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, cyclicality, 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 cyclicality of the bottom 99% of firms only has a modest impact on aggregate fluctuations. Third, differences in cyclicality are not simply explained by financing, and in fact appear largely unrelated to proxies for financial strength. We instead provide evidence for an alternative mechanism based on the industry scope of the very largest firms.

Establishment-level evidence instead suggests that firms operating across multiple industries account for the size effect.

Keywords: Firm size, business cycles, financial accelerator.

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1 Introduction

An important line of research in macroeconomics and corporate finance documents 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.[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 sensitivity of firms to the business cycle.

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 matched that of large firms? Third, is this greater sensitivity a manifestation of differences in access to financing?

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. The QFR uniquely provides balance-sheet and income-statement data for smaller, private firms over a long period; a priori, this is a set of firms that one expects to be most financially constrained. We use QFR micro records to assemble a representative, quarterly panel of US manufacturing firms from 1977 to 2014. The resulting dataset is made up of approximately 1.1 million observations on 90000 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, 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. In contrast to the public releases of the QFR, the microdata allows us to accurately measure the magnitude of differences in cyclicality by firms size and to introduce firm level controls to determine the financial or non-financial factors that drive the size effect. As we detail in the paper, the existing literature that relies on the public releases has disagreed on the former and cannot address the latter.[2] Finally, the firm level data allows us to determine whether any average differences across firm size are statistically significant.

Using the QFR microdata, we find evidence of greater cyclical sensitivity among small firms. On average over the sample, the difference between sales growth of the bottom 99% of firms and

[1] The 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, and which we discuss in Section 2.

[2] Estimates of the higher cyclicality of small firms range from small firms being approximately twice as responsive to monetary shocks than large firms (Gertler and Gilchrist, 1994), to being equally responsive to recessions (Chari, Christiano and Kehoe, 2013; Kudlyak and Sanchez, 2017), to being significantly *less* responsive (Moscarini and Postel-Vinay, 2012).

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. We adopt this stark notion of small and large in large measure because of the absence of measurable differences within the bottom 99%.

The size effect is concentrated at the very top of the distribution — the top 0.5% of firms; variation in elasticity of sales 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 cyclicality 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 such a wide range of firm size.

The greater sensitivity we uncover for sales growth at small firms also holds for inventory growth and investment rates. As with sales growth, this differential is concentrated at the top 0.5% of the asset distribution. Additionally, we show that these results survive a large battery of robustness tests and that they also hold in the retail and wholesale trade portions of the QFR sample. Finally, we compare our results to prior work on difference in cyclicality across size groups, in particular, we show how growth rates derived from the microdata deliver consistent and stable estimates of the size effect, improving on the previous literature.

We find that the greater sensitivity of the bottom 99% of firms, although statistically significant, is 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 cyclical sensitivities are the same in the cross-section and plot these counterfactuals against realized aggregate sales growth. The difference (seen in Figure 5) is negligible. This finding is due to combination of extreme skewness of the distribution of sales and investment in the cross-section and absence of sizable differences in cyclicality. 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.[3]

Our findings verifying the greater cyclicality of small firms beg the question of whether these differences in cyclicality are driven by a financial accelerator mechanism. Gertler and Gilchrist (1994) argued that size serves as a proxy for the degree of financial constraints given that small firms exhibit greater bank dependence, cannot issue debt publicly, and face greater 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

[3]This rise in concentration mirrors the findings of Autor et al. (2017), though we find that rising sales concentration in manufacturing comes in two waves (the early 1980s and late 1990s). Our findings with respect to skewness also echo Gabaix (2011), but we nevertheless find that cyclical fluctuations at the "median" firm (which is too small to affect aggregates) correlates strongly with aggregate fluctuations.

[4]However, importantly, these average differences in capital structure *across* size groups is dwarfed by heterogeneity in capital structure *within* each size group.

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 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 find that none of these controls eliminates the size effect; additionally, the quantitative magnitude of the size differential is almost unchanged. 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 an indication that the size effect may not due to financial frictions.

Second, to address the possibility that size is simply a better proxy for financing constraints than other balance sheet variables, we examine whether firm leverage behaves differently for small and large firms. A typical prediction of financial accelerator mechanisms is that the supply of credit to financially constrained firms should be more cyclically sensitive. Thus, external financial flows (in particular, net debt flows) should show a higher responsiveness to aggregate conditions among financially constrained firms.[5] We test this prediction using a simple event study framework around the recession dates in our sample. We find a statistically significant difference in the response of sales and investment across size groups, but no such difference in the response of debt. Total debt, bank debt, and short-term debt all behave very similarly among small and large firms.

Third, we investigate 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 impact firms' cost of capital more directly. Using the method from Jordà (2005), 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 (2019) up to 2007). Results from this approach are qualitatively consistent with the findings of Gertler and Gilchrist (1994) with small firms more responsive to the shock, but lack statistical significance for most dependent variables with the 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 differential responsiveness to monetary policy shocks provides strong support in favor of the view that the size effect reflects financial constraints.

Given the absence of compelling evidence in favor of financial amplification, we also search for non-financial explanations for the size effect. We merge the QFR with establishment-level data from Dun and Bradstreet and construct firm-level measures of industry scope of firms — the number of distinct industries in which a firm's establishments operate. Industry scope is correlated with size, but there remains substantial variation in industry scope among the largest firms. Crucially, when simultaneously controlling for size and industry scope, we find that differences in cyclicality by size disappear. This result is robust to adding other controls, including the total number of

[5] We illustrate this mechanism in a model in which firms differ by size and firm size is perfectly correlated with a binding financial constraint; the model is described and analyzed in Appendix A.

establishments belonging to a firm and they hold both in the manufacturing and trade samples. We consider a simple model in which firms can make their demand less elastic by investing in customer capital and enjoy economies of scope in making this investment across multiple industries. Our model makes multi-industry firms larger in equilibrium and less sensitive to aggregate fluctuations, providing a parsimonious, non-financial mechanism that accounts for our empirical findings.

The remainder of the paper is organized as follows. Section 2 discusses how our evidence informs theories of the financial transmission of aggregate shocks and provides some caveats for our findings. Section 3 details the construction of the QFR dataset and provides summary statistics for small and large firms. Section 4 provides time series and regression evidence on the response of small and large firms over the business cycle and in recessions. Section 5 analyzes the aggregate implications of size asymmetries between small and large firms. Section 6 presents findings on whether the size differences we document are evidence of a financial accelerator, including the effect of identified monetary policy shocks. Section 7 proposes a non-financial explanation for the size effect and presents supporting empirical evidence. Section 8 concludes.

2 Contribution and caveats

Why is the evidence in this paper useful? This paper tests two propositions: (1) small firms are more cyclically sensitive than large firms; (b) this difference is due to financial frictions. Our contribution is to show that while there is evidence of the former, our data shows very little evidence of the latter. Why are these findings are meaningful, and how do they inform theories of financial transmission of shocks to firms?

The two propositions that we test were the focus of an early empirical literature on the financial accelerator. The seminal theoretical contributions of Bernanke and Gertler (1989) and Bernanke, Gertler and Gilchrist (1999) show how aggregate shocks can be amplified by procyclical movements in credit supply. This insight led to an extensive literature seeking evidence of this mechanism. Though their models did not, strictly speaking, feature firm heterogeneity, the early empirical literature chose to focus on cross-sectional tests following a "difference-in-difference" intuition that, if the financial accelerator is operative, then financially constrained firms should be more responsive to aggregate shocks.[6] The form of cross-sectional heterogeneity that this literature explored was often size, as it was generally accepted as providing a good proxy for the degree of financial frictions.[7] The most influential contribution in this literature is Gertler and Gilchrist (1994), who show that sales and investment of small firms respond more to monetary policy shocks, but other early influential examples include Sharpe (1994) (employment cyclicality by size), Gilchrist and Himmelberg (1995) (cash flow shocks by size), and Oliner and Rudebusch (1996) (response of financing to

[6] Summarizing the theory, Bernanke, Gertler and Gilchrist (1996) write, "[A]t the onset of a recession, borrowers facing high agency costs should receive a relatively lower share of credit extended (the flight to quality) and hence should account for a proportionally greater part of the decline in economic activity."

[7] For instance, Gertler and Gilchrist (1994) argue, "While size per se may not be a direct determinant, it is strongly correlated with the primitive factors that do matter . . . [s]maller firms rely heavily on intermediary credit while large firms make far greater use of direct credit, including equity, public debt, and commercial paper."

monetary policy shocks by size).

Since then, another literature in macroeconomics and corporate finance has developed and analyzed models with heterogeneous firms and financial frictions which can be more closely compared to the cross-sectional evidence described above.[8] Our evidence can be useful in evaluating models that deliver the joint prediction that size is correlated with the severity of financial frictions and that more constrained firms are more cyclically sensitive.[9]

To be clear, as we show in Appendix A, financial amplification at small firms is not a robust prediction of all heterogenous firm models with financial constraints. What features must a heterogenous firm model have to deliver amplification at small firms? Details depend on the particular model, but we argue that models where ex-ante heterogeneity is generated by net worth and financing constraints are strongly procyclical will generate financial amplification at small firms.[10] Our evidence therefore rejects models where heterogeneity is driven by net worth or financing constraints are strongly procyclical.

Aside from the theoretical literature, our evidence also highlights the pitfalls of using differential responses by firm size as a way to diagnose the presence of a financial amplification channel in empirical work. Aside from the early literature cited above, more recent work on credit shocks in the Great Recession, for example by Mian and Sufi (2014) and Chodorow-Reich (2014), uses the absence or presence of differences across firm size as tests for a financial amplification channel.[11] Recent empirical work by Chaney, Sraer and Thesmar (2012), Siemer (2019), Duygan-Bump, Levkov and Montoriol-Garriga (2015), and Zwick and Mahon (2017) are also representative of how differential responses to shocks across firm size are used as evidence for financial amplification.

Our evidence also challenges the conventional wisdom on two other issues: the contribution of small firms to cyclical fluctuations and the view that financial amplification should be most prominent among privately traded firms.

[8] A non-exhaustive list of important contributions includes Whited (1992), Cooley and Quadrini (2001), Gomes (2001), Hennessy and Whited (2005), Cooley and Quadrini (2006), Hennessy and Whited (2007), Khan and Thomas (2013), Moll (2014), Buera and Moll (2015), Gopinath et al. (2017), Ottonello and Winberry (2017), Buera and Karmakar (2017), Zetlin-Jones and Shourideh (2017), Begenau and Salomao (2018), and Mehrotra and Sergeyev (2019).

[9] Examples of macro models that generate the joint prediction we test include Cooley and Quadrini (2006), Khan and Thomas (2013), Buera, Fattal Jaef and Shin (2015) and Mehrotra and Sergeyev (2019). These models show that financial shocks elicit a stronger response of employment at small firms relative to large firms. In the corporate finance literature, Hennessy and Whited (2007) estimate stronger financial frictions in small relative to large firms while Begenau and Salomao (2018) examine the cyclicality of equity and debt payouts by firm size in a model where small firms are more likely to be constrained.

[10] Persistent differences in productivity may mean large firms are constrained while small firms are not (Cooley and Quadrini, 2001; Mehrotra and Sergeyev, 2019). The slope of the credit supply curve and its responsive to aggregate shocks is also key; constrained firms that operate on a more inelastic portion of their credit supply curve may actually respond less to shocks (Ottonello and Winberry, 2017; Buera and Karmakar, 2017).

[11] Specifically, Mian and Sufi (2014) argue that the channel through which housing net worth lowers employment is through demand rather than tightening credit supply, using size to rule out this possibility: "If our main result were driven by credit supply tightening, then we would expect the result to be stronger among smaller establishments that are more likely to be credit-constrained." Chodorow-Reich (2014) relies primarily on banking relationships with Lehman to identify financially constrained firms but uses the differential sensitivity by size as further validation for the credit supply effects of the Lehman bankruptcy: "The finding of differential effects at large and small firms can serve as a specification check for the validity of the research design."

The empirical literature on the financial accelerator made the case that the cross-sectional effects it finds contribute meaningfully to aggregate fluctuations. Fazzari, Hubbard and Petersen (1988) argue that "financing constraints could account for a large proportion of the aggregate variability of investment". Kashyap, Lamont and Stein (1994) argued in a similar vein about the effect of financial constraints on inventory investment in the 1981-82 recession. Gertler and Gilchrist (1994) argue that small firms account for up to 60% of the total response of sales to monetary policy shocks (a finding we discuss in more detail in Section 4.4.2). More recently, Cloyne et al. (2018) argue that, in US data, the response of young firms makes up two-thirds of the total firm investment response of publicly traded firms to monetary policy shocks. Dinlersoz et al. (2018) argues that private, leveraged firms (likely to be smaller firms) contribute substantially to the decline in sales in the Great Recession.

Unlike studies that rely on public firm datasets like Compustat, the QFR allows for inferences about the role of small firms in aggregate fluctuations. Our results indicate that the higher cyclicality of small firms, while present, is generally not sufficient large to meaningfully amplify aggregate fluctuations. It is important to note that this is *not* a foregone conclusion; it depends both on the fact that small firms contribute a small and declining share to aggregates and *and* their cyclicality to be fairly close, in absolute terms, to that of large firms.

The view that financial accelerator effects would be most prominent in data set of nontraded, nonpublic firms has been articulated repeatedly in the literature.[12] More recently, Kudlyak and Sanchez (2017) allude to the advantage of firm-level QFR data.[14] Much of this literature assumed that firm-level data on nonpublic firms would most strongly demonstrate the presence of a financial accelerator; we find that this is not the case.

What the evidence in this paper does not say Before proceeding, we provide some cautionary notes for interpreting our findings. The absence of a size effect does not (1) imply the absence of a correspondence between firm size and access to external financing; (2) imply the generalized absence of a financial accelerator mechanism; (3) contradict evidence on the effects of financial frictions on employment in the Great Recession.

We cannot reject the view that firm size may be an important determinant of access to financing. Section 3.4 shows that the composition of leverage does vary across firm size, with smaller firms relying more heavily on bank debt and on short-term debt, which may reflect the presence of financing constraints. There persists an ongoing debate in the corporate finance literature over the best empirical proxies for measuring financial constraints at the firm level, and the relevance of size

[12] Bernanke, Gertler and Gilchrist (1996) and Kashyap, Lamont and Stein (1994) explicitly cited the advantages of a dataset of private firms.[13] Kashyap, Lamont and Stein (1994) stated, "Ideally, we would prefer to also examine nontraded firms, since we suspect that these companies are most dependent on bank financing and hence most likely to be susceptible to a credit crunch. Unfortunately, we are unaware of any consistent firm-level data for nontraded companies."

[14] Specifically, they write: "The publicly available QFR data used in the analysis are available in an aggregated form by a nominal asset class. Consequently, the data do not allow splitting the firms by other characteristics. We thus use the Compustat data ..."

in particular.[15] However, our results indicate that, if these constraints are present, they do not amplify the sales and investment fluctuations of small firms. Moreover, as we noted earlier, as a theoretical matter, firms may be simultaneously constrained but display no differential response to aggregate shocks by virtue of being constrained.

Additionally, our evidence should not be taken as implying that the financial accelerator mechanism is not operative; it may simply be the case that firm size is a poor proxy for financing constraints.[16] Appendix C explores this question in more detail by looking at sales, investment, and external financing in recessions for firm sorted along dimensions other than size. For most of the proxies for financial constraints used in this paper, these differences are insignificant. However, for dividend issuance, we find substantial differences in the behavior of investment during recessions. Our objective is to establish that *size* differences do not support the financial accelerator mechanism.

Finally, an important literature shows that *employment* contracted faster at firms that are identified as financially constrained (see Chodorow-Reich, 2014 and Duygan-Bump, Levkov and Montoriol-Garriga, 2015). Our data does not feature employment making it difficult to pinpoint the differences. In Section 5, we establish that, even if one finds modest differential cyclicality for employment by firm size, these differences will be more relevant for aggregate fluctuations in employment given the lower degree of skewness relative to sales or investment.

3 Data

3.1 The Quarterly Financial Report

The Quarterly Financial Report (QFR) is a survey of firms conducted each quarter by the US Census Bureau. The survey covers several sectors of the US economy: manufacturing, mining, wholesale and retail trade firms. Surveyed firms are required to report an income statement and a balance sheet each quarter. Data collected by the QFR is used 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.[17]

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

[15] Size is often used alone or as part of an index as a proxy for financial constraints; see, among many other examples, Rajan and Zingales (1995), Almeida, Campello and Weisbach (2004). Recently, general indices of financial constraints derived from structural models and computable using observable balance sheet data have been proposed, by e.g. Whited and Wu (2006) and Hadlock and Pierce (2010). These indices typically rely, at least in part, on firm size. More recently, Farre-Mensa and Ljungqvist (2016) question the validity of a host of measures including Whited-Wu and Hadlock-Pierce, based on a novel test examining the responsiveness of firm leverage to changes in state corporate tax rates.

[16] Our data are silent about the importance of financial frictions for firm growth and innovation in the medium and long-run because of the rotating panel structure. In particular, recessions may have a long-run scarring effects due to diminished firm entry (see Siemer, 2019, Moreira, 2016, and Alon et al., 2018).

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

firm that files a corporate income tax return (Form 1120 or 1120-S) with assets over $250K may be included in the QFR manufacturing sample. For other industries, the inclusion threshold is $50 million; for this reason, most of the analysis of this paper will be conducted using the manufacturing 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 less than $250 million in assets are instead sampled randomly, so that the microdata contains only a representative sample. Each quarter and for each sector, a set of firms with less than $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 firms with less than $250 million dollar, the microdata is thus a rotating panel, akin to the Current Population Survey (CPS). In manufacturing, 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.

Manufacturing 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. Manufacturing firms that are sampled with certainty, as well as all sampled firms in other sectors, receive a somewhat more detailed ("long") form, which requires them to provide more information on the composition of their debt and their financial assets.[18] Based on the underlying sampling frame, the Census Bureau then assigns sampling weights to each firm in order to generate population estimates of quantities of interest.[19]

3.2 Data construction

The micro files of the QFR required substantial initial work in order to construct a usable panel data set.[20] 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.[21] The Census Bureau provided

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

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

[20]An 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.

[21]The 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

raw data files from 1977q3 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.[22] These weights were also adjusted so that aggregate assets in the micro data 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 add up. 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 1977q3 and 2014q1, of which about 900K are manufacturing firms.

In this paper, we focus primarily on three samples. First, 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. Second, we use a subsample for computing growth rates or investment rates: we then require manufacturing 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.[23] Third, in section 6.3, where we construct the cumulative responses to identified monetary policy shocks, we focus on another subsample: firm-quarter observations in manufacturing 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.

exploit the panel dimension of the data, as we do here.

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

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

Additionally, in order to assess the extent to which our findings extend to other sectors, we replicate a number of key results using the sample of observations from retail and wholesale trade. The higher inclusion threshold those sectors however means that the sample is less representative of smaller firms, so that the results we obtain there should be interpreted with caution.

3.3 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 with more than $250K in assets; the sampling frame is drawn from IRS administrative data and response is mandatory.

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 measures 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.[24] Section 3.4 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 longer time horizon and higher frequency of observation needed to analyze cross-sectional differences in the business-cycle behavior of firms.

Finally, and as mentioned in the introduction, the Census Bureau also releases an aggregated version of the QFR each quarter. An important challenge facing the use of these releases by researchers is that the data are tabulated by nominal asset size bins. For instance, in 2014q1, the manufacturing segment of the public release of the QFR tabulates results by groups of firms with less than 5m$, 5-10m$, 10-25m$, 25-50m$, 50-100m$, 100-250m$, 250m$-1bn$, and more than 1bn$, respectively. These bins are changed infrequently: in particular, the list of bins described above has not changed, in nominal terms, since 1982. Because of both inflation and real growth, firms thus progressively reclassify toward higher size bins, making it more difficult to define or isolate smaller firms. With the underlying microeconomic data, on the other hand, the quantiles of the *current* distribution of book assets can be easily constructed and used to construct size groupings that do not suffer from the same reclassification issue.

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

3.4 Summary Statistics

Table 1 provides summary statistics on key real and financial characteristics for 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 1977q3 to 2014q1. Nominal values are deflated by the BEA price index for manufacturing, normalized to 1 in 2009q1.[25]

Summary statistics by size group Table 1, Panel A clearly illustrates the high degree of skewness in both sales and assets. The top 0.5% of firms in the size distribution have assets of \$6.7 billion and sales of \$1.5 billion 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 1 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 1, Panel B provides key financial ratios by firm size categories. A standard measure of leverage — the debt to asset ratio — generally decreases across firm size categories. However, a standard measure of liquidity — the cash to asset ratio — is also highest among smaller firms. Overall, net leverage (debt less cash over assets) is fairly stable across size classes. We do find that smaller firms are more reliant on short-term debt and bank debt (as a share of total debt), consistent with the notion that their access to public capital markets is more limited than firms at the top of the size distribution. Smaller firms also have more trade credit, as fraction of total liabilities, 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.[26]

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 3 provides an approximate interquartile range for sales growth, leverage, and liquidity.[27] 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

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

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

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

firms have zero leverage; these zero-leverage firms tend to be concentrated in the bottom 90% of the size distribution.

Comparison with Compustat Table 1 also reports summary statistics for firms in the Compustat manufacturing segment.[28] Panel A shows that the average size of Compustat manufacturing firms is close to, but lower than, the average size of QFR manufacturing firms in the top 1% of the cross-sectional distribution of assets (which is approximately \$3696m). Quarterly sales are also somewhat lower (\$502m 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.

4 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.

4.1 Methodology

Appendix D describes in detail the sample selection, the size groupings, and the measures of firm-level growth which we use throughout this section. Three points 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. We discuss this and other differences of our approach with prior work using the public releases of the QFR in Section 4.4.

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. Classifying firms by their *lagged* position in the size distribution helps alleviate the cyclical dimension of reclassification, as emphasized in Moscarini and Postel-Vinay (2012).[29] 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.

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

[28] Details on the construction of the sample and the definition of balance sheet ratios in terms of Compustat variables is reported in Appendix F.1.

[29] If 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.

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 4.3.

Finally, we first report our baseline results for the sample of manufacturing firms; in Section 4.3, we extend these results to the sample of wholesale and retail trade firms.

4.2 Results

Sales Figure 1 shows the time series for the average growth rate of sales of two size groups: the bottom 99% (denoted by $\hat{g}_t^{(\text{small})}$) and the top 1% (denoted by $\hat{g}_t^{(\text{large})}$). 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.[30]

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 0.597, with a Newey-West standard error of 0.196 (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.[31]

Table 4 reports estimates of the semi-elasticity of firm-level growth to GDP growth and confirms the visual impressions conveyed by Figure 2. The model estimated is:

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

[30]The specific definition of the time series reported for the small firm group is given in equation (26) of Appendix D, 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 4.3 further discusses results using alternative deflators.

[31]This 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.

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.[32] 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.[33] 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.[34]

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 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. 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 5 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 co-movement 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 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.[35]

[32] See Appendix D for a formal definition of the size groups.

[33] The baseline regression results are reported by classifying firms into durable and non-durable industries. Section 4.3 further discusses results under alternative industry classifications.

[34] Section 4.3 discusses the role of these industry controls.

[35] This lag structure also accounts for the fact that the contemporaneous correlation of GDP growth and investment

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.[36] 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.

4.3 Robustness

Exit and entry 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.[37] Although the point estimate for the size effect is higher including exit, it is not statistically different from the estimate excluding imputed exit. 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.

is not significantly positive among the largest firms in the QFR sample, as shown in Figure 3. Appendix F discusses this lag in more detail and shows that it is also present in both the annual and the quarterly Compustat data.

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

[37] Note that our main results use log growth rates, which are unbounded from below and therefore not usable for exiting firms. In this computation, we instead use growth rates that are bounded from below, in order to include exiting firms. We use the bounded growth rates of Davis, Haltiwanger and Schuh (1996), though strictly speaking, any bounded growth rate is sufficient. Appendix G contains a comparison of our baseline results in the continuing firm sample, which use log-growth rates, to those obtained in that same sample with DHS bounded growth rates; it shows that they are similar.

Figure A2 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 from overall employment fluctuations. Effectively, entry and exit do not appear to make an outsize contribution to employment fluctuations in manufacturing.[38]

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 size.) Firms do not explicitly report firm age in the QFR. Moreover, because of the rotating panel structure of survey, it is difficult to precisely measure it among small firms. 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 re-sampled 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 generally survives within the subsample of mature firms. Table A1 reports the results. For sales and for fixed investment, the size effect remains significant for both the [99,99.5] and [99.5,100] size groups. Moreover, relative to the baseline, the size effect for sales is approximately 75% of its baseline magnitude. For inventories, the size remains significant for the [99,99.5] size group; for top 0.5% of firms, it is negative, though not statistically significant. This suggests that while the size effect may be related to age, it is not solely driven by young firms (that is, it still appears among mature firms.)

The role of industry controls In our main specification, Equation (1), we control only for the industry composition of firms between the durable and non-durable industries. Moreover, size groups are defined based on the distribution of assets in the entire manufacturing sector, as opposed to within specific industries in manufacturing. Table A2 reports estimates of the size effect under alternative industry and size classifications. Three points are worth noting. First, without any industry controls (column 1), the size effect is more pronounced than in our baseline specification. For the top 0.5% of firms, for instance, omitting industry controls increases the estimate of the size effect by about 25%. Second, narrower industry controls than the simple durable/non-durable classification (column 3) do not substantially affect estimates of the size effect. This suggests that the durable/non-durable classification is sufficient to account for the bulk of the correlation between size and industry in the manufacturing sample. Third, defining the size distribution relative to a firm's industry (either durable/non-durable, or SIC 2-digit/NAICS 3-digit) does not substantially affect the estimates of the size effect.

[38] This statement should not be construed to mean that entry is not important; some subset of new firms are successful, and these firms will be sampled or will be surveyed with certainty once sufficiently large.

The size effect in the trade sector Because the QFR inclusion threshold is considerably lower in manufacturing ($250K) than in retail and wholesale trade ($50m), we chose to focus our main analysis on the manufacturing sample. However, the retail and wholesale trade samples can be used to check whether our main findings extend to those sectors. This is important in particular because trends in concentration in the manufacturing sectors — which we discuss in the following section — may have been at odds with those of other sectors. Table 5 reports estimates of the size effect among firms in the retail and wholesale trade sectors. Because of the higher inclusion threshold, we group the firms into three size bins, firms below the median by asset size, firms from in the 50-90 inter-quantile range of assets, and firms in the top 10% of assets.[39] For sales growth, inventory growth and investment, there is a significant size effect in the trade sector. The size effect is stronger for sales growth, and more muted for inventory growth and investment, than in the manufacturing sector. Finally, the finding that, in the manufacturing sector, the size effect is most pronounced at the very top also holds for sales in the trade sector, and in fact to an even higher degree. The size effect is also stronger for inventory growth in the top 10% of firms, though the difference there is not statistically significant. Investment is the exception: there, the size effect is similar between the [50,90] and the top 10% groups. Overall, the trade sector thus exhibits a size effect which, with the exception of fixed investment, is concentrated among the very top firms.

Other robustness checks Appendix E contains other robustness checks. Table A3 shows that estimates of the size effect are robust to using annual output deflators, rather than quarterly value-added deflators.[40] The table also shows that results are robust to controlling for industry-quarter effects. We cluster by firm on the basis that unobserved firm characteristics would be the most important factor generating correlated errors, but Table A4 shows that results are robust to alternative clustering levels. Finally, Figure A3 reports estimated average marginal effects of GDP growth on sales growth, inventory growth and investment — analogous to 3 — for a more disaggregated size classification. The results show that the size effect is remarkably homogeneous among firms in the $[0, 90]$; with the exception of investment in the top 25% of firms by size, and, very marginally, sales for the $[50, 75]$ size group, the sensitivity of firms in the bottom $[0, 90]$ is in general not different from the unconditional average sensitivity. By contrast, the sensitivity of firms in the top 0.5% by size is systematically and significantly lower than average.

4.4 Discussion

This section discusses two important questions about our results so far. First, what is to be gained from using firm-level data, rather than the public releases of the QFR? Second, how do our results

[39]We choose this classification in order to approximate the real asset thresholds corresponding to the top 10% and top 1% in manufacturing; for instance, the top 10% of firms in the trade segment of the QFR sample have approximately $2bn in constant 2009 dollars, close to average assets in the 1% of the firms in the manufacturing segment.

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

relate to the influential contribution of Gertler and Gilchrist (1994) — GG, in what follows?

4.4.1 Why is the micro data useful?

The Census Bureau publishes quarterly tabulations of the microeconomic data studied in this paper, which take the form of aggregates by bins of asset size.[41] Why use the microeconomic data, instead of these public tabulations?

The first column of Table 6 estimates the cyclicality of small and large firms using the public tabulations.[42] The asset size bins used in these tabulations are fixed in nominal terms, making it challenging to consistently define small and large size groups. The results in the first column of Table 6 use the methodology proposed by GG to address this issue. This methodology assumes that small firms account for a constant share (30%) of total sales.[43] The first column of Table 6 shows that using this methodology, the size effect, measured as the semi-elasticity of the difference between small and large firm growth to GDP growth, is not statistically distinct from 0 (the point estimate is in fact *negative*.) This result is consistent with Chari, Christiano and Kehoe (2013) and Kudlyak and Sanchez (2017), who also use the tabulations to document the cyclicality of small firms' sales does not appear to exceed that of large firms. By contrast, recall that when average small and large firm growth rates are constructed using the underlying microeconomic data and the methodology described in Section 4.1, the size effect is equal to approximately 0.6, and statistically different from 0, as reported in Figure 2 (the second column of Table 6 repeats this result.)

There are three potential reasons for this difference. First, using the tabulations, one can only measure *aggregate* growth rates, instead of firm-level growth rates. Second, using the tabulations, one cannot condition on the initial (or lagged) size of firms; firms migrating across size categories during downturns can lower estimates of the size effect, as argued by Moscarini and Postel-Vinay (2012). Third, the methodology of GG fixes the share of small firms in total sales, whereas it might instead be decreasing. This could weaken any potential size effect over time, as more firms need to be classified as small in order to meet the 30% sales threshold.

While it is difficult to establish precisely the role of each factor, one can isolate the role of the first one, the difference between firm-level growth rates and aggregate growth rates. In order to do so, in column 3 of Table 6, we report the size effect estimated using the *aggregate* growth rate of small and large firms, where small and large firms are otherwise defined as in our baseline approach.[44] This

[41]For instance, in 2014q1, the tabulations in manufacturing contain aggregates for firms in the 5m$, 5-10m$, 10-25m$, 25-50m$, 50-100m$, 100-250m$, 250m$-1bn$, and more than 1bn$ asset bins, respectively. These bins change infrequently: the last change, over the sample period we study, we consider occurred in 1981.

[42]We used the data available online from 1987 onwards; prior to that, we digitized paper records of the QFR.

[43]The challenge posed by the public tabulations is that smaller bins tend to mechanically be occupied by fewer and fewer firms over time. For instance, the cumulative share of total sales of firms with less than $100m in assets in the public tabulations fell from 24% to 14% from 1990q1 to 2010q1. In order to address this issue, GG suggest defining small firms as those in the smallest set of bins accounting for 30% of total sales in any given quarter, and large firms as the remainder. This methodology is described in detail in Appendix D.

[44]In other words, the only difference between the estimates of column 2 (that is, our baseline estimates) and the estimates of column 3 is the fact that column 3 uses aggregate growth rates — the underlying sample is identical. Note that these aggregate growth rates *cannot* be defined from public tabulations; they require knowing the entire cross-sectional distribution of firms by asset, and being able to condition on one-year-lagged size.

column shows that the magnitude of the size effect is positive, but much smaller, and statistically insignificant, when using aggregate growth rates. This suggests that value-weighting tends to dampen the relative cyclicality of the growth rate of small firms, which results in an attenuated size effect. In keeping with this intuition, Section 5 discusses the relationship between the size effect estimated at the firm level, and aggregate fluctuations in sales, inventory and investment, and generally documents a small amount of "amplification" due to the higher cyclicality of firm-level growth and investment at the firm level.

Aside from this comparison, it should be stressed that the goal of this paper is not simply to measure the size effect, but also to assess whether the higher cyclicality of small firms is related to financial frictions. The main advantage of using the microeconomic data over the public tabulations is that one can simultaneously control for size *and* other firm characteristics, in particular, proxies for financial constraints. This is the focus of Section 6.

4.4.2 Comparison to Gertler and Gilchrist (1994)

GG study changes in the sales of small and large firms around the six dates identified by Romer and Romer (1989, 1994) as exogenous contractions in monetary policy. The main finding is that sales of small firms decline by 10%, on average, in the three years following a Romer date, while sales of large firms only decline by 5% (their Figure II, p.321.) Therefore, small firms are twice as sensitive to Romer episodes as large firms. By contrast, our main estimates suggest that sales of small firms are only about 24% ($= (3.1 - 2.5)/2.5$) more sensitive to declines in GDP than large firms.

It should be noted that GG report *conditional* event study responses around the six Romer dates in their sample, while we document *unconditional* differences in cyclicality across size groups. In particular, it may be the case that differences between small and large firms are more pronounced around monetary policy contractions. Aside from this important distinction, our analysis differs from GG in two other ways: measurement methodology, and sample period. First, as mentioned in Section 4.4.1, GG rely on public tabulations of aggregates in order to conduct their analysis, whereas we use the underlying firm-level micro data. Second, we study a later period: GG study 1958q4 to 1991q4, while we study 1977q3 to 2014q1 as the micro data is not available prior to 1977q3.

Table 7 contains summary statistics from the exercise of GG, in the column marked "GG growth rates". We start by replicating their results, in their original sample of 1958q4 to 1991q4.[45] We find that for large firms, the cumulative decline in sales 3 years after the Romer date is $\Delta_L = -7.0\%$, while it is $\Delta_S = -13.1\%$ for small firms. Thus, in our replication of their exercise, small firms are 87% more sensitive to Romer episodes.

We then repeat their exercise in two other periods. First, in the period running from 1977q3

[45] In particular, after demeaning the GG growth rates, and removing quarter fixed effects in order to deseasonalized them, we construct the cumulative change in sales of small and large firms around each of the six Romer dates from the original GG analysis: 1966q2, 1968q4, 1974q2, 1978q3, 1979q4 and 1988q4. Appendix Figure A4 reports the correspond event study plots; this figure is directly comparable to Figure II, p.321, of GG.

to 1991q4 (the overlap between their original sample, and our sample), we find a lower gap (61%) between the response of small and large firms around Romer dates. In this subsample, we can compare their measurement methodology to ours. The second column of Table 7 reports results of the same event studies, using the equal-weighted, firm-level growth rates ("CM growth rates") plotted in Figures 1 and 2. With the CM growth rates, in the overlap sample, we also find substantial differences in the cumulative change in sales around Romer dates of small firms relative to large firms. This suggests that monetary policy contractions may indeed be associated with starker differences between small and large firms. Note, however, that in this sample, there are only three Romer dates: 1978q3, 1979q4 and 1988q4.

Whe finally repeat this exercise in the 1977q3-2014q1 sample. In this final analysis, we include, as Romer dates, 1978q3, 1979q4, 1988q4, 1994q2 and 2008q3, following Kudlyak and Sanchez (2017). We find a much smaller size effect with GG growth rates (14%). For CM growth rates, by contrast, the size effect is similar as in the 1977q3 to 1991q4 sample (58%). The smaller size effect for GG growth rates is due to the fact that, according to the GG measure, large firms responded *more* around 2008q3 than small firms did.

Overall, the GG growth rates give an inconsistent picture of the conditional size effect; it varies across sample periods. By contrast, with CM growth rates, the conditional size effect is more stable across sample periods, with small firms responding approximately 60% more to the Romer episodes than large firms. This suggests, again, that measurement matters: equal-weighted (CM) growth rates tend to produce larger and more stable estimates of the size effect than value-weighted (GG) growth rates, consistent with the discussion of Section 4.4.1.

However, it is worth emphasizing that the event study approach around Romer dates produces fragile results *even* using CM growth rates. Table A7 reports the average event study results in the 1977q3 to 2014q1 sample when dropping individual Romer dates. With CM growth rates, estimates for the conditional size effect ranges anywhere from 30% to 121%; the GG growth rate estimates of the conditional size effects are similarly dispersed. The fragility of the results obtained using the conditional event study approach around Romer dates motivates our analysis in Section 6, where we use local projections of firm-level growth rates on identified monetary policy shocks at the quarterly frequency to investigate the size effect in response to monetary policy contractions.

5 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 allows us to compute counterfactuals that quantify its contribution to aggregate fluctuations.

5.1 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 cyclicality 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 G 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:

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

Here, $s_{t-4} = \frac{X_{t-4}^{(small)}}{X_{t-4}}$ is the initial fraction of the aggregate accounted for by small firms, and $\hat{g}_t^{(small)}$ and $\hat{g}_t^{(large)}$ are the cross-sectional average growth rates considered in the previous section.[46] The term $\hat{g}_t^{(\text{large})} + s_{t-4}\left(\hat{g}_t^{(\text{small})} - \hat{g}_t^{(\text{large})}\right)$ represents average firm-level growth; the contribution of the product $s_{t-4}\left(\hat{g}_t^{(\text{small})} - \hat{g}_t^{(\text{large})}\right)$ 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, $\hat{cov}_t$. The term $\hat{cov}_t$ is itself a weighted average of two terms:

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

Each of the two terms $\hat{cov}_t^{(\text{small})}$ and $\hat{cov}_t^{(\text{large})}$ can be interpreted as the (group-specific) cross-sectional covariance between firms' initial size and their subsequent growth.[47] 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, $\hat{g}_t^{(\text{large})} + s_{t-4}\left(\hat{g}_t^{(\text{small})} - \hat{g}_t^{(\text{large})}\right)$. 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.[48]

[46] This 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 G derives a similar decomposition for the commonly used growth rates $\tilde{g}_{i,t} = \frac{x_{i,t}-x_{i,t-4}}{\frac{1}{2}\left(x_{i,t-4}+x_{i,t}\right)}$, 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.

[47] Specifically, $\hat{cov}_t^{(\text{j})} = \sum_{i \in \mathcal{I}_t^{(\text{j})}} \left(w_{i,t-4} - \frac{1}{\#\mathcal{I}_t}\right)\left(g_{i,t} - \hat{g}_t^{(j)}\right)$, where j is small or large firms and where $w_{i,t-4}$ is the four-quarter lagged share of the total value of the variable of interest accounted for by firm i. This term is a cross-sectional covariance up to a normalizing factor.

[48] Appendix G contains a precise decomposition of the contribution of the covariance terms and shows that it is small, whether one looks at small firms, large firms, or all firms jointly.

5.2 Results

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

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

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):

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

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 compare 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 8 reports the estimated slopes of the actual and counterfactual aggregate growth series for sales, inventory, fixed investment, and total assets. For sales (first line), the actual and counterfactual elasticities are close; the point estimates differ by approximately 13 basis points, and this difference is not statistically significant. 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 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.

For illustrative purposes, we consider two additional counterfactuals in Table 8. The last two columns construct counterfactuals $G_t^{(1)}$ and $G_t^{(2)}$ under the alternative assumption that small firms display twice the cyclicality of large firms. Gertler and Gilchrist (1994) documented that small firms where approximately twice as responsive as large firms after a shock to monetary policy. Counterfactuals 3 and 4 show that, if we had found differential responses of a similar magnitude, then, even given the high degree of skewness, small firms would significantly amplify fluctuations. For instance, for sales and inventories, if small firms were twice as cyclical, they would amplify aggregate fluctuations by 25% and 67% respectively.

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 cyclicality between small and large firms, i.e. the term $\left(\hat{g}_t^{(\text{small})} - \hat{g}_t^{(\text{large})}\right)$. Figure 6 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 6, 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.[49] The share of sales of the bottom 99% falls from 35.6% in 1977q3 to 20.4% in 2014q1, while their share of assets falls from 25.6% to 9.0%; this decline is secular over the period with an acceleration around the 2000's. This is not to say that cyclical movements in small firms' shares are completely absent: for instance, the raw correlation $corr\left(s_{t-4}, \Delta GDP_t\right)$ is approximately 0.37 in the sample. Although substantial cyclicality 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 6 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 6 indicate small firms' share is, on average, approximately 25%. The product of this with the differences in cyclicality 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 8 indicates that both cyclical movements in the covariance term and cyclical variation in small firms' share, have a limited impact on the cyclical fluctuations in aggregate growth.[50]

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).[51] 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

[49]Interestingly, sales concentration in the QFR in Figure 6 exhibits two waves of increasing concentration in the early 1980s and late 1990s. The QFR is unique in offering a higher frequency measure of changes in concentration relative to the Economic Census used in Autor et al. (2017).

[50]Figure 5 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.

[51]See Section 4.3 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).

business-cycle frequencies) and that they display more sensitivity to cycles than large firms do — that is, given that the term $\left(\hat{g}_t^{(\text{small})} - \hat{g}_t^{(\text{large})}\right)$ 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.

Finally, Appendix G reports results from an alternative decomposition of aggregate growth into a small firm term, a large firm term, and a reallocation component, similar to the Shimer (2012) decomposition of fluctuations in the unemployment rate. The results from this decomposition also support 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.

5.3 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.[52] However, we can estimate the employment threshold for large firms using firm counts from the Census Bureau's Business Dynamics Statistics (BDS). 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 approximately less than 10 employees are not sampled.[53] 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 6). 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 7, 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 correlated, but the degree of correlation is weaker than for the actual and counterfactual (excluding small firms) total sales growth series reported in Figure 5.

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

[52] In 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.

[53] The QFR provides the total number of firms in their sampling frame, which can be compared to firm counts by employment size in the BDS. When summing firm counts from the highest to lowest bin, the number of firms in the QFR sampling frame is more than the number of firms with 10+ employees, but less than the number of firms with 5+ employees.

(1-499 employees) and medium size firms (500-2499 employees) have employment growth rates of -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.

6 The financial origins of the cyclicality 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. Here, note that the use of microeconomic data plays a central role, as it allows us to condition *simultaneously* for size and financial factors for the entire sample of firms, so as to verify whether the role of size in explaining cyclicality can be accounted by these other factors.

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.

6.1 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 in the manufacturing sample:

$$\begin{aligned} g_{i,t} &= \sum_{j\in\mathcal{J}} (\alpha_j + \beta_j \Delta GDP_t)\, \mathbf{1}_{\left\{i\in\mathcal{I}_t^{(j)}\right\}} + \sum_{l\in\mathcal{L}} (\gamma_l + \delta_l \Delta GDP_t)\, \mathbf{1}_{\{i\in\mathcal{L}\}} \\ &+ \sum_{k\in\mathcal{K}} (\zeta_k + \eta_k \Delta GDP_t)\, \mathbf{1}_{\left\{i\in\mathcal{F}_t^{(k)}\right\}} + \epsilon_{i,t}. \end{aligned} \tag{5}$$

In these regressions, the size controls are the same as in 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.[54] In contrast to the baseline regression, $k \in \mathcal{K}$ now indexes groups of our measures of financial strength. We consider five different measures of financial strength: bank-dependence, leverage, liquidity, access to public debt markets, and dividend issuance. 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 9 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.[55]

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

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

[55] The 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.

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 C, 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 of recoveries.

In any case, the main message of Table 9 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. In Appendix H.1, 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 9). 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.

Additionally, in Appendix H.2, we re-estimate the same specification as equation (5), but for the trade segment of the QFR, where recall that, in Section 4.3, we documented a size effect for sales of similar magnitude as in the manufacturing segment. Table A15 shows that results are the same as in the manufacturing segment: namely, the greater sensitivity of small firms is unchanged after controlling for proxies for financial constraints.

Here, it is important to highlight a general limitation of these results: the simple proxies for financial constraints which we study may not adequately capture the wedge between the cost of internal and external finance, that is, the degree to which firms are financially constrained. This concerned is raised, in particular, by Farre-Mensa and Ljungqvist (2016), who use shifts the demand for credit induced by changes in the tax treatment of debt to show that, in a sample of publicly traded firms typical proxies for financial constraints, including the more advanced constraints indexes of Whited and Wu (2006) and Hadlock and Pierce (2010) may not properly indicate whether a firm is financially constrained or not. While we acknowledge these limitations, it is difficult to address them without auxiliary data sources, in particular on the price of external finance, which may not be available for the sample of smaller and potentially more financially constrained firms. However, note that the goal of this paper is not to provide a new metric for the degree to which a firm is financially constrained, but rather to rule out that financial constraints explain the differential cyclicality of small firms. The following section proposes to use two tests, motivated by theory, which use ex-post decisions to borrow and accumulate cash behavior (as opposed to ex-ante differences in financial characteristics) to further rule out the possibility that the differential cyclicality of small firms is driven by financial factors.

6.2 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 A 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 cyclicality 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; we estimate the model:

$$g_{i,t} = \alpha + \beta \mathbf{1}_{\left\{i \in \mathcal{I}_t^{(0,99)}\right\}} + \sum_{k=-4}^{10} \left(\alpha_k + \beta_k \mathbf{1}_{\left\{i \in \mathcal{I}_t^{(0,99)}\right\}} \right) \mathbf{1}_{\{t+k \in \mathcal{H}\}} + \epsilon_{i,t} \tag{6}$$

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:

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

as well as the associated standard errors. Note, in particular, that in order to avoid overlapping event windows, we only consider the second of the two recession start dates of the early 1980s.

Figure 8 reports the cumulative path of sales, inventory and fixed capital and the associated +/-2 standard error bands for firms in the manufacturing sector. 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 distinct from zero 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 seems to lag that of small firms by three to four quarters.[56] This lag is not visible in the sales response.[57]

Figure 9 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. This figure suggests that there is little difference in the cyclical behavior of

[56] Aggregate fixed capital formation, in the QFR data, lags real GDP growth by three to four quarters as well: the contemporaneous correlation with year-on-year real GDP growth is 0.19, while the three-quarter lagged correlation is 0.59. This is consistent with the recession behavior documented in Figure 8, since, as discussed below, large firms account for between 80-90% of total fixed capital formation in the QFR data.

[57] Also 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 8: 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.

debt financing at small and large firms. The left panel of Figure 9 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 small 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%).

Events studies analogous to Figures 8 and 9 for the Great Recession (not shown) display similar patterns. Small firms contracted inventories and investment (but not inventories) faster than large firms. But we find no statistical difference in the rates of deleveraging. The retail and wholesale trade segments of the data behave similarly, and we find even more muted effects comparing zero leverage and positive leverage firms. Our findings are consistent with Kudlyak and Sanchez (2017) but somewhat in tension with the findings on employment in Chodorow-Reich (2014), Duygan-Bump, Levkov and Montoriol-Garriga (2015), and Siemer (2019). These differences may be due to the fact the 1) employment behaves quite differently than sales, investment, etc., 2) firm credit effects may be more pronounced outside manufacturing (and the retail/wholesale firms covered by the QFR), 3) the set of financially constrained firms identified may be only weakly correlated with firm size. It should be noted as well that we do find notable differences in the behavior of inventories and investment in the *recovery* phase of the Great Recession (see Figure 4).

In Appendix H.2, we also conduct this exercise for the trade sample. We define small firms as those in the bottom 90% of the sample, and large firms as the remainder. As in the manufacturing sample, there is a statistically significant difference between the decline of sales of small firms and that of large firms around recession starts. Differences in the inventory and investment responses are even more muted, suggesting a limited role for financial amplification of investment responses. Additionally, while difference the response of debt flows between small and large firms are more pronounced than in the manufacturing sector, they are not statistically significant. Overall, findings in the trade sector also seem inconsistent with the view that recessions are associated with sharper contractions in credit supply among small firms which in turn lead to larger declines in debt flow and investment.

Finally, we note that an alternative mechanism through which financial constraints may affect firms is precautionary saving by firms anticipating the possibility of being financially constrained in the future.[58] This mechanism is studied, among others, by Bolton, Chen and Wang (2014)

[58] In the model of Figure 6.2, there is idiosyncratic or aggregate risk other than exit risk, against which cash holdings are not a hedge.

and Abel and Panageas (2020). For instance, small firms may be more likely to see their lines of credit cut by banks during a downturn. In anticipation of this possibility, they may decide to cut investment and accumulate cash. This response would not necessarily manifest itself in a larger decline in total borrowing by small firms — smaller firms may even possibly draw down their credit lines in response to anticipated cuts. This alternative mechanism would tend to predict that cash balances of small firms are *less* cyclically sensitive than those of large firms, or that they tend to decline by less (and potentially even increase) during recessions. The evidence presented in Table A16 and Figure A11 in Appendix speaks to this mechanism. Table A16 reports estimates of the size effect for different measures of cash holdings, and shows that cash holdings are *more* sensitive to aggregate conditions among smaller firms. Figure A11 show that, in the same recession event study framework as the one used in Figure 8, cash balances among small firms appear to decline substantially relative to those of large firms. Thus, while the precautionary saving mechanism may be an important implication of financial constraints, it does not appear that *smaller* firms are more likely to engage in precautionary savings in response to aggregate shocks.

6.3 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) 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.[59] 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 (2019). We construct the responses by firm size group using a projection method analogous to Jordà (2005). Our specification is:

$$\begin{aligned}\Delta y_{i,t,t+h} \quad = \quad & \sum_{j\in\mathcal{J}}\left(\alpha_j^{(h)}+\beta_j^{(h)}rr_{t-1,t}+\phi_j^{(h)}(L)X_t\right)\mathbf{1}_{\left\{i\in\mathcal{I}_t^{(j)}\right\}}+\sum_{l\in\mathcal{L}}\left(\gamma_l^{(h)}+\delta_l^{(h)}rr_{t-1,t}\right)\mathbf{1}_{\{i\in\mathcal{L}\}} \\ + \quad & \sum_{j\in\mathcal{J}}\sum_{q=1}^{4}\left(\mathbf{1}_{\left\{i\in\mathcal{I}_t^{(j)}\right\}}\times\mathbf{1}_{\{\mathbf{q}(t)=q\}}\right)s_{j,q}^{(h)}+\epsilon_{i,t,h}\end{aligned} \tag{7}$$

[59] The 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. For instance, Cooley and Quadrini (2006) show how monetary policy shocks generate a larger fall at small relative to large firms; Khan and Thomas (2013) provide similar predictions in response to a credit shock.

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.[60] 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.[61]

Results for sales and investment Figure 10 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.

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

[60] Results are qualitatively unchanged when using NAICS 3-digit sub-sectors instead.

[61] Results 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 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.

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 (7) 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 (7) 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 11 shows the cumulative change in each of these debt ratios after a exogenous tightening 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 4, 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.

7 An alternative mechanism for the size effect

This section proposes an alternative interpretation of the empirical finding that small firms are more cyclically sensitive than small firms. We start by documenting that, in the QFR sample, large firms tend to tend to operate across a larger range of industries than small firms. We then show that, controlling for the number of industries across which a firm operates, large firms do not appear to be less cyclically sensitive than small firms. We show that this finding is robust to additionally controlling for a number of factors, including the number of establishments, and that it holds in both the trade and manufacturing sample. Finally, we provide a simple mechanism, relying on economies of scope, that explains why multi-industry firms might be less responsive to aggregate shocks.

7.1 Empirical evidence

7.1.1 Data sources

The QFR is a firm-level survey; it contains no information on the establishment composition of firms.[62] In order to construct a measure of the establishment composition of firms, we merged the QFR to Dun and Bradstreet's Marketing Information files (DMI; Neumark, Wall and Zhang 2011, Walls 2013, Barnatchez, Crane and Decker 2017, Crane and Decker 2019.)[63] This dataset, which is publicly available, contains annual establishment level data since 1990. Crucially for our purposes, the dataset records corporate linkages across establishments, allowing us to construct, in each year, the list of establishments belonging to a particular firm.

The DMI annual files are the result of a large-scale data collection effort by Dun and Bradstreet, involving interviews, mailings, private third-party sources, and public data sources (such as records of incorporations of firms.) While the coverage of DMI is broad, the data has not yet been systematically assessed against sources based on administrative records. In particular, Haltiwanger, Jarmin and Miranda (2013) discuss the potential for measurement error in *growth rates* in the DMI data, because of the relatively high rate of imputation of sales and employment. However, Barnatchez, Crane and Decker (2017) argue that applying certain sample restrictions — in particular, eliminating establishments with very low or no employment —– leads to high correlations in the distributions for the *level* of employment at the industry and zipcode level between the DMI data and the LBD or the Quarterly Census of Employment and Wages (QCEW). Following this work, we apply systematic filters to the DMI data, excluding establishments organized as sole proprietorships, which are outside of the QFR scope, and limiting the sample to establishments with minimum of 5 employees. Additionally, we do not use the DMI data for measuring *growth rates* of employment; we only use *level* of the employment measure to verify that it is positively correlated to our QFR measure of size, and the *level* of the sales measure to compute a measure of sales concentration in manufacturing and trade within each firm. The merge is performed in two steps. The first step is to aggregate the DMI data to the firm level, specifically using the headquarters Duns (hqduns) number as the identifier for the firm. The second is to merge the resulting corporate entity to entities in the QFR, using the name, address and industry of each entity in both QFR and the DMI files as merging variables. This merge is conducted is separately in each year. Data

[62] The only related information reported by firms included in the long-form QFR survey is whether they own a majority stake in another corporation; in this case, they are instructed by QFR rules to consolidate this corporation, as described in Section 3.

[63] An ideal source for constructing the establishment composition of firms in the QFR would the Business Register (BR; see, among others, Becker et al. 2006 and Davis et al. 2007.) However, under current Census and IRS rules, a continuous (i.e., year-by-year) merge of the QFR with the Business Register is not authorized.

is available only after 1990; for this sample, we find matches for between 65% and 80% of firms in the QFR, depending on the year.

7.1.2 Findings

Table 10 reports summary statistics for the merged DMI/QFR manufacturing sample. The first column shows that average employment rises sharply across QFR size groups; average employment among the bottom 90% of matched firms by book assets is 59, whereas it is 9649 in the top 0.5% of firms. The second column reports establishment counts by firm, and shows that they also sharply rise with the QFR measure of size; firms in the bottom 90% of matched firms by book assets have 2 establishment on average, while the top 0.5% have 67.

The third column of Table 10 reports our measure of the number of industries across which a firm operates (the column marked "Lines of business".) In DMI, a primary industrial classification is reported for each establishment.[64] We define the number of lines of business as the number of distinct primary industry classifications of establishments within the firm. Unless the firm is single-establishment, we do not include establishments identified as headquarter locations in our counts. The third column of Table 10 shows that this measure of the industry composition of firms varies with QFR size; the largest QFR firms have on average 23 lines of business, while firms in the bottom 90% only have one. Note also that this measure is distinct from the number of establishments; in a simple regression of the number of lines of business on the number of establishments in the matched sample, the R^2 is 0.40; and their sample correlation is 0.62.[65] The final two columns of Table 10 also underscore differences in the industry composition of firms across sizes. The column marked "manufacturing index" reports the correlation between the percentage of total firm revenue generated by establishments classified as manufacturing within the firm (where establishment revenue is measured using the establishment revenue figures DMI files.) The largest firms appear to generate a non-trivial portion of their revenue (18.2%) in establishments not classified in manufacturing, while firm in the bottom 90% by book assets do not.[66]

Table 11 then studies how the size effect documented in Section 4 relates to the industry composition of a firm's establishments. The first column of Table 11 establishes that there is a size effect in the matched sample; it is somewhat larger than in the baseline QFR sample, though less precisely estimated (in particular because the data span fewer recessions.) The second column of Table 11 shows that firms with a higher number of lines of business are also substantially less cyclically sensitive. The third column shows that, when jointly controlling for size and the

[64]In DMI, the establishment classification consists of an 8-digit SIC code, with the four first digits corresponding to standard SIC-4 codes, and the remaining 4 digits corresponding to a proprietary industry classification by DnB; we keep only the first four. Moreover, for each establishment, the DMI files may contain several industry classification codes if the establishment engages in multiple activities each contributing to more than 10% of its revenue. We only consider the primary industry classifier, so that our measure of industry composition of establishments at the firm level is likely to understate the diversity of economic activity within firm.

[65]For the trade sample, which we discuss below, the R^2 is 0.20 and the correlation is 0.44.

[66]We verified that these differences remain significant after controlling for SIC-2 digit/NAICS 3-digit industry fixed effects.

industry scope of the firm, the point estimate of the effect the number of lines of business is roughly unchanged, but the estimate of the size effect vanishes. That is, there are no significant differences in the cyclicality of small and large firms over and above those accounted by the fact that large firms have more lines of business. Finally, the last column also controls for the number of establishments; the effects of the number of line of business survives, and is in fact strengthened, indicating that there is independent variation between the two measures of the establishment structure of firms.

Table 12 reports the results of similar regressions for the retail and wholesale trade portion of the QFR sample. From the standpoint of industry composition, matched firms tend to have more establishments, operate across fewer industries than in manufacturing (Table A18, in Appendix, reports summary statistics.) Nevertheless, Table 12 shows that the finding that lower cyclicality of large firms disappears if one controls for the industry scope of the firm also holds among retail and wholesale trade firms (though the role of the number of establishments, in that case, is more prominent.) Additionally, Tables A18 and A19 in Appendix I show that the same findings holds if one uses continuous measures of the number of lines of business and the number of establishments, rather than the groups used in Tables 11 and 12.

Overall, these findings indicate that the QFR measures of size is correlated with measures of the number of industries across which a firm's establishments operate. Moreover, this difference seems to help account, empirically, for the fact that larger firms are less sensitive to aggregate fluctuations.

7.2 A potential mechanism: economies of scope

We next propose a simple model that can rationalize the two empirical findings above: (a) large firms tend to operate across a higher number of industries than small firms; (b) multi-industry firms are less sensitive to aggregate shocks than single-industry firms. Our model relies on two key ingredients: non-homothetic demand for firms' products; and economies of scope across industries, which only multi-industry firms can enjoy. Here, we only describe the key results and underlying mechanisms; Appendix B reports a precise statement of the model and a derivation of these results.[67]

The model is static. A representative household is endowed with an amount I of a numeraire good and derives utility from a constant elasticity of substitution (CES) aggregate of goods pro-

[67]Our model relates to the literature on conglomerates. Both the basic facts and the supporting theories in this literature are not settled (see Maksimovic and Phillips, 2013 for a review). In particular, some theories explain the behavior of conglomerate using frictionless models of the firm (Maksimovic and Phillips, 2002), while others argue conglomerates may face advantages because of internal capital markets (Stein, 1997). We view the evidence we described as difficult to reconcile with internal capital market theories for three reasons. First, our evidence shows that industry scope explains the size effect, not the number of establishments; internal capital market mechanisms could in principle apply to firms with a large number of establishments even within an industry. Second, our evidence shows that industry scope is associated with slower growth of multi-industry firms during expansions, while internal capital market theories typically focus on their role during downturn, particularly financial ones (Matvos and Seru, 2014). Third, our evidence on the response of debt and cash between small and large firms, reported in section 6, suggests that internal capital markets differences across these two types of firms may not be sufficient to smooth investment and borrowing responses to cyclical fluctuations.

duced by a set of N industries. Each industry's good is itself a CES aggregate of two goods. The first good is produced by single-industry firms (S-firms), which operate only within the industry. The second good is produced by multi-industry firms (M-firms), which operate across all N industries. All firms are price-takers.

The first departure from standard models is that we assume that the household has non-homothetic preferences for each good. Specifically, the CES aggregate defining the consumption good of industry n is given by:

$$C_n = \left(\left(C_{n,S} - C^*_{n,S} \right)^{\epsilon} + \left(C_{n,M} - C^*_{n,M} \right)^{\epsilon} \right)^{\frac{1}{\epsilon}}, \quad \epsilon \in [0,1],$$

where $C_{n,x}$, $x = N, S$, represent purchases of the good by the household, and $C^*_{n,x}$, $x = N, S$, represents the inelastic part of the demand for the product of firms of type x in industry n. This preference specification is analogous to Geary (1950) and Stone (1954); in the macroeconomics literature, it has recently be used by Ravn, Schmitt-Grohé and Uribe (2006) and Ravn, Schmitt-Grohé and Uribe (2008), among others. Households take $C^*_{n,x}$ as given; it can be thought of, as either, in this specific model, subsistence levels of consumption of each good, or, more broadly, customer capital accrued by firms of type x in industry n.

The second non-standard feature is that we allow firms to invest in order to increase the inelastic component of their demand. Specifically, we assume that, subject to a convex cost $\gamma(.)$, firms can raise the inelastic component of their demand. (Production is otherwise standard: it uses a single input with fixed price MC^{-1} and has constant returns to scale.) Crucially, we assume that M-firms enjoy economies of scope in making these investments. Formally, we follow the definition of Panzar and Willig (1981) and Tirole (1988), and assume that the total cost of investing, $\Gamma(.)$, is subadditive. Specifically, we assume that total investment costs for a firm of type M are given by:

$$\Gamma\left(\left\{ C^*_{n,M} \right\}_{n=1}^{N} \right) = \left(\sum_{n=1}^{N} \gamma(C_{n,M})^{\alpha} \right)^{\frac{1}{\alpha}} \leq \sum_{n=1}^{N} \gamma\left(C_{n,M} \right), \quad \alpha \geq 1.$$

The parameter α controls the strength of the economies of scope: when $\alpha > 1$, the inequality above holds strictly and there are economies of scope; when $\alpha = 1$, there are no economies of scope. One interpretation of economies of scope is that firm invest in customer capital can benefit multiple products at once. For example, a multi-industry firm like General Electric advertises in terms of a general brand (GE), thereby building customer capital across all its products (jet engines, appliances, ...).

Result 1. *When there are no economies of scope ($\alpha = 1$), the S and the M firms produce identical amounts in a given industry ($C_{n,S} = C_{n,M}$). Moreover, the semi-elasticity of their total sales to a shock to household income I the same. When there are economies of scope ($\alpha > 1$), M firms produce more than S firms in a given industry ($C_{n,S} < C_{n,M}$). Moreover, the semi-elasticity of total sales of M firms in industry n is lower than that S-firms: $\frac{\partial \log(P_{n,M} C_{n,M})}{\partial \log(I)} < \frac{\partial \log(P_{n,S} C_{n,S})}{\partial \log(I)}$.*

The intuition for this result is straightforward. First, in the absence of economies of scope ($\alpha =$

1), within a particular industry, S and M firms are identical. In particular, they produce the same amounts and their sales respond in the same way to a shock to either marginal cost or household income. Note that, had we assumed a standard CES demand system with $C^*_{n,S} = C^*_{n,M} = 0$, a shock to household income, for instance, would have entirely passed through to industry sales. With investment in customer capital, the pass-through is imperfect; that is, a 1% decline in income translates to a less than 1% decline in sales in each industry.

Economies of scope ($\alpha > 1$) introduces asymmetries across M and S firms within each industry. Effectively, with economies of scope, in an otherwise symmetric equilibrium, M firms face a uniformly lower marginal cost of investing in customer capital (though it is still convex.) As a result, they choose to invest more in customer capital in equilibrium. Their prices are also lower, so that their overall demand is higher. Moreover, the higher investment in customer capital lowers the overall elasticity of their demand to household income shocks. Note that both S- and M-firms invest in customer capital, in equilibrium; so the pass-through of household income shocks is not perfect for any firm. However, it is weaker for the M-firms, due to the economies of scope.

Though mechanism is simple, it provides a parsimonious way of accounting for the two main empirical findings described above. Note that both customer capital and economies of scope are essential; if either were absent from the model, these two predictions would not hold.

8 Conclusion

This paper brings new evidence to bear on the cyclicality of small and large firms using novel firm-level data for the cover a large sample of US public and private firms from 1977 to 2014. We provide strong evidence that small are more cyclical: a 1% drop in GDP is associated with a 2.5% drop in sales for the top 1% of firms by size but a 3.1% contraction for the bottom 99%. This difference is statistically significant, holds across the trade and manufacturing sectors, holds for recession dates, and survives a battery of robustness checks. This modest difference in sensitivity combined with the high and rising concentration of sales and investment at the top 1% imply that small firms only have a negligible effect of aggregate fluctuations.

We provide evidence that suggests this size effect is not driven by access to financing. In particular, the size effect we document appears to be largely orthogonal to balance sheet proxies for financial strength and not extend to debt flows which appear to be equally cyclical among small and large firms. We find only small differences in the response of sales, investment and inventories to monetary policy shocks. Instead, we offer evidence for a non-financial explanation for the cyclicality of small and large firms based on differential investment in customer capital.

Our results challenge the commonly accepted view that small firms are more cyclical because of financial frictions. Additionally, they shed light on models of financial frictions where most ex-ante firm heterogeneity is driven by net worth and financing constraints are strongly procyclical, since these models will tend to predict that size is a good proxy for the tightness of financial constraints. Finally, our results caution against using differential responses by size as a way to diagnose the financial effects of aggregate shocks, a common practice in the empirical macro and corporate finance literature. Aside from these positive implications, our results are potentially relevant for countercyclical policies supporting small business credit; they suggest that their impact may be more limited than commonly assumed.[68] As we emphasize, our results do *not* imply that financial frictions are generally irrelevant to the transmission of shocks to firms or over the firm lifecycle. Our point is more specific: comparing the business cycle sensitivity of small and large firms is unlikely to be informative about financial amplification mechanisms. Other proxies for financial strength might well be. In this vein, Appendix C compares the behavior in sales and investment in firms sorted by some such proxies. These proxies show little power in predicting heterogeneous responses of firms in recessions with the notable exception of dividend issuance. While their lack of predictive power may be a challenge for certain models of financial amplification, they do not rule out others — in particular, those where borrowing capacity are limited by future cash flows, instead of assets in place or net worth. Recent work by Chodorow-Reich and Falato (2017) and Lian and Ma (2019) 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 financial amplification in the future.

[68] Credit support programs for SMEs are common in advanced economies; examples include the SBA's funding programs in the US, the Small Business Financing program in Canada, the Business Finance Partnership in the UK, the European Investment Bank's small business support programs in the EU, among others. For a discussion of theses programs during the Great Recession, see Wehinger (2014).

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Panel A: size and growth

Size group	*0-90th*	*90-99th*	*99-99.5th*	*>99.5th*	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

Size group	*0-90th*	*90-99th*	*99-99.5th*	*>99.5th*	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 1977q3 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 F. 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 D for more details on their construction.

Size group	*0-90th*	*90-99th*	*99-99.5th*	*>99.5th*
Assets				
Financial assets, incl. cash	0.149	0.099	0.074	0.055
Short-term assets				
Receivables	0.284	0.229	0.165	0.124
Inventory	0.218	0.241	0.172	0.130
Other	0.040	0.037	0.042	0.041
Long-term assets				
Net property, plant and equipment	0.269	0.288	0.289	0.287
Other, incl. intangibles	0.050	0.106	0.259	0.362
Liabilities				
Debt				
Due in 1 year or less				
Bank debt	0.083	0.083	0.032	0.016
Non-bank debt	0.035	0.019	0.019	0.028
Due in more than 1 year				
Bank debt	0.107	0.111	0.110	0.072
Non-bank debt	0.123	0.079	0.141	0.179
Trade payables	0.156	0.123	0.085	0.071
Other, incl. capital leases	0.099	0.121	0.187	0.233
Equity	0.393	0.463	0.426	0.416

Table 2: Average balance sheet, by size group. All numbers are expressed as fraction of total book assets. Fractions may not add up to 1 due to rounding. Financial assets are the sum of cash and deposits, treasury and federal agency securities, and all other financial assets. Other short-term assets include prepaid 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 D for more details on their construction.

Size group	*0-90th*	*90-99th*	*99-99.5th*	*>99.5th*
Sales growth, $<$ p25	-26.27%	-16.59%	-12.66%	-10.97%
Sales growth	0.19%	4.58%	4.34%	4.08%
Sales growth, $>$ p75	26.77%	25.83%	21.41%	19.19%
Leverage, $<$ p25	0.00	0.01	0.04	0.07
Leverage	0.35	0.29	0.30	0.28
Leverage, $>$ p75	0.47	0.39	0.39	0.36
Liquidity, $<$ p25	0.00	0.00	0.00	0.00
Liquidity	0.15	0.10	0.07	0.06
Liquidity, $>$ p75	0.20	0.13	0.10	0.07

Table 3: Approximate inter-quartile ranges for selected variables, by firm size group. All variables are averages from 1977q3 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 D for more details on their construction.

	Sales growth	Inventory growth	Fixed investment
$[90, 99] \times$ GDP growth	-0.160	-0.107	-0.299^{*}
	(0.142)	(0.174)	(0.157)
$[99, 99.5] \times$ GDP growth	-0.251^{*}	-0.299^{*}	-0.687^{***}
	(0.143)	(0.180)	(0.194)
$[99.5, 100] \times$ GDP growth	-0.600^{***}	-0.730^{***}	-1.257^{***}
	(0.140)	(0.206)	(0.355)
Observations	≈ 460000	≈ 460000	≈ 460000
Firms	≈ 60000	≈ 60000	≈ 60000
Adj. R^2	0.025	0.006	0.003
Clustering	Firm	Firm	Firm
Industry controls	D/ND	D/ND	D/ND

Table 4: Regression of sales growth, inventory growth, and fixed investment rates on GDP growth for the manufacturing sample. 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 $[0, 90]$ inter-quantile range). Size groups are defined with respect to the one-year lagged cross-sectional distribution of book assets; see Appendix D 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.

	Sales growth	Inventory growth	Fixed investment
$[50, 90] \times$ GDP growth	-0.335	-0.489^{*}	-0.442^{*}
	(0.125)	(0.072)	(0.054)
$[90, 100] \times$ GDP growth	-0.910^{***}	-0.592^{**}	-0.439^{*}
	(0.000)	(0.047)	(0.095)
Observations	≈ 120000	≈ 120000	≈ 120000
Firms	≈ 10000	≈ 10000	≈ 10000
Adj. R^2	0.017	0.005	0.004
Clustering	Firm	Firm	Firm
Industry controls	WHS/RET	WHS/RET	WHS/RET

Table 5: Regression of sales growth, inventory growth, and fixed investment rates on GDP growth for the trade sample. 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 $[0, 50]$ size group.) Because the threshold for inclusion in the trade segment of the QFR is higher, we use a lower quantiles of the distribution of book assets in order to define our size groups. Size groups are defined with respect to the one-year lagged cross-sectional distribution of book assets; see Appendix D for more details on the construction of these groups. All specifications contain an indicator for the wholesale/retail sector, 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.

	Elasticity to growth rate of GDP					
	GG growth rates		CM growth rates (firm-level)		CM growth rates (aggregate)	
Small firms sales growth	2.286^{***}	(0.373)	2.962^{***}	(0.362)	2.378^{***}	(0.446)
Large firms sales growth	2.564^{***}	(0.574)	2.365^{***}	(0.304)	2.278^{***}	(0.526)
Difference	-0.278	(0.359)	0.597^{***}	(0.196)	0.100	(0.287)

Table 6: The size effect estimated using the public aggregate tabulations of the QFR (first column), and using the firm-level micro data (second and third columns.) The first column focuses on growth rates for small and large firms constructed using the public tabulations of the QFR; the methodology follows Gertler and Gilchrist (1994) and is described in detail in Appendix D. Each line reports the elasticity of a variable of interest (small firms' sales growth, large firms' sales growth, and their difference) with respect to GDP growth, along with Newey-West standard errors robust up to 8 lags. The second and third column focus on growth rates constructed using the micro data. The second column uses the equal-weighted average firm-level growth rate among continuing firms; small firms are defined as the bottom 99%, and large firms as the top 1%. The time series used in the second column are thus identical to those plotted in Figures 1 and 2. The time series used in the third column are constructed based on the same group of continuing firms and the same size classification as column 2. However, instead of equal-weighted average firm-level growth rates, as in column 2, column 3 focuses on aggregate growth rates. Section 4.4 provides more detail on the comparison across data sources. The sample is 1977q3-2014q1. $*$, $**$ and $***$ indicate 10%, 5% and 1% significance levels, respectively.

	Average response around Romer dates	
Sample	GG growth rates	CM growth rates (firm-level)
1958q4 to 1991q4	$\Delta_L = -7.0\%$	n.a.
	$\Delta_S = -13.1\%$	n.a.
1977q3 to 1991q4	$\Delta_L = -6.8\%$	$\Delta_L = -7.0\%$
	$\Delta_S = -10.8\%$	$\Delta_S = -11.3\%$
1977q3 to 2014q1	$\Delta_L = -8.4\%$	$\Delta_L = -5.8\%$
	$\Delta_S = -9.5\%$	$\Delta_S = -9.2\%$

Table 7: Comparison with Gertler and Gilchrist (1994). Each line reports results from a different sample. The column marked "GG growth rate" report results computed using the GG methodology, described in Appendix D. The column marked "CM growth rate" report results computed the methodology of this paper: equal-weighted growth rates for firms belonging to the bottom 99% and the top 1% of the one-year lagged distribution of assets, respectively. Some cells are marked "n.a." because the underlying micro data is necessary for the construction of CM growth rates but unavailable before 1977q3. Romer dates are the dates identified by Romer and Romer (1989) as monetary policy contractions: 1966q2, 1968q4, 1974q2, 1978q3, 1979q4 and 1988q4. As in Kudlyak and Sanchez (2017), we add 1994q2 and 2008q3 to these two dates for the 1977q3-2014q1 sample. The statistics Δ_L and Δ_S are the average cumulative change in sales around the Romer dates, for large (L) and small (S) firms, respectively. Appendix Figures A4 and A5 report the underlying cumulative changes in sales growth around each Romer date using the GG methodology, for the 1958q4 to 1991q4, and the 1977q3 to 2014q1 samples, respectively. Appendix Figure A6 reports the underlying cumulative changes in sales around each Romer date using the firm-level growth rates studied in this paper, for the 1977q3 to 2014q1 sample.

	Actual β	Counterfactual 1 $\beta^{(1)}$	Counterfactual 2 $\beta^{(2)}$	Counterfactual 3 $\beta^{(3)}$	Counterfactual 4 $\beta^{(4)}$
Sales	2.293	2.154	2.270	1.700	1.817
	(0.342)	(0.342)	(0.366)	(0.326)	(0.351)
Inventory	0.919	0.719	0.770	0.589	0.640
	(0.226)	(0.250)	(0.226)	(0.243)	(0.218)
Fixed investment	0.584	0.569	0.569	0.525	0.525
	(0.145)	(0.151)	(0.148)	(0.150)	(0.147)
Total assets	0.876	0.787	0.838	0.703	0.754
	(0.121)	(0.129)	(0.119)	(0.129)	(0.119)
Observations	143	143	143	143	143

Table 8: Cyclical sensitivities of aggregate sales, inventory, fixed investment, and total assets. Each line reports the estimated slope in regressions of the form $Z_t = \alpha + \beta \log\left(GDP_t/GDP_{t-4}\right) + \epsilon_t$. 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. Columns 4 and 5 use the same counterfactuals as columns 2 and 3 respectively, but magnify the fluctuations of small firms to ensure that small firms display twice the elasticity with respect to GDP as large firms. Heteroskedasticity robust standard errors in parentheses.

	Sales growth					
	Baseline	(1)	(2)	(3)	(4)	(5)
$[90, 99] \times$ GDP growth	-0.160	-0.189	-0.195	-0.162	-0.193	-0.176
$[99, 99.5] \times$ GDP growth	-0.251^{*}	-0.257^{*}	-0.321^{**}	-0.282^{*}	-0.490^{***}	-0.247
$[99.5, 100] \times$ GDP growth	-0.600^{***}	-0.563^{***}	-0.675^{***}	-0.640^{***}	-1.097^{***}	-0.594^{***}
Bank share [0.10,0.90] $\times$ GDP growth		0.300				
Bank share $< 0.10 \times$ GDP growth		-0.315				
Leverage [0.15,0.50] $\times$ GDP growth			-0.126			
Leverage (0,0.15] $\times$ GDP growth			-0.474^{*}			
Leverage $= 0 \times$ GDP growth			-0.630^{**}			
Liquidity [0.01,0.20] $\times$ GDP growth				0.228		
Liquidity $> 0.20 \times$ GDP growth				-0.101		
Market access $\times$ GDP growth					0.826^{**}	
Dividend issuance $\times$ GDP growth						0.087
Observations	≈ 460000	≈ 460000	≈ 460000	≈ 460000	≈ 460000	≈ 460000
Firms	≈ 60000	≈ 60000	≈ 60000	≈ 60000	≈ 60000	≈ 60000
Adj. R^2	0.025	0.025	0.025	0.025	0.025	0.025
Industry controls	D/ND	D/ND	D/ND	D/ND	D/ND	D/ND
Clustering	Firm	Firm	Firm	Firm	Firm	Firm

Table 9: Regression of sales growth on firm size and proxies for financial constraints (model 5). 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. $*$, $**$ and $***$ indicate 10%, 5% and 1% significance levels, respectively.

	Employment (000's)	Establishments (00's)	Lines of business (00's)	Manufacturing index
$[0, 90]$	0.059	0.020	0.013	0.984
	(0.002)	(0.001)	(0.001)	(0.001)
$[90, 99]$	0.404	0.051	0.031	0.926
	(0.007)	(0.001)	(0.001)	(0.002)
$[99, 99.5]$	1.808	0.170	0.084	0.857
	(0.056)	(0.007)	(0.002)	(0.005)
$[99.5, 100]$	9.649	0.667	0.233	0.818
	(0.961)	(0.065)	(0.013)	(0.006)
Observations	≈ 200000	≈ 200000	≈ 200000	≈ 200000
Firms	≈ 30000	≈ 30000	≈ 30000	≈ 30000
Adj. R^2	0.137	0.153	0.379	0.986

Table 10: Summary statistics for the QFR manufacturing sample merged to the DMI database. Each line corresponds to a different size group; size groups are defined based on the cross-sectional distribution of book assets, as described in Section 4.1. Each column reports the coefficients in a regression of a particular outcome variable on a full set of dummies, excluding the constant; that is, they are the conditional mean of each outcome variable by size group in the matched sample. The numbers in parentheses are standard errors, clustered at the firm level. The first column reports the conditional mean for employment (in thousands). The second column reports the conditional mean of the number of establishments (in hundreds). The third column reports the conditional mean of the number of lines of business (that is, the distinct number of SIC-4 digit codes in the collection of all establishments belonging to a particular firm; in hundreds). The fourth column reports the conditional mean of the manufacturing index, defined as the percentage of total firm revenue generated by establishments with an SIC-4 digit code in manufacturing, where revenue is measured using the DMI files.

	Sales growth			
	(1)	(2)	(3)	(4)
$[90, 99] \times$ GDP growth	-0.222		-0.138	-0.255
	(0.261)		(0.302)	(0.315)
$[99, 99.5] \times$ GDP growth	-0.221		-0.033	-0.259
	(0.276)		(0.363)	(0.387)
$[99.5, 100] \times$ GDP growth	-0.802^{***}		0.048	-0.082
	(0.247)		(0.392)	(0.412)
lines of business $\in [2, 5] \times$ GDP growth		-0.426^{*}	-0.387	-0.548
		(0.374)	(0.340)	(0.420)
lines of business $\in [5, 20] \times$ GDP growth		-0.576^{*}	-0.507	-0.807
		(0.389)	(0.445)	(0.568)
lines of business $> 20 \times$ GDP growth		-0.900^{***}	-0.935^{**}	-1.329^{***}
		(0.420)	(0.418)	(0.599)
establishments $\in [2, 5] \times$ GDP growth				0.592
				(0.502)
establishments $\in [5, 50] \times$ GDP growth				0.527
				(0.569)
establishments $> 50 \times$ GDP growth				0.706
				(0.641)
Observations	≈ 200000	≈ 200000	≈ 200000	≈ 200000
Firms	≈ 30000	≈ 30000	≈ 30000	≈ 30000
Adj. R^2	0.033	0.031	0.034	0.035
Industry controls	D/ND	D/ND	D/ND	D/ND
Clustering	firm-level	firm-level	firm-level	firm-level

Table 11: The size effect and the establishment composition of firms in the QFR manufacturing sample. The dependent variable in all specifications is sales growth. The first three lines report the estimated sensitivity of firm-level sales growth to GDP growth for different size groups relative to a baseline category, when size is defined in terms of quantiles of book assets, as in Section 4.1; the baseline category is the group of firm in the [0,90] inter-quantile range for size. The fourth to sixth line report the estimated sensitivity of firm-level sales growth to GDP growth for groups of firms with different numbers of lines of business, relative to a baseline category. A firm's number of lines of business is the total number of distinct SIC-4 digit codes of the collection of establishments that make up the firm in a given quarter. The baseline category are firms with one line of business. The seventh to ninth lines report the estimated sensitivity of firm-level sales growth to GDP growth for groups of firms with different numbers of establishments, relative to a baseline category; the baseline category are single-establishment firms. Establishment counts and the industry composition of establishments for a given firm are obtained by merging the QFR with DMI. $*$, $**$ and $***$ indicate 10%, 5% and 1% significance levels, respectively; standard errors clustered at the firm level reported in parentheses.

	Sales growth			
	(1)	(2)	(3)	(4)
$[50, 90] \times$ GDP growth	-0.202		-0.153	-0.114
	(0.269)		(0.267)	(0.266)
$[90, 100] \times$ GDP growth	-0.669^{**}		-0.444	-0.350
	(0.295)		(0.298)	(0.298)
lines of business $\in [5, 20] \times$ GDP growth		-0.203	-0.134	-0.094
		(0.231)	(0.228)	(0.246)
lines of business $> 20 \times$ GDP growth		-1.270^{****}	-1.042^{***}	-0.657^{**}
		(0.318)	(0.324)	(0.366)
establishments $\in [10, 100] \times$ GDP growth				-0.493^{*}
				(0.269)
establishments $> 100 \times$ GDP growth				-0.613^{*}
				(0.353)
Observations	≈ 80000	≈ 80000	≈ 80000	≈ 80000
Firms	≈ 10000	≈ 10000	≈ 10000	≈ 10000
Adj. R^2	0.021	0.021	0.021	0.022
Industry controls	WHS/RET	WHS/RET	WHS/RET	WHS/RET
Clustering	firm-level	firm-level	firm-level	firm-level

Table 12: The size effect and the establishment composition of firms in the QFR trade sample. The dependent variable in all specifications is sales growth. The first three lines report the estimated sensitivity of firm-level sales growth to GDP growth for different size groups relative to a baseline category, when size is defined in terms of quantiles of book assets, as in Section 4.1; the baseline category is the group of firm in the [0,50] inter-quantile range for size. The fourth to fifth line report the estimated sensitivity of firm-level sales growth to GDP growth for groups of firms with different numbers of lines of business, relative to a baseline category. A firm's number of lines of business is the total number of distinct SIC-4 digit codes of the collection of establishments that make up the firm in a given quarter. The baseline category are firms with 1 to 5 lines of business. The sixth and seventh lines report the estimated sensitivity of firm-level sales growth to GDP growth for groups of firms with different numbers of establishments, relative to a baseline category; the baseline category are firms with less than 10 establishments. Establishment counts and the industry composition of establishments for a given firm are obtained by merging the QFR with DMI. $*$, $**$ and $***$ indicate 10%, 5% and 1% significance levels, respectively; standard errors clustered at the firm level reported in parentheses.

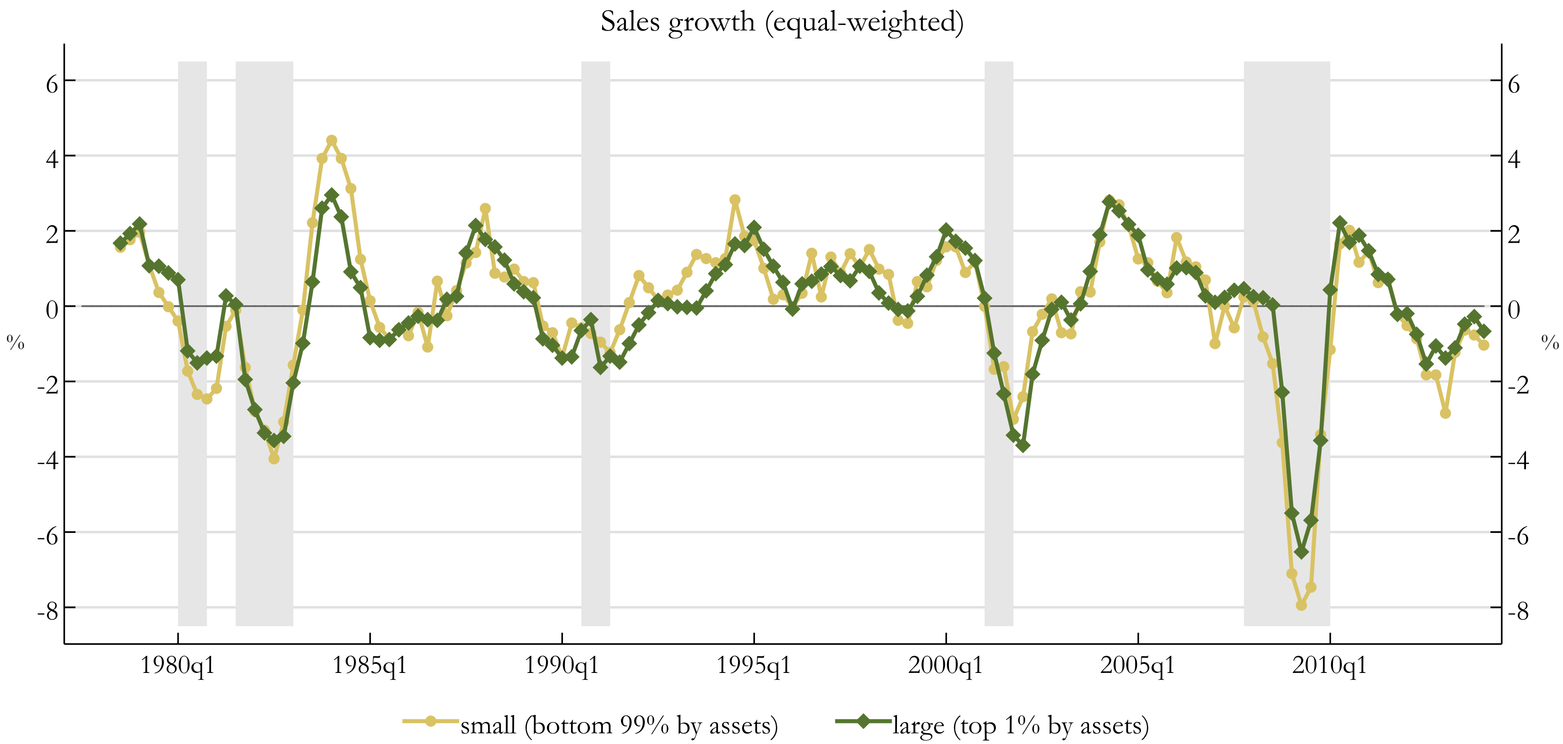


Figure 1: Average firm-level growth rate of sales of small (yellow, round markers) and large (green, diamond markers) firms. Times series are demeaned before plotting. Small firms are those belonging to the bottom 99% of the one-year lagged distribution of book assets, while large firms are those belonging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

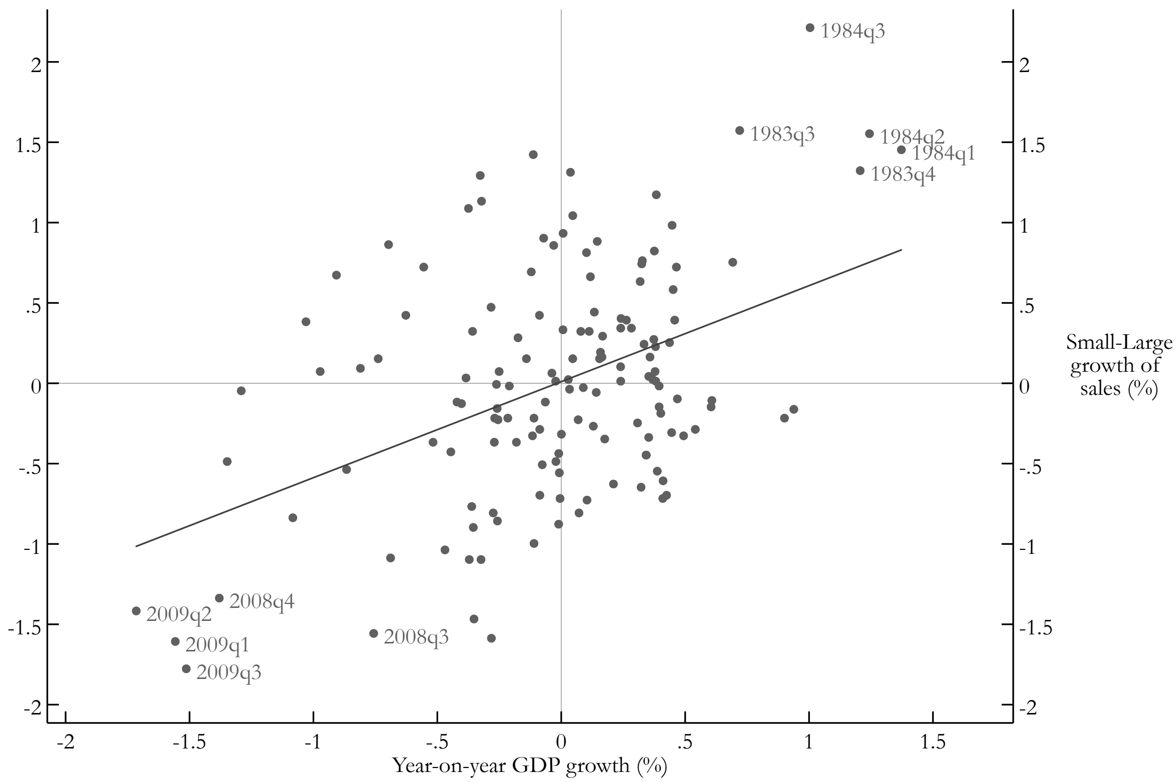


Figure 2: Difference between average growth rates of sales $\hat{g}_t^{(small)}(\text{sales}) - \hat{g}_t^{(large)}(\text{sales})$ (vertical axis) and year-on-year GDP growth (horizontal axis). Both series are demeaned. The OLS regression line has a slope of 0.597, with Newey-West standard error (allowing up to 8 lags) of 0.196.

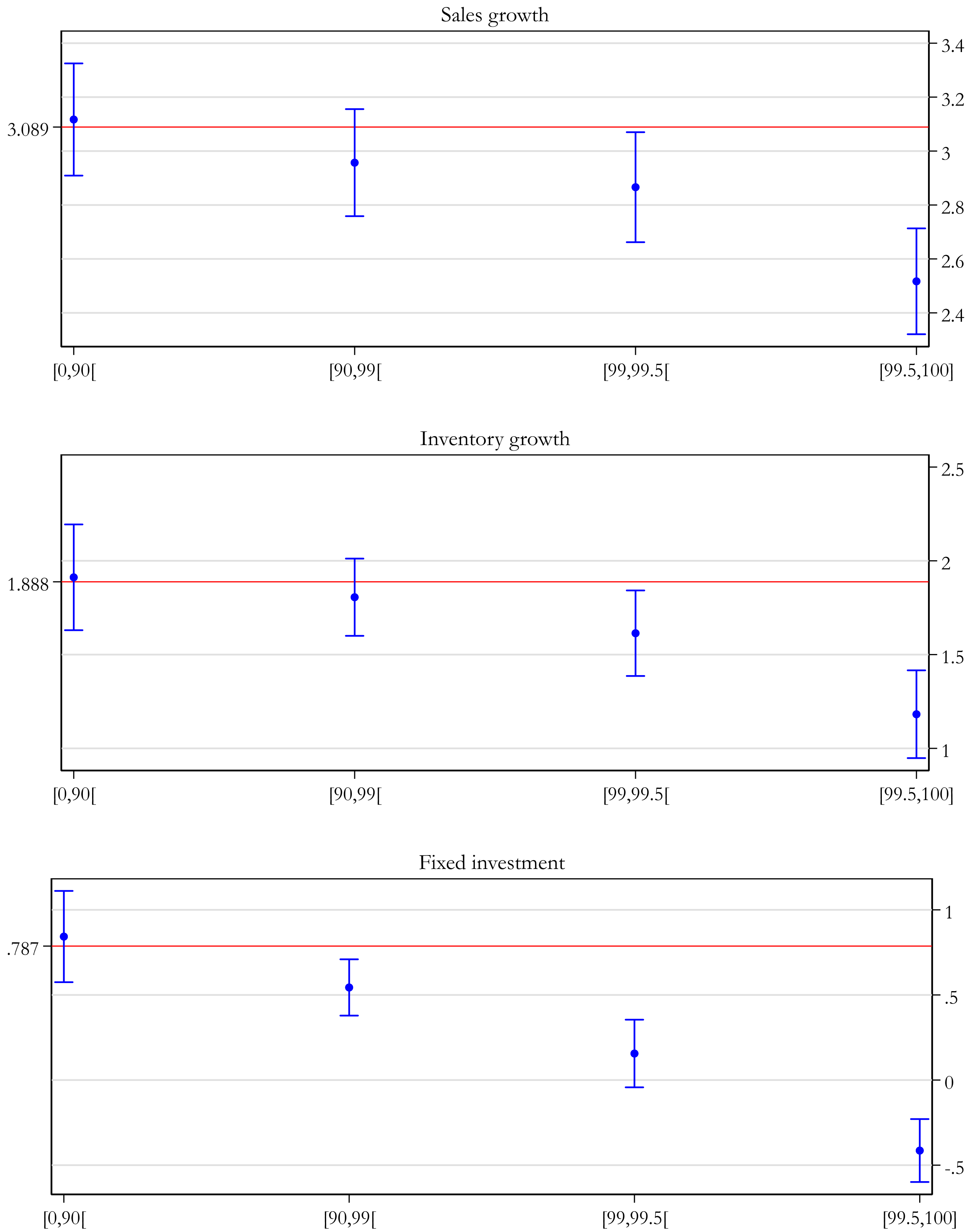


Figure 3: Average marginal effect of GDP growth on sales growth, inventory growth, and fixed investment, by size group and unconditionally. The marginal effects are computed using estimates of Equation (1), whose estimation results are reported in Table 4. Blue: conditional average marginal effect by size group, with $+/-2s.e.$ confidence interval. Red: unconditional average marginal effect.

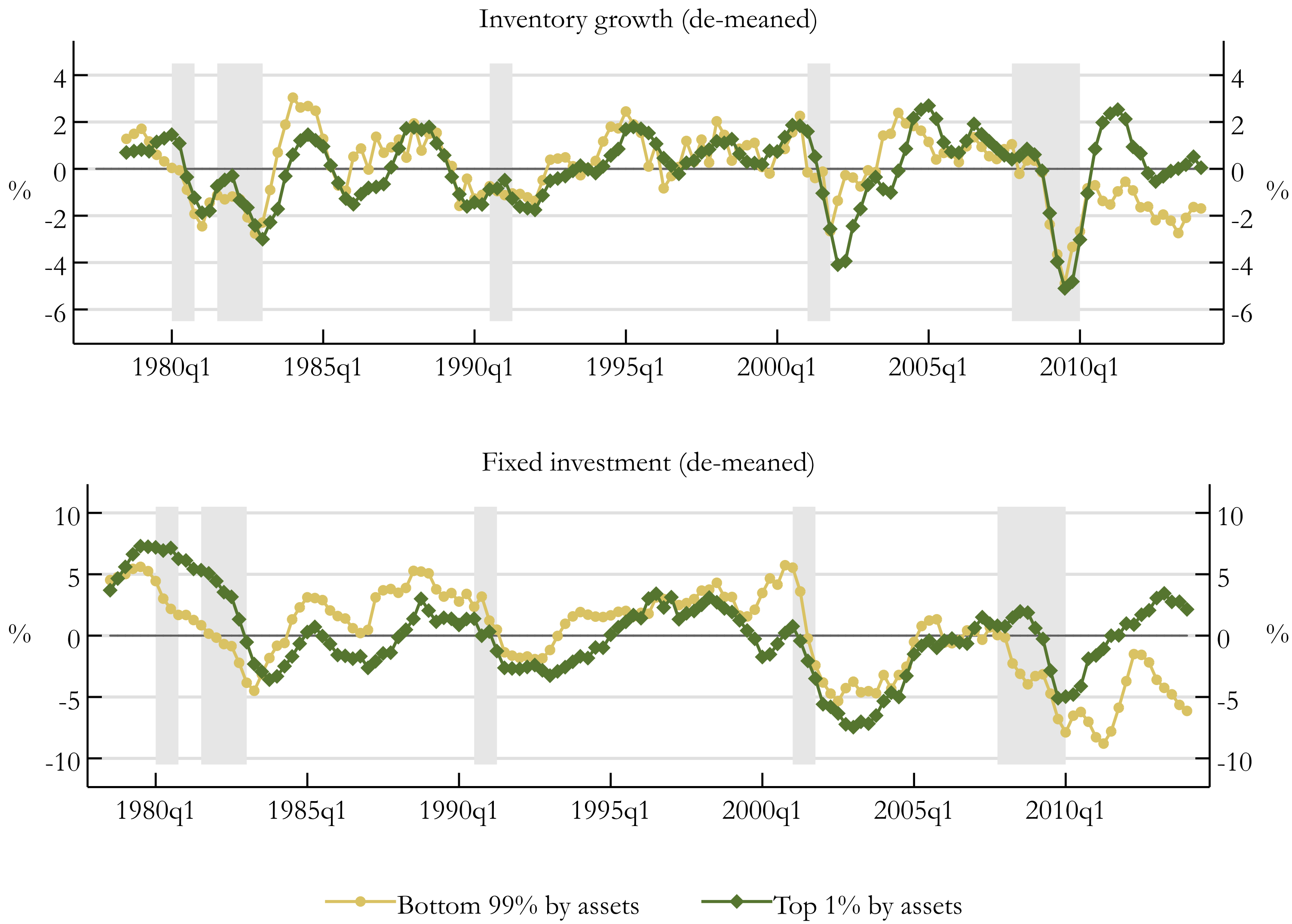


Figure 4: Average firm-level growth rate of small (yellow, round markers) and large (green, diamond markers) firms; top: inventory growth rate; bottom: fixed investment rate. All series are demeaned before plotting. Small firms are those belonging to the bottom 99% of the one-year lagged distribution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

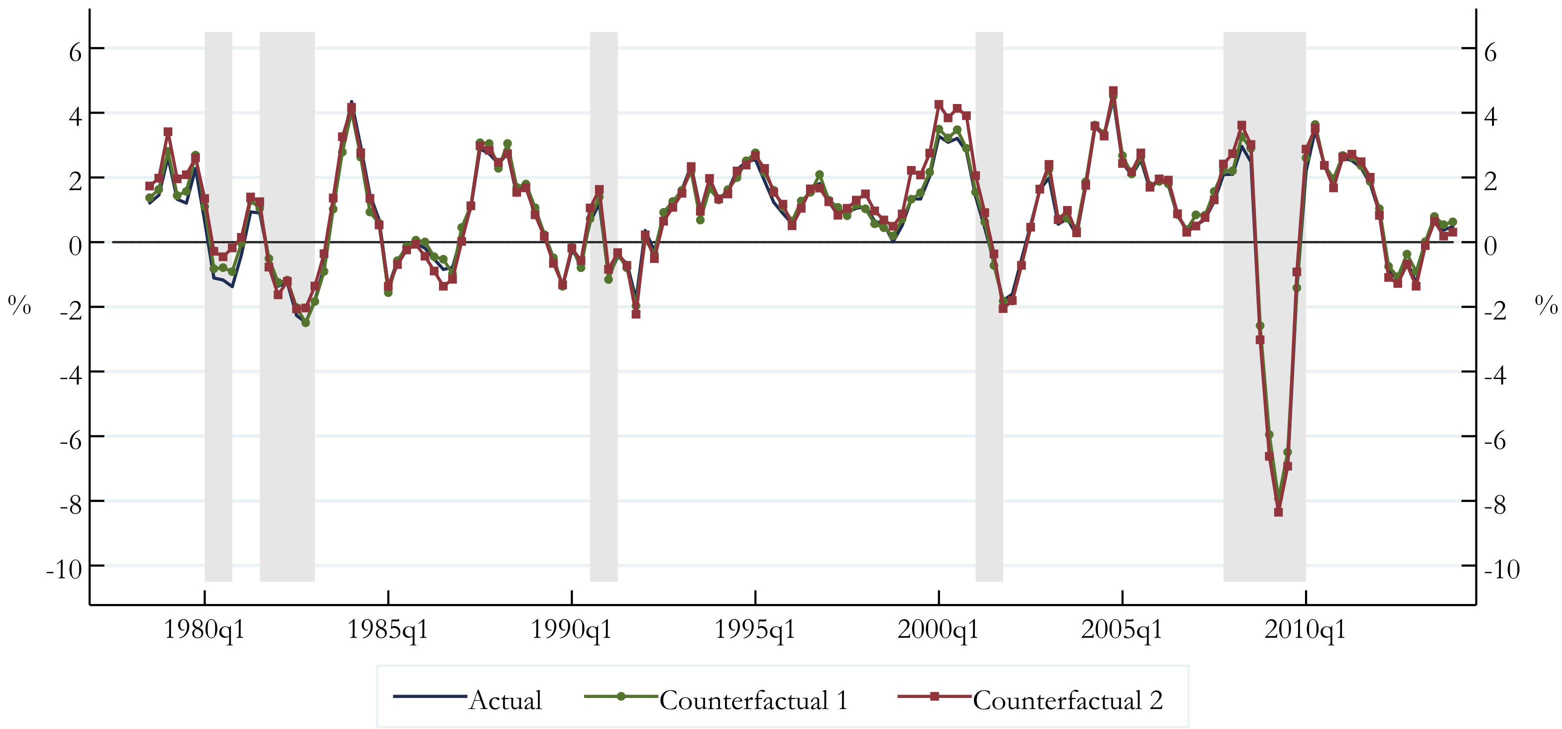


Figure 5: Aggregate growth rate of sales G_t (solid blue line); counterfactual growth rate $G_t^{(1)}$ (circled green line), which assumes that the average firm-level growth rate of small and large firms is equal; and counterfactual growth rate 2 $G_t^{(2)}$ (squared red line), which also assumes that the covariance between size and growth is the same between small and large firms.

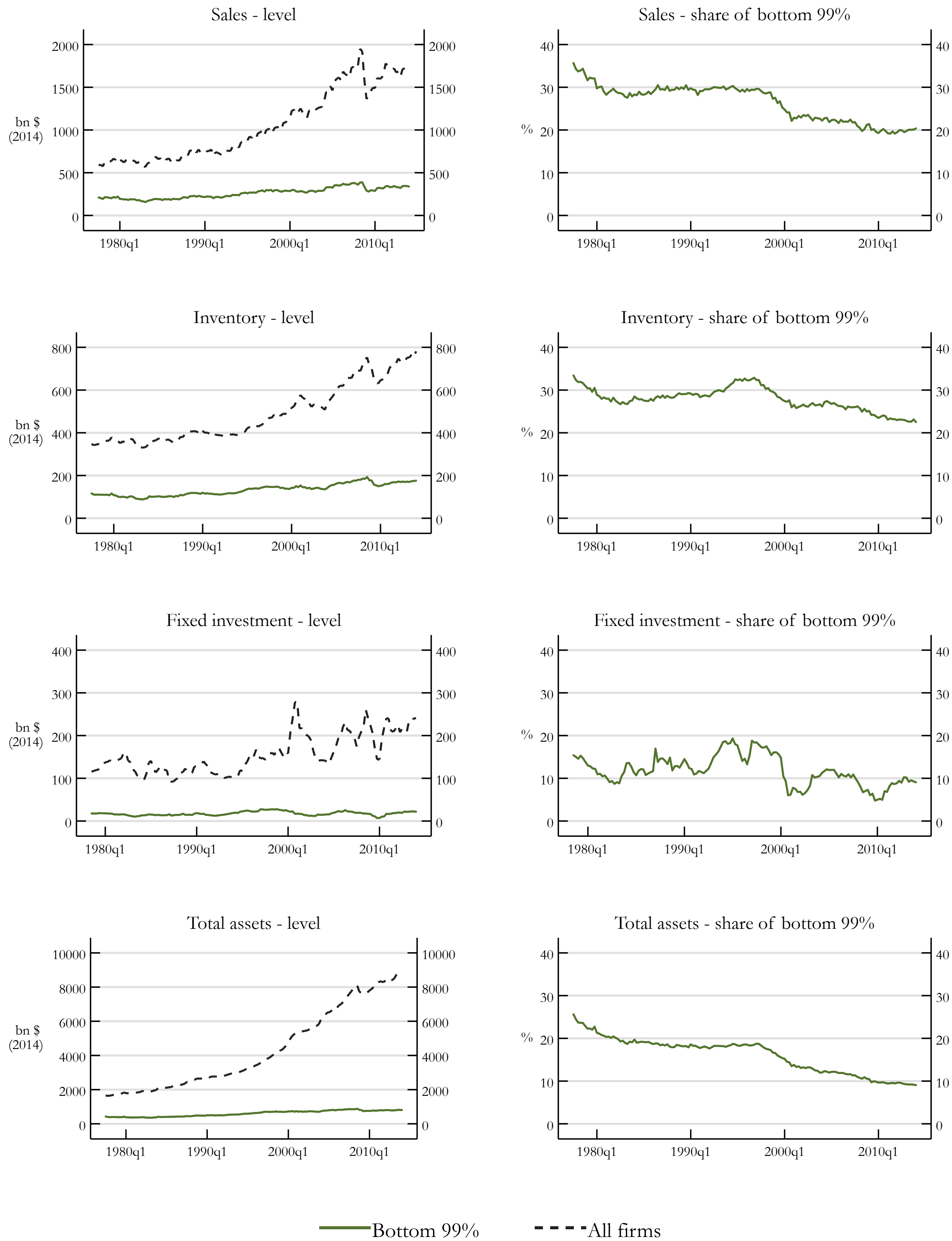


Figure 6: Concentration of sales, inventory, fixed investment, and total assets in the US manufacturing sector. The left column reports total nominal values for the bottom 99% and top 1% of firms by size. All series are deflated by the BEA price index for manufacturing, normalized to 1 in 2009q1; the 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.

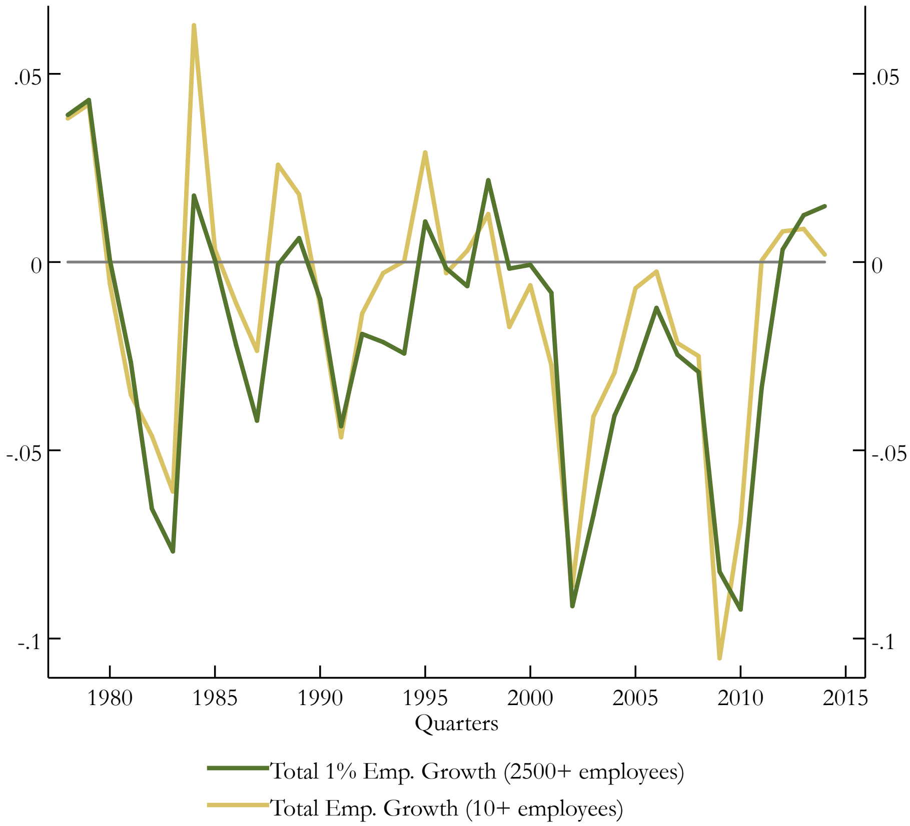


Figure 7: The green line displays annual employment growth for the estimated top 1% of manufacturing firms. The yellow line displays annual employment growth for all manufacturing firms with over 10 employees (our estimate of the portion of manufacturing employment captured in our data set).

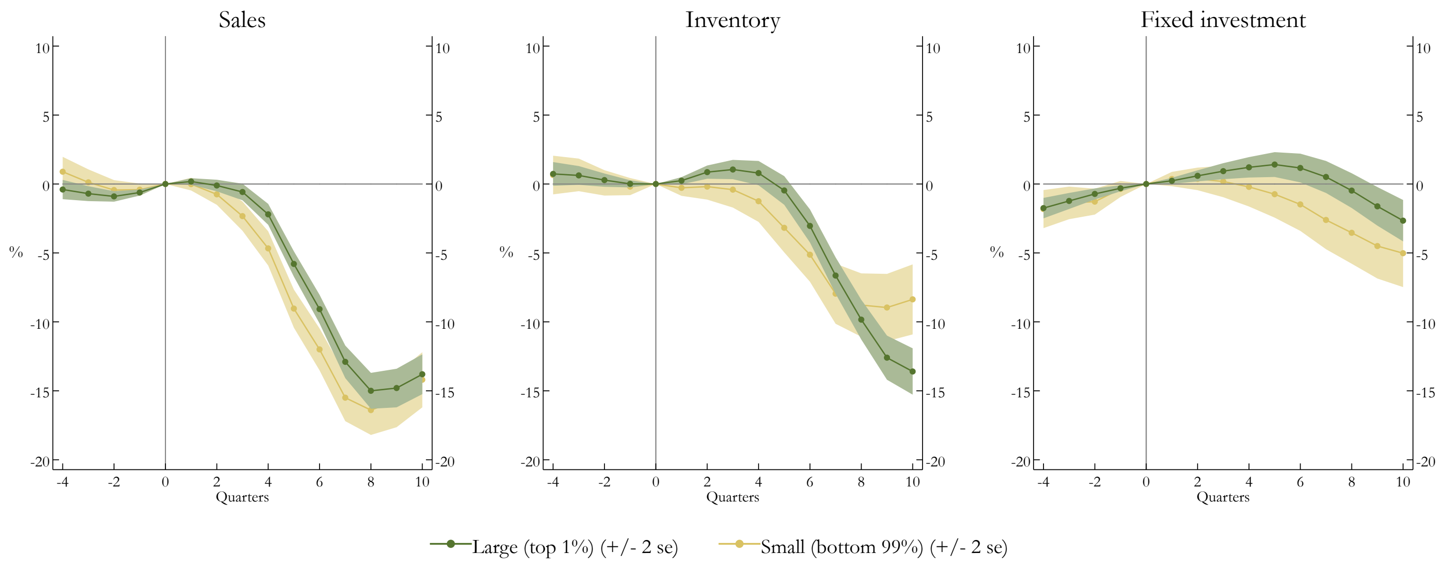


Figure 8: The behavior of sales, inventory and fixed capital after the start of a recession. Each graph reports the cumulative change in a variable of interest after the beginning of a recession. Shaded areas are +/- 2 standard error bands. All growth rates are computed year-on-year and expressed at the quarterly frequency. Recession start dates are 1981q3, 1990q3, 2001q1, and 2007q4. See Section 6.2 for more details.

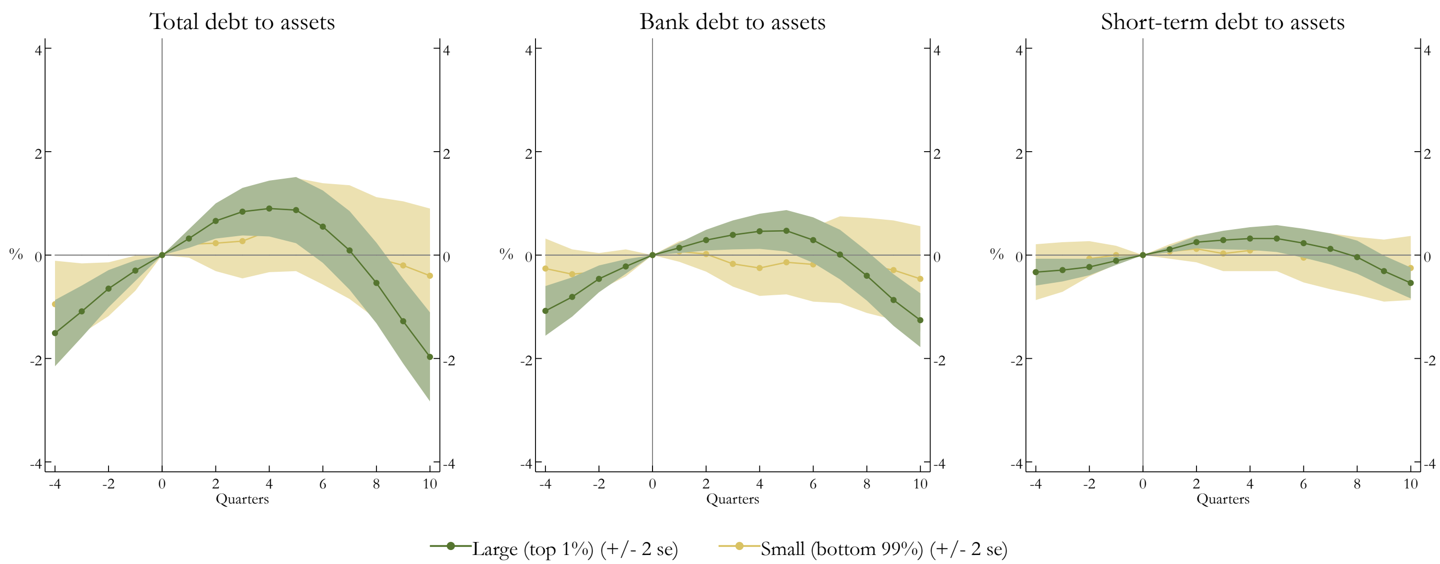


Figure 9: The behavior of debt overall, bank debt, and short-term debt after the start of a recession. Each panel reports changes relative to quarter 0 (the recession start date), computed using the cumulative sum of average growth rate of each size group. Growth rates at the firm-level are computed as $\frac{x_{i,t}-x_{i,t-4}}{assets_{i,t-4}}$, where $x \in \{\text{all debt}, \text{bank debt}, \text{short-term debt}\}$. Size groups are defined with a four-quarter lag.

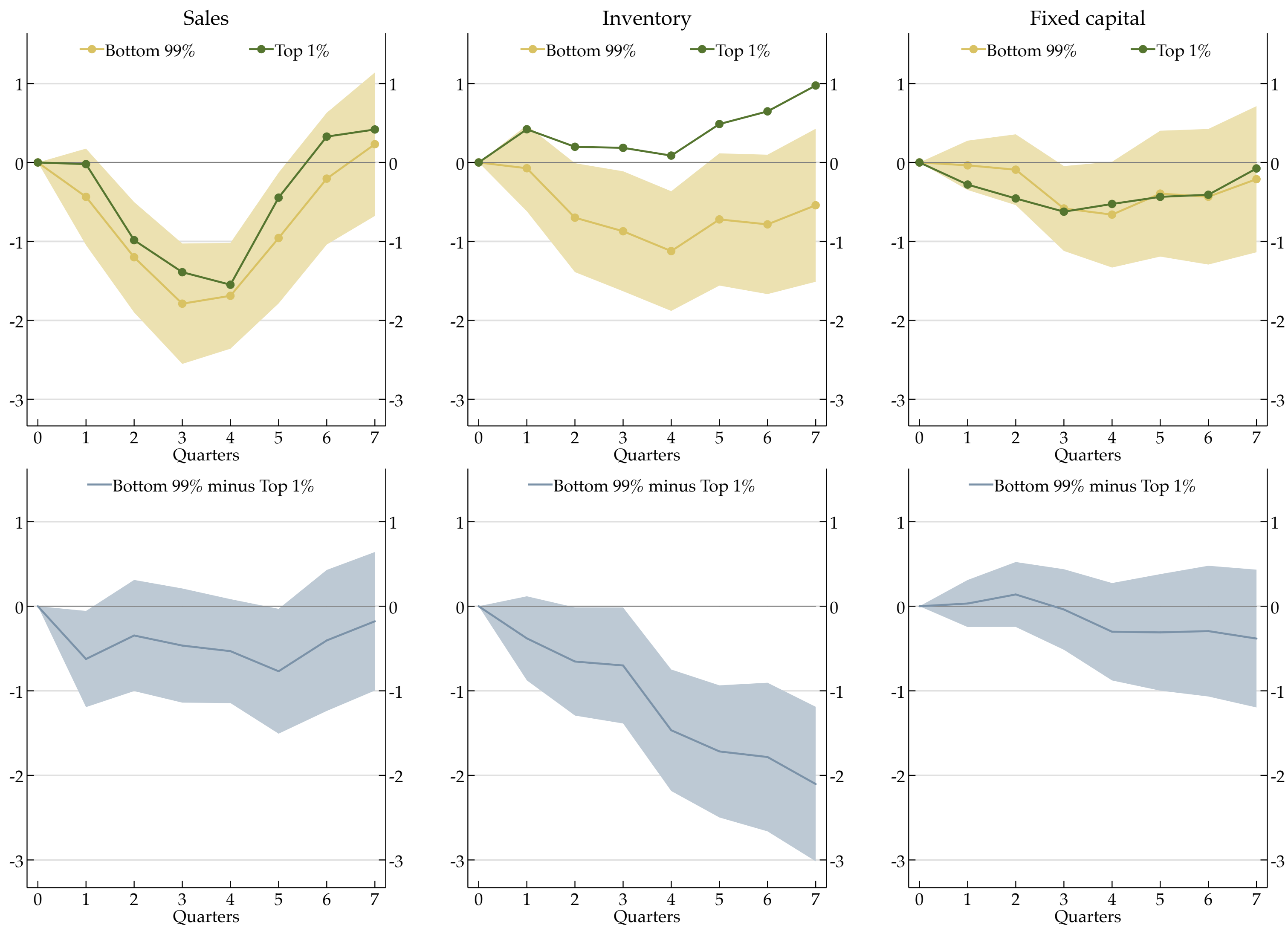


Figure 10: Firm-level response of sales, inventory and fixed capital to an innovation to the Romer and Romer (2004) shock. The estimated specification is model 7. The top row of graphs reports the average marginal effect at the mean of a one percentage point increase in $rr_{t-1,t}$, for the bottom 99% 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 $\beta^{(h)}_{(0,99)} - \hat{\beta}^{(h)}_{(99,100)}$, along with its 95% confidence interval. Data is from 1977q3 to 2007q4.

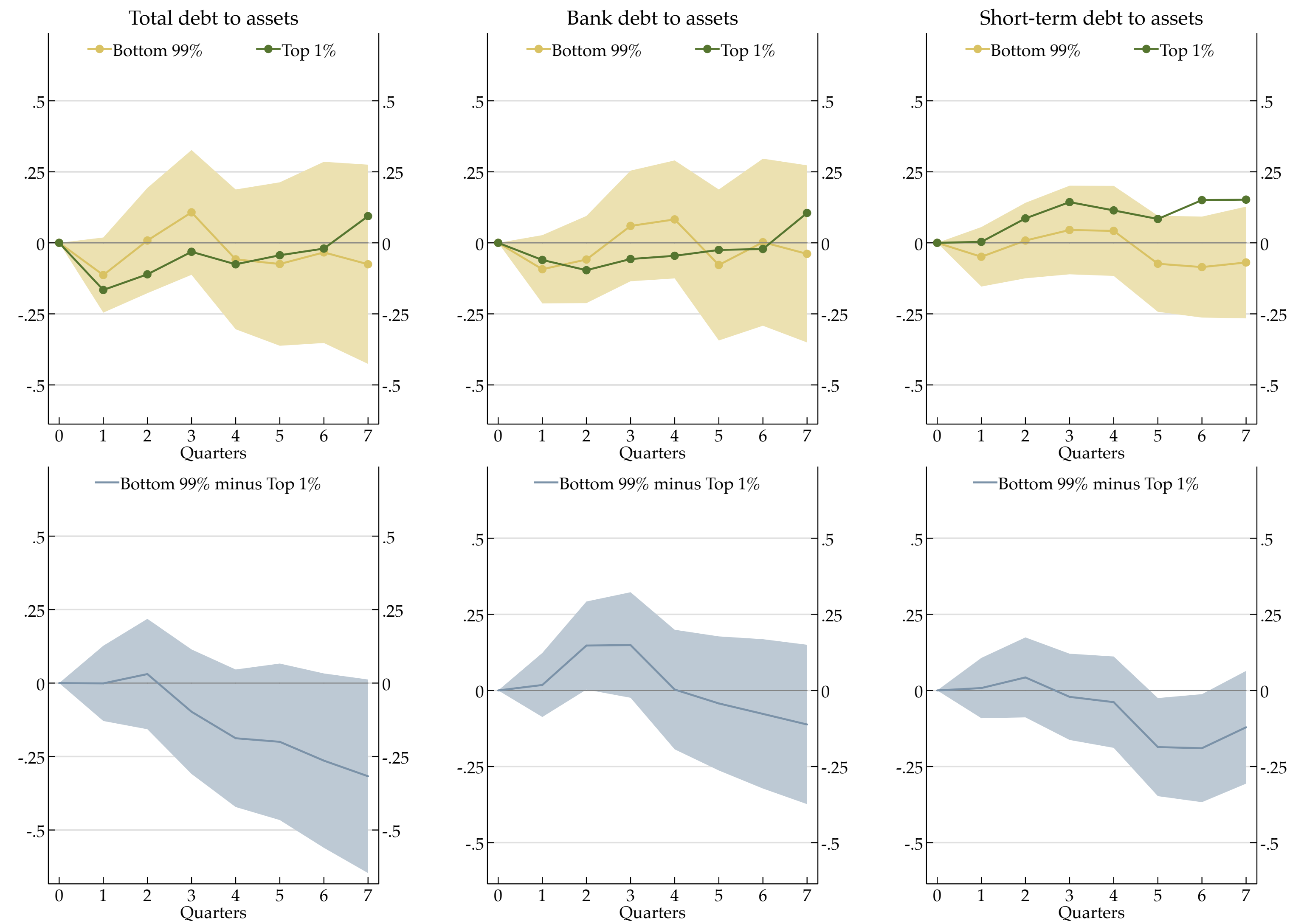


Figure 11: Firm-level response of the ratios of total debt, bank debt and short-term debt to assets to an innovation to the Romer and Romer (2004) shock. The estimated specification is model 7. The top row of graphs reports the average marginal effect at the mean of a one percentage point increase in $rr_{t-1,t}$, 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 $\beta^{(h)}_{(0,99)} - \hat{\beta}^{(h)}_{(99,100)}$, along with its 95% confidence interval. Data is from 1977q3 to 2007q4.

Appendices

[FOR ONLINE PUBLICATION.]

A A simple model where size and financial constraints coincide

A.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:

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

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.[69] 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): $n_{i,t} \gtrless k_{i,t}$. 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:

$$k_{i,t+1} = k^* \equiv \left(\frac{\zeta z}{r+\delta}\right)^{\frac{1}{1-\zeta}}, \quad \forall i, t. \tag{8}$$

[69] The 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.

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, the solution to the model with frictions is:

$$k_{i,t+1} = \begin{cases} n_{i,t} & \text{if } n_{i,t} < k^* \\ k^* & \text{if } n_{i,t} \geq k^* \end{cases} . \tag{9}$$

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 A.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 $z_t = z\exp\left(-\rho^t\epsilon\right)$, 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 A1 shows the perfect foresight response of output to a temporary decline in z_t, starting from the steady-state described by (9).[70] In the model with frictions, the most responsive firms are the largest ones — there are differences in cylicality 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.[71] Financial frictions, in this case,

[70] The calibration of the model is described in section A.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 $\epsilon = 0.01$.

[71] Below 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.

work like an adjustment cost, moderating the response of quantities.

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:

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

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).[72]

The solution to the firm's problem is similar to the case with no borrowing; the details and proofs are reported in section A.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.[73]

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 A1 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.[74] 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

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

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

[74] The 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.

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 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 A1 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.

A.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:

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

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:

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

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

$$k_j = \begin{cases} \mathbf{n}^j(k_e) & \text{if } 0 \leq j \leq N-1 \\ k^* & \text{if } j = N \end{cases} \tag{10}$$

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

$$\mu_j = \begin{cases} (1-\eta)^j M & \text{if } 0 \leq j \leq N-1 \\ \frac{(1-\eta)^N}{\eta} M & \text{if } j = N \end{cases} \tag{11}$$

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.

A.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:*

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

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

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

$$\begin{aligned} \underline{n}_t \quad &= \quad \max\left(\mathbf{c}^{-1}\left(k^*_{t+1}; z_{t+1}\right), -\left(\tfrac{1}{\zeta} - 1\right)(\delta + r_b)k^*_{t+1} + \tfrac{1}{1+r_b}\underline{n}_{t+1}\right), \\ \lim_{t\to+\infty}(1+r_b)^{-t}\underline{n}_t \quad &\leq \quad 0, \end{aligned} \tag{12}$$

where $\mathbf{c}\left(n, z\right) \equiv n + \mathbf{b}(n, z)$ *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*** $n_{i,t} < \mathbf{c}^{-1}\left(k^*_{t+1}; z_{t+1}\right)$*, the firm is constrained:*

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

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

- ***If*** $n_{i,t} \in \left[\mathbf{c}^{-1}\left(k^*_{t+1}; z_{t+1}\right), -\left(\frac{1}{\zeta} - 1\right)(\delta + r_b)k^*_{t+1} + \frac{1}{1+r_b}\underline{n}_{t+1}\right]$*, the firm is partially constrained;*

it invests at the currently optimal scale, but issues no dividends:

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

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:*

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

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 partically 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:

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

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:*

$$\forall t \geq 0, \quad g_t \equiv -\left(\frac{1}{\zeta} - 1\right) \frac{r_b + \delta}{1+r_b} \frac{k^*_{t+1}}{\mathbf{c}^{-1}\left(k^*_{t+1}, z_{t+1}\right)} + \frac{1}{1+r_b} \frac{\mathbf{c}^{-1}\left(k^*_{t+2}, z_{t+2}\right)}{\mathbf{c}^{-1}\left(k^*_{t+1}, z_{t+1}\right)}. \tag{13}$$

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

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

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

$$\underline{n}_t = \begin{cases} -\left(\frac{1}{\zeta}-1\right)\frac{r_b+\delta}{1+r_b}k^*_{t+1} + \frac{1}{1+r_b}\underline{n}_{t+1} & \text{if} \quad t \leq T-1, \\ \mathbf{c}^{-1}\left(k^*_{t+1}, z_{t+1}\right) & \text{if} \quad t \geq T. \end{cases} \tag{14}$$

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

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

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:

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

This parametrization captures some of the limit cases we are interested in. As $\theta \to 0$, 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:

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

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 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.

B Economies of scope and the size effect

This appendix describes a simple equilibrium model which produces two simple empirical regularities: (a) firms operating across multiple industries are larger than single-industry firms, even within the industries were they compete; (b) the sales, prices, and output of multi-industry firms respond less than those of single-industry to aggregate shocks (in the case of this model, a shock to household income.) The model relies on two simple ingredients: non-homotheticity in the demand for each industry's products; and economies of scope across industries. Both elements must be present in order to deliver the predictions.

B.1 Model description

Representative household There is a representative household with linear preferences over an aggregate of goods produced by N different industries, described by:

$$C = \left(\sum_{n=1}^{N} C_n^{\rho}\right)^{\frac{1}{\rho}},$$

where $\rho \in [0,1[$ governs the elasticity of substitution across goods from different industries. In each industry, two firms operate; a firm of type S (for Single-line firm), and a firm of type M (for Multi-line firm.) The differences between these firms are described below. The total consumption of goods in each industry, C_n, is an aggregate of the goods produced by these two firms, taking the following form:

$$C_n = \left(\left((C_{n,S} - C^*_{n,S}) \right)^{\epsilon} + (C_{n,M} - C^*_{n,M})^{\epsilon} \right)^{\frac{1}{\epsilon}}. \tag{15}$$

Here, $\epsilon \in [0,1[$ governs the elasticity of substitution across goods within industries. Moreover, $C^*_{n,x}$, for $x \in \{S, M\}$., represents the inelastic portion of the demand for each firm's product, as explained below. Finally, the household has an endowment I of a numeraire good. The household's problem is therefore:

$$\max \left(\sum_{n=1}^{N} C_n^{\rho} \right)^{\frac{1}{\rho}} \qquad \text{s.t.} \qquad \sum_{n=1}^{N} P_{n,S}C_{n,S} + P_{n,M}C_{n,M} \leq I,$$

and subject to equation (1), for $n = 1, ..., N$. In each industry, the first-order conditions with respect to $\{C_{n,S}, C_{n,M}\}_{n=1}^{N}$ imply that:

$$\begin{aligned} C_{n,x} &= C^*_{n,x} + \left(\frac{P_{n,x}}{P_n} \right)^{-\frac{1}{1-\epsilon}} C_n, \quad x \in \{S, M\} \\ P_n &= \left(P_{n,S}^{-\frac{\epsilon}{1-\epsilon}} + P_{n,M}^{-\frac{\epsilon}{1-\epsilon}} \right)^{-\frac{1-\epsilon}{\epsilon}} \end{aligned} \tag{16}$$

In particular, a fraction $s_{n,x}$ of total demand for the good produced by firm x in sector n is price-inelastic, where:

$$s^*_{n,x} = \frac{C^*_{n,x}}{C_{n,x}} \in [0,1[, \qquad x \in \{S, M\}.$$

The household takes the level of inelastic demand associated with each industry and firm, $\left\{C^*_{n,x}\right\}_{n,x}$, as given. Finally, the other first-order conditions of household's problem imply that:

$$\begin{aligned} PC &= I - \sum_{n=1}^{N} \left(P_{n,S}C^*_{n,S} + P_{n,M}C^*_{n,M} \right) \\ P &= \left(\sum_{n=1}^{N} P_n^{-\frac{\rho}{1-\rho}} \right)^{-\frac{1-\rho}{\rho}} \end{aligned} \tag{17}$$

Firms There are two groups of firms in the economy: a group of N firms of type S, each of which operates in a specific industry; and a single firm of type M, which operates across all N industries. In the first stage, both types of firms invest in order to create a given level of price-inelastic demand for their product, $\left\{C^*_{n,x}\right\}_{n,x}$. In the second stage, both types of firms choose an output level $C_{n,x}$. At both stages, both types of firms take prices for their product as given. The main difference between S-firms and the M-firm is that, when investing in order to raise the level of inelastic demand, the M-firm enjoys economies of scope across industries.

Firms of type S In the second stage, a firm S in industry n chooses its variable input L in order to solve:

$$\max_{L_{n,S}} \quad P_{n,S}Y_{n,S} - WL_{n,S}$$
$$\text{s.t.} \quad Y_{n,S} \leq ZL_{n,S}^{\zeta}.$$

Here, W is the price of the variable input and Z is the firm's productivity, and $\zeta < 1$ captures the degree of returns to scale in production. The solution to this problem can be written as:

$$Y_{n,S} \quad = \quad AP_{n,S}^{\frac{\zeta}{1-\zeta}}, \tag{18}$$

where $A \equiv \zeta^{\frac{\zeta}{1-\zeta}} Z^{\frac{1}{1-\zeta}} W^{-\frac{\zeta}{1-\zeta}}$. This leads to profits that are given by $\Pi_{n,S} = (1-\zeta)P_{n,S}Y_{n,S} = (1-\zeta)P_{n,S}\left(C_{n,S}^{*} + \left(\frac{P_{n,S}}{P_n}\right)^{-\frac{1}{1-\epsilon}} C_n\right)$. In the first stage, the S then firm solves:

$$\max_{C_{n,S}^{*}} \quad (1-\zeta)P_{n,S}\left(C_{n,S}^{*} + \left(\frac{P_{n,S}}{P_n}\right)^{-\frac{1}{1-\epsilon}} C_n\right) - \gamma\left(C_{n,S}^{*}\right)$$

The S firm faces a strictly increasing and convex cost of raising the inelastic portion of its demand, described by the function $\gamma(x)$. In what follows we assume this cost takes the form:

$$\gamma(x) = \frac{1-\zeta}{1+\delta}Bx^{1+\delta}, \quad \delta > 0, \quad B > 0.$$

We require that $\frac{\zeta}{1-\zeta} \leq \frac{1}{\delta}$, which is a sufficient condition to guarantee the existence of a symmetric equilibrium. The first-order condition is:

$$P_{n,S} = \gamma'\left(C_{n,S}^{*}\right). \tag{19}$$

Firms of type M and economies of scope In the first stage, the problem of the firm of type $x = M$, which operates across industries, is:

$$\max_{\{L_{n,M}\}_{n=1}^{N}} \quad \sum_{n=1}^{N}\left(P_{n,M}Y_{n,M} - WL_{n,M}\right)$$
$$\text{s.t.} \quad Y_{n,M} \leq ZL_{n,M}^{\zeta}, \quad n = 1, ..., N.$$

This problem is separable across industries; so it leads to the same solution as for the S-firms:

$$Y_{n,M} \quad = \quad AP_{n,M}^{\frac{\zeta}{1-\zeta}}. \tag{20}$$

In the first stage, we assume that the type-M firm potentially enjoys economies of scope in the production of the inelastic demand levels $\left\{C^*_{n,M}\right\}_{n=1}^{N}$. Specifically, we assume that:

$$\Gamma\left(\left\{C^*_{n,M}\right\}_{n=1}^{N}\right)=\left(\sum_{n=1}^{N}\gamma(C^*_{n,M})^{\alpha}\right)^{\frac{1}{\alpha}},\quad \alpha\geq 1,$$

where $\gamma(.)$ is the cost function for the S-firms. When $\alpha=1$, there are no economies of scope. When $\alpha>1$, there are economies of scope. Indeed, when $\alpha>1$, this cost function satisfies:

$$\Gamma\left(\left\{C^*_{n,M}\right\}_{n=1}^{N}\right)=\left(\sum_{n=1}^{N}\gamma(C^*_{n,M})^{\alpha}\right)^{\frac{1}{\alpha}}<\sum_{n=1}^{N}\gamma(C^*_{n,M})=\sum_{n=1}^{N}\Gamma\left(\left\{0,...,0,C^*_{n,M},0,...,0\right\}\right).$$

In other words, when $\alpha>1$, the cost function is sub-additive, and so exhibits economies of scope in the sense of Panzar and Willig (1981) or Tirole (1988).[75] In the first stage, the M-firm's profit maximization problem can then be written as:

$$\max_{\left\{C^*_{n,M},Y_{n,M}\right\}_{n=1}^{N}}\quad\sum_{n=1}^{N}P_{n,M}\left(C^*_{n,M}+\left(\frac{P_{n,M}}{P_n}\right)^{-\frac{1}{1-\epsilon}}C_n\right)-\left(\sum_{n=1}^{N}\gamma\left(C^*_{n,M}\right)^{\alpha}\right)^{\alpha}$$

The first-order conditions are:

$$P_{n,M}=\Gamma_M^{1-\alpha}\gamma(C_{n,M})^{\alpha-1}\gamma'\left(C^*_{n,M}\right),\quad n=1,...,N,\tag{21}$$

Finally, we close the model by assuming that there is an infinitely elastic supply of the variable input L at fixed price W.

B.2 Analysis

Equilibrium For given values of I,W,Z, an equilibrium of the model is a set of values for the endogenous variables:

$$P,C,MC,\Gamma_M,\left\{P_n,C_n,P_{n,S},P_{n,M},C_{n,S},C_{n,M},C^*_{n,S},C^*_{n,M}\right\}_{n=1}^{N}$$

that solve the equations given above. Since the model is symmetric across sectors, in what follows, we only study symmetric equilibria, where:

$$\forall x\in\{S,M\},\quad \forall n=1,...,N,\quad P_{n,x}=P_x,\quad C_{n,x}=C_x,\quad C^*_{n,x}=C^*_x,$$

Additionally, in a symmetric equilibrium, $\forall n=1,...,N,\quad P_n=N^{-\frac{1-\rho}{\rho}}P\equiv\tilde{P},\quad C_n=N^{\frac{1}{\rho}}C\equiv\tilde{C}$. In this equilibrium, the total cost of raising inelastic demand for the M firm is given by $\Gamma_M=$

[75] The inequality follows from the fact that $\sum_i x_i^{\alpha}<\left(\sum_i x_i\right)^{\alpha}$ when $\alpha>1$ and $x_i\geq 0$ for all i.

$N^{\frac{1}{\alpha}}\gamma(C_M^*)$. Therefore, the first-order condition for investment in C_M^* in each industry are:

$$P_{n,M} = N^{\frac{1-\alpha}{\alpha}}\gamma'(C_M^*) = N^{\frac{1-\alpha}{\alpha}}B\left(C_M^*\right)^{\delta}.$$

Recall that for S-firms, this first-order condition is $P_{n,S} = B\left(C_S^*\right)^{\delta}$. In what follows, we denote $B_S = B$ the cost shifter for S-firms, and $B_M = N^{\frac{1-\alpha}{\alpha}}B < B = B_S$ the cost shifter for M-firms.

Analysis The equilibrium above has the following properties. When there are no economies of scope ($\alpha = 1$), within a particular industry, the M firm and the S firm invest to generate the same amount of inelastic demand. Moreover, they produce the same output, charge the same prices. Moreover, they respond identically to a shock to household income, I. This result is immediate; indeed, when there are no economies of scope, the two firms are identical.

However, when there are economies of scope ($\alpha > 1$), in each industry, the M-firm invests to generate more inelastic demand than the S firm. As a result, the inelastic portion of the firm's demand, s_x^*, is higher for the M-firm. Therefore, the M-firm charges higher prices, produces more, and has higher sales than the S-firm. Moreover, the M-firm is less responsive than the S-firm to a shock to household income. We discuss these results in the two lemmas that follow.

Lemma 3 (Economies of scope and firm size)**.** *Assume that there are economies of scope: $\alpha > 1$. Then:*

$$C_S^* < C_M^*, \quad C_S < C_M, \quad P_S < P_M, \quad S_S = P_S C_S < S_M = P_M C_M.$$

Proof. Consider the market clearing condition in each industry:

$$AP_x^{\frac{\zeta}{1-\zeta}} = C_x = Y_x = \left(\frac{P_x}{B_x}\right)^{\frac{1}{\delta}} + \left(\frac{P_x}{\tilde{P}}\right)^{-\frac{1}{1-\epsilon}}\tilde{C}, \quad x \in \{S, M\}.$$

The market clearing condition above implies:

$$\frac{B_x}{P_x}\frac{\partial P_x}{\partial B_x} = -\frac{\frac{1}{\delta}s_x}{\frac{\zeta}{1-\zeta} + \frac{1}{1-\epsilon}(1-s_x) - \frac{1}{\delta}s_{i,x}} \leq 0,$$

where the inequality holds because $\frac{\zeta}{1-\zeta} \geq \frac{1}{\delta}$, and where we defined $s_x = \frac{C_x^*}{C_x}$, the inelastic consumption share for each firm. Therefore, equilibrium prices are decreasing with B_x. But recall that, when there are economies of scope ($\alpha < 1$); $B_M = N^{\alpha-1}B < B = B_S$. Therefore, prices charged by the M-firm are higher. Additionally, the equilibrium share of inelastic demand for the M-firm is always higher:

$$s_M > s_S.$$

To see why, note that:

$$s_x = 1 - \frac{\tilde{P}^{\frac{1}{1-\epsilon}}\tilde{C}}{A}P_x^{-\frac{1}{1-\epsilon}-\frac{\zeta}{1-\zeta}}.$$

This expression is increasing with P_x. Since $P_M > P_S$, this implies that $s_M > s_S$. The rest of the results follow. $\square$

Lemma 4 (Economies of scope and aggregate shocks)**.** *Assume that there are economies of scope: $\alpha > 1$. Then, in a response to a given shock to household income, I, sales of M-firms decline by strictly less than sales of S-firms.*

Proof. We denote by η_X the elasticity of variable X with to I. The market clearing condition can be log-linearized as:

$$\frac{\zeta}{1-\zeta}\eta_{P_x} = \frac{s_x}{\delta}\eta_{P_x}(1-s_x)\left(\eta_{\tilde{C}} - \frac{1}{1-\epsilon}\left(\eta_{P_x} - \eta_{\tilde{P}}\right)\right), \quad x \in \{S, M\}.$$

This implies that:

$$\eta_{P_x} = \frac{(1-s_x)(1-\zeta)(1-\epsilon)}{\zeta(1-\epsilon) + (1-s_x)(1-\zeta) - \frac{s_x}{\delta}(1-\zeta)(1-\epsilon)}\left(\eta_{\tilde{C}} + \frac{1}{1-\epsilon}\eta_{\tilde{P}}\right), \quad x \in \{S, M\}.$$

Note that sales elasticities are related to price elasticities through:

$$\eta_{S_x} = \frac{1}{1-\zeta}\eta_{P_x}, \quad x \in \{S, M\},$$

where $S_x = P_x C_x$ denotes the total sales of the firm of type x in one of the sectors. So,

$$\eta_{S_x} = \frac{(1-s_x)(1-\epsilon)}{\zeta(1-\epsilon) + (1-s_x)(1-\zeta) - \frac{s_x}{\delta}(1-\zeta)(1-\epsilon)}\left(\eta_{\tilde{C}} + \frac{1}{1-\epsilon}\eta_{\tilde{P}}\right).$$

Simple algebra, using the fact that $\zeta/(1-\zeta) > \frac{1}{\delta}$, then shows that:

$$\eta_{S_M} \leq \eta_{S_S} \iff s_M \geq s_S,$$

which, as discussed above, holds whenever $B_M < B_S$. Therefore, when there are economies of scope ($\alpha < 1$), the M-firm is less responsive to an aggregate shock than S-firms. $\square$

C Non-size evidence of a financial accelerator

Finally, in this appendix, 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 A12 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 6.2. 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 A12 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 A13 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.

D Measurement

D.1 The measurement framework used in this paper

The following paragraphs provide the details of the way in which we construct the size classification and growth measures used in section 4.

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

$$\mathcal{I}_t(x) \quad \equiv \{ \quad i \quad \text{ s.t. } \quad x_{i,t-4} > 0 \quad \text{ and } \quad x_{i,t} > 0 \quad \} \tag{22}$$

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

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

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

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

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

$$\mathcal{I}_t^{(k_1,k_2)} = \left\{ \quad i \in \mathcal{I}_t \quad \text{s.t.} \quad a_{i,t-4} \in \left[\bar{a}_{t-4}^{(k_1)}, \bar{a}_{t-4}^{(k_2)}\right[\quad \right\}. \tag{23}$$

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

$$\begin{aligned} \mathcal{I}_t^{(\text{small})} &= \mathcal{I}_t^{(0,99)}, \\ \mathcal{I}_t^{(\text{large})} &= \mathcal{I}_t^{(99,100)} = \mathcal{I}_t \setminus \mathcal{I}_t^{(0,99)}. \end{aligned} \tag{24}$$

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

$$g_{i,t}(x) = \begin{cases} \log\left(\frac{x_{i,t}}{x_{i,t-4}}\right) & \text{if} \quad x \in \{\text{sales, inventory, NPPE stock, assets}\} \\ \frac{nppe_{i,t} - nppe_{i,t-4} + dep_{i,t-4,t}}{nppe_{i,t-4}} & \text{if} \quad x = \text{fixed investment.} \end{cases} \tag{25}$$

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 5. Annual differences (instead of quarterly differences) are the main specification both because they are consistent with the size classification (which is based on one-year lags, so as to adequately capture initial size), and because they neutralize the issue of seasonal variation in the variables of interest. Cross-sectional averages of growth rates are then defined as:

$$\begin{aligned} \hat{g}_t^{(k_1,k_2)}(x) &\equiv \frac{1}{\mathcal{Z}_{t-4}^{(k_1,k_2)}} \sum_{i \in \mathcal{I}_t^{(k_1,k_2)}} z_{i,t-4}\, g_{i,t}(x) \\ Z_{t-4}^{(k_1,k_2)} &\equiv \sum_{i \in \mathcal{I}_t^{(k_1,k_2)}} z_{i,t-4}. \end{aligned} \tag{26}$$

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

Robustness Our results for sales, inventory, the stock of net property, plant and equipment are robust to using half-growth rates of the form $2\frac{x_{i,t}-x_{i,t-4}}{x_{i,t}+x_{i,t-4}}$. Qualitatively and quantitatively, results do not change substantially whether one uses the one-year lagged or current weights in computing average growth rates of the form (26). Since the sample is titled toward larger firms, carrying the analysis using unweighted data ($z_{i,t} = 1, \forall(i,t)$) leads to qualitatively identical results, but somewhat smaller magnitudes.

D.2 The Gertler and Gilchrist (1994) measurement framework

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 definition is driven by the fac that the publicly released QFR data only reports total sales of firms by bins of nominal asset size.

We next describe our implementation of the GG methodology. Let x denote nominal assets, let $\{x^{(1)}, ..., x^{(n)}\}$ denote the QFR's nominal asset bins' cutoffs, and let y denote nominal sales. For each quarter t, define $\underline{x}_t$ by:

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

Furthermore, let $\underline{x}_t^+$ be the cutoff immediately above $\underline{x}_t$ in the list $\{x^{(1)}, ..., x^{(n)}\}$. 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 analysis, we use one-quarter lagged growth rates, consistent Gertler and Gilchrist (1994); moreover, we de-seasonalize the data by removing quarter fixed effects. Finally, consistent with GG, we de-mean the small and large growth series before computing cumulative growth rates in event study analyses.

Appendix Figure A4 reports changes in total sales of small and large firms constructed using this methodology, using publicly available QFR data from 1958q4 to 1991q4 — the period originally studied by Gertler and Gilchrist (1994). This graph most closely approximates figure II, p.321 from that paper. Appendix figure A4 reports the same event study responses, again for the GG growth rates, in the 1977q3 to 2014q1 period. These event study result highlight, in particular, the fact that using the GG methodology, sales large firms declined *more* than those of small firms during 2008q3. Finally, figure A6 reports the same event study response, constructed using the CM growth rates, that is, the growth rates for the top 1% and bottom 99% of firms by assets, the time series reported in Figure 1.

E Robustness results on the size effect

Robustness checks discussed in the main text Figure A2 reports estimates of the contribution of entering firms to employment in manufacturing. Table A1 reports estimates of the size effect after controlling for age. Table A2 contains estimates of the size effect under various levels of controls for industry effects, and using alternate size classifications.

Deflators 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 A3 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, 1977q3-2014q1. Column 1 reports results from the specification of Equation (1), using the same 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 NAICS 3-digit industries). Estimates of the size effect in columns 1-3 are all very close in magnitude. Overall, these results indicate that estimates of the size effect in manufacturing are not sensitive to the choice of deflators.

Controlling for industry-quarter effects In most of our specifications, we absorb industry differences in cyclicality by controlling with set of dummies for industries interacted with GDP growth. An alternative approach is to instead control for a full set of industry-time fixed effects. The drawback of this approach is that it complicate the estimation of average marginal effects by size group, which are useful to our analysis of aggregate in Section 5. Column 4 of Table A3 reports results from estimating a specification with industry-quarter fixed effects in the Compustat manufacturing sample. The results from that specification are also very close in magnitude to those of specifications 1-3 of the same table, which are obtained using industries dummies interacted with

GDP. This suggests that estimates of the relative size effect are robust to whether one uses our approach or whether one controls for industry-size effects.

Disaggregated estimates of the size effect Figure A3 contains disaggregated estimates of the size effect. Specifically, we disaggregate the smallest size category from our baseline analysis (the $[0, 90]$) group, into four smaller sub-groups, the $[0, 25]$, $[25, 50]$, $[50, 75]$ and $[75, 90]$ interquantile range for book assets. We then re-estimate the size effect using a specification identical to Equation (1), but with this richer size classification. (In particular, we use the durable/non-durable industry classification to control for differences in industry cyclicality.) The findings indicate that the size effects is in general homogeneous among the group of firms belonging to the $[0, 90]$ group. The notable exception is the $[50, 75]$ group for sales, which seems to display a higher cyclical sensitivity than average, though the difference is only marginally significant.

Sales and value added in manufacturing The income statements which firms reports 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 cyclicality of sales is also informative about the relative cyclicality 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 A5 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 A6 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 A5. 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.

F The cyclicality 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.[76]

F.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.[77] 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.[78] 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 indexes 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 A8, 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

[76] Replication code for this exercise is available from the authors upon request.

[77] We 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`.

[78] We 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.

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.[79] 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: $ik^q_{i,t} = \frac{k^q_{i,t} - k^q_{i,t-4} + dep_{i,t-4,t}}{k^q_{i,t-4}}$. Here, t now denotes a quarter; $k^q_{i,t}$ denotes the net stock of property, plant and equipment (variable `ppentq`) deflated by the price 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 $dep_{i,t-4,t} \geq k^q_{i,t-4}$ 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 A8 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 $\frac{\texttt{dlc}+\texttt{dltt}}{at}$; cash to asset ratio is $\frac{\texttt{che}}{at}$; net leverage is the difference between the debt and the cash to asset ratios; the short-term debt ratio is $\frac{\texttt{np}}{\texttt{dlc}+\texttt{dltt}}$; the trade credit ratio is $\frac{\texttt{ap}}{\texttt{lt}}$, 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 $\frac{\texttt{intan}}{\texttt{at}-\texttt{act}}$; 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.

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

F.2 The cyclical properties of investment

We first document unconditional estimates of the cyclicality 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 cyclicality; 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 A9 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.[80] The baseline industry group corresponding to the coefficient reported in the first line of Table A9 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 6.2 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 A9 — and the bottom size group — groups 1 and 2 from Table A9. Figure A7 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.

[80] The t-statistic for the tests are -0.24 in annual data and 1.41 in annual data, respectively.

G Decompositions of aggregate growth

G.1 Baseline decomposition

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

$$\begin{aligned}
X_t &= \sum_{i\in\mathcal{I}_t} x_{i,t}, & X_{t-4} &= \sum_{i\in\mathcal{I}_t} x_{i,t-4}, & G_t &= \tfrac{X_t}{X_{t-4}}, \\
X_t^{(\text{small})} &= \sum_{i\in\mathcal{I}_t^{(\text{small})}} x_{i,t}, & X_{t-4}^{(\text{small})} &= \sum_{i\in\mathcal{I}_t^{(\text{small})}} x_{i,t-4}, & G_{t-4}^{(\text{small})} &= \tfrac{X_t^{(\text{small})}}{X_{t-4}^{(\text{small})}}, \\
X_t^{(\text{large})} &= \sum_{i\in\mathcal{I}_t^{(\text{large})}} x_{i,t}, & X_{t-4}^{(\text{large})} &= \sum_{i\in\mathcal{I}_t^{(\text{large})}} x_{i,t-4}, & G_{t-4}^{(\text{large})} &= \tfrac{X_t^{(\text{large})}}{X_{t-4}^{(\text{large})}}.
\end{aligned} \tag{27}$$

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:

$$\begin{aligned}
g_{i,t} &= \tfrac{x_{i,t}}{x_{i,t-4}} \\
w_{i,t-4} &= \begin{cases} \frac{x_{i,t-4}}{X_{t-4}^{(\text{small})}} & \text{if } i \in \mathcal{I}_t^{(small)} \\ \frac{x_{i,t-4}}{X_{t-4}^{(\text{large})}} & \text{if } i \in \mathcal{I}_t^{(large)} \end{cases}
\end{aligned} \tag{28}$$

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

$$G_t^{(small)} = \hat{g}_t^{(\text{small})} + \hat{cov}_t^{(\text{small})}, \tag{29}$$

where:

$$\begin{aligned}
\hat{g}_t^{(small)} &= \frac{1}{\#\mathcal{I}_t^{(\text{small})}} \sum_{i\in\mathcal{I}_t} g_{i,t} \\
\hat{cov}_t^{(\text{small})} &= \sum_{i\in\mathcal{I}_t^{(\text{small})}} \left(w_{i,t-4} - \frac{1}{\#\mathcal{I}_t} \right) \left(g_{i,t} - \hat{g}_t^{(small)} \right).
\end{aligned} \tag{30}$$

The first term in this decomposition, $\hat{g}_t^{(\text{small})}$, is the cross-sectional average growth rate of the variable x. (Up to a constant and up to the approximation $log(x) \approx x - 1$ for x close to 1, this is the

[81] See appendix D 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.

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

$$\begin{aligned} G_t &= s_{t-4} G_t^{(\text{small})} + (1 - s_{t-4}) G_t^{(\text{large})} \\ &= G_t^{(\text{large})} + s_{t-4} \left(G_t^{(\text{small})} - G_t^{(\text{large})} \right). \end{aligned} \tag{31}$$

Combining the two equations, we obtain the decomposition:

$$\begin{aligned} G_t &= \hat{g}_t^{(\text{large})} \\ &+ s_{t-4} \left(\hat{g}_t^{(\text{small})} - \hat{g}_t^{(\text{large})} \right) \\ &+ \hat{cov}_t, \end{aligned} \tag{32}$$

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

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

G.2 The contribution of the covariance terms to the cyclicality of aggregate growth

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

$$\begin{aligned} G_t^{(\text{small})} &= g_t^{(\text{small})} + \hat{cov}_t^{(\text{small})}, \\ G_t^{(\text{large})} &= g_t^{(\text{large})} + \hat{cov}_t^{(\text{large})}. \end{aligned} \tag{33}$$

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:

$$corr(G_t^{(\text{small})}, Y_t) = \frac{\sigma_{\hat{g}_t^{(\text{small})}}}{\sigma_{G_t^{(\text{small})}}} corr\left(\hat{g}_t^{(\text{small})}, Y_t\right) + \frac{\sigma_{\hat{cov}_t^{(\text{small})}}}{\sigma_{G_t^{(\text{small})}}} corr\left(\hat{cov}_t^{(\text{small})}, Y_t\right). \tag{34}$$

Here, σ_Z denote the standard deviation of variable Z. Equation (34) 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 A10 reports the values of the different elements of the right-hand side of (34), 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 A8.

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 $\frac{\sigma_{\hat{g}_t^{(\text{large})}}}{\sigma_{G_t^{(\text{large})}}} corr\left(\hat{g}_t^{(\text{large})}, Y_t\right)$, and $-0.02 = 0.45 \times (-0.05)$, coming from the term $\frac{\sigma_{\hat{cov}_t^{(\text{large})}}}{\sigma_{G_t^{(\text{large})}}} corr\left(\hat{cov}_t^{(\text{large})}, Y_t\right)$. This simple decomposition thus suggest that, up to first order, business-cycle variation in the covariance terms contribute little to aggregate growth; instead, average firm-level growth is the dominant factor.

G.3 Results using DHS growth rates

We finally replicate the decomposition results of section 5 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:

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

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 G, it is straightforward to verify that the following decomposition holds exactly:

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

where:

$$\tilde{G}_t = \frac{X_t - X_{t-4}}{\frac{1}{2}(X_t + X_{t-4})}$$

$$\tilde{s}_{t-4} = \frac{X_t^{(small)} + X_t^{(large)}}{X_t + X_{t-4}}$$

$$\hat{\tilde{g}}_t^{(small)} = \frac{1}{\#\mathcal{I}_t^{(\text{small})}} \sum_{i \in \mathcal{I}_t} \tilde{g}_{i,t}$$

$$\hat{\tilde{cov}}_t^{(\text{small})} = \sum_{i \in \mathcal{I}_t^{(\text{small})}} \left(\tilde{w}_{i,t-4} - \frac{1}{\#\mathcal{I}_t} \right) \left(\tilde{g}_{i,t} - \hat{\tilde{g}}_t^{(small)} \right),$$

and $\hat{\tilde{g}}_t^{(large)}$, $\hat{\tilde{cov}}_t^{(\text{large})}$ 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 5, 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, $\hat{\tilde{g}}_t^{(small)}$ and $\hat{\tilde{g}}_t^{(large)}$. Table A11 makes this point; its contents are almost identical to those of Table A11 in the main text. Second, estimated elasticities of counterfactual time series for aggregate growth attempting to remove either the "greater sensitivity" or the cycliality of small firms overall are very close to the actual elasticities of time series for aggregate growth. Table A12 reports these results; again, they are almost identical to the results from the same exercise conducted using log growth rates, and reported in Table 8 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.

G.4 An alternative decomposition

The following, complementary approach can be used to evaluate the relative contribution of small and large firms to aggregate fluctuations.[82] In general, aggregate growth G_t can be decomposed

[82] This 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.

as:

$$
\begin{aligned}
G_t &= s_{t-4} G_t^{(\text{small})} + (1 - s_{t-4}) G_t^{(\text{large})} \\
&= \underbrace{s_{t-4} \bar{G}^{(\text{small})} + (1 - s_{t-4}) G_t^{(\text{large})}}_{\equiv \tilde{G}_t^{\text{large}}} + \underbrace{s_{t-4} G_t^{(\text{small})} + (1 - s_{t-4}) \bar{G}^{(\text{large})}}_{\equiv \tilde{G}_t^{\text{small}}} \\
&\quad - \underbrace{\left(s_{t-4} \bar{G}^{(\text{small})} + (1 - s_{t-4}) \bar{G}^{(\text{large})} \right)}_{\equiv -R_t} \\
&= \tilde{G}_t^{\text{large}} + \tilde{G}_t^{\text{small}} + R_t .
\end{aligned}
\tag{35}
$$

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: 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 A13 contains results from a variance decomposition based on equation (35). 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 6.

H Additional results on the size effect and external financing

H.1 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 (5), 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 A14. In this table, all estimates of the size effect are expressed relative to the bottom $[0,90]$ group.[83] 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 year, whereas firms in the high bank-dependence group had a ratio of bank debt to total debt over 0.9.[84] 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.[85] 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.

H.2 External financing and the size effect for the trade sector

Table A15 and Figures A9 and A10 speak to the financial origins of the size effect in the trade sector. They replicate, respectively, Table 9 and Figures A9 and A10 for the manufacturing sector. For Table 9, which documents how the size effect changes when other proxies for financial constraints are controlled for, we use three size groups: the $[0,50]$, $[50,90]$ and $[90,100]$ interquantile range of book assets. Section 4.3 discusses this classification in more detail. For the event study regressions, the results of which are reported in figures A9 and A10, we classify firms in two groups, the bottom 90% and the top 10% by book assets.

[83]This 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.

[84]In 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 9.

[85]For 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.

H.3 The behavior of cash

Table A16 reports estimates of the cyclical sensitivity by firm size for three measures of cash holdings: cash growth, the cash to asset ratio, the growth rate of total financial assets, and the ratio of total financial assets to total assets. Estimates are obtained using our baseline framework, equation (1). Figure A11 reports the event study response of cash growth and the ratio of cash to total asset to the onset of a recession, estimated using the methodology described in section 6.2. Both speak to the possibility that financial constraints may induce small firms to hoard more cash during downturns than large firms. Empirically, the opposite seems to hold; the cash to asset ratio of small firms declines during recessions, while the cash to asset ratio of large firms increases.

I Additional results on the establishment composition of firms

Tables A17 to A19 report additional results regarding the matched QFR-DMI sample and the role of the establishment composition of firms in accounting for the size effect. For the manufacturing sector, table A17 reports results using continuous measures of the establishment composition of firms. For the trade sector, table A18 reports summary statistics, and table A18 reports results using continuous measures of the establishment composition of firms.

	Sales growth		Inventory growth		Fixed investment	
	(a)	(b)	(a)	(b)	(a)	(b)
$[90, 99]$ × GDP growth × post-82	−0.242		−0.274		−0.290	
	(0.151)		(0.175)		(0.111)	
$[99, 99.5]$ × GDP growth × post-82	-0.314^{*}		-0.518^{**}		-0.927^{***}	
	(0.059)		(0.013)		(0.001)	
$[99.5, 100]$ × GDP growth × post-82	-0.622^{***}		-0.596^{***}		-1.158^{***}	
	(0.001)		(0.004)		(0.001)	
$[90, 99]$ × GDP growth × post-82 × old		−0.109		−0.060		−0.076
		(0.154)		(0.173)		(0.178)
$[99, 99.5]$ × GDP growth × post-82 × old		-0.530^{**}		-0.471^{**}		-1.495^{***}
		(0.024)		(0.023)		(0.001)
$[99.5, 100]$ × GDP growth × post-82 × old		-0.462^{**}		−0.160		-0.482^{**}
		(0.021)		(0.120)		(0.015)
Observations	≈ 460000	≈ 460000	≈ 460000	≈ 460000	≈ 460000	≈ 460000
Firms	≈ 60000	≈ 60000	≈ 60000	≈ 60000	≈ 60000	≈ 60000
Adj. R^2	0.025	0.028	0.006	0.009	0.004	0.005
Clustering	Firm	Firm	Firm	Firm	Firm	Firm
Industry controls	D/ND	D/ND	D/ND	D/ND	D/ND	D/ND

Table A1: The size effect and age in the QFR manufacturing sample. The dependent variable in the first two columns is sales growth; in the third and fourth column, inventory growth; and in the fifth and sixth column, the investment rate. The first three lines report the estimated sensitivity of firm-level sales growth to GDP growth for different size groups relative to a baseline category, when size is defined in terms of quantiles of book assets, as in Section 4.1. The baseline category is the group of firm in the [0,90] interquantile range for size. In the first three lines, size and GDP growth are also interacted with an indicator for the post-1982 sample, in which a lower bound on firm age can be estimated. The baseline category for the post-1982 indicator is defined so that the coefficients reported in the first three lines should be interpreted as the *level* of the size effect in the post-1982 sample. We choose this approach, rather than a regression in the post-1982 subsample, so as to avoid creating and additional subsample, which complicates disclosure. Lines four through six report the estimated coefficients when the size effect is estimated conditional on being at least five years of age, as described in Section 4.3. This is done by further interacting size, GDP, and the post-1982 indicator with an indicator for whether the firm is at least 5 years of age; baseline categories are again defined so that the coefficients reported should be interpreted as the *level* of the size effect among the group of firms of at least five years of age. $*$, $**$ and $***$ indicate 10%, 5% and 1% significance levels, respectively; p-values are reported in parentheses, with standard errors are clustered at the firm level.

	Sales growth				
	(1)	(2)	(3)	(4)	(5)
$[90, 99] \times$ GDP growth	-0.249^{*}	-0.160	-0.070	-0.177	-0.139
	(0.084)	(0.142)	(0.630)	(0.220)	(0.326)
$[99, 99.5] \times$ GDP growth	-0.382^{***}	-0.251^{*}	-0.256^{*}	-0.240	-0.052
	(0.009)	(0.081)	(0.117)	(0.103)	(0.745)
$[99.5, 100] \times$ GDP growth	-0.757^{***}	-0.600^{***}	-0.607^{***}	-0.535^{***}	-0.655^{***}
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Observations	≈ 460000	≈ 460000	≈ 460000	≈ 460000	≈ 460000
Firms	≈ 60000	≈ 60000	≈ 60000	≈ 60000	≈ 60000
Adj. R^2	0.023	0.025	0.031	0.025	0.032
Clustering	Firm	Firm	Firm	Firm	Firm
Industry controls	None	D/ND	2D SIC/3D NAICS	D/ND	2D SIC/3D NAICS
Size classification	All manuf.	All manuf.	All manuf.	D/ND	2D SIC/3D NAICS

Table A2: The role of industry controls in the QFR sample. 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). In specifications (1)-(3), the size classification of firms is constructed by pooling all manufacturing firms. In specification (4), the size classification is constructed within the durable and non-durable industry. Finally, in specification (5), the size classification is constructed with each 3-digit NAICS industry (after 2000) or 2-digit SIC industry (before 2000). All values are deflated by the quarterly manufacturing price index. $*$, $**$ and $***$ indicate 10%, 5% and 1% significance levels, respectively, with p-values reported in parentheses.

	Sales growth			
	(1)	(2)	(3)	(4)
$[25, 50] \times$ GDP growth	-0.18	-0.20	-0.20	-0.22
	(0.511)	(0.458)	(0.479)	(0.430)
$[50, 75] \times$ GDP growth	-0.09	-0.10	-0.10	-0.12
	(0.746)	(0.691)	(0.707)	(0.657)
$[75, 100] \times$ GDP growth	-0.25	-0.27	-0.26	-0.28
	(0.318)	(0.268)	(0.294)	(0.248)
Observations	238421	238421	238421	238421
Firms	6079	6079	6079	6079
Clustering	Firm	Firm	Firm	Firm
Industry controls	D/ND	D/ND	D/ND	None
Deflator type	Value-added	Output	Output	Output
Deflator level	Manufacturing	Manufacturing	BEA subsectors	BEA subsectors
Industry-quarter effects	No	No	No	Yes

Table A3: The effect of alternate deflators. The sample is the quarterly manufacturing sample from Compustat. The table shows results for the sample from 1977q3 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. $*$, $**$ and $***$ indicate 10%, 5% and 1% significance levels, respectively; standard errors are clustered at the firm level in all specifications.

	Sales growth				
	(1)	(2)	(3)	(4)	(5)
$[90, 99] \times$ GDP growth	-0.160	-0.160	-0.160	-0.160	-0.160
	(0.142)	(0.111)	(0.141)	(0.150)	(0.157)
$[99, 99.5] \times$ GDP growth	-0.251^{*}	-0.251^{**}	-0.251	-0.251	-0.251
	(0.143)	(0.122)	(0.157)	(0.156)	(0.165)
$[99.5, 100] \times$ GDP growth	-0.600^{***}	-0.600^{***}	-0.600^{***}	-0.600^{***}	-0.600^{***}
	(0.140)	(0.137)	(0.169)	(0.212)	(0.220)
Observations	≈ 460000	≈ 460000	≈ 460000	≈ 460000	≈ 460000
Firms	≈ 60000	≈ 60000	≈ 60000	≈ 60000	≈ 60000
Adj. R^2	0.033	0.032	0.034	0.035	0.034
Clustering	Firm	Quarter	Firm and quarter	Year	Firm and year
Industry controls	D/ND	D/ND	D/ND	D/ND	D/ND

Table A4: Clustering and the significance of the size effect in the QFR manufacturing sample. The dependent variable in all specifications is sales growth. The first column reports estimates from the baseline specification, where standard errors are clustered at the firm level. In the second column, standard errors are clustered at the quarter level; in the third column, standard errors are clustered at the firm and quarter levels; in the fourth column, standard errors are clustered at year level; and in the last column, standard errors are clustered at the firm and year levels. $*$, $**$ and $***$ indicate 10%, 5% and 1% significance levels, respectively; standard errors are reported in parentheses.

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 A5: 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_GO_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% × GDP growth	-0.22	-0.21	-0.13	-0.33
	(0.430)	(0.449)	(0.670)	(0.340)
50-75% × GDP growth	-0.12	-0.12	0.02	-0.02
	(0.657)	(0.671)	(0.951)	(0.958)
75-100% × GDP growth	-0.28	-0.31	-0.25	-0.36
	(0.248)	(0.219)	(0.367)	(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 × GDP growth control	No	No	No	No
Industry-quarter effects	Yes	Yes	Yes	Yes

Table A6: 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 1, 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 A5 for details on those sectors. Standard errors are clustered at the firm level in all specifications.

Romer date dropped	CM growth rates (firm-level) Δ_S	Δ_L	$\frac{\Delta_S - \Delta_L}{\Delta_L}$	GG growth rates Δ_S	Δ_L	$\frac{\Delta_S - \Delta_L}{\Delta_L}$
None	-9.2%	-5.8%	58%	-9.5%	-8.4%	14%
1978q3	-10.3%	-8.0%	30%	-8.7%	-8.7%	0%
1979q4	-5.3%	-2.4%	121%	-6.6%	-4.7%	39%
1988q4	-10.0%	-4.7%	115%	-8.0%	-7.4%	8%
1994q2	-14.5%	-10.4%	40%	-14.0%	-13.2%	6%
2008q3	-5.7%	-3.7%	55%	-8.4%	-5.9%	42%

Table A7: Event study results using the data from 1977q3 to 2014q1. The table reports the average cumulative change in sales for small (columns 2 and 5) and large (columns 3 and 6) firms in the three years following Romer dates, and their relative magnitude (columns 4 and 7.) Columns 5 to 7 report results using growth rates constructed following the Gertler and Gilchrist (1994) methodology and using publicly available data (GG growth rates), while columns 2 to 4 report results using growth rates constructed using micro data and reported in Figure 1 (CM growth rates). Each line reports the results dropping one Romer date from the set of six Romer dates identified by Romer and Romer (1989, 1994) and Kudlyak and Sanchez (2017) for the 1977q3 to 2014q1 sample: three original Romer dates, 1978q3, 1979q4, 1988q3, and two additional dates, 1994q2 and 2008q3.

	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 A8: 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 Compsutat samples and the computation of investment rates.

	QFR	Compustat (annual)	Compustat (quarterly)
GDP growth	0.912^{***}	1.082^{***}	0.537^{***}
	(0.258)	(0.306)	(0.174)
Size group 2 × GDP growth	-0.299^{*}	-0.235	-0.103
	(0.157)	(0.197)	(0.223)
Size group 3 × GDP growth	-0.687^{***}	-0.329^{*}	-0.250
	(0.194)	(0.189)	(0.216)
Size group 4 × GDP growth	-1.257^{***}	-0.921^{***}	-0.572^{***}
	(0.355)	(0.260)	(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	Firm	firm-level

Table A9: 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
$corr(G_t, Y_t)$	0.68	0.62	0.65
$\frac{\sigma_{\hat{g}_t}}{\sigma_{G_t}}$	1.02	0.83	0.89
$corr(\hat{g}_t, Y_t)$	0.84	0.77	0.80
$\frac{\sigma_{\hat{cov}_t}}{\sigma_{G_t}}$	0.54	0.45	0.41
$corr(\hat{cov}_t, Y_t)$	−0.32	−0.05	−0.15

Table A10: Decomposition of the correlation of aggregate sales growth with GDP growth. The decomposition used is $corr(G_t, Y_t) = \frac{\sigma_{\hat{g}_t}}{\sigma_{G_t}} corr\,(\hat{g}_t, Y_t) + \frac{\sigma_{\hat{cov}_t}}{\sigma_{G_t}} corr\,(\hat{cov}_t, Y_t)$, 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 $\hat{cov}_t$ 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 Appendix G for more details on the decomposition.

	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
$corr(\hat{\tilde{g}}_t, Y_t)$	0.84	0.77	0.80
$\frac{\sigma_{c\hat{o}v_t}}{\sigma_{\tilde{G}_t}}$	0.51	0.45	0.41
$corr(c\hat{\tilde{o}}v_t, Y_t)$	-0.26	-0.04	-0.10

Table A11: 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 Appendix G for details on the decomposition.

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

Table A12: 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.

	$\tilde{G}_t^{\text{large}}$	$\tilde{G}_t^{\text{small}}$	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 A13: 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).

Panel A	Baseline	Bank dependence			Leverage			Liquidity		
		Low	High	Diff	Low	High	Diff	High	Low	Diff
$[90, 99] \times$ GDP growth	−0.160	−0.094	−0.286	−0.192	−0.195	0.010	0.205	−0.257	0.179	0.436
$[99, 99.5] \times$ GDP growth	−0.251*	−0.270	−0.184	0.085	−0.182	−0.570	−0.387	−0.384**	0.042	0.376
$[99.5, 100] \times$ 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		firm-level			firm-level			firm-level	

Panel B	Baseline	Bond market access			Dividend issuance		
		Yes	No	Diff	High	low	Diff
$[90, 99] \times$ GDP growth	−0.160				−0.178	−0.146	0.032
$[99, 99.5] \times$ GDP growth	−0.251*	−2.907	−0.421***	2.486	−0.150	−0.385	−0.235
$[99.5, 100] \times$ 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		firm-level			firm-level	

Table A14: 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 9 describes the groups of financial constraints in more detail. Standard errors clustered at the firm level. $*$, $**$ and $***$ indicate 10%, 5% and 1% significance levels.

	Baseline	(1)	(2)	(3)	(4)
$[50, 90] \times$ GDP growth	-0.335	-0.302	-0.347	-0.319	-0.351
$[90, 100] \times$ GDP growth	-0.910^{***}	-0.883^{***}	-0.915^{***}	-0.890^{***}	-0.961^{***}
Bank share [0.10,0.90] $\times$ GDP growth		0.075			
Bank share $< 0.10 \times$ GDP growth		-0.101			
Leverage [0.15,0.50] $\times$ GDP growth			-0.168		
Leverage (0,0.15] $\times$ GDP growth			-0.104		
Leverage $= 0 \times$ GDP growth			-0.307		
Liquidity [0.01,0.20] $\times$ GDP growth				-0.169	
Liquidity $> 0.20 \times$ GDP growth				-0.499	
Market access $\times$ GDP growth					0.098
Observations	≈ 120000	≈ 120000	≈ 120000	≈ 120000	≈ 120000
Firms	≈ 10000	≈ 10000	≈ 10000	≈ 10000	≈ 10000
Adj. R^2	0.017	0.019	0.018	0.018	0.017
Industry controls	yes	yes	yes	yes	yes
Clustering	Firm	Firm	Firm	Firm	Firm

Table A15: Regression of sales growth on firm size and proxies for financial constraints (model 5), for firms in the trade sector. 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. $*$, $**$ and $***$ indicate 10%, 5% and 1% significance levels.

	Financial assets growth	Financial to total assets	Cash growth	Cash to total assets
$[90, 99] \times$ GDP growth	-1.368^{***}	-0.080^{**}	-1.426^{***}	-0.084^{***}
	(0.001)	(0.016)	(0.001)	(0.010)
$[99, 99.5] \times$ GDP growth	-1.169^{***}	-0.009	-1.724^{***}	-0.045
	(0.006)	(0.792)	(0.001)	(0.142)
$[99.5, 100] \times$ GDP growth	-1.142^{***}	-0.032	-1.681^{***}	-0.001
	(0.006)	(0.290)	(0.001)	(0.961)
Observations	≈ 460000	≈ 460000	≈ 460000	≈ 460000
Firms	≈ 60000	≈ 60000	≈ 60000	≈ 60000
Adj. R^2	0.001	0.001	0.001	0.001
Clustering	Firm	Firm	Firm	Firm
Industry controls	D/ND	D/ND	D/ND	D/ND

Table A16: The size effect for financial assets and cash in the QFR manufacturing sample. Each column reports estimates of a specification similar to the baseline framework, Equation (1), but where the outcome variable is a measure of changes in the financial assets or cash held by the firm. In the first column, the dependent variable is the log growth rate of total financial assets. In the second column, the dependent variable is the one-year change in the level of total financial assets, divided by one-year lagged total assets. The third and fourth columns are similarly defined, but using cash specifically, as opposed to total financial assets. See Tables 1 and 2 for a comparison of the ratios of financial assets and cash to total assets across different size groups. $*$, $**$ and $***$ indicate 10%, 5% and 1% significance levels, respectively; p-values in parentheses.

	Sales growth			
	(1)	(2)	(3)	(4)
$[90, 99] \times$ GDP growth	-0.222		-0.267	-0.261
$[99, 99.5] \times$ GDP growth	-0.221		-0.331	-0.317
$[99.5, 100] \times$ GDP growth	-0.802^{***}		-0.297	-0.309
Nr. of lines of business $\times$ GDP growth		-0.018^{**}	-0.011^{**}	-0.020^{**}
Nr. of establishments $\times$ GDP growth				0.004
Observations	≈ 200000	≈ 200000	≈ 200000	≈ 200000
Firms	≈ 30000	≈ 30000	≈ 30000	≈ 30000
Adj. R^2	0.033	0.032	0.034	0.035
Industry controls	D/ND	D/ND	D/ND	D/ND
Clustering	Firm	Firm	Firm	Firm

Table A17: The size effect and the establishment composition of firms in the QFR manufacturing sample, using continuous measures of the establishment composition of firms. The dependent variable in all specifications is sales growth. The first three lines report the estimated sensitivity of firm-level sales growth to GDP growth for different size groups relative to a baseline category, when size is defined in terms of quantiles of book assets, as in Section 4.1; the baseline category is the group of firm in the [0,90] inter-quantile range for size. The fourth line reports the estimated coefficient on the interaction between the number of lines of business and GDP growth. A firm's number of lines of business is the total number of distinct SIC-4 digit codes of the collection of establishments that make up the firm in a given quarter. The fifth line reports estimated coefficient on the interaction between the number of establishments and GDP growth. Establishment counts and the industry composition of establishments for a given firm are obtained by merging the QFR with DnB, as discussed in section 7. $*$, $**$ and $***$ indicate 10%, 5% and 1% significance levels, respectively; standard errors are clustered at the firm level.

	Employment (000's)	Establishments (00's)	Lines of business (00's)	Manufacturing index	Trade index
$[0, 50]$	0.522	0.184	0.045	0.104	0.879
	(0.025)	(0.009)	(0.001)	(0.005)	(0.005)
$[50, 90]$	1.994	0.642	0.071	0.123	0.836
	(0.112)	(0.046)	(0.002)	(0.006)	(0.006)
$[90, 100]$	16.95	2.326	0.154	0.133	0.797
	(4.63)	(0.382)	(0.010)	(0.011)	(0.013)
Observations	≈ 80000	≈ 80000	≈ 80000	≈ 80000	≈ 80000
Firms	≈ 10000	≈ 1000	≈ 1000	≈ 1000	≈ 1000
Adj. R^2	0.060	0.138	0.445	0.174	0.911

Table A18: Summary statistics for the QFR trade sample merged to the DnB database. Each line corresponds to a different size group; size groups are defined based on the cross-sectional distribution of book assets, as described in Section 4.1. Each column reports the coefficients in a regression of a particular outcome variable on a full set of dummies, excluding the constant; that is, they are the conditional mean of each outcome variable by size group in the matched sample. The numbers in parentheses are standard errors, clustered at the firm level. The first column reports the conditional mean for employment (in thousands). The second column reports the conditional mean of the number of establishments (in hundreds). The third column reports the conditional mean of the number of lines of business (that is, the distinct number of SIC-4 digit codes in the collection of all establishments belonging to a particular firm; in hundreds). The fourth column reports the conditional mean of the manufacturing index, defined as the fraction of establishments with an SIC-4 digit code in manufacturing. The fifth column reports the conditional mean of the trade index, defined as the fraction of establishments with an SIC-4 digit cot in retail or wholesale trade.

	Sales growth			
	(1)	(2)	(3)	(4)
$[50, 90] \times$ GDP growth	-0.202		-0.135	-0.103
$[90, 100] \times$ GDP growth	-0.669^{**}		-0.4333	-0.359
Nr. of lines of business $\times$ GDP growth		-0.034^{***}	-0.027^{***}	-0.016^{**}
Nr. of establishments $\times$ GDP growth				-0.069
Observations	≈ 80000	≈ 80000	≈ 80000	≈ 80000
Firms	≈ 10000	≈ 10000	≈ 10000	≈ 10000
Adj. R^2	0.021	0.021	0.021	0.022
Industry controls	D/ND	D/ND	D/ND	D/ND
Clustering	Firm	Firm	Firm	Firm

Table A19: The size effect and the establishment composition of firms in the QFR trade sample, using continuous measures of the establishment composition of firms. The dependent variable in all specifications is sales growth. The first three lines report the estimated sensitivity of firm-level sales growth to GDP growth for different size groups relative to a baseline category, when size is defined in terms of quantiles of book assets, as in Section 4.1; the baseline category is the group of firm in the [0,50] inter-quantile range for size. The fourth line reports the estimated coefficient on the interaction between the number of lines of business and GDP growth. A firm's number of lines of business is the total number of distinct SIC-4 digit codes of the collection of establishments that make up the firm in a given quarter. The fifth line reports estimated coefficient on the interaction between the number of establishments and GDP growth. Establishment counts and the industry composition of establishments for a given firm are obtained by merging the QFR with DnB. $*$, $**$ and $***$ indicate 10%, 5% and 1% significance levels, respectively; standard errors are clustered at the firm level.

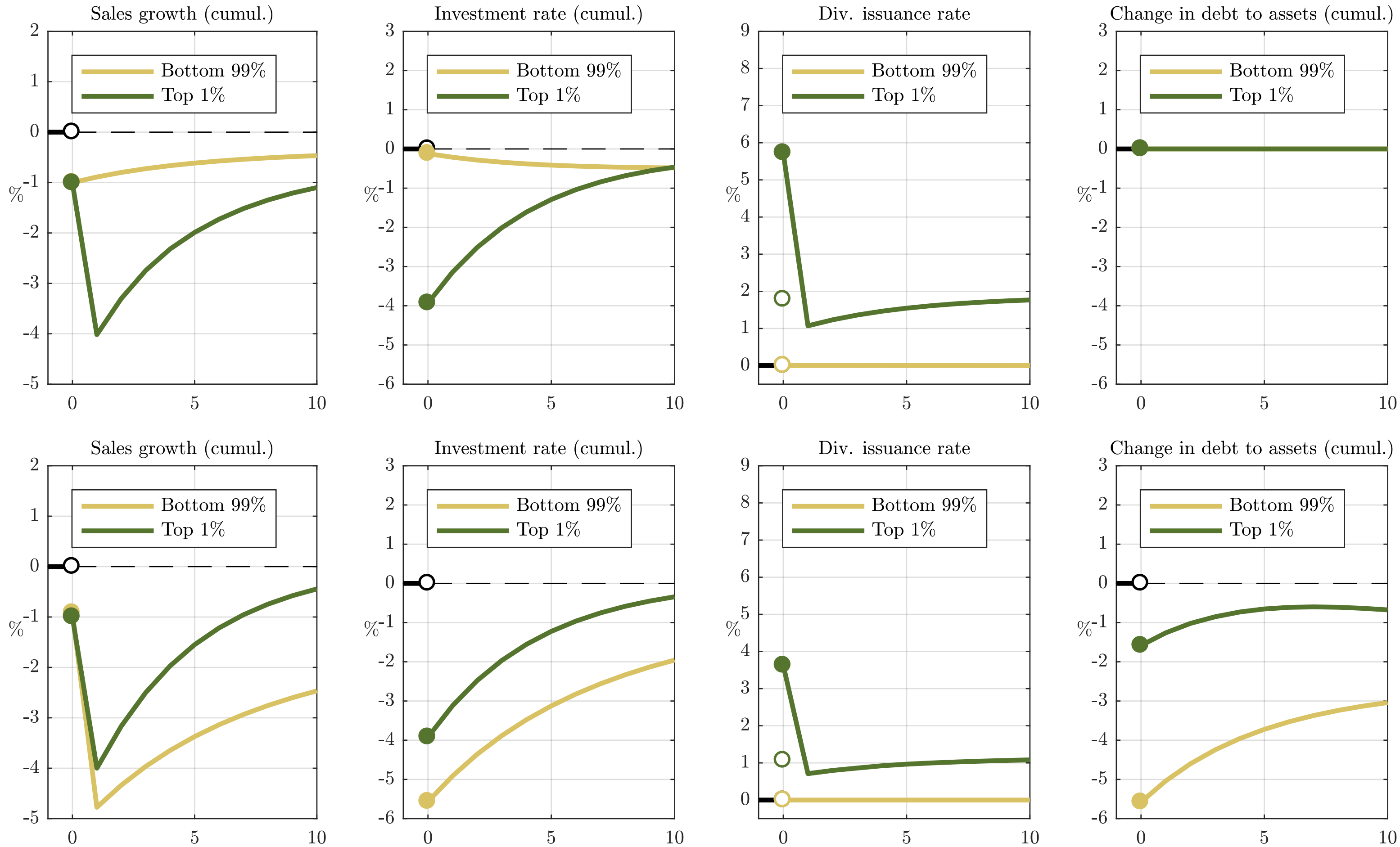


Figure A1: Impulse responses to an aggregate shock in the models of section 5.2. The green lines correspond to firms in the top 1% of the one-quarter lagged distribution of book assets, and the yellow lines correspond to firms in the bottom 99%; book assets in the model are defined as $k_{i,t}$. The top row reports impulse responses in the model with no external financing. The bottom row show the impulse responses in the model with borrowing.

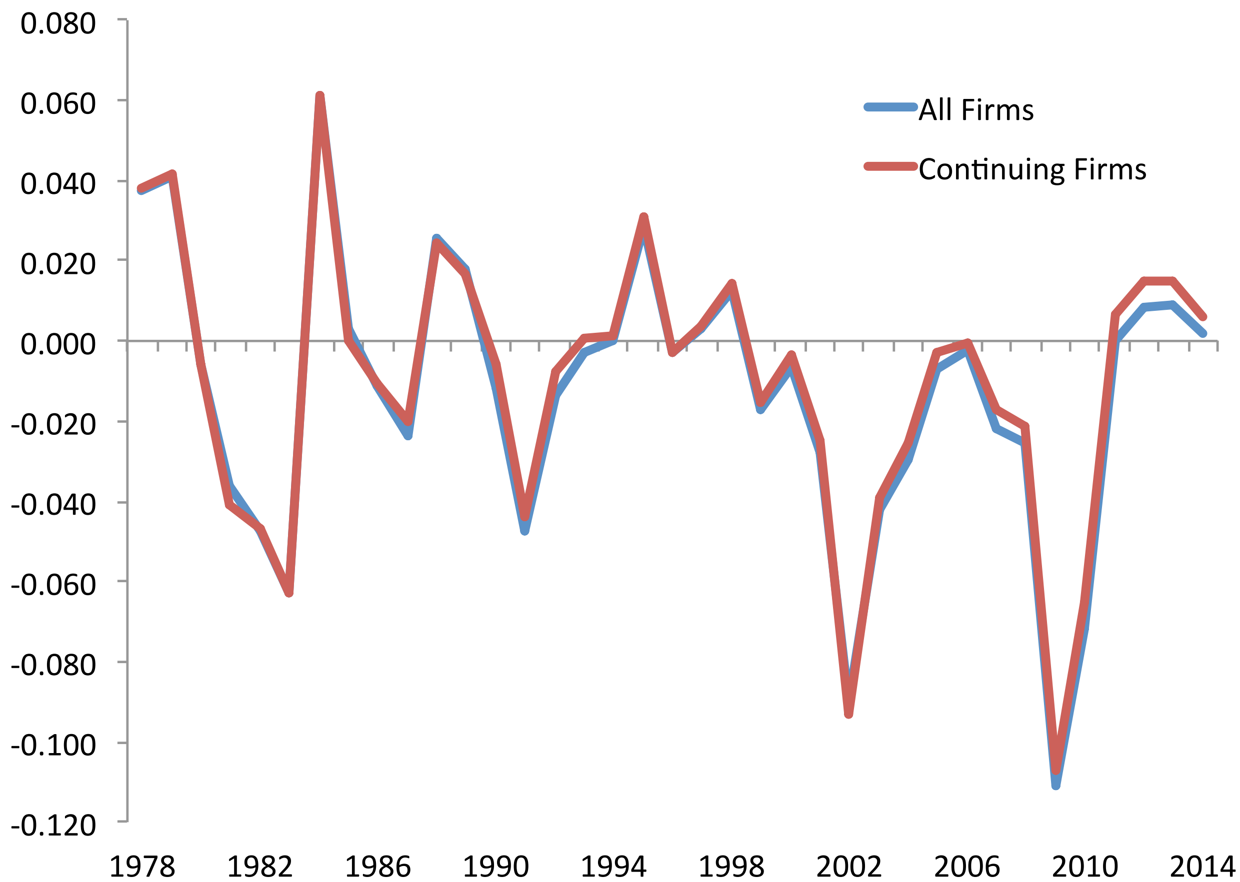


Figure A2: The blue line is employment growth at firms with initial firm size of 10 employees or more in manufacturing from the Business Dynamics Statistics (BDS) from 1978-2014. The red line is employment growth at continuing firms with initial firms size of 10 employees or more in manufacturing. Employment 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.

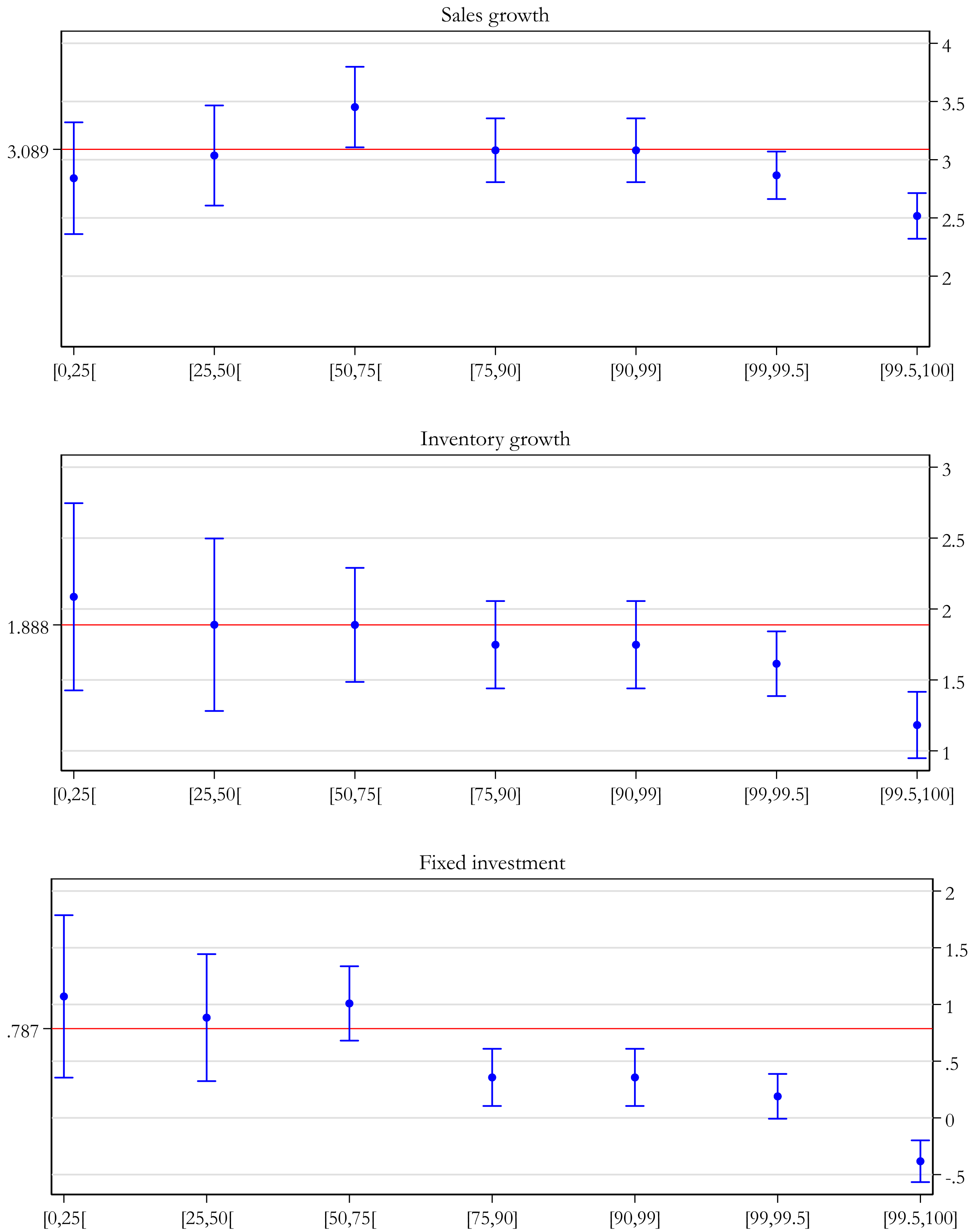
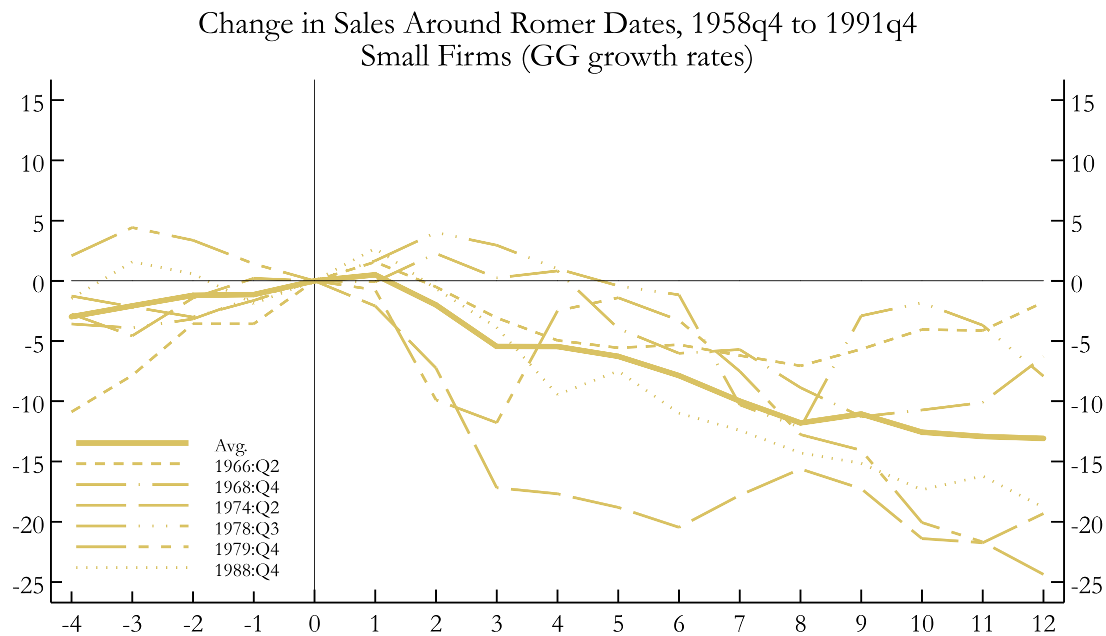


Figure A3: Average marginal effect of GDP growth on sales growth, inventory growth, and fixed investment, by disaggregated size groups and unconditionally. The marginal effects are computed a model similar to (1), but a larger number of size groups. Size is defined as described in Section 4.1 — that is, in terms of the one-year lagged cross-sectional distribution of book assets — but in this figure, we use seven size groups: the $[0, 25]$, $[0, 50]$, $[50, 75]$, $[75, 90]$, $[90, 99]$, $[99, 99.5]$ and $[99.5, 100]$ groups, thus disaggregating the smallest size group from our baseline specification into four sub-groups. Blue: conditional average marginal effect by size group, with $+/-2s.e.$ confidence interval. Red: unconditional average marginal effect.



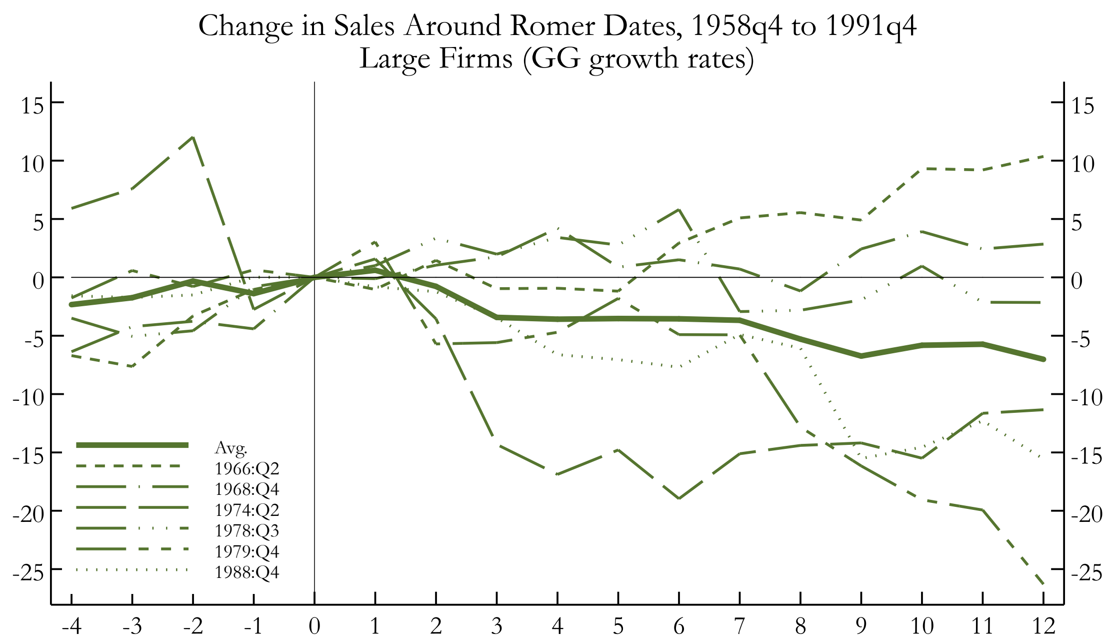
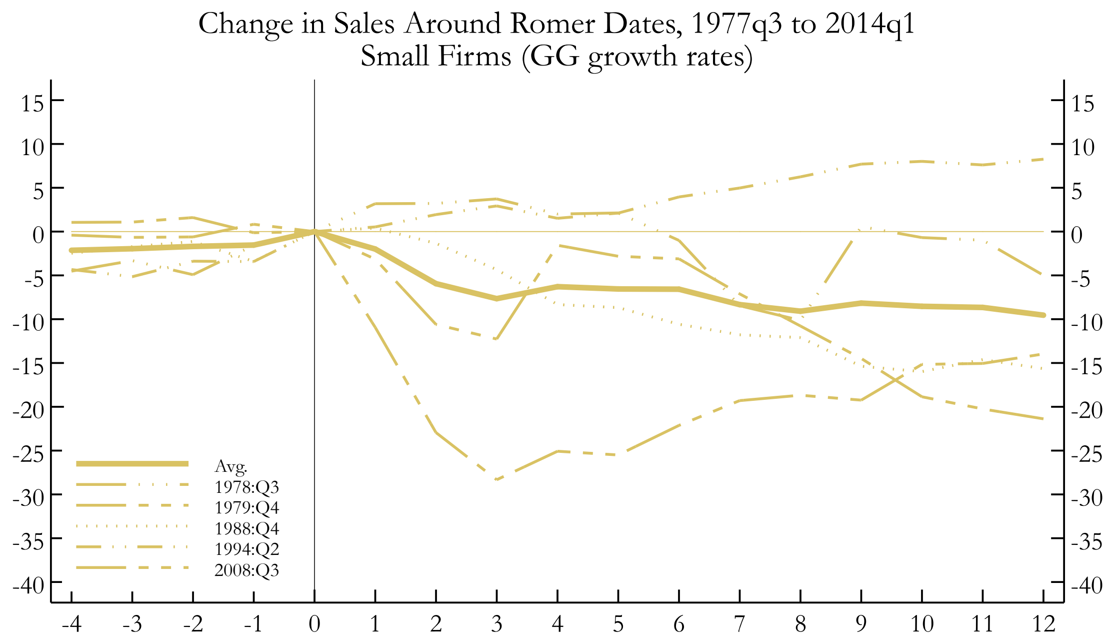


Figure A4: Event study of sales growth around Romer dates, using the publicly available QFR data and the Gertler and Gilchrist (1994) methodology for constructing small and large firm growth rates. The event study uses only data from 1958q4 to 1991q4, consistent with the original Gertler and Gilchrist (1994) analysis. The methodology used for constructing small and large firm growth rates is described in Appendix D. The growth rates are de-seasonalized by eliminating quarter fixed effects, and de-meaned in the 1954q1 to 1994q1 sample before constructing the event study responses.



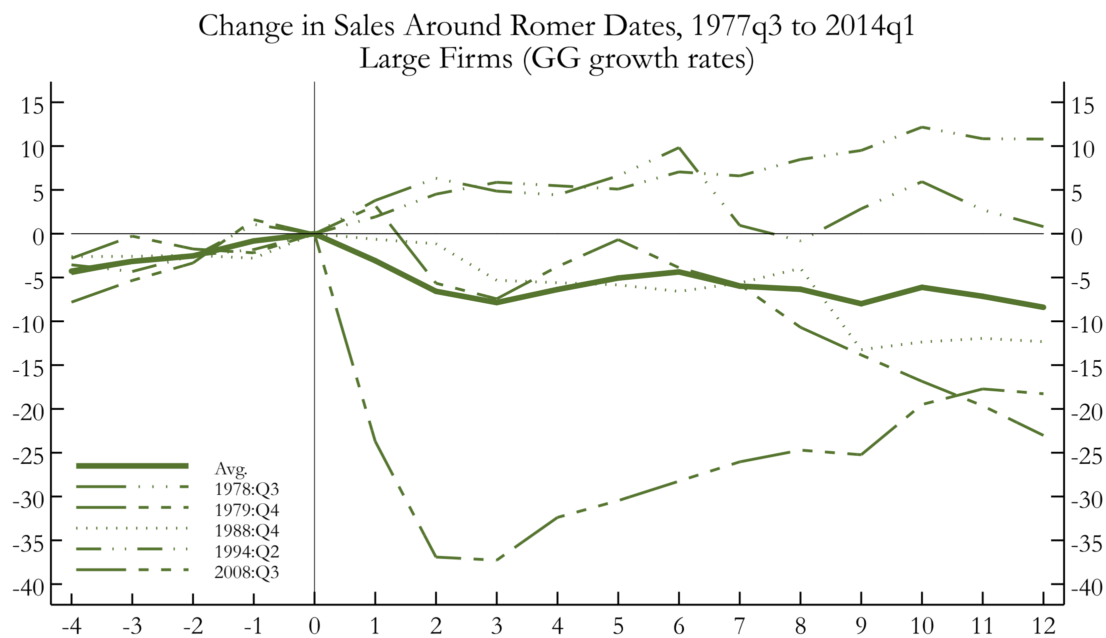
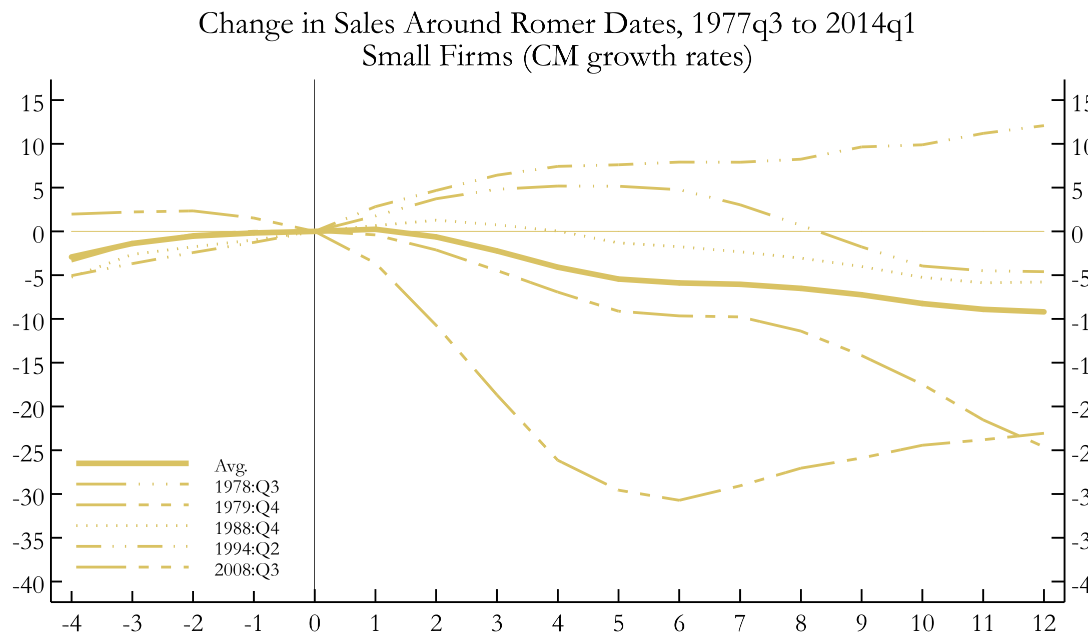


Figure A5: Event study of sales growth around Romer dates, using the publicly available QFR data and the Gertler and Gilchrist (1994) methodology for constructing small and large firm growth rates. The event study uses the data from 1977q3 to 2014q1, over which the micro data is available and the CM growth rates can be constructed. The methodology used for constructing small and large firm growth rates is described in Appendix D. The growth rates are de-seasonalized by eliminating quarter fixed effects, and de-meaned in the 1977q3 to 2014q1 sample before constructing the event study responses.



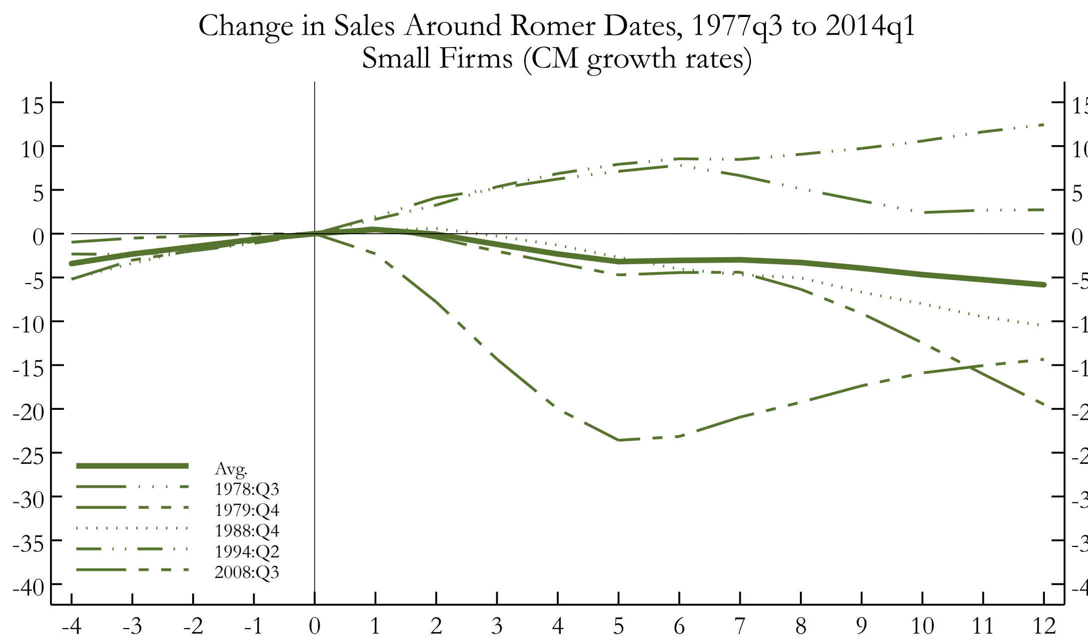


Figure A6: Event study of sales growth around Romer dates, using the average equal-weighted growth rates constructed from the micro data underlying the QFR. The time series used to construct these event study graphs are reported in Figure 1. The event study uses the data from 1977q3 to 2014q1. The growth rates are de-meaned before constructing the event study responses.

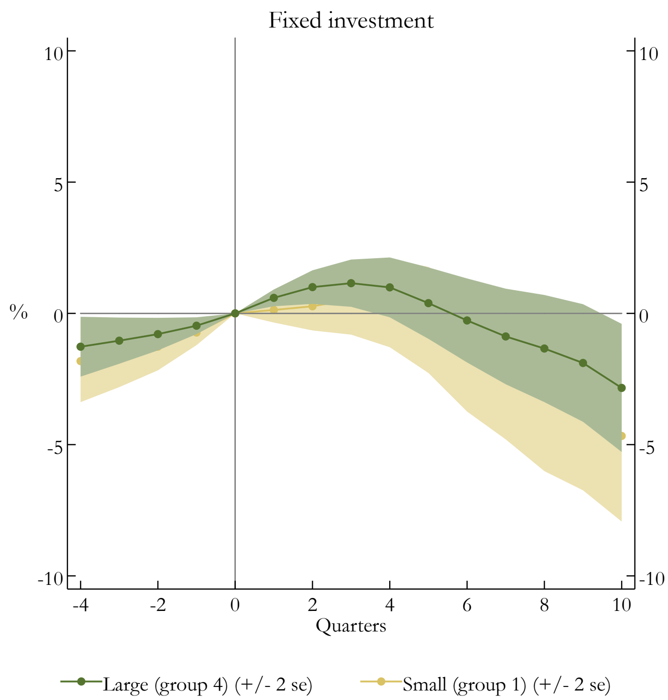


Figure A7: The behavior of fixed investment after the start of a recession in the quarterly Compustat sample. The graph reports the cumulative investment rate relative to the beginning of the recession; see section 6.2 for details on the estimation. Shaded areas are +/- 2 standard error bands. See appendix D for details on the definition of size groups. Recession start dates are 1981q3, 1990q3, 2001q1, and 2007q4.

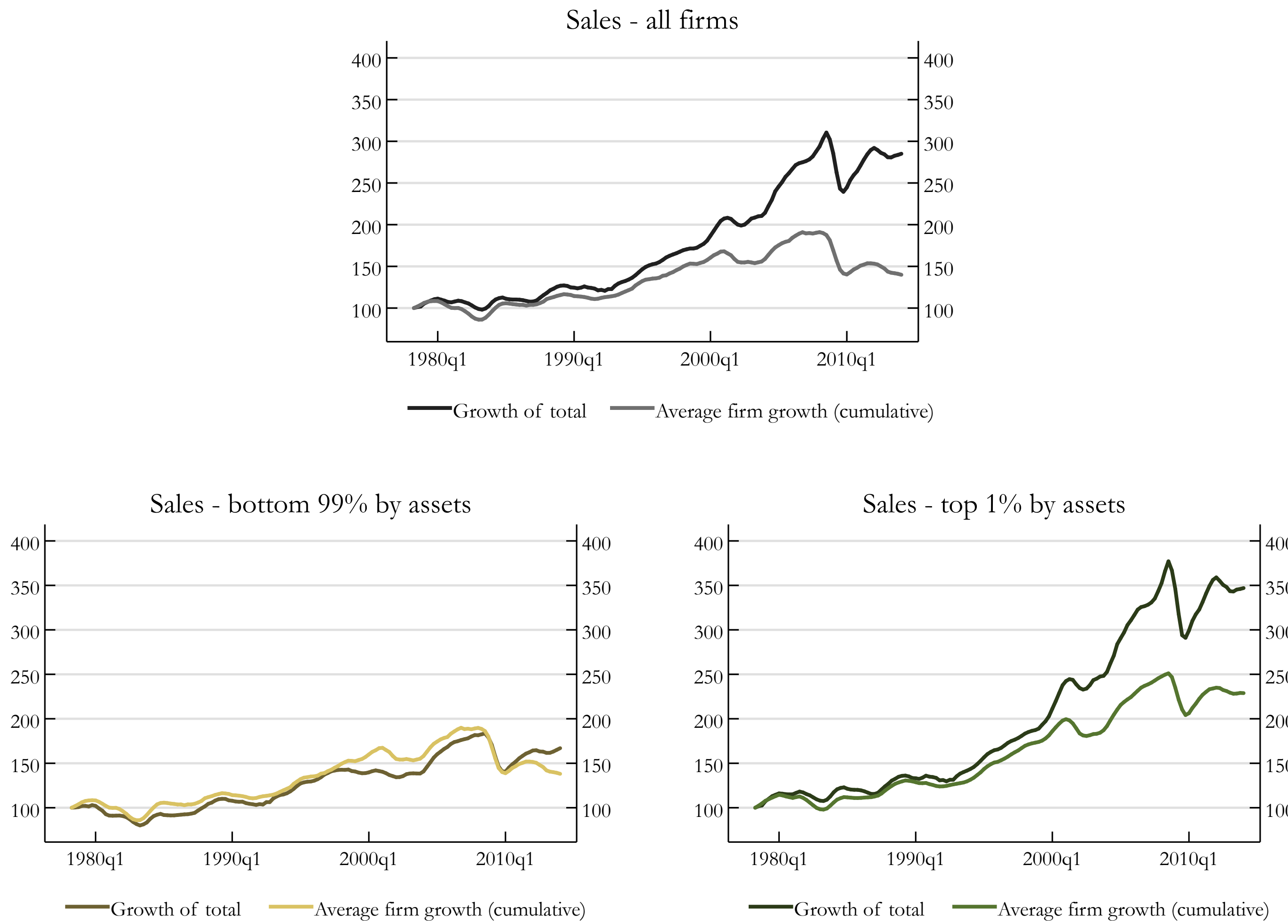


Figure A8: Aggregate sales and average within-firm cumulative growth rate of sales. Each panel reports total annual sales normalized to 100 at the beginning of the sample, and the cumulative firm-level average growth rate of sales, for a different group of firms, also normalized to 100 at the beginning of the sample.

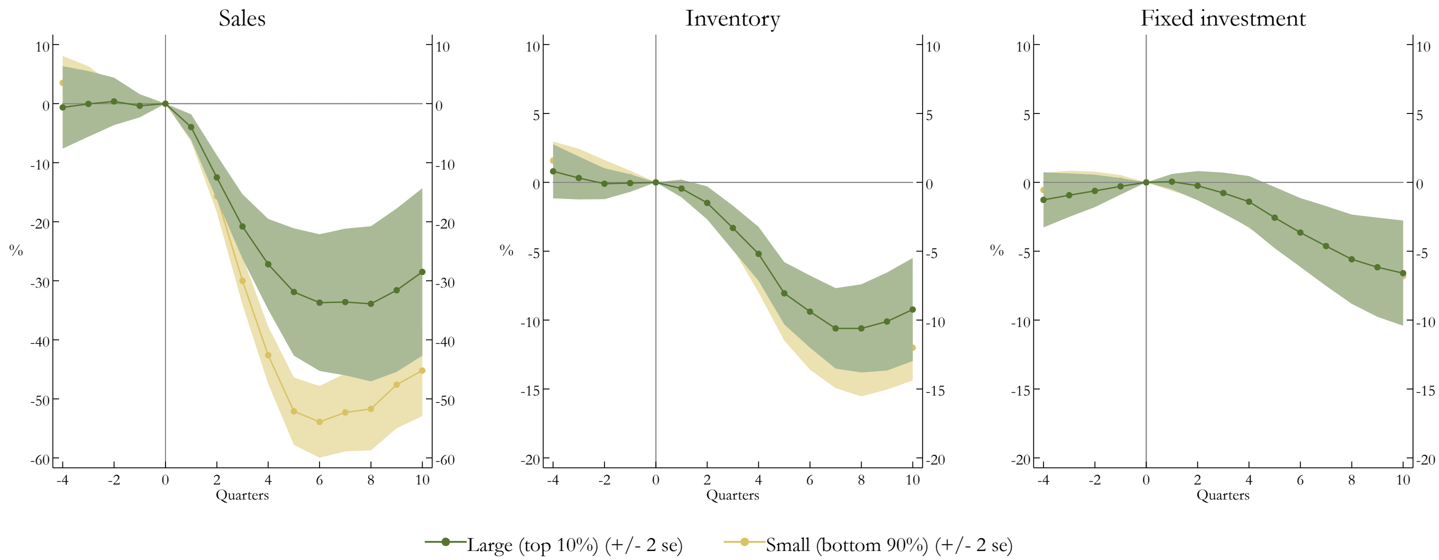


Figure A9: The behavior of sales, inventory and fixed capital after the start of a recession in the trade sector. Each graph reports the cumulative change in a variable of interest after the beginning of a recession. Shaded areas are +/- 2 standard error bands. All growth rates are computed year-on-year and expressed at the quarterly frequency. Recession start dates are 1981q3, 1990q3, 2001q1, and 2007q4. See section 6.2 for more details on the construction of these cumulative responses.

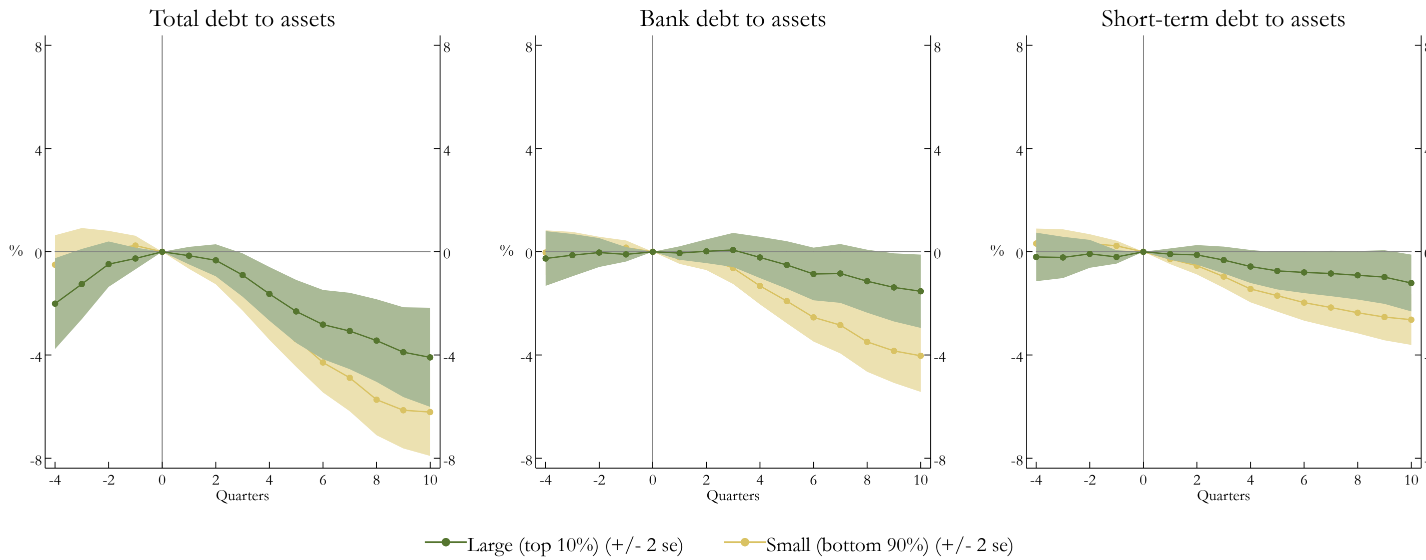


Figure A10: The behavior of debt overall, bank debt, and short-term debt after the start of a recession in the trade sector. Each panel reports changes relative to quarter 0 (the recession start date), computed using the cumulative sum of average growth rate of each size group. Growth rates at the firm-level are computed as $\frac{x_{i,t}-x_{i,t-4}}{assets_{i,t-4}}$, where $x \in \{\text{all debt}, \text{bank debt}, \text{short-term debt}\}$. Size groups are defined with a four-quarter lag. See section 6.2 for more details on the construction of these cumulative responses.

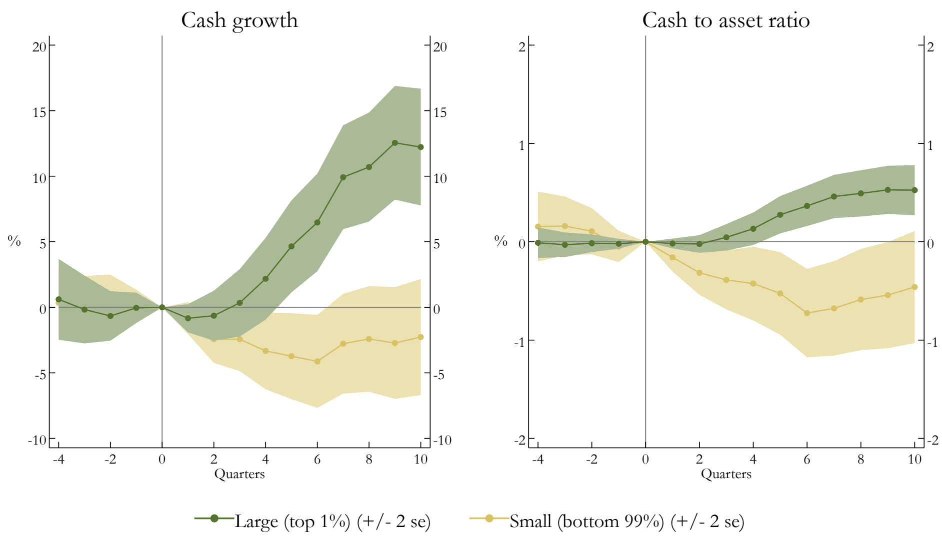


Figure A11: The behavior of cash growth and of the ratio of cash to total assets during recessions. The left panel reports the cumulative change in log cash around a recession start. The second panel reports the cumulative change in the ratio of cash to assets. Each graph reports the cumulative change in one of the two variables variable of interest after the beginning of a recession. Shaded areas are +/- 2 standard error bands. All changes are computed year-on-year and expressed at the quarterly frequency. Recession start dates are 1981q3, 1990q3, 2001q1, and 2007q4. See section 6.2 for more details.

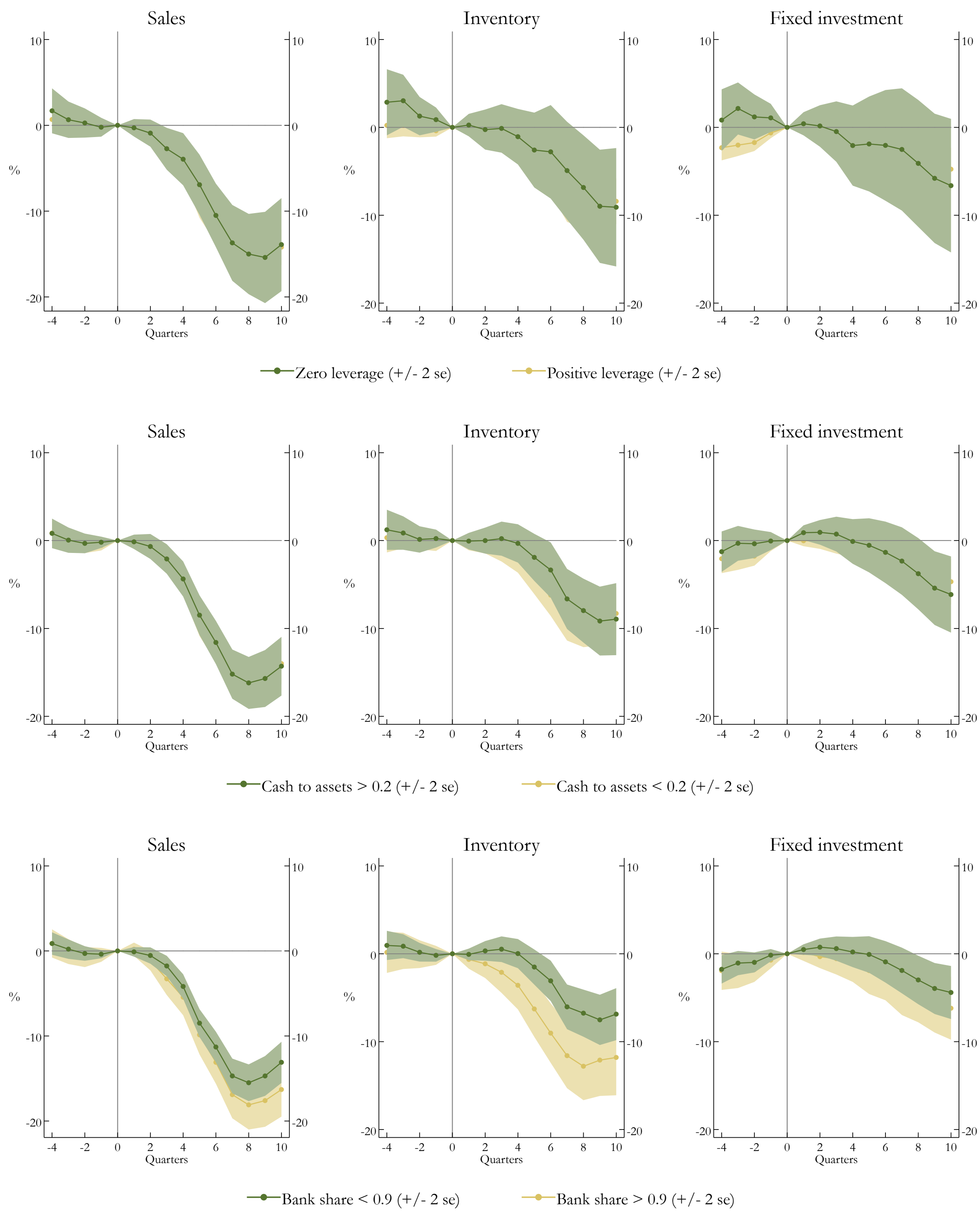


Figure A12: Sales, inventory and fixed capital after the start of a recession, across firms sorted by leverage, liquidity and bank dependence. Each graph reports the cumulative change in a variable of interest after the beginning of a recession; see section 6.2 for details on the estimation. Shaded areas are +/- 2 standard error bands. Variable definitions are given in appendix (D). 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.

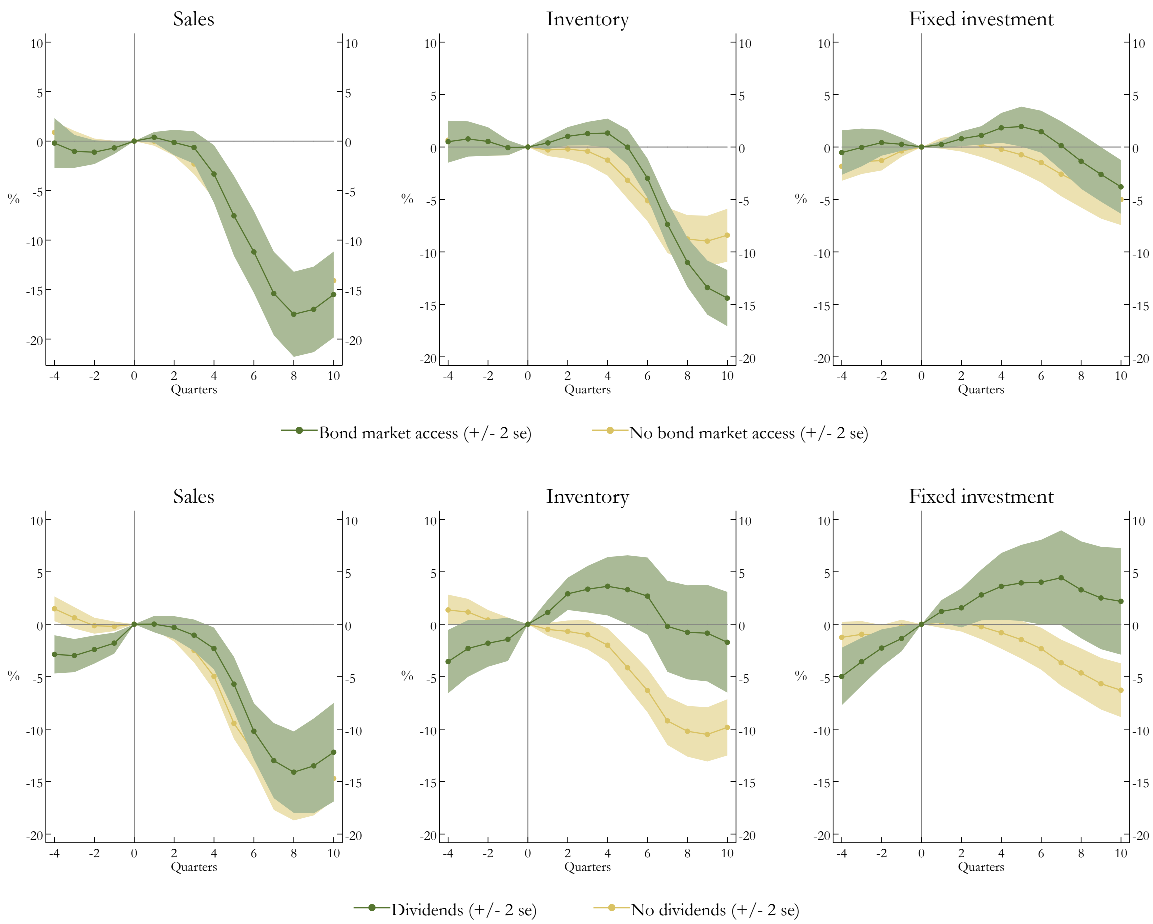


Figure A13: Sales, inventory and fixed capital after the start of a recession, across firms sorted by market access and dividend issuance. Each graph reports the cumulative change in a variable of interest after the beginning of a recession; see section 6.2 for details on the estimation. Shaded areas are +/- 2 standard error bands. Variable definitions are given in appendix D. Top row: firms sorted based on lagged access to bond market; bottom row: firms sort based on lagged dividend issuance.