraint is necessary. Constrained firms' investment is given by their total financing capacity:

$$k_{i,t+1} = n_{i,t} + \mathbf{b}(n_{i,t}, z_t),$$

while unconstrained firms' investment is simply the optimal path $k_{t+1}^* = \left(\frac{\zeta z_{t+1}}{r+\delta} \right)^{\frac{1}{1-\zeta}}$. The latter is a convex function of the aggregate shock; intuitively, so long as the borrowing function is chosen so that the total borrowing capacity $n_{i,t} + \mathbf{b}(n_{i,t}, z_t)$ is a “more” convex function of the aggregate

⁵⁸Additionally, we restrict attention to solutions which satisfy the following transversality condition: $\lim_{t \rightarrow \infty} (1+r)^{-t} \mathbf{V}_t(k_{i,t+1}, b_{i,t+1}) \leq 0$.

⁵⁹The appendix provides detailed conditions under which the partially constrained regime exists. It is worth noting that it never exists in steady-state.

⁶⁰The appendix derives a simple sufficient condition on the elasticity of the borrowing constraint with respect to the aggregate shock that ensures the model generates greater sensitivity for investment.

shock, the investment response of small/constrained firms will be larger.

However, a byproduct of the assumption of a procyclical borrowing constraint is that debt financing flows among small firms should also respond strongly to the aggregate shock. The bottom panel of Figure 16 reports the cumulative change in debt among small and large firms. The contraction in debt among small firms is deeper and more protracted than among large firms. This is the financial flipside of the greater sensitivity of investment which the model generates. The model thus suggests that if small firms display greater sensitivity in investment because of financial constraints, then, we should also expect to find greater sensitivity in debt flows.

G.2 Detailed results for the model with no external finance

Sufficient conditions for greater sensitivity First note that, in the stationary equilibrium of the model, the (gross) growth rate of the capital stock of a constrained firm is given by:

$$\begin{aligned}
g_{i,cons} &= \frac{k_{i,t+1}}{k_{i,t}} \\
&= \frac{n_{i,t}}{k_{i,t}} \\
&= \frac{zk_{i,t}^\zeta + (1-\delta)k_{i,t}}{k_{i,t}} \\
&= 1 - \delta + zk_{i,t}^{1-\zeta} \\
&\geq 1 - \delta + \frac{1}{\zeta}(r + \delta) \equiv g_{cons}
\end{aligned}$$

where the last line comes from the fact that $k_{i,t} \leq k^*$. Note that $g_{cons} > 1$. By contrast, in steady-state, the (gross) growth rate of unconstrained firms is $g_{uncons} = 1$.

Now consider a firm which is constrained at $t = -1$ and stays constrained at $t = 0$, when the shock occurs. Following similar steps, the gross growth rate of its capital stock will be given by:

$$\begin{aligned}
g_{cons}^{(0)} &= \frac{k_{i,1}}{k_{i,0}} \\
&= \frac{n_{i,1}}{k_{i,0}} \\
&= \frac{z \exp(-\epsilon)k_{i,0}^\zeta + (1-\delta)k_{i,0}}{k_{i,0}} \\
&= 1 - \delta + z \exp(-\epsilon)k_{i,0}^{1-\zeta} \\
&\geq 1 - \delta + \frac{1}{\zeta}(r + \delta) \exp(-\epsilon) \\
&\approx g_{cons} - \frac{1}{\zeta}(r + \delta)\epsilon
\end{aligned}$$

Thus, the drop in growth relative to g_{cons} is approximately:

$$\Delta g_{cons.} = -\frac{1}{\zeta}(r + \delta)\epsilon.$$

By contrast, for unconstrained firms, it is straightforward to see that the drop in growth relative to g_{unc} is:

$$\Delta g_{unc.} = -\frac{\rho}{1-\zeta}\epsilon.$$

Thus, for sales growth among large firms to fall more, relative to trend, that growth among small firms, it must be the case that:

$$\frac{\rho}{1-\zeta} \geq \frac{1}{\zeta}(r + \delta),$$

which holds in the calibration we study. Note here that in both the data and the model, growth among small and large firms is measured relative to its long-run average. The “de-trending” used in this derivation is approximate, in that it substitutes the long-run average growth rate of small firms for its lower bound, $g_{cons.}$, instead of the actual cross-sectional average growth rate of small firms in steady-state. However, the impulse responses reported are constructed using the actual long-run average growth rate of small firms in the stationary steady-state; this does not change the conclusion that small firms do not display greater sensitivity in this model.

Calibration of the model We construct a quarterly calibration of the model; in particular, we set $\zeta = 0.8$, $\delta = \frac{0.20}{4}$ and $r = \frac{0.02}{4}$. Additionally, we set:

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

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 $\mathbf{n}^j(\cdot)$ 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:

$$k_j = \begin{cases} \mathbf{n}^j(k_e) & \text{if } 0 \leq j \leq N-1 \\ k^* & \text{if } j = N \end{cases} \quad (24)$$

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

$$\mu_j = \begin{cases} (1-\eta)^j M & \text{if } 0 \leq j \leq N-1 \\ \frac{(1-\eta)^N}{\eta} M & \text{if } j = N \end{cases} \quad (25)$$

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 $k_e = (0.001)k^*$, similar to the $p50/p99$ ratio of book assets in the QFR. Given that $\log(k^*) = 0$, this requires $\log(k_e) = \log(0.001)$. Given this choice of k_e , $N(k_e)$ is determined; given

the calibration above, we have $N = 113$. 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 $\eta = 0.040$. 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, it is straightforward to obtain lower implied exit rates; moreover, the qualitative implications of the model are independent of the value chosen for η .

G.3 Detailed results for the model with debt financing

Characterization of optimal policies The following lemma, and the figure that accompanies it, gives the solution to the problem of the firm with financial constraints. For brevity, the proofs of the lemma and the others that follow are omitted, but they are available from the authors upon request.

Lemma 1 (Constrained solution). *Assume that the borrowing constraint is $\mathbf{C}^1$ and satisfies:*

$$\frac{\partial \mathbf{b}}{\partial n_{i,t}}(n_{i,t}, z_{t+1}) \geq 0, \quad \mathbf{b}(0, z_{t+1}) = 0;$$

$$\frac{\partial \mathbf{b}}{\partial z_{t+1}}(n_{i,t}, z_{t+1}) \geq 0.$$

Let $\{\underline{n}_t\}_{t \geq 0}$ be the unique solution to:

$$\begin{aligned} \underline{n}_t &= \max \left(\mathbf{c}^{-1}(k_{t+1}^*; z_{t+1}), -\left(\frac{1}{\zeta} - 1\right)(\delta + r_b)k_{t+1}^* + \frac{1}{1+r_b}\underline{n}_{t+1} \right), \\ \lim_{t \rightarrow +\infty} (1 + r_b)^{-t} \underline{n}_t &\leq 0, \end{aligned} \tag{26}$$

where $\mathbf{c}(n, z) \equiv n + \mathbf{b}(n, z)$ is the maximum investment capacity of a firm with net worth n , conditional on aggregate productivity being equal to z . The solution to the firm's problem takes one of three forms, corresponding to three regions for net worth:

- **If** $n_{i,t} < \mathbf{c}^{-1}(k_{t+1}^*; z_{t+1})$, the firm is constrained:

$$k_{i,t+1} = \mathbf{c}(n_{i,t}, z_{t+1}), \quad d_{i,t} = 0, \quad \frac{1}{1+r_b}b_{i,t+1} = \mathbf{b}(n_{i,t}, z_{t+1}), \quad \mathbf{V}_t(k_{i,t}, b_{i,t}) < \mathbf{V}_t^{(unc)}(k_{i,t}, b_{i,t}).$$

Investment is strictly smaller than the optimal unconstrained level: $k_{i,t+1} = \mathbf{c}(n_{i,t}, z_{t+1}) < k_{t+1}^*$. The marginal value of net worth is strictly above 1.

- **If** $n_{i,t} \in \left[\mathbf{c}^{-1}(k_{t+1}^*; z_{t+1}), -\left(\frac{1}{\zeta} - 1\right)(\delta + r_b)k_{t+1}^* + \frac{1}{1+r_b}\underline{n}_{t+1} \right]$, the firm is partially constrained; it invests at the currently optimal scale, but issues no dividends:

$$k_{i,t+1} = k_{t+1}^*, \quad d_{i,t} = 0, \quad \frac{1}{1+r_b}b_{i,t+1} = n_{i,t} - k_{t+1}^*, \quad \mathbf{V}_t(k_{i,t}, b_{i,t}) < \mathbf{V}_t^{(unc)}(k_{i,t}, b_{i,t}).$$

The marginal value of net worth is strictly above 1.

- **If** $n_{i,t} > \underline{n}_t$, the firm is fully unconstrained, can invest at the optimal scale today and at all future dates:

$$k_{i,t+1} = k_{t+1}^*, \quad d_{i,t} \geq 0, \quad \frac{1}{1+r_b} b_{i,t+1} \leq \mathbf{b}(n_{i,t}, x_t), \quad \mathbf{V}_t(k_{i,t}, b_{i,t}) = \mathbf{V}_t^{(unc)}(k_{i,t}, b_{i,t}).$$

The marginal value of net worth is equal to 1.

The lemma says that there are three possible regions for firms' policies: either firms are constrained, in that they issue no dividends, borrow as much as possible, and invest below the optimal level today; or, they are partially constrained, in that they issue no dividends, but invest at the optimal level today and borrow less (strictly) than the maximum possible; or, they are fully unconstrained. Firms move up across these three regions as their net worth increases.

In the constrained region, investment today is entirely constrained by the firms' investment capacity,

$$k_{i,t+1} = \mathbf{c}(n_{i,t}, z_{t+1}) = n_{i,t} + \mathbf{b}(n_{i,t}, z_{t+1}) < k_{t+1}^*.$$

So the responsiveness of these firms' investment to shocks depend on their effect on *current* net worth, and potentially future productivity. By contrast, in the partially constrained and unconstrained region, investment today depends only on fundamentals tomorrow $k_{i,t} = k_{i,t+1}^*$.

The partially constrained region need not exist. Namely, for it to exist, it needs to be the case that:

$$\mathbf{c}^{-1}(k_{t+1}^*; z_{t+1}) < -\left(\frac{1}{\zeta} - 1\right)(\delta + r_b)k_{t+1}^* + \frac{1}{1+r_b}n_{t+1}.$$

The right-hand side of this equation is the level of net worth necessary today in order to be able to implement the unconstrained optimal plan *starting tomorrow*; the left-hand side is the level of net worth necessary to implement the unconstrained optimal level of investment *today*. So, the partially constrained region only exists if the fundamentals process is such that firms will need high(er) levels of net worth in the future in order to implement the unconstrained plan. Most likely, that will be when fundamentals are low today relative to what they will be in the future.

It is immediate to see that there are no partially constrained firms in the stationary steady-state of the model. Additionally, one can rule out the possibility by imposing some restrictions on the aggregate process $\{z_t\}_{t \geq 0}$ and on the borrowing constraint $\mathbf{c}$.

Lemma 2. *Let:*

$$\forall t \geq 0, \quad g_t \equiv -\left(\frac{1}{\zeta} - 1\right) \frac{r_b + \delta}{1+r_b} \frac{k_{t+1}^*}{\mathbf{c}^{-1}(k_{t+1}^*, z_{t+1})} + \frac{1}{1+r_b} \frac{\mathbf{c}^{-1}(k_{t+2}^*, z_{t+2})}{\mathbf{c}^{-1}(k_{t+1}^*, z_{t+1})}. \quad (27)$$

Assume that $\{z_t\}_{t \geq 0}$ is increasing and bounded from above, and that $\{g_t\}_{t \geq 0}$ is strictly decreasing. Let:

$$T \equiv \min \{ \quad t \geq 0 \quad s.t. \quad g_t \leq 1 \quad \}.$$

Then the net worth threshold $\{\underline{n}_t\}_{t \geq 0}$ is given by:

$$\underline{n}_t = \begin{cases} -\left(\frac{1}{\zeta} - 1\right) \frac{r_b + \delta}{1 + r_b} k_{t+1}^* + \frac{1}{1 + r_b} \underline{n}_{t+1} & \text{if } t \leq T - 1, \\ \mathbf{c}^{-1}(k_{t+1}^*, z_{t+1}) & \text{if } t \geq T. \end{cases} \quad (28)$$

In particular, if $g_0 \leq 1$, then the unconstrained threshold is always given by:

$$\underline{n}_t = \mathbf{c}^{-1}(k_{t+1}^*, z_{t+1});$$

as a result, firms are never partially constrained.

This lemma essentially places a restriction on the fundamentals of the model that ensures that the unconstrained threshold $\underline{n}_t$ does not grow “too fast” in the wake of the shock. The calibration below (and the particular functional form for $\mathbf{c}$ chosen) satisfy the restriction provided by lemma 5. This ensures that firms are always completely constrained, or completely unconstrained, which simplifies the analysis of the model.

Borrowing constraint and sufficient conditions for greater sensitivity We assume that the borrowing constraint is given by:

$$\mathbf{b}(n_t, z_{t+1}) = \left(\frac{1}{\theta} \left(\frac{z_{t+1}}{z} \right)^\alpha - 1 \right) n_t, \quad \alpha \geq 0, \quad \theta \leq 1.$$

This parametrization captures some of the limit cases we are interested in. As $\theta \rightarrow 0$, the frictionless model obtains; when $\theta = 1$ and $\alpha = 0$, firms cannot borrow and the baseline model (with the addition of saving) obtains. Finally, the parameter α controls the sensitivity of the borrowing threshold to the aggregate shock, z_t ; when $\alpha = 0$, the borrowing constraint only depends on net worth, and not on the shock; when $\alpha \in [0, 1]$, the borrowing constraint is a concave function of the aggregate shock; and when $\alpha \in [1, +\infty]$, it is a convex function of the aggregate shock. Having a specific functional form will also allow us to plot impulse responses of the model.

Note that, given the functional form chosen for the borrowing constraint, the parameter α is irrelevant to the determination of the steady state. In what follows, we use:

$$\theta = 0.8,$$

implying a debt-to-asset ratio of about 0.2 in the version of the model with borrowing constraints that do not vary with productivity. This figure is consistent with the average net debt-to-asset ratio which we documented in the QFR data. We leave other parameters unchanged relative to the baseline model without borrowing.

The parameter α controls the ability for the model to generate greater sensitivity of sales and investment. To see this, first note that, following the same steps as in the model without borrowing, an approximation to the growth rate of constrained firms in the stationary steady-state of the model

is:

$$g_{cons} = \frac{1}{\theta} \left(1 - \delta + \frac{1}{\zeta}(r + \delta) \right).$$

The impact growth rate on impact, on the other hand, can be bounded from below by:

$$g_{cons}^{(0)} \geq \frac{1}{\theta} \exp(-\alpha\epsilon) \left(1 - \delta + \frac{1}{\zeta}(r + \delta) \exp(-\epsilon) \right)$$

Thus, the impact response of growth among constrained firms, relative to the long-run steady-state, is:

$$\Delta g_{cons} = -\frac{1}{\zeta}(r + \delta)\epsilon - \frac{1}{\theta}\alpha\epsilon \left(\frac{1}{\zeta}(r + \delta) + (1 - \delta) \right) + o(\epsilon).$$

The impact response of unconstrained firms is the same as in the previous model. Thus, greater sensitivity of small/constrained firms will obtain so long as:

$$\frac{\rho}{1 - \zeta} \leq \frac{1}{\zeta}(r + \delta) + \frac{1}{\theta}\alpha \left(\frac{1}{\zeta}(r + \delta) + (1 - \delta) \right),$$

and in particular, for sufficiently high values of α . In the reported impulse responses, we use $\alpha = 5$, which ensures that this condition holds.

H Triple Interaction Regressions

These regressions are meant to answer the following question: is the size effect weaker among groups of financially stronger firms? These regressions allow us to investigate if size effect meaningfully differs within group of financially strong or financially weak firms (see [Sharpe \(1994\)](#) for a similar analysis for Compustat firms investigating the relationship between financial frictions and employment). In order to measure financial strength, we use the same five ratios as in the horse-race regressions. We estimate a regression of the same form as (6), but where observations are effectively double sorted by their position in the firm size distribution and bins of a measure of financial strength. As in previous regressions, we also include industry fixed effects and interactions of industry effects and GDP growth.

Results are reported in Table 16. In this table, all estimates of the size effect are expressed relative to the bottom $[0, 90]$ group.⁶¹ The first column is the baseline regression without triple interaction - the same regression as in Table 4. The coefficient -0.60 , for instance, indicating that the sales elasticity to GDP of firms in the $[99.5, 100]$ group is 0.6 points lower than that of firms in the $[0, 90]$ group.

The second and third columns report similar elasticities when size and bank dependence categories are interacted. The estimates are organized by bank dependence groups; in order to keep the table readable, we have kept only two groups for bank dependence. Firm-year observations in the low bank-dependence group had a ratio of bank debt to total debt below 0.9 in the prior

⁶¹This is with the exception of regressions conditioning on bond market access where results are reported relative to the $[0, 99]$ group as there are too few observations with bond market access in the $[0, 90]$ group.

year, whereas firms in the high bank-dependence group had a ratio of bank debt to total debt over 0.9.⁶² The reported coefficients denote relative elasticities within each bank dependence group. The estimates suggest that among firms with low to moderate bank dependence, the size estimate has the same sign, and a similar magnitude as in the unconditional regressions. Among highly bank-dependent, the size effect is slightly *smaller*, although the high minus low difference (reported in the right column) is not statistically significant. Had the size effect been a reflection of financial constraints, one might have expected it to be much weaker among firms with access to other sources of financing than bank debt; instead, it is somewhat stronger.

The following columns repeat this exercise for other proxies for financial constraints.⁶³ While results differ across measures of financial constraints, it is worth noting that, with the exception of the last indicator — firms’ dividend issuance behavior — measures of the size effect are never statistically different across groups of financial strength proxies. Directionally, the estimates of the relative size effect for leverage and dividend issuance groups are consistent with the view that the size effect is weaker among financially stronger firms; on the other hand, estimates using liquidity and bond market access are not. Overall, the lack of significance in the cross-group differences in the size effect paired with its significance within group bolsters the view that the size effect may not be financially driven.

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

This appendix compares our results to those of [Gertler and Gilchrist \(1994\)](#). That paper studies the behavior of small and large firms around dates identified by [Romer and Romer \(1989\)](#) as exogenous contractions in monetary policy. In this appendix, we replicate their analysis on the QFR micro-data for the period 1977q3-2014q1. There are two important differences between our analysis and theirs: the methodology, and the sample period analyzed. We start by discussing these differences, and then provide a reconciliation of their results to ours.

I.1 The methodology of [Gertler and Gilchrist \(1994\)](#)

The analysis of [Gertler and Gilchrist \(1994\)](#) centers around computing the cumulative change in revenue of an “aggregate” small and “aggregate” large firm. Revenues of the “aggregate” small firm are defined as the total sales of the group of firms which, starting from the smallest (by assets), account for a cumulative 30% of total sales at any point in time. Conversely, the revenues of the “aggregate” large firms are the total sales of firms which, starting from the largest (by assets), account for a cumulative 70% of revenue. This methodology differs from our analysis in two main ways: first, it focuses on aggregate, not firm-level growth; second, it results in a different definition

⁶²In order to avoid creating non-overlapping groups, which would complicate disclosure of results, we are limited to using a grouping by financial strength indicators that is a coarser version of the grouping of Table 16.

⁶³For leverage, we split the sample above and below 0.5. For liquidity, we use a 0.01 cash to asset ratio as the threshold between low and high liquidity. These choices correspond approximately to the top quartile of the distribution of leverage and the bottom quartile of the distribution of the cash to asset ratio.

of the relative importance of small and large firms. For completeness, what follows is a formal description of the construction of these series.

Let x denote nominal assets, let $\{x^{(1)}, \dots, x^{(n)}\}$ denote the QFR’s nominal asset bins’ cutoffs, and let y denote nominal sales. For each quarter t , define $\underline{x}_t$ by:

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

Furthermore, let $\underline{x}_t^+$ be the cutoff immediately above $\underline{x}_t$ in the list $\{x^{(1)}, \dots, x^{(n)}\}$. 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.

I.2 The choice of dates

The analysis of [Gertler and Gilchrist \(1994\)](#) also differs from ours in that it focuses on specific dates around which monetary policy changes stance. The outcome measured is then the average cumulative change in the revenue of the “aggregate” small and large firm defined above, across these dates. There are six such “Romer” dates in their analysis; only three directly overlap with our sample: 1978q3, 1979q4 and 1988q4. The recent analysis of [Kudlyak and Sanchez \(2017\)](#) has proposed adding two other dates to this list: 1994q2 and the credit crunch of 2008q3. In our comparison, we will therefore repeat their analysis on the 3 dates which directly overlap, and then on the set of 5 “Romer” dates used by [Kudlyak and Sanchez \(2017\)](#).

I.3 Replication and comparison

Figure [17](#) replicates the Gertler-Gilchrist analysis on the overlapping portion of our sample: 1977q3 to 1990q4. The lines reported in each panel are averages over the three Romer-Romer dates of 1978q3, 1979q4 and 1988q4. The top left panel plots the path of sales when small and large firms are defined as we do in the main text: using percentiles of the lagged distribution of assets, and reporting equal-weighted (as opposed to value-weighted) growth rates. The cumulative change in sales is between -13.8% for small firms and -6.3% for large firms under this methodology. The second panel repeats this exercise, but moving from equal- to value-weighted growth rates. Results

are very similar, consistent with the evidence, in section 5, that the covariance term which connects equal- and value-weighted growth rates does not have a strong cyclical component. The black line in this graph is the cumulative change in total sales in the sample over these dates. The cumulative aggregate sales decline for sales overall is -8.8%, versus -6.2% for large firms. Thus, small firms substantially “amplify” the response of aggregate sales (by 42%, or $\frac{8.8-6.2}{6.2}$). Finally, the third panel exactly replicates the methodology of [Gertler and Gilchrist \(1994\)](#), in particular using the aggregated micro-data in the same format as original published by the QFR. It finds substantially the same differential response as the left and middle panels. Thus, for this sample period, the results are quantitatively and qualitatively consistent across methodologies, and lead to the conclusion that small firms “amplify” the response of aggregate sales by about 40%.

Figure 18 next replicates the Gertler-Gilchrist analysis on the 1977q3-2014q3 sample. The lines reported in each panel are averages over the fixe Romer-Romer dates of 1978q3, 1979q4, 1988q4, 1994q2 and 2008q3, as updated by [Kudlyak and Sanchez \(2017\)](#). The top left panel, which reports the cumulative change in sales using the same methodology as we do in the main text, leads to a sales decline of -9.2% for small firms and -5.6% for large firms. The second panel, using value-weighted growth rates, shows an aggregate decline of -5.9% for large firms, -9.7% for small firms, and -7.2% overall. The black line in this graph is the cumulative change in total sales in the sample over these dates. The last panel, using the methodology of [Gertler and Gilchrist \(1994\)](#), finds approximately the same results. The three methodologies therefore again deliver the same results. However, small firms (under all three methods) are now responsible for a smaller amount of amplification: 22% ($= \frac{7.2-5.9}{5.9}$) instead of 42%.

This discussion suggests that most of the difference between our conclusions and the conclusions of [Gertler and Gilchrist \(1994\)](#) primarily stems not from methodological distinctions, but from differences in the periods which we study. Their focus on specific dates differs from our approach of measuring an average difference in business-cycle (or monetary shock) sensitivity. In particular, the Volcker recessions lead to a particularly sharp greater response of small firms, which likely dominates the original findings of [Gertler and Gilchrist \(1994\)](#). Most importantly, the tendency for small firms to respond more to monetary policy tightenings may have declined over the second half of the sample, as also argued by [Kudlyak and Sanchez \(2017\)](#). This difference in the response to monetary shock across periods may reflect either changes in the conduct of monetary policy, or changes in the transmission of these shocks to small firms.

J Non-size evidence of a financial accelerator

In this section, we document 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 19 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. This plot is constructed using the same event study methodology as in section 5.2. 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 19 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. Results based on leverage sorts would appear to be inconsistent with a financial accelerator mechanism. 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 20 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 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 issued dividends during the prior year also reduce inventories and investment more gradually than firms that did not.

BEA subsector	Name	Share of manufacturing nominal value added (2001)	Share of manufacturing nominal gross output (2001)	Correlation between value added growth and gross output growth (1977-2014)	
				Nominal	Real
336MO	Transportation Equipment	0.137	0.119	0.849	0.335
3250	Chemical Products	0.131	0.116	0.381	0.636
311A	Food and Beverage and Tobacco Products	0.119	0.150	-0.151	0.360
3340	Computer and Electronic Products	0.117	0.117	0.817	0.823
3320	Fabricated Metal Products	0.075	0.066	0.875	0.896
3330	Machinery	0.072	0.069	0.893	0.892
3240	Petroleum and Coal Products	0.047	0.056	0.474	0.059
3260	Plastics and Rubber Products	0.043	0.044	0.531	0.730
338A	Miscellaneous Manufacturing	0.039	0.030	0.496	0.367
3220	Paper Products	0.036	0.041	0.623	0.389
3350	Electrical Equipment, Appliances, and Components	0.030	0.029	0.540	0.527
3230	Printing and Related Support Activities	0.029	0.027	0.864	0.699
3270	Nonmetallic Mineral Products	0.028	0.024	0.743	0.723
3310	Primary Metal Products	0.027	0.036	0.905	0.430
3370	Furniture and Related Products	0.021	0.019	0.864	0.002
3210	Wood Products	0.019	0.023	0.843	0.597
313T	Textile Mills and Textile Product Mills	0.017	0.020	0.665	0.691
315A	Apparel and Leather and Applied Products	0.013	0.015	0.551	0.446

Table 9: Correlation between gross output and value added at the BEA sub-sector level. The data are from the BEA's GDP by industry tables, specifically: https://www.bea.gov/sites/default/files/2018-04/GDPbyInd_G0_1947-2017.xlsx for gross output and https://www.bea.gov/sites/default/files/2018-04/GDPbyInd_VA_1947-2017.xlsx for value added. The data are annual from 1977 to 2014.

Outcome variable: sales growth (log)				
Compustat quarterly, manufacturing, 1977q4-2014q1				
	(1)	(2)	(3)	(4)
25-50% $\times$ GDP growth	-0.22 (0.430)	-0.21 (0.449)	-0.13 (0.670)	-0.33 (0.340)
50-75% $\times$ GDP growth	-0.12 (0.657)	-0.12 (0.671)	0.02 (0.951)	-0.02 (0.958)
75-100% $\times$ GDP growth	-0.28 (0.248)	-0.31 (0.219)	-0.25 (0.367)	-0.36 (0.255)
Observations	238421	231184	196667	169069
Firms	6079	5917	4993	4351
Deflator type	Output	Output	Output	Output
Deflator level	BEA subsectors	BEA subsectors	BEA subsectors	BEA subsectors
Industry $\times$ GDP growth control	No	No	No	No
Industry-quarter effects	Yes	Yes	Yes	Yes

Table 10: The size effect in quarterly Compustat, including and excluding sub-sectors in which total sales and total gross output have a low correlation. All specifications include industry-quarter fixed effects. Specification (1) is identical to specification (4) in column table 5, and includes all subsectors. Specifications (2), (3) and (4) exclude, respectively, the 2, 5 and 8 BEA subsectors with the lowest correlation between real output growth and real value added growth; see table 9 for details on those sectors. Standard errors are clustered at the firm level in all specifications.

	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
$\frac{\sigma_{\hat{c}ov_t}}{\sigma_{G_t}}$	0.54	0.45	0.41
$corr(\hat{c}ov_t, Y_t)$	-0.32	-0.05	-0.15

Table 11: Decomposition of the correlation of aggregate sales growth with GDP growth. The decomposition used is $corr(G_t, Y_t) = \frac{\sigma_{\hat{g}_t}}{\sigma_{G_t}} corr(\hat{g}_t, Y_t) + \frac{\sigma_{\hat{c}ov_t}}{\sigma_{G_t}} corr(\hat{c}ov_t, Y_t)$, where Y_t is year-on-year GDP growth, G_t is year-on-year growth in total sales, $\hat{g}_t$ is year-on-year average firm-level growth, and $\hat{c}ov_t$ is a term capturing the covariance between initial size and subsequent growth. The results are reported for all firms (first column), small firms (second column) and large firms (third column). See section D for more details on the decomposition.

	Size group			
	(1)	(2)	(3)	(4)
Assets (2009 m\$)				
QFR	2.0	48.8	626.0	6766.3
Compustat (annual)	22.6	94.4	375.7	7348.9
Compustat (quarterly)	23.6	102.3	409.6	7989.8
Investment rate				
QFR	26.50%	24.91%	21.89%	20.36%
Compustat (annual)	30.93%	32.00%	27.94%	21.87%
Compustat (quarterly)	28.83%	31.89%	28.90%	22.69%

Table 12: Summary statistics for the QFR sample and the two Compustat samples. Each column corresponds to a different size group. For QFR data, size groups are defined as in the main text. For Compustat (annual and quarterly), size groups are quartiles of the distribution of book assets (variable `at` in the annual files and `atq` in the quarterly files). Assets are nominal book values deflated by the BEA price deflator for manufacturing value added, as in the main text. See appendix E for details on the construction of the annual and quarterly Compustat samples and the computation of investment rates.

	QFR	Compustat (annual)	Compustat (quarterly)
GDP growth	0.912*** (0.258)	1.082*** (0.306)	0.537*** (0.174)
Size group 2 $\times$ GDP growth	-0.299* (0.157)	-0.235 (0.197)	-0.103 (0.223)
Size group 3 $\times$ GDP growth	-0.687*** (0.194)	-0.329* (0.189)	-0.250 (0.216)
Size group 4 $\times$ GDP growth	-1.257*** (0.355)	-0.921*** (0.260)	-0.572*** (0.199)
N	≈ 460000	72363	186784
nr. firms	≈ 60000	6550	5944
adj. R^2	0.003	0.022	0.017
industry controls	yes	yes	yes
s.e. clustering	firm-level	firm-level	firm-level

Table 13: Investment cyclicality by size in the QFR data (first column) and for the annual and quarterly Compustat samples (second and third columns. The baseline coefficient (first line) refers to firms in the durable sector. All values are deflated by the quarterly manufacturing price index. *, ** and *** indicate 10%, 5% and 1% significance levels, respectively with standard errors reported in parentheses.

	Small firms	Large firms	All firms
$corr(\tilde{G}_t, Y_t)$	0.68	0.61	0.65
$\frac{\sigma_{\hat{g}_t}}{\sigma_{\tilde{G}_t}}$	0.97	0.81	0.86
$corr(\hat{g}_t, Y_t)$	0.84	0.77	0.80
$\frac{\sigma_{cov_t}}{\sigma_{\tilde{G}_t}}$	0.51	0.45	0.41
$corr(\hat{cov}_t, Y_t)$	-0.26	-0.04	-0.10

Table 14: Decomposition of the correlations of aggregate sales growth among all firms, small firms, and large firms, to GDP growth, constructed using DHS growth rates. See section F for details on the decomposition.

	Actual	Counterfactual 1	Counterfactual 2
	β	$\beta^{(1)}$	$\beta^{(2)}$
Sales	2.285 (0.339)	2.174 (0.339)	2.263 (0.362)
Inventory	0.918 (0.225)	0.758 (0.250)	0.768 (0.226)
Fixed investment	0.583 (0.145)	0.576 (0.151)	0.567 (0.148)
Total assets	0.876 (0.121)	0.791 (0.129)	0.857 (0.745)
Observations	143	143	143

Table 15: Cyclical sensitivities of aggregate sales, inventory, fixed investment, and total assets using DHS growth rates. Each line reports the estimated slope in regressions of the form $Z_t = \alpha + \beta \log \left(\frac{GDP_t}{GDP_{t-4}} \right) + \epsilon_t$. The first column reports results for $Z_t = G_t$, where G_t is the actual aggregate growth rate. The second column uses $Z_t = G_t^{(1)}$, where $G_t^{(1)}$ is a counterfactual aggregate growth rate series in which we have assumed that the average firm-level growth rate of small and large firms is equal (so that small firms do not have greater average sensitivity to business cycles than large firms). The third column uses $Z_t = G_t^{(2)}$, where $G_t^{(2)}$ is another counterfactual time series in which we have also assumed that the covariance between initial size and subsequent growth is also the same between small and large firms. Heteroskedasticity robust standard errors in parentheses.

Panel A	Baseline	Bank dependence			Leverage			Liquidity		
		Low	High	Diff	Low	High	Diff	High	Low	Diff
$[90, 99] \times \text{GDP growth}$	-0.160	-0.094	-0.286	-0.192	-0.195	0.010	0.205	-0.257	0.179	0.436
$[99, 99.5] \times \text{GDP growth}$	-0.251*	-0.270	-0.184	0.085	-0.182	-0.570	-0.387	-0.384**	0.042	0.376
$[99.5, 100] \times \text{GDP growth}$	-0.600***	-0.616***	-0.429**	0.187	-0.530***	-0.974***	-0.444	-0.604***	-0.482*	0.122
N	≈ 460000	≈ 460000			≈ 460000			≈ 460000		
nr. firms	≈ 60000	≈ 60000			≈ 60000			≈ 60000		
adj. R^2	0.025	0.025			0.025			0.025		
industry controls	yes	yes			yes			yes		
s.e. clustering	firm-level	firm-level			firm-level			firm-level		

Panel B	Baseline	Bond market access			Dividend issuance		
		Yes	No	Diff	High	low	Diff
$[90, 99] \times \text{GDP growth}$	-0.160				-0.178	-0.146	0.032
$[99, 99.5] \times \text{GDP growth}$	-0.251*	-2.907	-0.421***	2.486	-0.150	-0.385	-0.235
$[99.5, 100] \times \text{GDP growth}$	-0.600***	-3.568*	-0.832***	2.736	-0.395**	-0.758*	-0.363**
N	≈ 460000	≈ 460000			≈ 460000		
nr. firms	≈ 60000	≈ 60000			≈ 60000		
adj. R^2	0.025	0.025			0.025		
industry controls	yes	yes			yes		
s.e. clustering	firm-level	firm-level			firm-level		

Table 16: Triple-interaction regressions. The dependent variable is sales growth. The columns marked baseline, bank dependence, leverage, liquidity, bond market access, and dividend issuance each correspond to one regression. For each financial indicator, coefficients are reported by sub-groups corresponding to firms which are less likely to be financially constrained (left column) and firms which are more likely to be financially constrained (middle column). The coefficients shown are differences in elasticities to GDP growth relative to the $[0, 90]$ size group *within each sub-group*. That is, the coefficient -0.616 in the right column of the bank dependence regression indicates that *within* firms with low bank dependence, the top 0.5% of firms has an elasticity of sales growth -0.616 points smaller than the $[0, 90]$ group. The last column, denoted Diff, reports the difference across groups of the size effect, as well as its significance level. The Bond market access regressions only compare the $[0, 99]$ group to others in order to avoid violating disclosure limits as there are too few observations with a bond issuance history in the $[0, 90]$ size group. Table describes the groups of financial constraints in more detail. Standard errors clustered at the firm level. *, ** and *** indicate 10%, 5% and 1% significance levels.

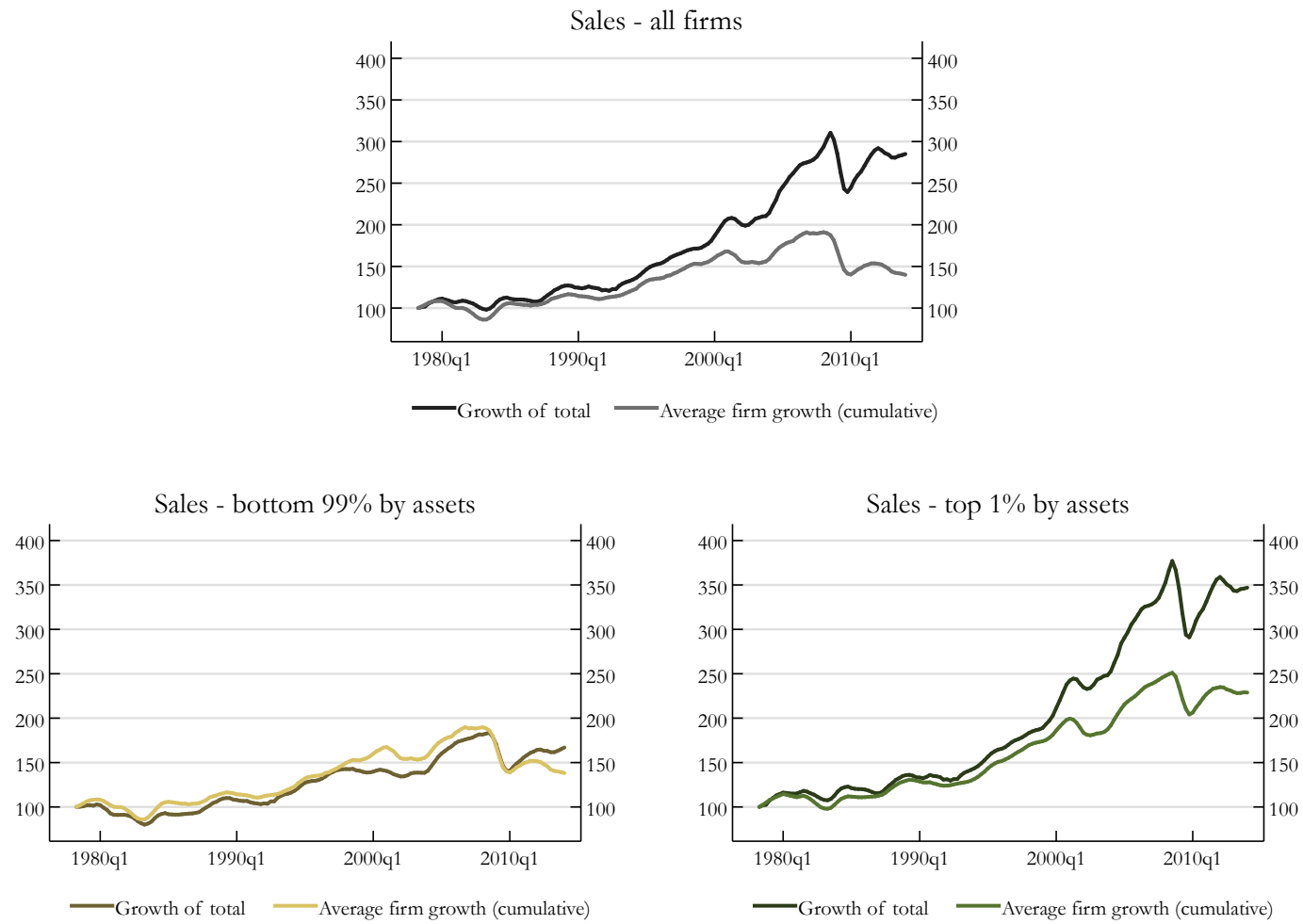


Figure 14: Aggregate sales and average within-firm cumulative growth rate of sales. Each panel reports total annual sales normalized to 100 at the beginning of the sample, and the cumulative firm-level average growth rate of sales, for a different group of firms, also normalized to 100 at the beginning of the sample.

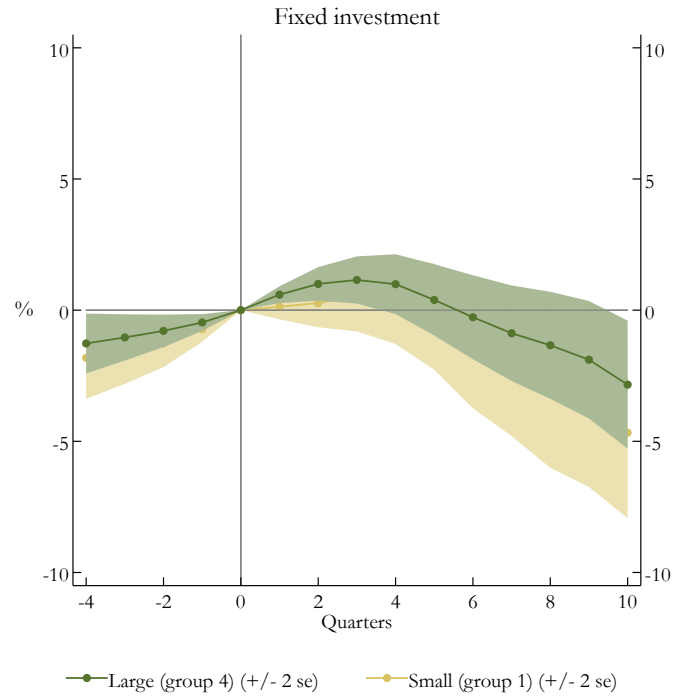


Figure 15: The behavior of fixed investment after the start of a recession in the quarterly Compustat sample. The graph reports the cumulative investment rate relative to the beginning of the recession; see section 5.2 for details on the estimation. Shaded areas are ± 2 standard error bands. See appendix A for details on the definition of size groups. Recession start dates are 1981q3, 1990q3, 2001q1, and 2007q4.

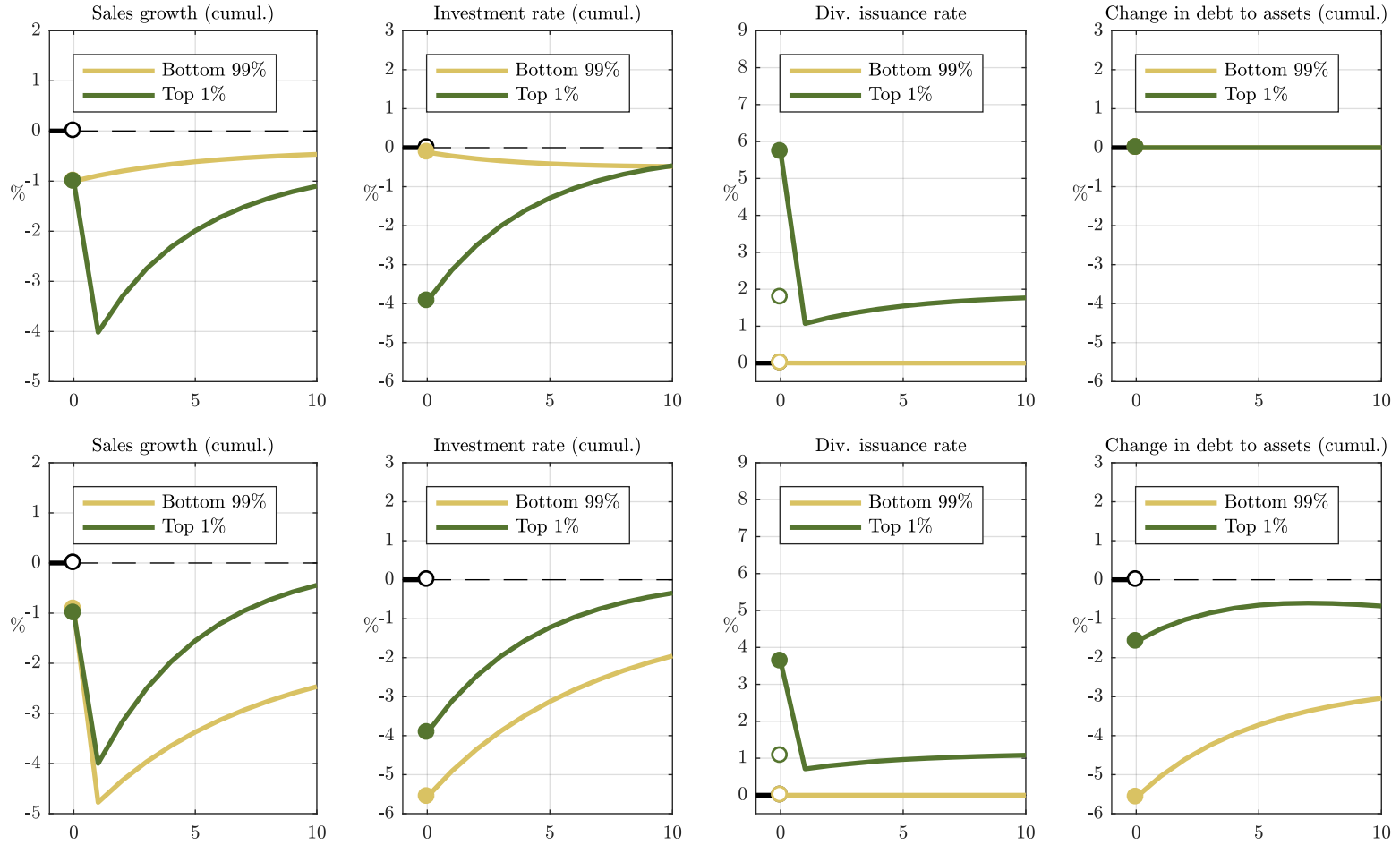


Figure 16: Impulse responses to an aggregate shock in the models of section 5.2. The green lines correspond to firms in the top 1% of the one-quarter lagged distribution of book assets, and the yellow lines correspond to firms in the bottom 99%; book assets in the model are defined as $k_{i,t}$. The top row reports impulse responses in the model with no external financing. The bottom row show the impulse responses in the model with borrowing.

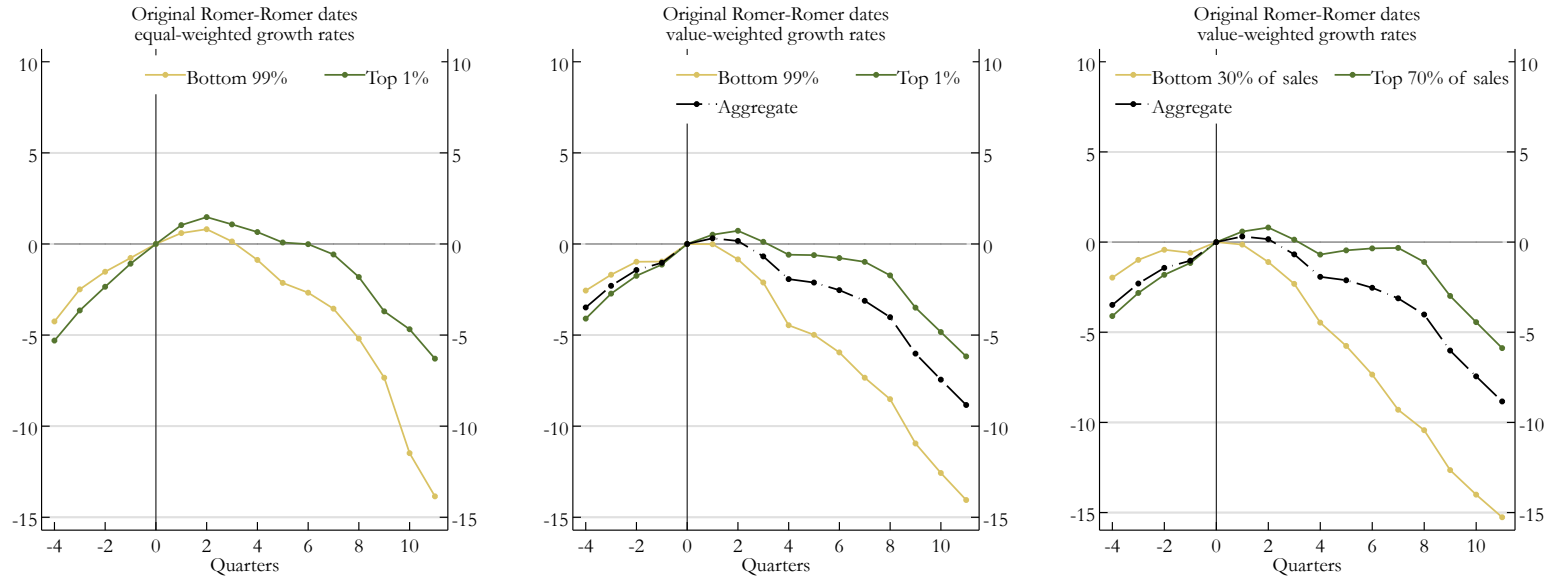


Figure 17: Cumulative change of sales around the three original Romer dates of 1978q3, 1979q4 and 1988q4, using different methodologies. The top left panel uses the equal-weighted growth rates and the (0,99)/(99,100) size classification from the main text. The middle panel uses value-weighted growth rates and the same size classification. The right panel uses the size classification and growth rate construction of [Gertler and Gilchrist \(1994\)](#), as described in appendix I. We use data from 1977q3 to 1990q4, the overlapping portion of our and [Gertler and Gilchrist \(1994\)](#)'s sample. All time-series are de-meaned.

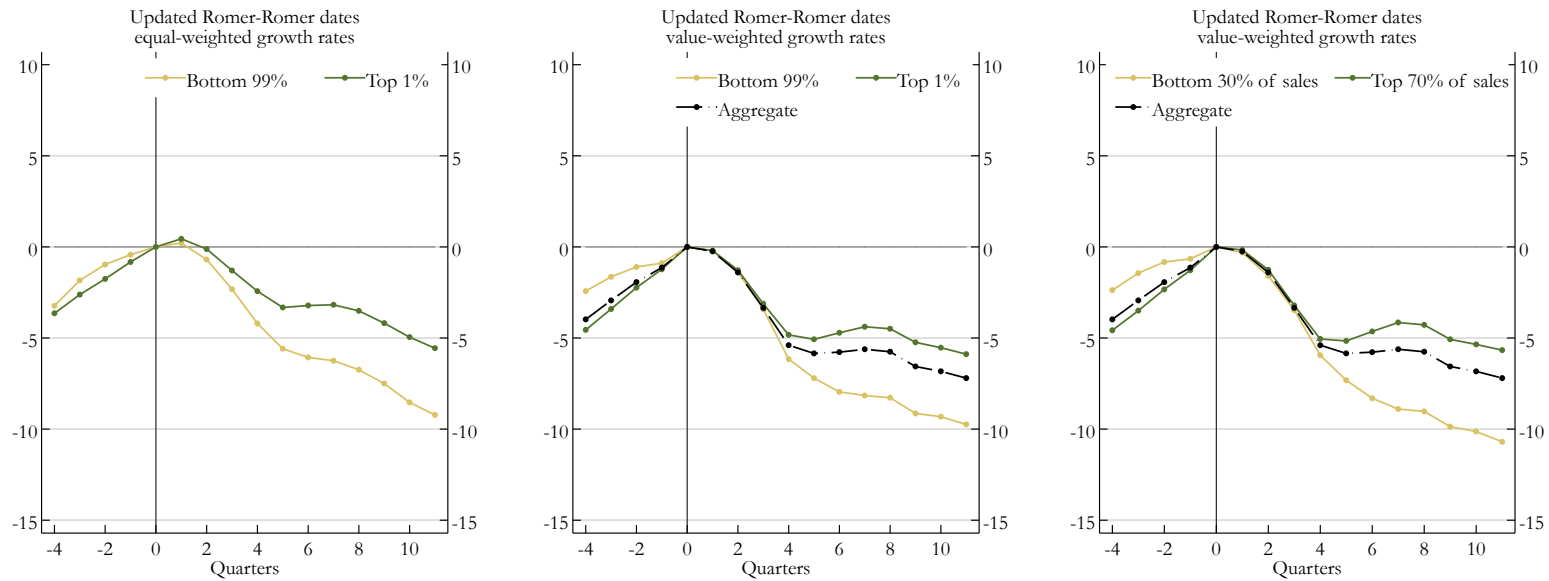


Figure 18: Cumulative change of sales around the five updated Romer dates of 1978q3, 1979q4, 1988q4, 1994q2 and 2008q3, using different methodologies. The top left panel uses the equal-weighted growth rates and the (0,99)/(99,100) size classification from the main text. The middle panel uses value-weighted growth rates and the same size classification. The right panel uses the size classification and growth rate construction of [Gertler and Gilchrist \(1994\)](#), as described in appendix I. We use data from 1977q3 to 2014q1. All time-series are de-meant.

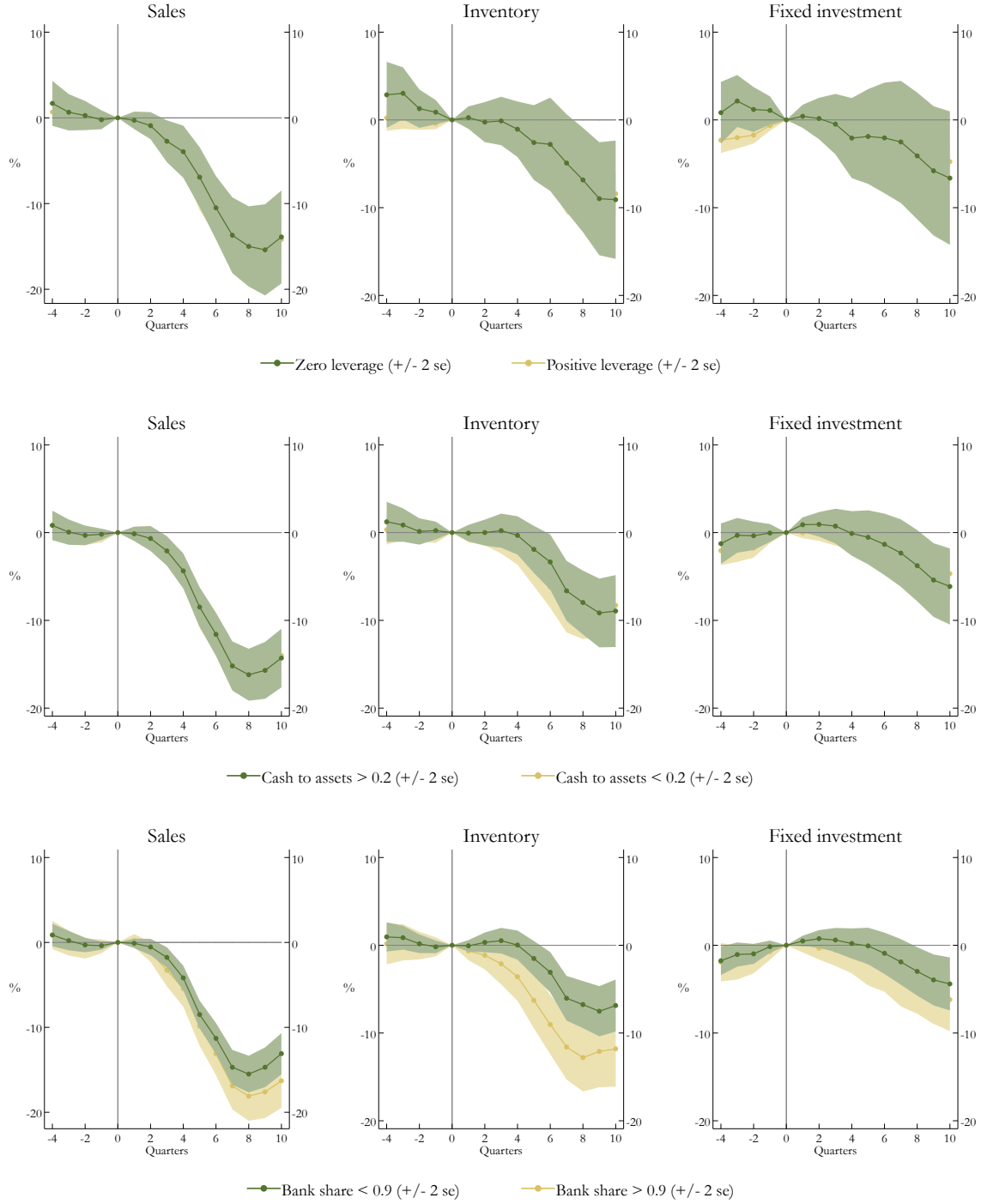


Figure 19: Sales, inventory and fixed capital after the start of a recession, across firms sorted by leverage, liquidity and bank dependence. Each graph reports the cumulative change in a variable of interest after the beginning of a recession; see section 5.2 for details on the estimation. Shaded areas 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.

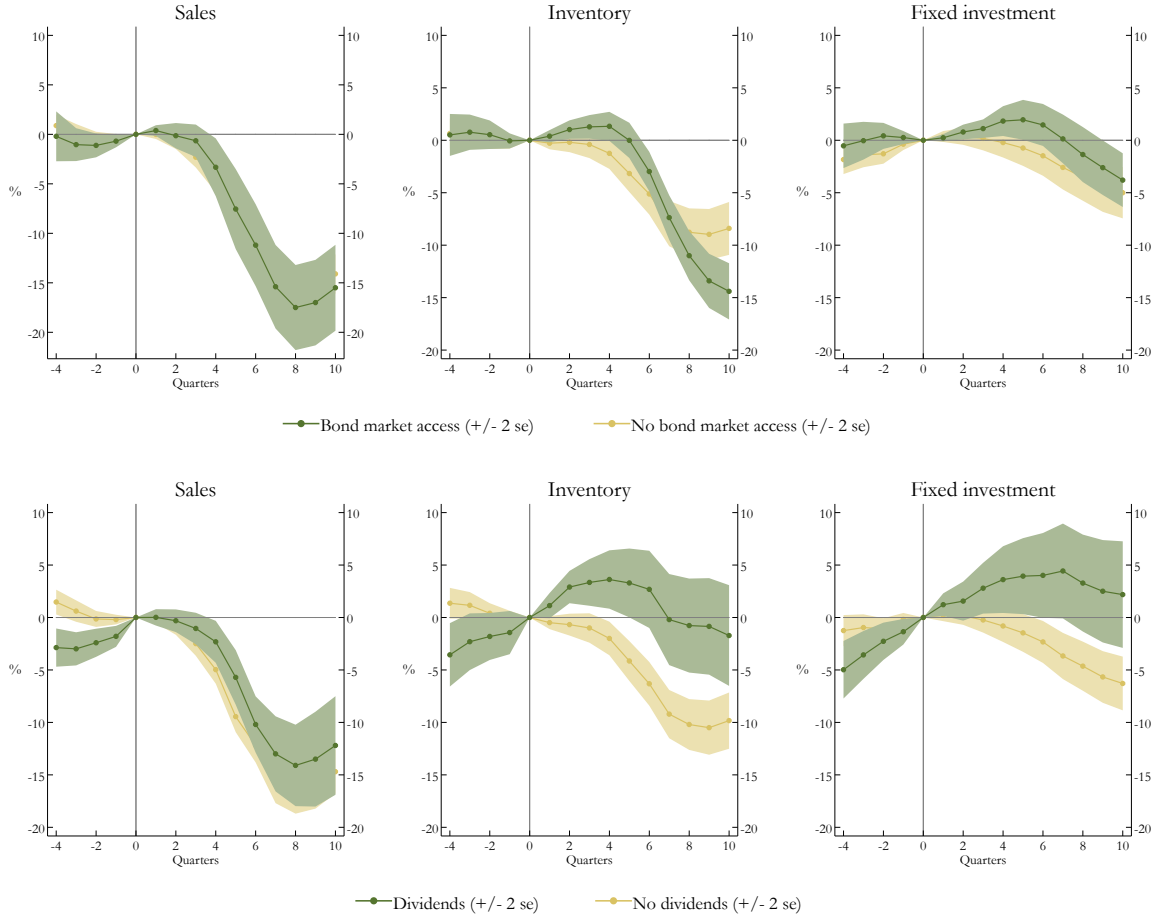


Figure 20: Sales, inventory and fixed capital after the start of a recession, across firms sorted by market access and dividend issuance. Each graph reports the cumulative change in a variable of interest after the beginning of a recession; see section 5.2 for details on the estimation. Shaded areas 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.