Firms, Destinations, and Aggregate Fluctuations*

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Abstract

This paper uses a database covering the universe of French firms for the period 1990–2007 to provide a forensic account of the role of individual firms in generating aggregate fluctuations. We set up a simple multi-sector model of heterogeneous firms selling to multiple markets to motivate a theoretically-founded decomposition of firms' annual sales growth rate into different components. We find that the firm-specific component contributes substantially to aggregate sales volatility, mattering about as much as the components capturing shocks that are common across firms within a sector or country. We then decompose the firm-specific component to provide evidence on two mechanisms that generate aggregate fluctuations from microeconomic shocks highlighted in the recent literature: (i) when the firm size distribution is fat-tailed, idiosyncratic shocks to large firms directly contribute to aggregate fluctuations; and (ii) aggregate fluctuations can arise from idiosyncratic shocks due to input-output linkages across the economy. Firm linkages are approximately three times as important as the direct effect of firm shocks in driving aggregate fluctuations.

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1 Introduction

A long tradition in macroeconomics seeks to understand the microeconomic underpinnings of aggregate fluctuations. Starting with the seminal work of Long and Plosser (1983), an important line of research explores the role of sectoral shocks in generating aggregate fluctuations (see, e.g., Stockman, 1988; Foerster et al., 2011; Carvalho and Gabaix, 2013, among many others). A running theme in this literature is that idiosyncratic shocks to a single sector can have sizeable aggregate effects if the sector is strongly interconnected with others in the economy through input linkages (Horvath, 1998, 2000; Dupor, 1999; Shea, 2002; Conley and Dupor, 2003; Acemoglu et al., 2012). The role of individual firms in the aggregate business cycle has received comparatively less attention. Gabaix (2011) argues that because the firm size distribution is extremely fat-tailed – the economy is "granular" – idiosyncratic shocks to individual (large) firms will not average out, and instead lead to movements in the aggregates. However, there is currently little empirical evidence on the role of individual firms and firm-to-firm linkages in aggregate fluctuations.

This paper constructs a novel database covering the universe of French firms' domestic sales and destination-specific exports for the period 1990–2007, and uses it to provide a forensic account of the contribution of individual firms to aggregate fluctuations. To guide the empirical exercise, we set up a simple multi-sector model of heterogeneous firms in the spirit of Melitz (2003) and Eaton et al. (2011a). The model implies that the growth rate of sales of an individual firm to a single destination market can be decomposed additively into a macroeconomic shock (defined as the component common to all firms), a sectoral shock (defined as the component common to all firms in a particular sector), and a firm-level shock.

Relative to standard empirical assessments of the role of sectoral or firm-specific shocks, a novel aspect of our approach is that it accounts explicitly for the sector- and firm-level participation in export markets. When firms sell to multiple, imperfectly correlated markets, total firm sales do not admit an exact decomposition into macroeconomic, sectoral, and firm-specific shocks, whereas sales to an individual destination do. Thus, in our analysis macroeconomic, sectoral, and firm-specific shocks are defined for each destination market. The heterogeneity across markets also allows us to distinguish the firm-specific shocks affecting a firm's sales to all markets it serves from shocks particular to individual markets.

We compute macroeconomic, sectoral, and firm-specific shocks using data on the annual firm-destination sales growth rates. The firm-specific component accounts for the overwhelming majority (98.7%) of the variation in sales growth rates across firms.[1] In addition, about half of the variation in the firm-specific component is explained by variation in that component across destinations, which can be interpreted as destination-specific demand shocks in our conceptual framework.

We extract the time series of the macroeconomic, sectoral, and firm-specific shocks for each destination served by each firm. We use these realizations of shocks to assess whether *microeconomic* shocks contribute significantly to *aggregate* volatility, and if yes, through which channels. We derive a decomposition of aggregate volatility in the economy into the contributions of macroeconomic/sectoral and firm-specific shocks, and quantify the importance of the latter for aggregate volatility.

Our main finding is that the firm-specific components contribute substantially to aggregate fluctuations. The standard deviation of the firm-specific shocks' contribution to aggregate sales growth amounts to 80% of the standard deviation of aggregate sales growth in the whole economy, and 69% in the manufacturing sector. This contribution is similar in magnitude to the combined effect of all sectoral and macroeconomic shocks. The standard deviation of the sectoral and macroeconomic shocks' contribution to aggregate sales growth is 53% of the standard deviation of aggregate sales growth for the overall economy, and 64% for the manufacturing sector.[2] To investigate whether exports differ systematically from domestic sales, we then carry out the aggregate volatility decomposition for domestic and export sales separately.[3] The firm-specific component contributes more to the volatility of exports than that of overall sales in both the economy as a whole and in the manufacturing sector, where exporting is more prevalent. Nonetheless, firm-specific shocks contribute substantially to the volatility of aggregate domestic sales as well.

The overall contribution of firm-specific shocks to aggregate volatility can be decomposed additively into terms that capture two proximate explanations for why firm-specific shocks matter: (i) a weighted sum of all the variances of firm-specific shocks, and (ii) a weighted sum of all the covariances between the firm-specific shocks. We refer to the first as the

[1] This number is the share of the variance in the firm-destination growth rates that is not accounted for by the macro- and sectoral components. Using the same metric, Haltiwanger (1997) and Castro et al. (2011) find that idiosyncratic shocks account for more than 90% of the variation in firm growth rates in the U.S. Census Longitudinal Research Database.

[2] These numbers add up to more than 1 because they have been converted to standard deviations. Since the aggregate variance is additive in the firm-specific and macro-sectoral variance components, the aggregate standard deviation is smaller than the sum of the standard deviations of the components.

[3] The analysis of the export subsample is motivated by two well-known facts: (i) aggregate exports are more volatile than GDP, and (ii) the largest firms tend to be exporters. Canals et al. (2007) show that international trade is very granular, both at the firm- and sector-destination level.

direct effect, since this is the aggregate variance that would obtain directly from shocks to individual firms, and would be there even in the complete absence of interconnectedness between the firms. Gabaix (2011) shows that firm-specific idiosyncratic shocks do not average out because of the presence of very large firms. The second term collects cross-firm covariances, and can thus be thought of as arising at least in part from interconnectedness between firms (sector-level versions of this argument are explored in Horvath, 1998, 2000; Dupor, 1999; Shea, 2002; Conley and Dupor, 2003; Acemoglu et al., 2012, among others).[4] We refer to this as the *linkages* effect. Though both channels matter quantitatively, the majority of the contribution of firm-specific shocks to the aggregate variance is accounted for by the linkages term – the covariances of the firm-specific components of the sales growth rates.

We then exploit cross-sectoral heterogeneity to provide further evidence on the direct and linkages mechanisms. Gabaix (2011) shows that the direct effect of shocks to individual firms on aggregate fluctuations will be more pronounced the larger is the Herfindahl index of firm sales – a common measure of concentration. Confirming this result, firm-specific shocks in more concentrated industries – such as transport, petroleum, and motor vehicles – contribute more to aggregate volatility than firm-specific shocks in less concentrated sectors such as metal products or publishing. We also compare the covariances of the firm-specific shocks aggregated to the sector level to a measure of sectoral linkages taken from the Input-Output Tables.[5] Sectors with stronger input-output linkages tend to exhibit significantly greater correlation of firm-specific shocks. We thus find direct corroboration in the data for the mechanisms behind both the direct and the linkages effects.

The results are robust in a number of dimensions. First and foremost, we continue to find a large contribution of firm-specific shocks to aggregate fluctuations when we allow for heterogeneous responses of firm sales growth to common shocks. In the baseline model all firms have the same elasticity of sales with respect to the macroeconomic and sectoral shocks. While our framework shares this feature with the large majority of quantitative models in both macroeconomics and international trade, it is important to check whether the results are driven by this feature. In an alternative approach, we thus allow for the impact of sector-destination shocks on the growth rate of sales to vary by a wide variety of firm characteristics, such as size, age, access to capital markets, R&D intensity, or export

[4] Note that in this literature, the structural shocks are uncorrelated but generate positive covariances in firm sales.

[5] Ideally, we would relate the covariance of firm-specific shocks to a measure of linkages at the firm level. However, currently firm-to-firm Input-Output Tables do not exist for France, and thus we must look for these relationships at the sector level.

orientation. As additional checks, we also implement the model under several alternative definitions of the sales growth rates, accounting for local geographical area effects, different levels of sectoral disaggregation, and using multi-year growth rates instead of yearly ones. The results are robust to all of these alternative implementations.

Our paper draws on, and contributes to, three key themes in macroeconomics. The first is the quest to understand how aggregate fluctuations can arise from microeconomic sources. This literature dates back to Long and Plosser (1983) and has traditionally focused on shocks at the sectoral level (see, e.g., Jovanovic, 1987; Stockman, 1988; Carvalho and Gabaix, 2013, among many others). The second theme is that input-output linkages are the key mechanism through which microeconomic shocks propagate and lead to aggregate fluctuations. Once again, this literature has predominantly focused on sector-level linkages (see, e.g., Horvath, 1998, 2000; Dupor, 1999; Shea, 2002; Conley and Dupor, 2003; Foerster et al., 2011; Acemoglu et al., 2012).[6]

The third theme is that studying firm- and plant-level behavior is essential for understanding aggregate fluctuations. For instance, evidence on large gross employment flows at the micro level has stimulated a line of research into their aggregate implications (Davis and Haltiwanger, 1992; Davis et al., 1996; Caballero et al., 1997; Davis et al., 2006). Similarly, plant-level investment is dominated by infrequent and large spikes, and an active literature has explored whether these micro-level patterns affect the behavior of aggregate investment (see, among many others, Doms and Dunne, 1998; Cooper et al., 1999; Cooper and Haltiwanger, 2006; Gourio and Kashyap, 2007). Also closely related are studies of firm-level volatility (see, e.g., Comín and Philippon, 2006; Davis et al., 2007; Castro et al., 2011; Thesmar and Thoenig, 2011; Moscarini and Postel-Vinay, 2012; Lee and Mukoyama, 2012). These research agendas have tended to emphasize that studying micro behavior is important as a way to learn what are the salient frictions in the economy. By and large, this literature has not pursued the idea that shocks to *individual* firms can impact aggregate fluctuations. A landmark recent exception is Gabaix (2011), who shows how idiosyncratic shocks to firms can lead to aggregate fluctuations in an economy dominated by very large firms, and provides empirical evidence for this phenomenon using U.S. data. Di Giovanni and Levchenko (2012a) extend this model to a multi-country framework, and argue that it can help rationalize cross-country differences in the magnitude of aggregate fluctuations.

In line with the first two themes, our analysis emphasizes both the role of individual

[6]Important exceptions are Cohen and Frazzini (2008), Hertzel et al. (2008), and Kelly et al. (2013) who relate the supplier relationships among U.S. listed firms to movements in their stock prices and sales volatility.

shocks and of input-output linkages. In line with the third theme but in contrast to the earlier literature, we shift the focus from sectors to firms. Our paper is the first to provide comprehensive empirical evidence on firms' contribution to aggregate fluctuations using the population of firms in a particular country. In addition, we incorporate the international dimension and show that it is important for a reliable computation of shocks. Finally, our data enable us to examine in detail the mechanisms behind the role of individual firms in generating aggregate volatility.

The rest of the paper is organized as follows. Section 2 presents a simple heterogeneous firms model and derives a theoretically-founded decomposition of firm sales growth in each market into firm-specific, sector-level, and macroeconomic components. The section then derives a procedure to compute each component's contribution to aggregate volatility. Section 3 describes the data. Section 4 presents the main results. Section 5 concludes.

2 Conceptual Framework

Total aggregate sales X_t by all French firms to all destinations in year t are by definition given by: $X_t \equiv \sum_{f,n \in I_t} x_{fnt}$, where x_{fnt} is defined as the sales of firm f to market n in year t, and I_t is the set of firms f *and destinations* n being served at t. Thus, the unit of observation is a firm-destination pair, rather than a firm.[7] The growth rate of aggregate sales is then defined simply as $\gamma_{At} = X_t/X_{t-1} - 1$, where we assume that X_{t-1} and X_t are the aggregate sales of all firms that exist both at $t-1$ and t, i.e. we restrict attention to the *intensive margin* of aggregate sales growth. The choice to focus on the intensive margin is motivated in part by the difficulty of measuring the extensive margin reliably. Online Appendix A develops a complete decomposition of the total sales growth into extensive and intensive margins, and presents the results for the relative contributions of the extensive (as best as we can measure it) and intensive margins to aggregate volatility. The main result is that the large majority of the variance of aggregate sales is accounted for by the volatility of the intensive margin, with the extensive margin playing only a minor role.[8] Section 4.4.2 demonstrates the robustness of the results to an alternative definition of firm sales growth

[7] That is, suppose that there are two firms $f \in \{Renault, Peugeot\}$ and two markets, $n \in \{France, Germany\}$, and both firms sell to both markets, then $I_t = \{\{Renault, France\}, \{Renault, Germany\}, \{Peugeot, France\}, \{Peugeot, Germany\}\}$, and X_t is simply a summation over the sales of each firm to each destination.

[8] These results are consistent with other work on the role of the extensive margin in short-run aggregate fluctuations in the French economy. For instance, Osotimehin (2013) finds that entry and exit contribute little to the year-on-year variability of French aggregate productivity.

rates, that treats entries and exits symmetrically with other sales.[9]

2.1 A Motivating Model of Firm Sales Growth

To motivate the decomposition of the growth of firm sales in a given year into (i) firm-destination, and (ii) sector and country components, we set up a multi-sector heterogeneous firms model in the spirit of Melitz (2003) and Eaton et al. (2011a). While the model is largely illustrative and we will not use its full structure for estimation purposes, it serves to illustrate three main points. First, the sales decomposition adopted in the paper follows naturally from the workhorse heterogeneous firms model used in the literature. Second, the decomposition works only when applied to firm sales to an individual destination, rather than total (domestic plus export) sales. This result motivates our approach of extracting macro, sectoral, and idiosyncratic components for each individual destination market. And third, the model provides a simple and natural economic interpretation of the shocks as combinations of the demand and cost shocks that affect (sets of) firm-destinations.

There is a large number of countries indexed by n, and J sectors indexed by j. In country n, consumer within-period utility is Cobb-Douglas in the sectors $1, \ldots, J$:

$$U_{nt} = \prod_{j=1}^{J} (C_{jnt})^{\varphi_{jnt}}, \tag{1}$$

where C_{jnt} is consumption of sector j in country n at time t, and φ_{jnt} is a time-varying demand shock for sector j in country n (as in Eaton et al., 2011b). The Cobb-Douglas functional form for the utility function leads to the well-known property that expenditure on sector j is a fraction φ_{jnt} of the total expenditure in the economy: $Y_{jnt} = \varphi_{jnt} Y_{nt}$, where Y_{nt} is aggregate expenditure in country n at time t, and Y_{jnt} is the expenditure in sector j.

Each sector j is a CES aggregate of Ω_{jnt} varieties available in country n at time t, indexed by f:

$$C_{jnt} = \left[\sum_{f \in \Omega_{jnt}} (\omega_{fnt})^{\frac{1}{\theta}} \, C_{fnt}^{\frac{\theta-1}{\theta}} \right]^{\frac{\theta}{\theta-1}}, \tag{2}$$

where ω_{fnt} is a time-varying demand shock for variety f in market n.

Every firm belongs to exactly 1 sector. Sector j in the producing country (d=France) is populated by I_{jdt} firms. Each of these firms sells a unique variety, and thus has some market power. Firms also differ in productivity, with firm f characterized by a time-varying

[9] Recent work focuses on the importance of the extensive adjustment at the *product* level – potentially within a firm (e.g., Bernard et al., 2010; Bilbiie et al., 2012), whereas in our data it is only possible to measure the extensive margin at the firm level.

unit input requirement a_{fdt}. It takes firm f a_{fdt} input bundles to produce one unit of its good in period t. The input bundle in sector j in country d and period t has a cost c_{jdt}. Note that it can vary by sector, but not across firms within a sector. This input bundle can include, for instance, labor costs and the cost of capital. It is well known that these firms will price at a constant markup over their marginal cost, and conditional on selling to market n, sales by a French firm f (i.e., residing in country d) to market n in period t are given by:

$$x_{fnt} = \omega_{fnt} \frac{\varphi_{jnt} Y_{nt}}{(P_{jnt})^{1-\theta}} \left(\frac{\theta}{\theta - 1} \kappa_{jnd} c_{jdt} a_{fdt} \right)^{1-\theta}, \tag{3}$$

where P_{jnt} is the price level in sector j in country n at time t, and κ_{jnd} is the iceberg cost of selling from France to country n in sector j. This equation assumes that (i) κ_{jnd} is sector-specific but does not vary over time (though that assumption can easily be relaxed, in which case the time variation in κ_{jnd} will be absorbed in the sector-destination shock), and (ii) the cost bundle c_{jdt} and the marginal cost a_{fdt} may vary over time, but are not destination-specific.

Sales to a single destination are then multiplicative in the macroeconomic, sectoral, and firm-specific components. The sales growth rate γ_{fnt} of firm f in sector j to market n between time $t-1$ and time t is approximated by a log difference:

$$\gamma_{fnt} = \tilde{\delta}_{nt} + \tilde{\delta}_{jnt} + \varepsilon_{fnt}, \tag{4}$$

where $\tilde{\delta}_{nt} = \Delta \log Y_{nt}$ is the aggregate ("macroeconomic") shock to the destination demand (to France if $n = d$), $\tilde{\delta}_{jnt} = \Delta \log \varphi_{jnt} + (1-\theta)(\Delta \log c_{jdt} - \Delta \log P_{jnt})$ captures the sectoral (country n-specific) demand and cost shocks, and $\varepsilon_{fnt} = \Delta \log \omega_{fnt} + (1-\theta)\Delta \log a_{fdt}$ is the firm-specific demand and cost shock. Equation (4) characterizes firm sales growth to the domestic French market and to every foreign market.

While the theoretical framework distinguishes between macroeconomic shocks that are common to all firms selling goods in the same market and sectoral shocks in that market, in practice the macroeconomic shock and all of the sectoral shocks cannot be computed separately without further restrictions on the form they can take. However, since we are ultimately interested in the firm-specific component and its contribution to aggregate fluctuations, this does not pose a problem. In what follows, we work with a simpler model:

$$\gamma_{fnt} = \delta_{jnt} + \varepsilon_{fnt}, \tag{5}$$

that decomposes sales growth into a firm-specific shock ε_{fnt} and a sector-destination shock $\delta_{jnt} = \tilde{\delta}_{nt} + \tilde{\delta}_{jnt}$ encompassing the macroeconomic and sectoral shocks.

2.2 Econometric Model

The analysis below views the ε_{fnt}'s and δ_{jnt}'s as a set of stochastic processes that are (potentially) both cross-sectionally and serially correlated. Our ultimate goal is to assess the impact of firm-specific shocks ε_{fnt} on aggregate fluctuations. Under the log-difference approximation (5) to the growth rates of individual firms, the growth rate γ_{At} of aggregate sales between $t-1$ and t can be written as:

$$\gamma_{At} = \sum_{j,n} w_{jnt-1}\delta_{jnt} + \sum_{f,n} w_{fnt-1}\varepsilon_{fnt}, \tag{6}$$

where w_{jnt-1} is the share of sector j's sales to market n in total sales of French firms to all sectors and destinations, and w_{fnt-1} is the share of firm f's sales to destination n in total sales. Unfortunately, working with equation (6) directly to produce a variance decomposition is impractical because time-varying weights w_{fnt-1} make the stochastic process (6) difficult to analyze.

Instead, we work with a closely related set of stochastic processes:

$$\gamma_{At|\tau} = \sum_{j,n} w_{jn\tau-1}\delta_{jnt} + \sum_{f,n} w_{fn\tau-1}\varepsilon_{fnt}. \tag{7}$$

For a given τ, $\gamma_{At|\tau}$ is a stochastic process in which weights $w_{fn\tau-1}$ are fixed over time at their $\tau-1$ values, and combined with shocks from period t. Naturally, when $\tau = t$, the "synthetic" aggregate growth rate $\gamma_{At|\tau}$ coincides with the actual aggregate growth rate γ_{At}. The last term in (7), $\sum_{f,n} w_{fn\tau-1}\varepsilon_{fnt}$, is none other than Gabaix (2011)'s "granular residual," with the key difference that we build it with the ε_{fnt}'s of all firms in the economy, rather than the top 100 firms as in Gabaix (2011).

Denote by $\sigma^2_{A\tau}$ the variance of $\gamma_{At|\tau}$.[10] Using (7), it can be written as:

$$\sigma^2_{A\tau} = \sigma^2_{JN\tau} + \sigma^2_{F\tau} + COV_\tau, \tag{8}$$

[10] Online Appendix B presents further discussion of how our $\sigma^2_{A\tau}$'s relate to the variances of actual aggregate growth rate γ_{At} and its components.

where

$$\sigma^2_{JN\tau} = \text{Var}\left(\sum_{j,n} w_{jn\tau-1}\delta_{jnt}\right) \qquad \text{(Sector-Destination Volatility)}$$

$$\sigma^2_{F\tau} = \text{Var}\left(\sum_{f,n} w_{fn\tau-1}\varepsilon_{fnt}\right) \qquad \text{(Firm-Specific Volatility)}$$

$$COV_\tau = \text{Cov}\left(\sum_{j,n} w_{jn\tau-1}\delta_{jt}, \sum_{f,n} w_{fn\tau-1}\varepsilon_{fnt}\right)$$

(covariance of the shocks from different levels of aggregation).

The intuition for this procedure can be conveyed as follows. Since δ_{jnt} and ε_{fnt} are random variables, the growth rate of aggregate sales at time τ in (7) is itself a random variable, and its variance is given by (8). The estimate of $\sigma^2_{A\tau}$ for a particular year can thus be thought of as the estimated variance of the aggregate growth rate in year τ. We are interested in exploiting the form of $\gamma_{At|\tau}$ to decompose the overall variance of $\gamma_{At|\tau}$ into firm-specific and other components, in order to assess the importance of firm-specific shocks for aggregate fluctuations.

In practice, we will be reporting estimates of $\sigma^2_{A\tau}$ and its components for each $\tau = 1991, ..., 2007$, as well as their averages over this period. The approach of constructing aggregate variances under weights that are fixed period-by-period follows Carvalho and Gabaix (2013), who perform a related exercise using sectoral data.

2.3 Estimation

The main goal of the paper is to provide estimates for $\sigma^2_{A\tau}$, $\sigma^2_{JN\tau}$, and $\sigma^2_{F\tau}$. Using sales data γ_{fnt}, the macro-sectoral shock δ_{jnt} is computed as the average growth rate of sales of all firms selling in sector j to market n. The firm-specific shock ε_{fnt} is computed as the deviation of γ_{fnt} from δ_{jnt}. This approach to identifying firm-specific shocks is adopted by Gabaix (2011) and Castro et al. (2011), and follows in the tradition of Stockman (1988), who applied it at the sector level.

Our estimator for $\sigma^2_{F\tau}$ is simply the sample variance of the T realizations of the scalar-valued time series $\sum_{f,n} w_{fn\tau-1}\varepsilon_{fnt}$. Similarly, the estimators for $\sigma^2_{A\tau}$ and $\sigma^2_{JN\tau}$ are the sample variances of the realizations of $\gamma_{At|\tau}$ and $\sum_{j,n} w_{jnt-1}\delta_{jnt}$, respectively. Our sample consists of the realizations of the stochastic processes δ_{jnt} and ε_{fnt} for $T = 17$ years. Our framework allows for both cross-sectional and time dependence in the data-generating process. That is, ε_{fnt} for firm f can be correlated with another firm's ε_{gnt}, as well as with its own past values. However, we do assume that the stochastic process for ε_{fnt} and δ_{jnt} is jointly stationary, that its degree of time dependence is not too high, and that $\gamma_{At|\tau}$ as well as its constituent parts have enough finite moments. Since both ε_{fnt} and δ_{jnt} describe growth rates, stationarity and limited time dependence are plausible assumptions. In practice, in our sample the autocorrelation in the series for $\gamma_{At|\tau}$ and its constituent parts is minimal. Online Appendix C states these conditions precisely and proves the consistency and asymptotic normality of the estimators as T grows large. The Appendix also gives formulas for the analytical standard errors of these estimators, that we use below to construct confidence intervals. For robustness, we also report confidence intervals based on bootstrapping procedures.

We follow the convention in the literature and use the standard deviation as our measure of volatility. Therefore, when discussing contributions to aggregate volatility we will present the results in terms of *relative standard deviations*, such as $\sigma_{F\tau}/\sigma_{A\tau}$.

2.4 Discussion

The first term in (8) measures the volatility of sector-destination shocks, which affect all firms in a sector selling to a particular destination market. It can be expressed as $\sigma^2_{JN\tau} = \sum_{k,m} \sum_{j,n} w_{jn\tau-1} w_{km\tau-1} \mathrm{Cov}\left(\delta_{jnt}, \delta_{kmt}\right)$, making it clear that it is driven by the volatility of the sector-destination shocks ($\mathrm{Var}(\delta_{jnt})$) and their covariance across countries and sectors ($\mathrm{Cov}(\delta_{jnt}, \delta_{kmt})$). Obviously, the importance of any country- or sector-specific shock in explaining aggregate volatility is increasing in the relative size of that market (measured by $w_{jn\tau-1}$). Thus, French shocks have a larger impact on aggregate volatility than shocks affecting French firms' sales to, say, Japan. Likewise, a country specializing in highly volatile sectors is likely to display larger aggregate fluctuations (Koren and Tenreyro, 2007; di Giovanni and Levchenko, 2012b). In that sense, diversification of sales across markets and sectors helps reduce aggregate fluctuations. In the meantime, comovement across countries or sectors tends to amplify aggregate fluctuations. For instance, an increased synchronization of business cycles among EMU members might drive up French volatility. Cross-sector correlations, created for example by input-output linkages, will also increase aggregate volatility (see, e.g., di Giovanni and Levchenko, 2010).

The second term in (8), $\sigma^2_{F\tau}$, is the variance of the granular residual. It measures the contribution of firm-specific shocks to aggregate fluctuations. As in Gabaix (2011), the firm-specific contribution to aggregate volatility is likely to be larger, everything else equal, the more fat-tailed is the distribution of sales across firms. Furthermore, volatility also increases if the larger firms face more volatile shocks. Finally, a positive correlation of shocks across firms, for instance driven by input-output linkages, will increase firms' contribution to aggregate fluctuations. Section 4.3 discusses in more detail the microeconomic underpinnings of $\sigma^2_{F\tau}$, both in theory and in our data.

The firm-specific shocks ε_{fnt} need not be uncorrelated with each other as in Gabaix (2011). For example, these shocks may covary among firms if their activity is interconnected, say through input-output linkages (e.g., Foerster et al., 2011; Acemoglu et al., 2012), or other potential firm interactions. To illustrate this possibility, Online Appendix E presents a simple extension of the model that includes intermediate inputs specific to the firm. These intermediate linkages lead to positive comovement of firm-specific shocks through the propagation of productivity shocks from input providers to downstream firms. To assess the relevance of this channel, below we develop a decomposition of the firm-specific variance and covariance contributions to aggregate volatility, and provide evidence that industry structure and other proxies for linkages matter.

We had argued that from a theoretical perspective, it is important to compute shocks for each market separately. In our theoretical framework, the firm-specific shock $\varepsilon_{fnt} = \Delta\log\omega_{fnt} + (1-\theta)\Delta\log a_{fdt}$ contains a component common across all destination markets and a component that is destination-specific. Thus it can be further decomposed as:

$$\varepsilon_{fnt} = \varepsilon^1_{ft} + \varepsilon^2_{fnt}, \tag{9}$$

where ε^1_{ft} is the firm-specific shock common to all destinations, and ε^2_{fnt} captures the destination-specific demand shock. Specifically, we compute ε^1_{ft} as the time t average of ε_{fnt} for each firm that serves multiple destinations (including the domestic market). Note that this procedure does not allow us to separate demand shocks from cost shocks cleanly, because ε^1_{ft} captures not only the productivity shock $(1-\theta)\Delta\log a_{fdt}$ but also other firm-level shocks that are common across destinations, for instance common taste shocks. Nonetheless, we can get a sense of the relative importance of the firm-wide vs. destination-specific shocks by computing the share of variation in ε_{fnt} that is absorbed by ε^1_{ft}.

3 Data and Summary Statistics

The analysis employs firm-level data containing the universe of domestic and export sales of French firms over the 1990–2007 period. Even though the time dimension is somewhat limited, we are still able to pick up cycles of the French economy, including the 1992–93 and

2000–01 recessions and the acceleration of growth at the end of the nineties. The firm-level information is sourced from two rich datasets provided to us by the French administration. The first dataset, obtained from the fiscal administration, contains balance-sheet information collected from the firms' tax forms, most importantly total firm sales. The second dataset is the firm-level export data from the French customs authorities. This database gives the (free on board) value of each French firm's exports to each of its foreign destination markets in a given fiscal year.

Online Appendix D contains a detailed description of the data. Our final dataset covers 1,577,039 firms undertaking activities in 52 NAF (*Nomenclature d'Activités Française*) sectors, representing around 30% of industrial and service firms but more than 90% of aggregate sales. Of those firms, 208,596 belong to the manufacturing sector (22 NAF industries), which accounts for around 30% of aggregate sales. In our sample, 18% of all firms (and 42% of manufacturing firms) export at some point in time. The total sales and export sales in this sample of firms mimic aggregate activity quite well: the growth rate of total sales tracks the growth rate of GDP (Figure 1), while the growth of total export sales moves with the growth of country exports over time (Figure 2).

Table 1 presents summary statistics for firm-level growth rates for the whole economy and the manufacturing sector. The average growth rate of aggregate sales, 0.0369 for the whole economy and 0.0290 for manufacturing, is lower than the (unweighted) average growth rate of individual firm-destinations, which is 0.0465 for the whole economy and 0.0537 for manufacturing. This is to be expected, as smaller firms tend to grow faster than larger firms, conditional on survival. The average firm-destination has a standard deviation of sales growth of 0.23 in the whole economy and 0.28 in manufacturing. The table also reports averages of firm sales volatility by quintile. Smaller firms are more volatile than large ones. The very top firms, however, are even less volatile than the top quintile firms. While the top 20% of firm-destinations by size have an average standard deviation of sales growth of almost 20%, the top 100 firm-destinations have an average standard deviation of 13%, and the top 10 firms slightly lower still. Finally, the table also reports the square root of the firm-destination Herfindahl index of sales shares, as well as the square root of the overall firm sales Herfindahl index. The Herfindahl indices have an order of magnitude consistent with what has been conjectured by Gabaix (2011), and show that the economy is "granular:" shocks to the large firms have the potential to lead to aggregate fluctuations. All in all, the patterns for the manufacturing sector are quite similar to the whole economy.

Table A1 presents the average standard deviations of firm-destination growth rates across sectors, along with the shares of each sector in total sales. The raw volatility of sales growth varies across sectors, with the standard deviation ranging from a low of 0.1489 (Health and social work) to a high of 0.3248 (Coke, refined petroleum and nuclear fuel), and a cross-sectoral mean standard deviation of 0.2593. The wholesale and retail trade sector has by far the highest share in aggregate sales, at nearly 37% of the total. While the standard deviation of sales growth, at 0.2188, is quite typical of the rest of the economy, clearly wholesale and retail trade is quite special in other ways. To establish the robustness of the results, all of the analysis below is carried out both on the whole economy and on the manufacturing sector.

The analysis in the paper uses the growth rates of firm-destination sales. Other related work focuses on measures of firm productivity such as value added per worker (e.g. Gabaix, 2011; Castro et al., 2011) or TFP (Carvalho and Gabaix, 2013), or employment (e.g. Moscarini and Postel-Vinay, 2012). Unfortunately, neither employment nor value added per worker data can be broken down into destinations – it is of course impossible to know which workers in the firm are producing for exports and which for domestic sales – whereas we show above that to carry out our analysis, the destination-by-destination breakdown is essential. This is the reason we use sales growth in the baseline analysis. As a robustness check, Section 4.2 presents the results for value added growth, under the (non-trivial) assumption that a firm's value added has the same breakdown across markets as its sales do. We cannot compute the firms' TFP process for the additional reason that we do not have firm-specific input and output deflators (Klette and Griliches, 1996, among others, discuss the serious shortcomings of firm-level TFP estimation that does not employ firm-specific price data). We can also calculate the means and standard deviations of employment and value added per worker growth rates, and compare them to firm-destination sales growth rates. It turns out that these series have very similar first and second moments. For the whole economy, employment growth is 0.0345 at the mean, with an average standard deviation of 0.2437; value added per worker growth is 0.0400, with an average standard deviation of 0.2586. All of these are quite close to the corresponding numbers for sales growth in Table 1.[11]

[11]Average sales growth reported in the table is lower than the sum of average value added per worker growth and average employment growth. Value added is defined as total sales minus input purchases (taking into account changes in the value of input inventories) plus changes in inventories plus subsidies minus taxes. Thus, sales would grow slower than value added if these other categories had slower growth rates than value added. This appears to be the case in our data, reconciling the seeming discrepancy.

4 Empirical Results

4.1 Properties of Shocks

Before assessing the impact of firm-specific shocks on aggregate volatility, we present the importance of the different components in explaining the variation in sales growth at the firm-destination level. The top panels of Table 2 and Table 3 report the relative standard deviations of the firm-destination components and the sector-destination shocks for the whole economy and the manufacturing sector, respectively. The last column reports the correlation of each component with the actual firm sales growth. The bottom two panels report the same statistics for domestic and export firm sales.

It is clear that at the level of an individual firm-destination, variation in sales growth is dominated by the firm-specific component, rather than the sector-destination shocks. The standard deviation of the firm-specific component is nearly the same as the standard deviation of actual sales growth, and the correlation is almost perfect. By contrast, the estimated sector-destination shocks are much less volatile, and have much lower correlation with actual sales growth. These results are of course not surprising, and confirm the conventional wisdom that most shocks hitting firms are firm-specific (Haltiwanger, 1997; Castro et al., 2011).[12] Examining the bottom two panels, it is clear that the importance of the firm-specific component is similar for both domestic and export sales.

It has been less well-understood whether the firm-specific shocks are mostly common to all destination markets served by the firm or mostly destination-specific. Table 4 presents the results of extracting the common firm component from firm-destination effects as in equation (9), for both the whole economy and the manufacturing sector.[13] Looking at the data through the lens of the model in Section 2, this decomposition is suggestive of whether supply or demand shocks are driving firms' sales growth. Since the firm's marginal cost of serving each market (modulo iceberg trade costs) is the same, productivity shocks will be part of the component of the firm-specific shock that is common to all destinations. In addition, the common component will also include the part of the taste shock ω_{fnt} for firm f that is common across locations n. The destination-specific component of the firm shock is then interpreted as a demand shock idiosyncratic to a particular location.

Results are similar for the two sets of firms. For the economy as a whole, the destination-

[12] A variance decomposition of the firm-level growth rates indicates that 98.7% is accounted for by the firm-specific component for the whole economy (98.2% for the manufacturing sector).

[13] Note that this decomposition can only be done for firms that serve at least two markets. Therefore, the number of firm-destination and firm-common observations will be smaller than the total number of firm-specific shocks in Tables 2 and 3.

specific component has a higher relative standard deviation than the common factor (0.30 vs. 0.19). It is also more correlated with the total estimated firm-specific component (correlation coefficient of 0.87 compared to 0.49 for the common component). For the manufacturing sector, the relative standard deviation of the destination-specific shock is 0.31, whereas that of the common shocks is 0.19. Similarly, the correlation with the overall firm-specific component is higher for the destination-specific component than for the common component (0.89 vs. 0.46). We conclude from this exercise that destination-specific shocks at the firm level are more important than the shocks common to all destinations.[14]

4.2 The Aggregate Impact of Firm-Specific Shocks

The fact that most of the variation in the growth rate of sales is accounted for by firm-specific shocks does not mean that firm-specific shocks manifest themselves in aggregate fluctuations. To assess the importance of the different types of shocks for the aggregate, we must take into account the distribution of firm size by decomposing the aggregate sales volatility as in Section 2.2.

Figure 3 and Table 5 report the main results of the paper. Figure 3 depicts the estimates of $\sigma_{A\tau}$ and its main components: firm-specific ($\sigma_{F\tau}$), and sector-destination ($\sigma_{JN\tau}$) for the whole economy (Panel I) and the manufacturing sector (Panel II). The figure also displays two kinds of 95% confidence intervals: analytical and bootstrapped. Table 5 reports the averages of our estimates of $\sigma_{A\tau}$, $\sigma_{JN\tau}$, and $\sigma_{F\tau}$, as well as their ratios, over the sample period. The results for the whole economy are in the first two columns, and for the manufacturing sector in the next two columns.

Not surprisingly, the firm-destination component matters much less for the aggregate sales volatility than for the volatility of individual firm sales. However, its importance is non-negligible: for the whole economy the relative standard deviation of the firm-specific component of aggregate sales is 0.8 relative to that of actual sales volatility. In fact, our results show that the firm-specific component is more important for aggregate fluctuations than the contribution of sector-destination shocks, which has a relative standard deviation of 0.53.

The standard deviation of the firm-specific component comoves with the standard deviation of aggregate sales over time, whereas the standard deviation of sector-destination

[14] This result is consistent with the findings of Eaton et al. (2011a) who estimate a structural trade model on French export data and find that a firm-destination specific shock has to be added for the model to fit the data. This suggests that firm-specific shocks common across destinations are not sufficient for explaining aggregate exports.

shocks is nearly constant over time. Recalling how the different components are calculated from (8), note that the time variation in sales' share (at the firm and sector-destination levels) will drive the time variation in the different volatility measures. These shares do not change dramatically at the sector-country level. More interestingly, the firm-specific shocks increase in importance over time. For the whole economy, the relative standard deviation of the firm-specific to total sales is about 0.5 at the beginning of the sample, and about 0.85 at the end. These results are a first glimpse of the importance of large firms and firm linkages on aggregate fluctuations. We discuss further what drives these findings in Section 4.3.

The contributions of firm-specific and macro-sector shocks are both statistically significant throughout the sample. In spite of computing the sample variance on a time series of only 17 observations for each $\sigma_{F\tau}$ and $\sigma_{JN\tau}$, we always have enough power to reject the null that the contribution of $\sigma_{F\tau}$ and $\sigma_{JN\tau}$ is nil. The analytical standard errors are computed as detailed in Online Appendix C. These standard errors may not capture the full extent of estimation uncertainty in such a small sample. To explore robustness of the results further, we also use a block bootstrapping procedure in which for each τ we sample 10001 draws of 17 observations with replacement from the time series of $\gamma_{At|\tau}$, $\sum_{j,n} w_{jn\tau-1}\delta_{jnt}$, and $\sum_{f,n} w_{fn\tau-1}\varepsilon_{fnt}$. The results are robust to using bootstrapped rather than analytical confidence intervals.[15]

The results for the manufacturing sector largely mimic those of the economy as a whole. The relative standard deviation of the firm-specific component of aggregate sales is 0.69 of actual sales volatility. In this set of firms, the firm-specific component is about as important for aggregate fluctuations as the sector-destination shocks, which have a relative standard deviation of 0.64. The contribution of firms to aggregate fluctuations also increases over time in the manufacturing sector, from 0.45 in 1991 to 0.81 in 2007.

Panels II and III of Table 5 check the results on domestic and export sales separately. Both panels confirm the importance of firm-specific shocks for aggregate fluctuations. Moreover, export sales are dominated by firm-specific shocks while the relative weights of firm-specific and sector-destination components as a driver of aggregate fluctuations are roughly equal for domestic sales. The greater relative importance of firm shocks for exports compared to domestic sales is exactly as expected given that exports are more granular than overall sales (Canals et al., 2007).

Since GDP is measured in value added, GDP fluctuations correspond more closely to

[15] To account for time dependence in the data, the bootstrap procedure samples (overlapping) blocks of 1, 2, and 3 observations. The figures report the confidence intervals under a block size of 1, but differences are minimal if we instead use blocks of size 2 or 3.

fluctuations in firm value added. We thus repeat the analysis using firm value added instead of gross sales. This exercise entails a non-trivial assumption. Namely, our framework makes it clear that for proper identification of shocks, we must use data on each destination separately. Since both exports and domestic sales are recorded in gross terms, when we use sales this is non-controversial: total firm sales are the sum of sales to each destination market served by the firm. Indeed, this is the reason that we work with sales throughout the paper.

However, for value added we do not have the right data, because value added exports are not recorded. The data we have are (i) gross domestic sales and exports and (ii) total firm value added. The assumption we make to move forward is that the breakdown of value added across markets follows the same proportions as total sales. Thus, to compute a firm's value added exports to Germany, we multiply total firm value added by the share of exports to Germany in the firm's total gross sales. In the absence of value added export data, this is the best we can do. It amounts to the restriction that the input usage inside the firm is identical for each destination of its output. For an advanced economy like France, this appears to be a reasonable assumption.

With that caveat, Table 5 reports the results. Shocks to firm value added explain if anything more of the fluctuations in aggregate value added. The results are similar if we break up value added into the domestic and export components, and thus we do not report them to conserve space.

4.3 Channels for Firms' Contribution to Aggregate Fluctuations

Having established the substantial contribution of the firm-specific component to aggregate fluctuations, we next examine the estimates in greater detail in order to disentangle the economic mechanisms at work. Aggregate firm-specific volatility $\sigma^2_{F\tau}$ can be written as:

$$\sigma^2_{F\tau} = \mathrm{Var}\left(\sum_{f,n} w_{fn\tau-1}\varepsilon_{fnt}\right) = \sum_{g,m}\sum_{f,n} w_{gm\tau-1}w_{fn\tau-1}\mathrm{Cov}(\varepsilon_{gmt},\varepsilon_{fnt}).$$

We decompose it following Carvalho and Gabaix (2013) into the contribution of individual variances and comovements between firms:

$$\sigma^2_{F\tau} = \underbrace{\sum_{f,n} w^2_{fn\tau-1}\mathrm{Var}(\varepsilon_{fnt})}_{DIRECT_\tau} + \underbrace{\sum_{g\neq f,m\neq n}\sum_{f,n} w_{gm\tau-1}w_{fn\tau-1}\mathrm{Cov}(\varepsilon_{gmt},\varepsilon_{fnt})}_{LINK_\tau}. \qquad (10)$$

This decomposition emphasizes two potential proximate channels through which shocks to individual firms may lead to a large variance of the firm-specific component: (i) the variance of individual shocks, labelled $DIRECT$, and (ii) the covariance of shocks across firms, labelled $LINK$.

The first term in (10) captures the direct effect of shocks to firms on aggregate volatility, in the sense that it would obtain in the complete absence of firm-to-firm linkages. The predominant tradition in macroeconomics has been to assume that the $DIRECT$ term is negligible due to the Law of Large Numbers: when the distribution of firm size has finite variance, the impact of shocks to individual firms on aggregate volatility converges to zero at the rate $\sqrt{N}$, where N is the number of firms (or, more precisely in our context, firm-destination sales) in the economy. However, recent literature in macroeconomics (most notably Gabaix, 2011) challenges this view, by arguing that the observed firm size distribution is so fat-tailed that the conventional Law of Large Numbers does not apply and shocks to individual (large) firms do in fact translate into aggregate fluctuations.[16] The $LINK$ component has also been ignored by most of the macroeconomics literature based on the argument that covariances between firms were in fact an artefact of firms being hit by common aggregate or sectoral shocks. This view has also been challenged in recent papers, such as Acemoglu et al. (2012) or Foerster et al. (2011).

Figure 4 presents the decomposition graphically for the whole economy and the manufacturing sector. The $LINK$ component explains the majority of total firm-specific volatility: $\sqrt{LINK_\tau}/\sigma_{F\tau}$ is over 90% on average over the sample period for both the whole economy and the manufacturing sector. However, it is apparent from the figures that the $DIRECT$ component is also non-negligible. The ratio of $\sqrt{DIRECT_\tau}$ to $\sigma_{F\tau}$ is 26% on average over this period for the whole economy, and 40% for the manufacturing sector.

4.3.1 The Contribution of the Direct Effect

As shown by Gabaix (2011), when the distribution of firm size is sufficiently fat-tailed (i.e., the economy is "granular"), idiosyncratic shocks to individual firms do not wash out at the aggregate level, because the idiosyncratic shocks to large firms do not cancel out with shocks to smaller units. This idea can be discussed most easily in the simplest case when shocks are uncorrelated across firms (i.e., $\text{Cov}(\varepsilon_{gmt}, \varepsilon_{fnt}) = 0 \ \forall \ (g, m) \neq (f, n)$) and across markets within a firm ($\text{Cov}(\varepsilon_{fmt}, \varepsilon_{fnt}) = 0, m \neq n$), and the variance of shocks is identical across firms ($\text{Var}(\varepsilon_{fnt}) = \sigma^2 \ \forall \ f, n$). Under these assumptions, aggregate firm-specific volatility

[16] Gabaix (2011) shows that when the distribution of firm size follows a power law with an exponent close to 1 in absolute value – a distribution known as Zipf's Law – aggregate volatility declines at the rate $\log N$, and idiosyncratic shocks will not cancel out in aggregate under a realistic number of firms in the U.S. economy. Di Giovanni et al. (2011) use the census of French firms to show that the firm size distribution in France does indeed follow Zipf's Law.

(10) is

$$\sigma_{F\tau}^2 = \sigma^2 \sum_{f,n} w_{fn\tau-1}^2 = \sigma^2 \times Herf_{\tau-1}, \tag{11}$$

where $Herf_{\tau-1} = \sum_{f,n} w_{fn\tau-1}^2$ denotes the Herfindahl index. The more fat-tailed is the distribution of firm size, the larger will be the Herfindahl index, and the greater will be the aggregate volatility generated by firm-specific shocks. In the opposite extreme case, if all firm-destination sales are instead symmetric in size ($w_{fn\tau-1} = 1/N_{\tau-1}$ where $N_{\tau-1}$ is the number of firm-destination sales in the economy), $\sigma_{F\tau} = \sigma/\sqrt{N_{\tau-1}}$ and the contribution of firms to aggregate volatility decays rapidly with the number of firms in the economy.

The role of the firm size distribution emphasized by Gabaix (2011) can be illustrated using the following simple counterfactual. We calculate the $DIRECT$ component under the assumption that all firms and markets are of equal weight (i.e., $w_{fn\tau-1} = 1/N_{\tau-1} \; \forall \; f, n$). When shocks are independent across firms, this "equal-weighted" aggregate variance is expected to be vanishingly small. Instead, the contribution of firms to aggregate volatility that takes into account the actual distribution of sales across firms is expected to be larger.

This is indeed what happens. For the whole economy, the $\sqrt{DIRECT}$ component implied by equal weights is 0.0003, or 13 times smaller than the average $\sqrt{DIRECT}$ component, which is equal to 0.004. For the manufacturing sector, the standard deviation implied by equal weights is 0.0008, an order of magnitude smaller than the $\sqrt{DIRECT}$ component of 0.0065. This comparison clearly shows that the firm size distribution does matter a great deal quantitatively for the contribution of individual firms' shocks to aggregate fluctuations.

Next, we exploit differences across sectors to evaluate the importance of the direct effect. To do so, we decompose the $DIRECT$ component in equation (10) into sectors, where sector j's $DIRECT$ component is defined as $DIRECT_{j\tau} \equiv \sum_{(f,n)\in j} w_{fn\tau-1}^2 \mathrm{Var}(\varepsilon_{fnt})$, and $DIRECT_\tau = \sum_{j=1}^{J} DIRECT_{j\tau}$. Again, if $\mathrm{Var}(\varepsilon_{fnt}) = \sigma^2 \; \forall \; f, n$, we would expect that more concentrated sectors would display larger volatilities.[17] Figure 5 evaluates this prediction, by plotting (the square root of) mean sectoral $DIRECT_{j\tau}$ against the (square root of the) mean sectoral Herfindahl index for the whole economy and the manufacturing sector. In Figure 5, $DIRECT_{j\tau}$ and the Herfindahl are computed with weights normalized by the size of each sector in aggregate sales. Otherwise, they would mechanically be proportional to the contribution of each sector to overall sales. The correlation is strongly positive – sectors with higher sales concentration contribute more to the total $DIRECT$ component, which

[17] The firm-specific volatilities do in fact vary by sector, to the same degree as the standard deviations of the raw growth rates in Table A1 – the correlation between the standard deviations of the actual growth rates and the firm-specific shocks is 0.996 across sectors.

is consistent with granularity. The correlation is lower for the whole economy (0.86) than for the manufacturing sector (0.93). The correlation is less than perfect because firm-level variances differ both across and within sectors. In the data, small firms tend to be more volatile on average (Table 1). This heterogeneity in firm-level volatilities counteracts the impact of sales concentration, thus reducing the overall size of the $DIRECT$ component relative to what would be expected in a purely "granular" world with identical variances across firms.

4.3.2 The Contribution of Firm Linkages

The second explanation for why firm shocks can drive aggregate fluctuations is inspired by the literature on the role of sectoral input-output linkages in aggregate fluctuations (Horvath, 1998, 2000; Dupor, 1999; Shea, 2002; Conley and Dupor, 2003; Gabaix, 2011; Acemoglu et al., 2012), and is captured by the covariance term $LINK$ in (10). The idea is that idiosyncratic shocks do not wash out at the aggregate level because they propagate across firms or sectors through "interconnections." If firms in the economy are connected, say through input-output linkages, shocks affecting upstream firms propagate to downstream firms via adjustments in the price of inputs. This propagation mechanism amplifies the initial impact of structural shocks. Moreover, it generates positive covariances in the residual growth rate of sales for firms that are connected.

Note that simply observing positive covariances in the firm-specific components (gathered in the $LINK$ term) is not conclusive evidence that input-output linkages are responsible for the comovement, as there may be other reasons for cross-sectional dependence between firms, such as local labor market interactions. While we cannot identify the precise share of the $LINK$ term that is due to input-output linkages *per se*, we provide direct, if suggestive, evidence that input-output linkages are at least partly responsible for the positive $LINK$ term.

Online Appendix E lays out a simple model of such firm-level interconnections. Firms produce with a constant marginal cost using labor and intermediate inputs bought from other firms in the economy. Input-output linkages create a positive covariance of sales growth rates for any two firms that are connected. For instance, take firms f and g and assume firm g sells inputs to firm f. If the only source of shocks is productivity shocks to firm g, then the covariance between the sales growth rates of those two firms is

$$\mathrm{Cov}(\varepsilon_{gmt}, \varepsilon_{fnt}) = (1-\theta)^2(1-\lambda_f)\rho_{fg}\mathrm{Var}(a_{gmt}),$$

where θ is the elasticity of substitution, $(1-\lambda_f)$ is the share of intermediate goods in firm f's total costs, ρ_{fg} is the share of those inputs that is sourced from firm g and $\text{Var}(a_{gmt})$ is the volatility of firm g's productivity. The covariance is positive, and increasing in the strength of the connection between f and g, i.e., in the share of inputs from g used in f's production, $(1-\lambda_f)\rho_{fg}$. In this setup, the propagation goes from upstream to downstream firms, through the price of inputs. In a more general setting, one can also expect shocks to propagate from downstream to upstream firms through the demand of intermediates.[18]

Ideally, one would test the linkage hypothesis using firm-level measures of interconnections. Since information on firm-to-firm input linkages (ρ_{fg}) is not available, we instead proxy for production networks using sector level data, and use the Input-Output (IO) tables for France compiled by the OECD. Assuming that the share of intermediates in total costs is homogeneous across firms within a sector (i.e. $\lambda_f = \lambda_i \ \forall \ f \in i$) and that all firms within a sector interact with the same input providers (i.e. $\rho_{fg} = \rho_{ij}\tilde{w}_{g/j} \ \forall \ f \in i, \ g \in j$, where $\tilde{w}_{g/j}$ is the share of firm g in total sector j intermediate input sales to i), the structure of sectoral IO matrices can be used to approximate the intensity of IO linkages between firms from each pair of sectors. The intensity of IO linkages between a pair of sectors can then be related to the magnitude of covariances between firms in those sectors. We expect the weighted sum of covariances to be higher for sector pairs that display stronger IO linkages.[19]

Figure 6 examines this hypothesis. We decompose the $LINK$ component in equation (10) across sector pairs, where the $LINK$ term specific to the pair (i,j) is defined as $LINK_{ij\tau} \equiv \sum_{(f,n)\in i} \sum_{(g,m)\in j} w_{fn\tau-1} w_{gm\tau-1} \text{Cov}(\varepsilon_{fnt}, \varepsilon_{gmt})$, and $LINK_\tau = \sum_{i=1}^{J} \sum_{j=1;j\neq i}^{J} LINK_{ij\tau}$. We then correlate the (square root of) the average $LINK_{ij\tau}$ of a pair of sectors to the mean intensity of IO linkages between them. $LINK_{ij\tau}$ is normalized by the size of each sector to control for the mechanical impact of sector sizes on the magnitude of the aggregated covariance terms. The mean intensity of IO linkages is defined as $0.5 \times [(1-\lambda_i)\rho_{ij} + (1-\lambda_j)\rho_{ji}]$, where λ_i is the share of value added in sector i's total output and ρ_{ij} the share of inputs from j in sector i's spending on intermediates, both taken from the French IO tables for 1995. IO linkages are thus stronger if either one or both sectors intensively use intermediates from the other sector.

The correlation between the $LINK$ term and the intensity of IO linkages is positive, both for the whole economy (Figure 6a) and the manufacturing sector (Figure 6b).[20] The

[18] This is ruled out in the setting of Online Appendix E as well as in the model of Acemoglu et al. (2012) because of the Cobb-Douglas assumption on the production function. More flexible specifications of technology would allow downstream firms' productivity shocks to propagate upstream to input providers.

[19] See Online Appendix E for details.

[20] Note that Figure 6 drops negative bilateral covariance terms as well as zero input-output linkages, since

relationship is marginally more pronounced for the manufacturing sector, with a correlation coefficient of 0.34 compared to 0.29 for the whole economy. The results are direct empirical evidence that input-output linkages across firms are important in transmitting microeconomic shocks across the economy.

4.4 Extensions and Robustness

4.4.1 Differences in Firm Sensitivity to Macro and Sectoral Shocks

In the baseline model the elasticity of firm sales with respect to aggregate and sectoral shocks is the same across firms. Our conceptual framework shares this feature with Dixit and Stiglitz (1977), Krugman (1980), Melitz (2003), and the enormous literature that followed in this tradition. However, it is possible that firms will systematically react differently to sector- and country-level shocks. In that case the computed values of ε_{fnt} will be combinations of firm-specific shocks and the heterogeneous responses to the aggregate and sectoral shocks. There are several theoretical channels that would deliver a heterogeneous response. One example is a model laid out in Online Appendix F, in which firms react heterogeneously to sector-destination shocks because of variable markups. Di Giovanni and Levchenko (2012a) argue that the impact of this channel on aggregate volatility is small. However, as a robustness check we carry out alternative estimations in which we instead impose the following augmented model:

$$\gamma_{fnt} = \delta_{jnt} + \delta_{jnt} \times CHAR_{fnt} + \beta CHAR_{fnt} + \varepsilon_{fnt}, \tag{12}$$

where $CHAR_{fnt}$ is a particular observable firm characteristic. In this model, heterogeneity of firm responses to macroeconomic and sectoral shocks is thus systematically related to observable firm characteristics. We attempt a variety of different types of $CHAR_{fnt}$: measures of (i) firm size (log sales or sales quintile dummy);[21] (ii) firm age (log years or dummy for whether the firm is less or more than 5 years old);[22] (iii) R&D intensity (dummy for whether R&D expenses are higher than 1% of value added);[23] (iv) patent intensity (dummy

we are taking log transformations. Input-output linkages would not explain negative covariances according to the model. Such negative numbers should instead reflect substitution effects across competing firms. Likewise, our stylized model is unable to explain a strictly positive $LINK$ term between firms in sectors that do not interact through IO linkages. Fortunately, observations with negative covariance terms and/or zero input-output linkages are rare in our data, representing less than 6% of the total possible sector pairs.

[21] Following the accepted practice in the literature, our preferred specification captures size differences using quintile dummies, since that allows for greater (non-parametric) flexibility in the functional form. See Firpo et al. (2011) for an exhaustive survey on decomposition methods.

[22] Fort et al. (2013) report that in the United States, young/small businesses are more sensitive to the cycle than older/larger businesses.

[23] Comín and Philippon (2006) report that in the United States, sectors with largest increases in R&D have become less correlated with the business cycle.

for whether patent expenses are more than 5% of value added); v) export intensity (ratio of exports to total firm sales);[24] and (vi) debt to sales ratio.[25] We also implement a model in which all of these characteristics are included together.

Table A2 reports the results. Allowing firm sensitivity to aggregate and sectoral shocks to differ by firm size leaves the conclusions unchanged. The table reports the implementation in which firm size is captured by sales quintile dummies. The results are unaffected if we instead use a continuous measure of size, such as log sales, or use employment or total assets as measures of size. If we allow a firm's sensitivity to shocks to differ by firm age, the contribution of firm shocks to aggregate fluctuations falls somewhat. Nonetheless, the relative importance of firm-specific shocks for aggregate volatility, $\sigma_{F\mathcal{T}}/\sigma_{A\mathcal{T}}$ is still nearly 0.6. The table reports the results of using a dummy for whether the firm is more than 5 years old. Using actual years of age instead leaves the results unchanged. Allowing sensitivity to differ by any of the other characteristics we consider – R&D and patent intensity, overall export orientation, or debt structure, also leaves the results unchanged. While the table reports the results using the quintile dummies for the debt to total sales ratio of the firm, the results are unchanged if we instead use bond debt, bank debt, ratio of bond to bank debt, each in both continuous and quintile dummy forms.

Finally, the last row of the table reports the results of allowing firm sensitivity to aggregate and sectoral shocks to depend on all of the above characteristics simultaneously. The importance of firm specific shocks is somewhat lower than in the baseline, with $\sigma_{F\mathcal{T}}/\sigma_{A\mathcal{T}}$ equal to 0.65 for the whole economy and 0.5 for the manufacturing sector. Nonetheless, this contribution is still sizeable. We take this as evidence that our results are robust to allowing for firm-destination sales growth to react heterogeneously to macroeconomic and sectoral shocks.

4.4.2 Entry and Exit

The baseline analysis is carried out on the intensive margin, that is, sales growth rates for continuing firm-destinations. Online Appendix A presents an explicit decomposition of aggregate sales growth into extensive and intensive margins, and argues that the bulk of aggregate sales fluctuations is driven by the intensive margin. As an alternative approach, we report results for the growth rates adopted by Davis et al. (1996) and the large literature

[24] There is evidence that firms substitute domestic for foreign sales in response to demand shocks abroad (e.g. Blum et al., 2013). Thus, it may be that exporters exhibit systematically different sensitivity to shocks in an individual market.

[25] There is evidence that access to capital markets affects firms' responses to aggregate shocks (Gertler and Gilchrist, 1994; Kashyap et al., 1994).

that followed:

$$\gamma'_{fnt} \equiv \frac{x_{fnt} - x_{fnt-1}}{0.5(x_{fnt} + x_{fnt-1})}. \tag{13}$$

This growth rate, which we label DHS, has a number of attractive properties: it encompasses entries and exits (treating them in the same way as other observations), it ranges from -2 to 2 and thus limits the impact of outliers, and it lends itself to consistent aggregation. Under this definition of growth rates, the correct weights for aggregation are

$$w'_{fnt} \equiv \frac{(x_{fnt} + x_{fnt-1})}{\sum_{f,n}(x_{fnt} + x_{fnt-1})},$$

and the aggregate growth rate of x is:

$$\gamma'_{At} \equiv \frac{X_t - X_{t-1}}{0.5(X_t + X_{t-1})} = \sum_{f,n} w'_{fnt}\gamma'_{fnt}.$$

Note however that a firm growth defined this way does not admit a log-difference decomposition (4) into macro, sectoral, and firm-specific components, and thus the results using these growth rates should be interpreted as approximations. The results are presented in Table A3, in the panel labelled "DHS growth rates." Using these growth rates changes the sample of firms and produces lower aggregate volatility, but the share of the firm-specific contribution to the aggregate volatility remains very similar to the baseline, at $\sigma_{F\tau}/\sigma_{A\tau}$ of about 0.7 for both the whole economy and the manufacturing sector.

4.4.3 Other Robustness Checks

One may be concerned about differential trend growth rates across firms (especially of different sizes) can affect the calculation of the firms' contribution to aggregate volatility. To check if this mattered, we demean each firm-destination growth rate by the average growth rate of that firm-destination. The results are presented in Table A3, in the panel labelled "Demeaned growth rates." The contribution of the firm-specific component is still important.

It may be that firms in different regions of France are subject to shocks specific to their geographical location. This could be because factor (or goods) markets are local, for instance. To check for this possibility, we implement an augmented model in which we add a geographic location-specific shock, that affects all firms located in a particular geographic area within France. The definition of geographic area corresponds to the "employment zone" (*zone d'emploi*), that is intended to capture the extent of the local labor market. It is larger than a city (at least when the city is small), but smaller than a county. There are about

300 *zones d'emploi* in France. The results are reported in Table A3, panel "Additional local market effects." Adding shocks specific to the local labor market leaves the basic results unchanged.

All of the above results use a particular level of disaggregation (about 50 sectors, among them 22 manufacturing). It could be that sectoral shocks take place at a more detailed level. To check for this possibility, panel "More disaggregated sectors" of Table A3 implements the model under more finely disaggregated sectors: 5-digit NAF, or about 700 distinct sectors. The results are virtually unchanged from the baseline.

Finally, as a different robustness check, the bottom panel in Table A3 presents results when implementing the baseline model on three-year average firm-destination growth rates, instead of yearly growth rates. The results are robust to time aggregation.[26]

5 Conclusion

Do firm-level dynamics have an impact on aggregate fluctuations? Recent contributions argue that idiosyncratic shocks to firms can indeed manifest themselves in aggregate fluctuations if the firm size distribution is sufficiently fat-tailed (Gabaix, 2011), or when linkages propagate microeconomic shocks across firms leading to positive endogenous comovement (e.g. Acemoglu et al., 2012). However, the empirical evidence supporting these different theories has been limited. This paper constructs a novel dataset that merges French domestic and export sales at the firm level over the period 1990–2007, and provides a forensic account of the role of individual firms in generating aggregate fluctuations.

We begin by proposing a simple model, in the spirit of Melitz (2003) and Eaton et al. (2011a), to motivate an estimation framework that allows us to extract the macroeconomic, sectoral, and firm-specific components of a firm's sales to a given destination. These estimates are then aggregated up to explain the relative contribution of each component to the volatility of aggregate sales. Our main results can be summarized as follows. First, the firm-specific component accounts for an important part of the fluctuations of aggregate sales growth. The standard deviation of the aggregated firm-specific shocks amounts to 80% of the standard deviation of aggregate sales in the whole economy, and 69% in the manufacturing sector. We interpret this as evidence for the relevance of firm-level shocks for aggregate fluctuations. Second, while the direct effect of firm shocks on aggregate volatility is quantitatively relevant, the majority of the contribution of firm shocks' to aggregate fluc-

[26]We also ran specifications restricting the sample to firms that exist for at least eight years. Results were similar to the baseline specification, and are available from the authors upon request.

tuations is accounted for by firm-to-firm covariance terms, which we interpret as evidence of linkages.

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Table 1. Summary Statistics

	Whole Economy	*Manufacturing Sector*
Average aggregate growth rate	0.0369	0.0290
Mean of individual growth rates	0.0465	0.0537
Standard deviation of sales growth rate		
Average	0.2342	0.2829
0-20 size percentile	0.3011	0.3550
21-40 size percentile	0.2425	0.3252
41-60 size percentile	0.2163	0.2654
61-80 size percentile	0.2043	0.2409
81-100 size percentile	0.2069	0.2278
top 100	0.1319	0.1816
top 10	0.1269	0.1364
Average $\sqrt{Herf(f,n)}$	0.0301	0.0447
Average $\sqrt{Herf(f)}$	0.0332	0.0592

Notes: This table presents the summary statistics for the whole economy and manufacturing firms over 1991–2007. $Herf(f,n)$ is the Herfindahl index of the firm-destination sales shares. $Herf(f)$ is the Herfindahl index of the total firm sales shares.

Table 2. Summary Statistics and Correlations of Actual Firm-Destination-Level Growth and Firm-Specific versus Sector-Destination-Specific Components: Whole Economy

	I. Total Sales			
	(1)	(2)	(3)	(4)
	Obs.	Mean	St. Dev.	Correlation
Actual	9,856,891	0.0467	0.2601	1.0000
Firm-Specific	9,856,891	0.0000	0.2584	0.9935
Sector-Destination	16,235	0.0762	0.1209	0.1140
	II. Domestic Sales			
	(1)	(2)	(3)	(4)
	Obs.	Mean	St. Dev.	Correlation
Actual	8,031,453	0.0410	0.2266	1.0000
Firm-Specific	8,031,453	0.0000	0.2255	0.9954
Sector-Destination	595	0.0453	0.0297	0.0957
	III. Export Sales			
	(1)	(2)	(3)	(4)
	Obs.	Mean	St. Dev.	Correlation
Actual	1,825,438	0.0718	0.3723	1.0000
Firm-Specific	1,825,438	0.0000	0.3697	0.9931
Sector-Destination	15,640	0.0774	0.1229	0.1171

"Actual" refers to γ_{fnt}, "Firm-Specific" to ε_{fnt}, and "Sector-Destination" to δ_{jnt} (equation (5)). Column (2) reports the average γ_{fnt}, ε_{fnt}, and δ_{jnt} in the sample of firm-destinations and years. Column (3) reports the average sample standard deviation of γ_{fnt}, ε_{fnt}, and δ_{jnt}. Column (4) presents the correlation between γ_{fnt} and γ_{fnt}, ε_{fnt}, and δ_{jnt}.

Table 3. Summary Statistics and Correlations of Actual Firm-Destination-Level Growth and Firm-Specific versus Sector-Destination-Specific Components: Manufacturing Sector

	I. Total Sales			
	(1)	(2)	(3)	(4)
	Obs.	Mean	St. Dev.	Correlation
Actual	2,436,013	0.0542	0.3038	1.0000
Firm-Specific	2,436,013	0.0000	0.3011	0.9909
Sector-Destination	10,269	0.0727	0.0885	0.1342
	II. Domestic Sales			
	(1)	(2)	(3)	(4)
	Obs.	Mean	St. Dev.	Correlation
Actual	1,233,902	0.0378	0.2233	1.0000
Firm-Specific	1,233,902	0.0000	0.2214	0.9917
Sector-Destination	306	0.0416	0.0313	0.1285
	III. Export Sales			
	(1)	(2)	(3)	(4)
	Obs.	Mean	St. Dev.	Correlation
Actual	1,202,111	0.0709	0.3679	1.0000
Firm-Specific	1,202,111	0.0000	0.3652	0.9927
Sector-Destination	9,963	0.0737	0.0895	0.1207

Notes: "Actual" refers to γ_{fnt}, "Firm-Specific" to ε_{fnt}, and "Sector-Destination" to δ_{jnt}. Column (2) reports the average γ_{fnt}, ε_{fnt}, and δ_{jnt} in the sample of firm-destinations and years. Column (3) reports the average sample standard deviation of γ_{fnt}, ε_{fnt}, and δ_{jnt}. Column (4) presents the correlation between γ_{fnt} and γ_{fnt}, ε_{fnt}, and δ_{jnt}.

Table 4. Summary Statistics and Correlations of Firm-Specific Growth and Components

	I. Whole Economy			
	(1)	(2)	(3)	(4)
	Obs.	Mean	St. Dev.	Correlation
Firm	2,273,943	0.0009	0.3450	1.0000
Firm-Dest.	2,273,943	0.0000	0.3011	0.8728
Firm-Com.	479,101	0.0020	0.1949	0.4881
	II. Manufacturing Sector			
	(1)	(2)	(3)	(4)
	Obs.	Mean	St. Dev.	Correlation
Firm	1,448,234	-0.0003	0.3436	1.0000
Firm-Dest.	1,448,234	0.0000	0.3052	0.8880
Firm-Com.	258,530	0.0007	0.1854	0.4598

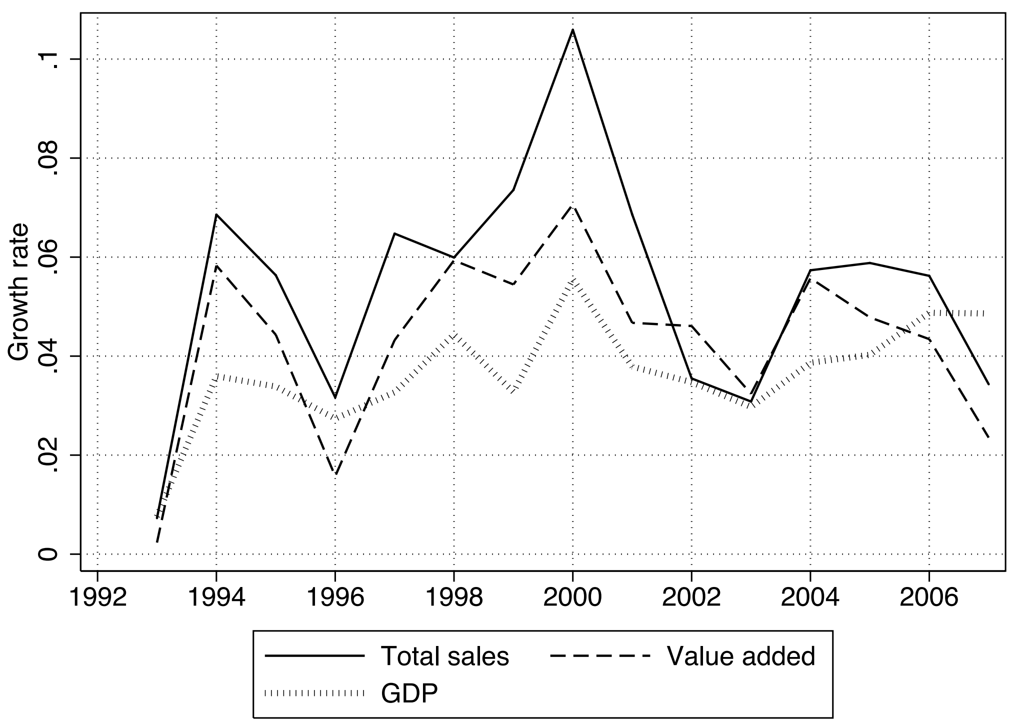
Notes: "Firm" refers to ε_{fnt}, "Firm-Dest." to ε^2_{fnt}, and "Firm-Com." to ε^1_{ft} (equation (9)). This table presents the average growth rates and standard deviations of ε_{fnt}, ε^2_{fnt}, and ε^1_{ft} in the sample, as well as the correlations between ε_{fnt} and ε_{fnt}, ε^2_{fnt}, and ε^1_{ft}. The set of firm-destinations is restricted to firms that serve at least 2 markets.

Table 5. The Aggregate Impact of Firm-Specific Shocks on Aggregate Volatility: Whole Economy and Manufacturing Sector

	Whole Economy		*Manufacturing Sector*	
I. Total Sales				
	(1)	(2)	(3)	(4)
	St. Dev.	Relative SD	St. Dev.	Relative SD
Actual	0.0206	1.0000	0.0244	1.0000
Firm-Specific	0.0165	0.8010	0.0168	0.6885
Sector-Destination	0.0109	0.5291	0.0157	0.6434
II. Domestic Sales				
	Whole Economy		*Manufacturing Sector*	
	(1)	(2)	(3)	(4)
	St. Dev.	Relative SD	St. Dev.	Relative SD
Actual	0.0196	1.0000	0.0231	1.0000
Firm-Specific	0.0154	0.7857	0.0151	0.6537
Sector-Destination	0.0112	0.5714	0.0167	0.7229
III. Export Sales				
	Whole Economy		*Manufacturing Sector*	
	(1)	(2)	(3)	(4)
	St. Dev.	Relative SD	St. Dev.	Relative SD
Actual	0.0361	1.0000	0.0374	1.0000
Firm-Specific	0.0304	0.8421	0.0287	0.7674
Sector-Destination	0.0129	0.3573	0.0153	0.4091
IV. Value Added				
	Whole Economy		*Manufacturing Sector*	
	(1)	(2)	(3)	(4)
	St. Dev.	Relative SD	St. Dev.	Relative SD
Actual	0.0210	1.0000	0.0215	1.0000
Firm-Specific	0.0190	0.9048	0.0184	0.8558
Sector-Destination	0.0107	0.5095	0.0123	0.5721

Notes: This table presents the averages of $\sigma_{A\tau}$ ("Actual"), $\sigma_{F\tau}$ ("Firm-Specific"), and $\sigma_{JN\tau}$ ("Sector-Destination") over the sample period: $\frac{1}{T}\sum_{\tau=1991}^{2007}\sigma_{A\tau}$, $\frac{1}{T}\sum_{\tau=1991}^{2007}\sigma_{F\tau}$, $\frac{1}{T}\sum_{\tau=1991}^{2007}\sigma_{JN\tau}$; and in relative terms with respect to the actual: $\frac{1}{T}\sum_{\tau=1991}^{2007}\frac{\sigma_{Ft}}{\sigma_{A\tau}}$, $\frac{1}{T}\sum_{\tau=1991}^{2007}\frac{\sigma_{JNt}}{\sigma_{A\tau}}$.

Figure 1. Growth of Aggregate Sales, Aggregate Value Added, and GDP



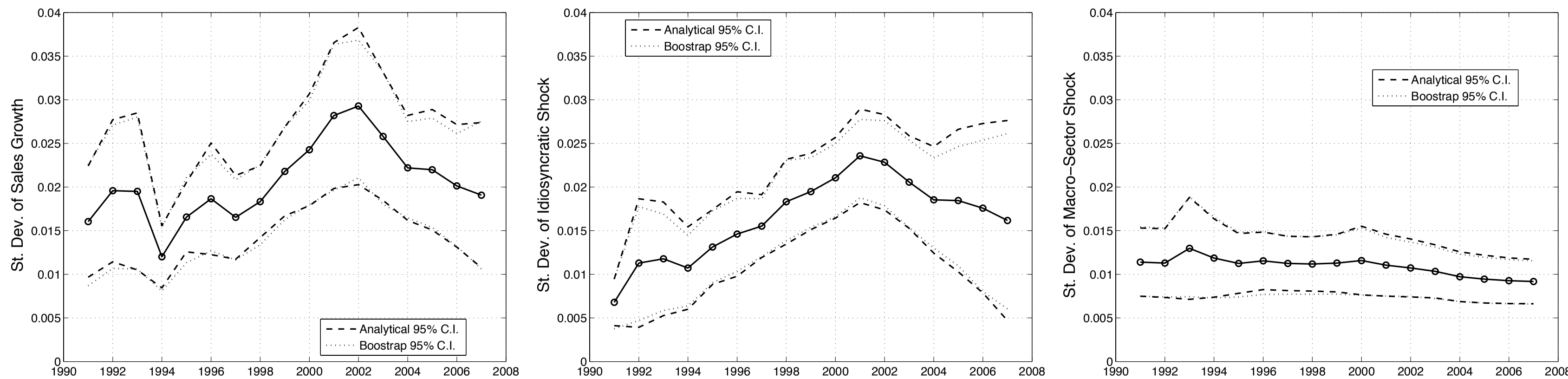
Notes: This figure presents the time series of the growth rates of total sales, before-tax value added, in our data and GDP sourced from the IMF International Financial Statistics.

Figure 2. Growth of Aggregate Exports

Notes: This figure presents the time series of the growth rates of total exports in our data and total French exports sourced from the IMF International Financial Statistics.

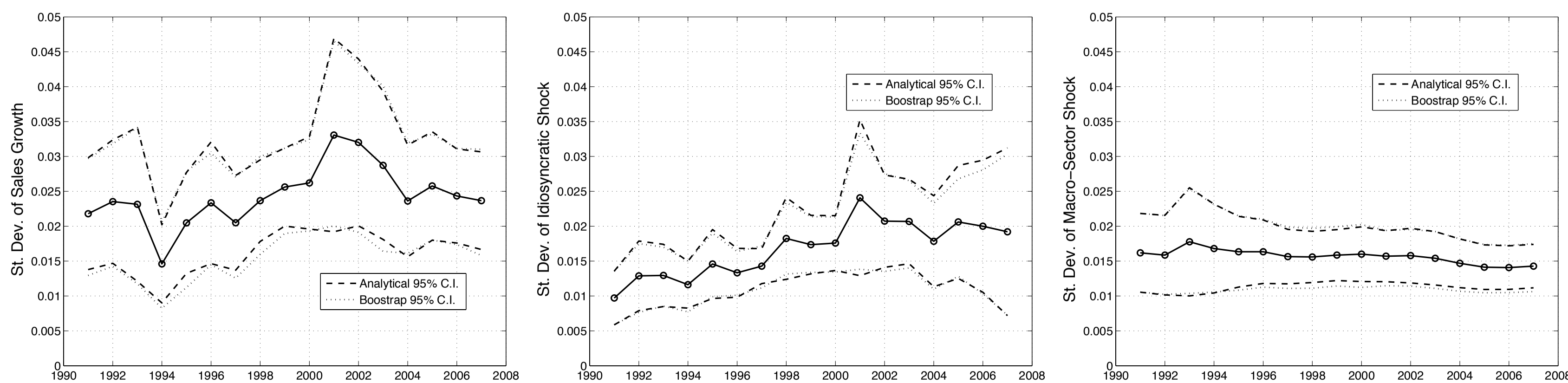
Figure 3. Volatility of Sales Growth and its Components

I. Whole Economy



(a) Sales **(b)** Idiosyncratic **(c)** Macroeconomic

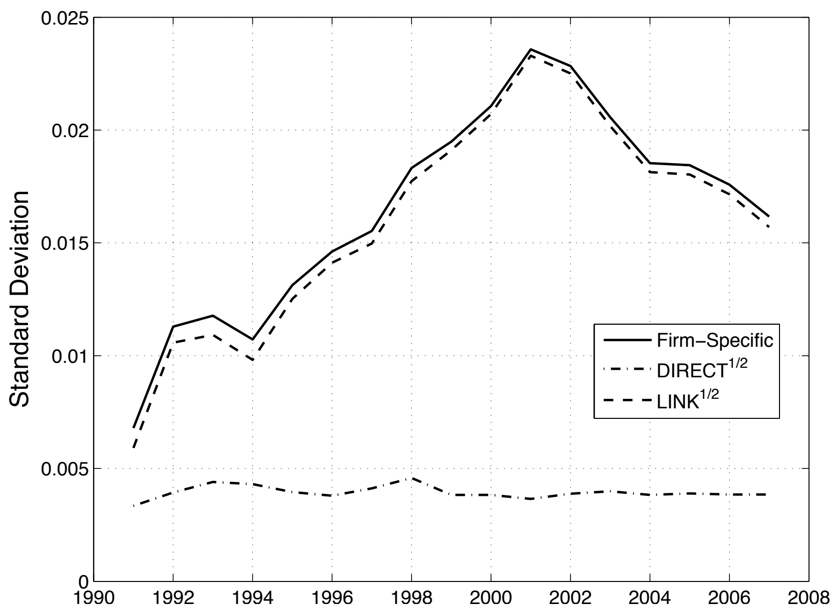
II. Manufacturing Sector



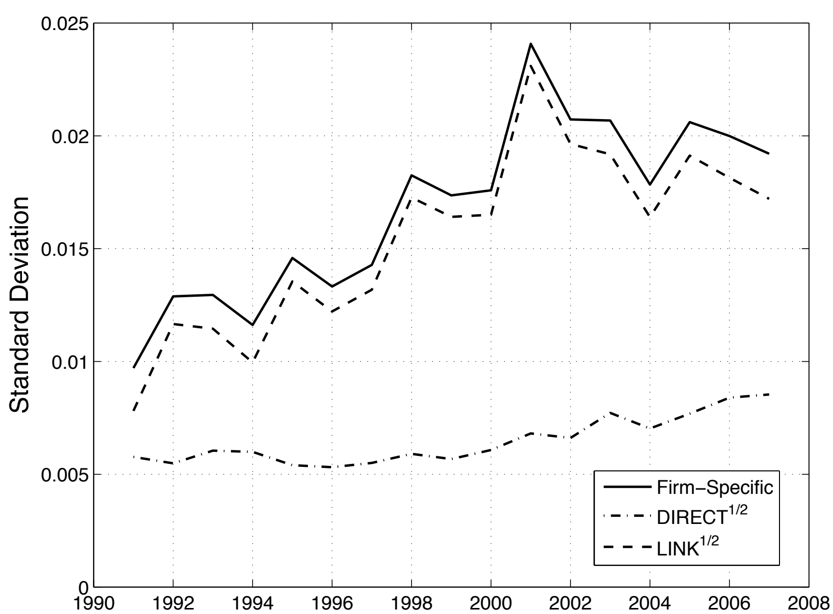
(d) Sales **(e)** Idiosyncratic **(f)** Macroeconomic

Notes: This figure presents the estimates of $\sigma_{A\tau}$, $\sigma_{F\tau}$, and $\sigma_{JN\tau}$ for the whole economy (Panel I) and the manufacturing sector (Panel II), along with both analytical and bootstrap 95% confidence intervals.

Figure 4. Contribution of Individual Volatilities and Covariance Terms to Firm-Specific Fluctuations



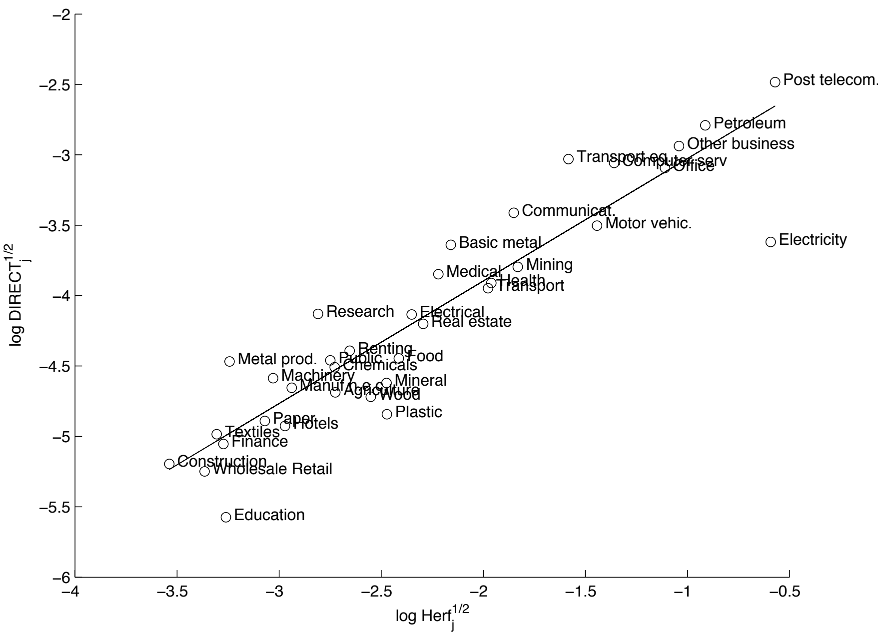
(a) Whole Economy



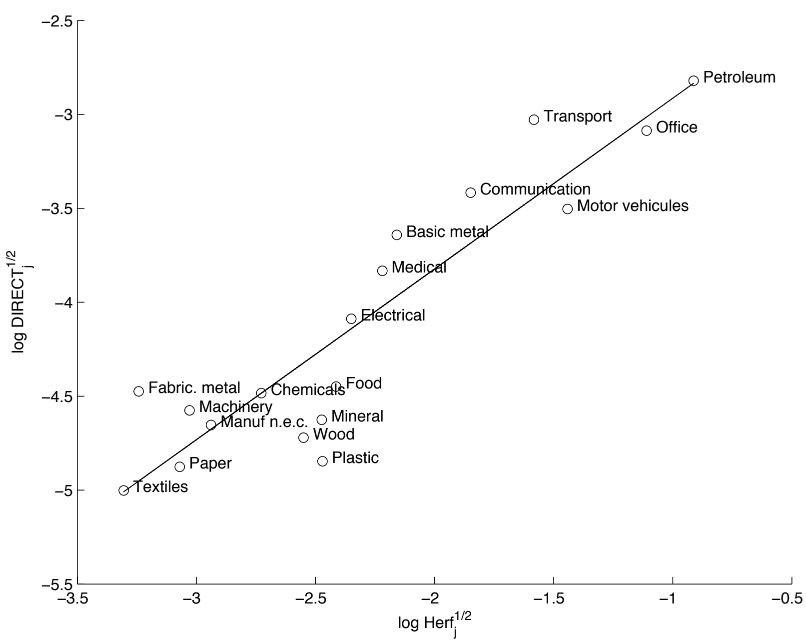
(b) Manufacturing Sector

Notes: This figure presents a decomposition of the Firm-Specific aggregate variance into two components that measure the contribution of firm-specific variances ($\sqrt{DIRECT_\tau}$), and of covariances across firms ($\sqrt{LINK_\tau}$). The decomposition is based on equation (10).

Figure 5. Firm-Specific Volatility Aggregated at the Sector-Level and the Sectoral Mean Herfindahl Index



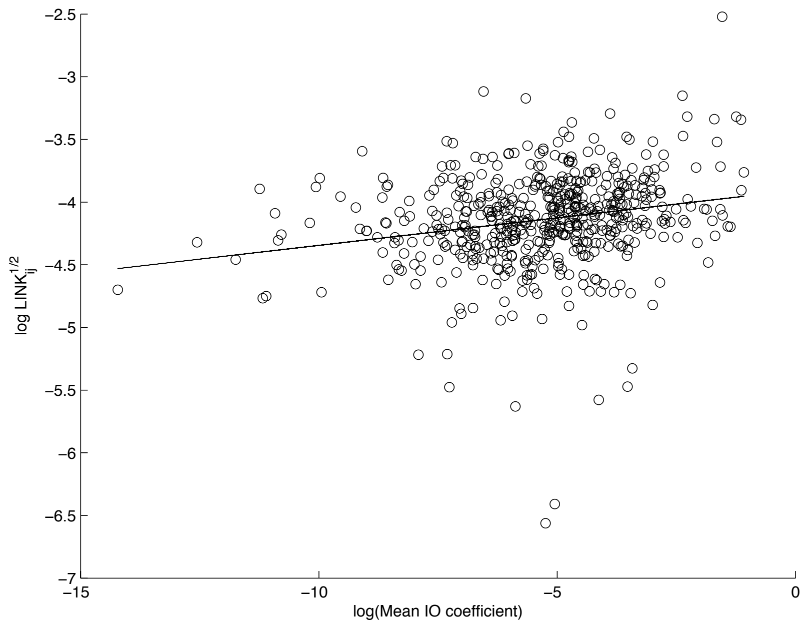
(a) Whole Economy



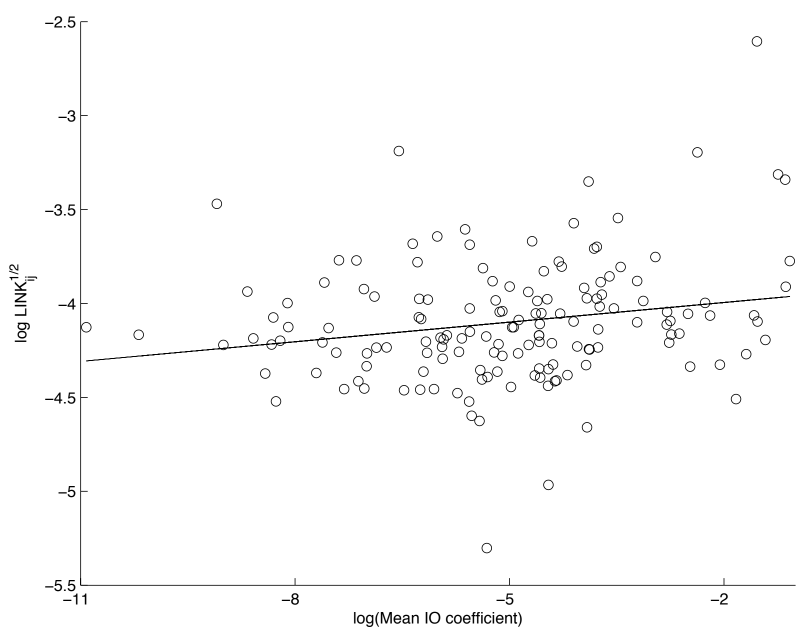
(b) Manufacturing Sector

Notes: This figure plots the time average of the sectoral $\sqrt{DIRECT_{j\tau}}$ component against the square root of the sectoral mean Herfindahl index. The correlation between time average $\sqrt{DIRECT_{j\tau}}$ and $\sqrt{Herf_{j\tau}}$ is 0.86 for the whole economy and 0.93 for the manufacturing sector.

Figure 6. Covariances of Firm-Specific Shocks Across Sectors and their Input-Output Linkages



(a) Whole Economy



(b) Manufacturing Sector

Notes: This figure plots the time average of the sector-pair $\sqrt{LINK_{ij\tau}}$ component against the mean IO linkage (share of intermediate inputs in total costs times the share of the upstream sector in intermediate consumption between sectors i and j). The correlation between the time average $\sqrt{LINK_{ij\tau}}$ and the IO linkages is 0.29 for the whole economy and 0.34 for the manufacturing sector.

Table A1. Firm-Level Volatility by Sector

I. Firm-Destination Sales Volatility by Sector							
NAF	Sector	St. Dev.	Share	NAF	Sector	St. Dev.	Share
01-05	Agriculture, forestry and fishing	0.2389	0.0049	35	Other transport equipment	0.3232	0.0113
10-14	Mining and quarrying	0.2533	0.0037	36-37	Manufacturing n.e.c.	0.2853	0.0096
15-16	Food and tobacco	0.2340	0.0635	40-41	Electricity, gas, water supply	0.2103	0.0292
17-19	Textile, wearing apparel and leather	0.3118	0.0150	45	Construction	0.2314	0.0495
20	Wood products	0.2606	0.0049	50	Wholesale and retail trade	0.2188	0.3689
21-22	Paper products, publishing	0.2558	0.0235	55	Hotels and restaurants	0.1614	0.0141
23	Coke, refined petroleum, nuclear fuel	0.3255	0.0241	60-63	Transport	0.2033	0.0399
24	Chemical industry	0.3193	0.0421	64	Post and telecommunications	0.2425	0.0226
25	Rubber and plastics	0.3066	0.0145	70	Real estate activities	0.2102	0.0235
26	Mineral products	0.2689	0.0114	71	Rental without operator	0.2158	0.0070
27	Basic metals	0.3189	0.0129	72	Computer services	0.2695	0.0114
28	Metal products	0.2715	0.0207	73	Research and development	0.2915	0.0015
29	Machinery and equipment	0.3122	0.0203	74	Other business services	0.2384	0.0578
30	Office machinery	0.3241	0.0051	75	Public administration	0.1734	0.0003
31	Electrical equipment	0.3096	0.0111	80	Education	0.2283	0.0014
32	Radio, TV and communication	0.3161	0.0100	85	Health and social work	0.1490	0.0069
33	Medical and optical instruments	0.3017	0.0079	90-93	Personal services	0.1986	0.0164
34	Motor vehicles	0.2950	0.0332				

Notes: This table presents the standard deviations of firm-destination growth rates broken down by sector over 1991–2007. “Share” is the share of the sector in total sales. The manufacturing sector covers NAF sectors 15 to 37.

Table A2. The Impact of Firm-Specific Shocks on Aggregate Volatility: Differing Firm Sensitivity to Sectoral and Macroeconomic Shocks

	Whole Economy		*Manufacturing Sector*	
	(1)	(2)	(3)	(4)
	St. Dev.	Relative SD	St. Dev.	Relative SD
Actual	0.0206	1.0000	0.0244	1.0000
	Firm-Specific Component (average $\sigma_{F\tau}$)			
Differing Sensitivity				
By size	0.0169	0.8204	0.0172	0.7049
By age	0.0122	0.5922	0.0133	0.5451
By R&D intensity	0.0164	0.7961	0.0167	0.6844
By patenting intensity	0.0162	0.7864	0.0167	0.6844
By openness	0.0166	0.8058	0.0167	0.6844
By debt	0.0164	0.7961	0.0167	0.6844
By all of the above	0.0134	0.6505	0.0123	0.5041

Notes: The row labelled "Actual" reports the average standard deviation of actual aggregate sales growth over 1991–2007: $\frac{1}{T}\sum_{\tau=1991}^{2007}\sigma_{A\tau}$. The rest of the table reports the average standard deviation of the firm-specific component, $\frac{1}{T}\sum_{\tau=1991}^{2007}\sigma_{F\tau}$, and its average value relative to the actual, $\frac{1}{T}\sum_{\tau=1991}^{2007}\frac{\sigma_{F\tau}}{\sigma_{A\tau}}$, under a series of augmented models (12), in which firms have heterogeneous sensitivity to sector-destination shocks. "Size" is the dummy for the firm's quintile in the sales distribution. "Age" is the dummy for whether the firm is more than 5 years old. "R&D intensity" is a dummy for whether R&D expenses are higher than 1% of value added. "Patent intensity" is a dummy for whether patent expenses are more than 5% of value added. "Export intensity" is the ratio of exports to total firm sales. "Debt" is the quintile dummy for the firm's debt to sales ratio.

Table A3. The Impact of Firm-Specific Shocks on Aggregate Volatility: Robustness Checks

	Whole Economy		*Manufacturing Sector*	
I. DHS growth rates				
	(1)	(2)	(3)	(4)
	St. Dev.	Relative SD	St. Dev.	Relative SD
Actual	0.1420	1.0000	0.1203	1.0000
Firm-Specific	0.1014	0.7141	0.0833	0.6924
II. Demeaned growth rates				
	Whole Economy		*Manufacturing Sector*	
	(1)	(2)	(3)	(4)
	St. Dev.	Relative SD	St. Dev.	Relative SD
Actual	0.0206	1.0000	0.0244	1.0000
Firm-Specific	0.0128	0.6214	0.0152	0.6230
III. Additional local market effects				
	Whole Economy		*Manufacturing Sector*	
	(1)	(2)	(3)	(4)
	St. Dev.	Relative SD	St. Dev.	Relative SD
Actual	0.0206	1.0000	0.0244	1.0000
Firm-Specific	0.0165	0.8010	0.0164	0.6721
IV. More disaggregated sectors				
	Whole Economy		*Manufacturing Sector*	
	(1)	(2)	(3)	(4)
	St. Dev.	Relative SD	St. Dev.	Relative SD
Actual	0.0209	1.0000	0.0244	1.0000
Firm-Specific	0.0169	0.8086	0.0156	0.6393
V. Three-Year Growth Rates				
	Whole Economy		*Manufacturing Sector*	
	(1)	(2)	(3)	(4)
	St. Dev.	Relative SD	St. Dev.	Relative SD
Actual	0.0290	1.0000	0.0323	1.0000
Firm-Specific	0.0266	0.9140	0.0269	0.8885

Notes: The rows labelled "Actual" report the average standard deviation of actual aggregate sales growth over 1991–2007: $\frac{1}{T}\sum_{\tau=1991}^{2007}\sigma_{A\tau}$. The rows labelled "Firm-Specific" report the average standard deviation of the firm-specific component, $\frac{1}{T}\sum_{\tau=1991}^{2007}\sigma_{F\tau}$, and its average value relative to the actual, $\frac{1}{T}\sum_{\tau=1991}^{2007}\frac{\sigma_{F\tau}}{\sigma_{A\tau}}$, under a series of alternative models. The panel "DHS growth rates" implement the model under the firm growth rate defined as in (13). The panel "Demeaned growth rates" reports the results under first demeaning firm sales growth by the firm-destination specific average growth rate. The panel "Additional local market effects" reports the results of augmenting the model to include location-specific shocks. The panel "More disaggregated sectors" reports the results under defining sectors according to the 5-digit NAF level of disaggregation (about 700 sectors in the whole economy). The last panel uses the baseline model, but takes the average firm-destination growth rates over three year periods: 1990–93, 1994–97, 1998–2001, 2002–05. Means of standard deviations and relative standard deviations are presented.

ONLINE APPENDIX

Firms, Destinations, and Aggregate Fluctuations

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Appendix A Intensive and Extensive Margins

This appendix decomposes the growth rate of aggregate sales into the intensive and extensive components, and shows that the bulk of the aggregate sales volatility is driven by the intensive margin. The intensive component at date t is defined as the growth rate of sales of firm-destination pairs that had positive sales in both year t and year $t-1$. The extensive margin is defined as the contribution to total sales of the appearance and disappearance of firm-destination-specific sales. The log-difference growth rate of total sales can be manipulated to obtain an (exact) decomposition into intensive and extensive components:

$$\begin{aligned}
\tilde{\gamma}_{At} &\equiv \ln \sum_{f,n\in I_t} x_{fnt} - \ln \sum_{f,n\in I_{t-1}} x_{fnt-1} \\
&= \ln \frac{\sum_{f,n\in I_{t/t-1}} x_{fnt}}{\sum_{f,n\in I_{t/t-1}} x_{fnt-1}} - \left(\ln \frac{\sum_{f,n\in I_{t/t-1}} x_{fnt}}{\sum_{f,n\in I_t} x_{fnt}} - \ln \frac{\sum_{f,n\in I_{t/t-1}} x_{fnt-1}}{\sum_{f,n\in I_{t-1}} x_{fnt-1}} \right) \\
&= \underbrace{\gamma_{At}}_{Intensive\ margin} - \underbrace{\ln \frac{\pi_{t,t}}{\pi_{t,t-1}}}_{Extensive\ margin},
\end{aligned} \tag{A.1}$$

where $I_{t/t-1}$ is the set of firm-destination pairs active in both t and $t-1$ (the intensive subsample of firms×destinations in year t) and $\pi_{t,t}$ ($\pi_{t,t-1}$) is the share of output produced by this intensive sub-sample of firms in period t ($t-1$). Thus, the extensive margin calculation treats symmetrically entry into domestic production (a new firm appearing) and entry into exporting (an existing firm beginning to export to a particular destination n). Entrants have a positive impact on growth while exiters push the growth rate down, and the net impact is proportional to the share of entrants'/exiters' sales in aggregate sales.[27] Meanwhile, an observation only belongs to the intensive margin if an individual firm serves an individual destination in both periods.

Using equation (A.1), the impact of the intensive and extensive margins on aggregate volatility then can be written as:

$$\tilde{\sigma}_A^2 = \sigma_A^2 + \sigma_\pi^2 - 2\text{Cov}(\gamma_{At}, g_{\pi t}), \tag{A.2}$$

where $g_{\pi t} \equiv \ln \pi_{t,t}/\pi_{t,t-1}$ is the extensive margin component of equation (A.1), σ_π^2 is its variance, σ_A^2 is the variance of the intensive margin growth rate γ_{At}, and $\text{Cov}(\gamma_{At}, g_{\pi t})$ is the covariance between the two.

Inclusive of entry and exit, the volatility of total sales $\tilde{\sigma}_A^2$ is the sum of three components: i) the volatility of output produced by incumbent firms – the intensive margin, ii) the

[27] This decomposition follows the same logic as the decomposition of price indices proposed by Feenstra (1994).

volatility of entries and exits during the sample period – the extensive margin and iii) the (potential) covariance of those two terms. A convenient feature of this decomposition is that it accounts for the impact of extensive margin adjustments on aggregate volatility in a very simple way.

Though we do our best to estimate the extensive margin of firm-destination sales, there are several features of the data that may lead to overestimation of the importance of the extensive margin. First, mergers and acquisitions will appear as exits for the acquired firms, which would incorrectly add to the (negative) extensive margin.[28] Second, we cannot observe a firm's behavior prior to and after our sample period. This censoring will lead to an upward bias of the extensive margin in the first and last year of our sample, and thus we ignore these years in calculating the volatility of the extensive margin. Third, new entrants will be more likely to exhibit high growth rates as they start production and are growing towards their "steady-state" size. If young firms exhibit growth rates above the cutoff in the trimming procedure, we may record short-run entries and exits where only one entry took place. This will again overstate the importance of the extensive margin.[29]

Table OA.1. Intensive and Extensive Margins and Aggregate Volatility

	Whole Economy		*Manufacturing Sector*	
	(1)	(2)	(3)	(4)
	St. Dev.	Relative SD	St. Dev.	Relative SD
Actual	0.0228	1.0000	0.0309	1.0000
Intensive	0.0206	0.9022	0.0260	0.8429
Extensive	0.0083	0.3650	0.0103	0.3322

Notes: This table presents the standard deviations, in absolute and relative terms with respect to the actual, for the two components of aggregate growth: intensive and extensive margins, over 1992–2006.

Table OA.1 presents the standard deviations of the intensive and extensive margins, both in absolute terms and relative to the standard deviation of aggregate sales growth. We restrict attention to the period 1992–2006, because it is not possible to measure the extensive margin in the first and last years of the sample due to sampling issues discussed above. It is clear that the impact of the extensive margin on aggregate volatility is minor. While the

[28] M&A's will also lead to artificially large growth rates for the acquiring firm in the year of the M&A, which will appear in the intensive margin. The data do not record whether an M&A takes place, but our cleaning procedure discussed in Section 3 – i.e., dropping extreme growth rates – should drop the acquiring firm observation because of its large sales growth rate in the first year of acquisition.

[29] To reduce the impact of this effect on the baseline results carried out on the intensive margin, we aggregate the data over three-year periods, and the results are robust (see Section 4.4).

intensive margin aggregate volatility accounts for 90% and 84% of the overall sales volatility in the whole economy and the manufacturing sectors, respectively, the extensive margin accounts for only 37% and 33%. The results are robust to estimation of the extensive margin at three-year intervals, as well as five-year intervals, though there are fewer observations to calculate the variance for the latter, given the length of our sample period.[30]

Appendix B Relationship of $\sigma^2_{A\tau}$ to Aggregate Growth Volatility

Denote by σ^2_A the variance of γ_{At}, the growth rate of aggregate sales. Taking the variance of the right-hand side of (6), σ^2_A can be *exactly* written as the sum of the variances and covariances of the aggregated shocks:

$$\sigma^2_A = \sigma^2_{JN} + \sigma^2_F + COV, \tag{B.1}$$

where $\sigma^2_{JN} = \text{Var}\left(\sum_{j,n} w_{jnt-1}\delta_{jnt}\right)$ is the contribution of the sector-destination-specific shocks to aggregate volatility; $\sigma^2_F = \text{Var}\left(\sum_{f,n} w_{fnt-1}\varepsilon_{fnt}\right)$ is the contribution of firm-specific shocks to aggregate volatility, and $COV = \text{Cov}\left(\sum_{j,n} w_{jnt-1}\delta_{jnt}, \sum_{f,n} w_{fnt-1}\varepsilon_{fnt}\right)$ is the covariance between the shocks from different levels of aggregation.

While equation (B.1) represents an exact decomposition of the variance of γ_{At}, it is inconvenient for our purposes because it conflates the variances of shocks δ_{jnt} and ε_{fnt} with movements of the shares w_{jnt-1} and w_{fnt-1} over time. As a result, the properties of the stochastic processes $\sum_{j,n} w_{jnt-1}\delta_{jnt}$ and $\sum_{f,n} w_{fnt-1}\varepsilon_{fnt}$ are difficult to establish and relate to the properties of the primitive shocks δ_{jnt} and ε_{fnt}.

If the shares were constant over time, and the sample of firms did not change, then the aggregate variance would simply reflect the influence of the volatility of the different shocks, and (B.1) and (8) would coincide. However, this is not the case in our data: the shares and the firm-specific shocks are actually negatively correlated over time. This in turn mechanically reduces the volatility of the aggregated firm-specific shocks. To understand why this would happen, imagine a firm that either has low sales or high sales. When switching from low sales to high sales between $t-1$ and t, the firm's growth rate is large but it is weighted by the sales in $t-1$, which are low, when calculating the aggregated firm-specific component. On the other hand, when switching from high to low, the growth rate is low but this is weighted by lagged sales that are high. A negative covariance between

[30]These results are available upon request.

the shocks and weights is then created when computing the contribution of this firm to the aggregate variance.

However, this does not appear to be a large force in practice. While we cannot make precise statements about the stochastic processes governing γ_{At}, $\sum_{f,n} w_{fnt-1}\varepsilon_{fnt}$, and $\sum_{j,n} w_{jnt-1}\delta_{jnt}$, we can use observed δ_{jnt}, ε_{fnt}, and w_{fnt-1}'s to calculate sample variances, which we could think of as estimators of σ_A^2, σ_{JN}^2, and σ_F^2 in (B.1). Overall, these match up both qualitatively and quantitatively with the time averages of $\sigma_{A\tau}^2$, $\sigma_{JN\tau}^2$, and $\sigma_{F\tau}^2$ reported in the main text (Table 5): $\sigma_A = 0.021$ and 0.026, and $\sigma_F = 0.009$ and 0.012 for the whole economy and the manufacturing sector, respectively. The firm-specific contribution is somewhat smaller using the definition (B.1): the relative standard deviations, $\frac{\sigma_F}{\sigma_A} = 0.45$ and 0.46 for the whole economy and the manufacturing sector, respectively.

Appendix C Properties of the Estimators for $\sigma_{A\tau}^2$, $\sigma_{JN\tau}^2$, and $\sigma_{F\tau}^2$

C.1 Obtaining δ_{jnt}'s and ε_{fnt}'s

Our approach to computing δ_{jnt}'s and ε_{fnt}'s has a natural fixed effects regression interpretation. It amounts to regressing the cross-section of γ_{fnt}'s in a given year t and market n on the set of sector fixed effects, and retaining the residual as the firm-specific shock. This way of looking at things also makes it clear why we cannot isolate the macroeconomic shocks δ_{nt}. For any given market n at time t the full set of sector effects will span the country effect. Therefore, to include a constant term, a sector effect would have to be dropped, and the constant term would then capture a conflation of the aggregate shock and a shock to a "reference" sector. In turn, sector effects would then pick up sectoral shocks relative to the reference sector shock. Changing this reference sector can affect the values of δ_{nt} and δ_{jnt} as well as their variance. The combined overall impact of the macro and sectoral components remains the same regardless of the choice of the reference sector, and thus does not affect our computed values of firm-specific shocks, or their impact on the aggregate economy. The extended model (12) is implemented by fitting a linear regression on the cross-section of γ_{fnt} for each t and n, in which sector effects are interacted with the observable firm characteristics.

Note that we assume the realizations δ_{jnt} and ε_{fnt} to be observed perfectly, rather than themselves estimated. We can justify this by appealing to the fact that we are working with the universe of French firms, rather than a sample. This assumption is imposed for technical reasons. In order to establish the properties of the sample variances of a set of observed realizations of $\gamma_{At|\tau}$ and its constituent parts as estimators of their variances, as well as state the conditions on the primitives (i.e. properties of δ_{jnt} and ε_{fnt}) under which we can prove results about the properties of this estimator, we rely on the assumptions that (i) there is a well-defined and fixed set of firm-destinations, and (ii) the weights $w_{fn\tau-1}$ are fixed and known for all f, n. If we had instead assumed that we only observe estimates $\hat{\delta}_{jnt}$ and $\hat{\varepsilon}_{fnt}$ of δ_{jnt} and ε_{fnt}, asymptotics would involve proving consistency of $\hat{\delta}_{jnt}$ and $\hat{\varepsilon}_{fnt}$ as estimators of δ_{jnt} and ε_{fnt} as the sample size of firm-destinations goes to infinity. This, however, would not be logically consistent with keeping a fixed set of firm-destinations comprising the summation in $\gamma_{At|\tau}$, or with the assumption of fixed weights $w_{fn\tau-1}$.

C.2 Consistency and Asymptotic Normality

The proof follows the same steps to establish the properties of our estimators for $\sigma^2_{A\tau}$, $\sigma^2_{JN\tau}$, and $\sigma^2_{F\tau}$. Consider a vector-valued random variable $\boldsymbol{\psi_t} = \begin{pmatrix}\psi_{1t} & \psi_{2t} & \cdots & \psi_{Ft}\end{pmatrix}'$, $\boldsymbol{\psi_t} \in \mathbb{R}^F$, and a set of time-invariant weights $\mathbf{w} = \begin{pmatrix}w_1 & w_2 & \cdots & w_F\end{pmatrix}'$, $\mathbf{w} \in \mathbb{R}^F_+$. Denote by $Z_t = \mathbf{w}'\boldsymbol{\psi_t} = \sum_{i=1}^F w_i \psi_{it} \in \mathbb{R}$ a scalar-valued random variable that is a weighted sum of ψ_{it}'s. Assume we observe a stochastic process $\{\boldsymbol{\psi_t} : t = 1, \ldots T\}$, and consequently a stochastic process $\{Z_t : t = 1, \ldots T\}$.

In specific cases relevant for us, when $\boldsymbol{\psi_t} = \begin{pmatrix}\cdots & \varepsilon_{fnt} & \cdots\end{pmatrix}'$ is the vector of ε_{fnt} and $\mathbf{w} = \begin{pmatrix}\cdots & w_{fn\tau-1} & \cdots\end{pmatrix}'$ is the vector of firm weights at time $\tau - 1$, then $Z_t = \sum_{f,n} w_{fn\tau-1}\varepsilon_{fnt}$ is the contribution of firm-specific shocks to $\gamma_{At|\tau}$ (the "granular residual"), and its variance $\sigma^2_{F\tau}$ is what we are interested in estimating. Similarly, when $\boldsymbol{\psi_t} = \begin{pmatrix}\cdots & \delta_{jnt} & \cdots\end{pmatrix}'$ and $\mathbf{w} = \begin{pmatrix}\cdots & w_{jn\tau-1} & \cdots\end{pmatrix}'$, then $Z_t = \sum_{j,n} w_{jn\tau-1}\delta_{jnt}$ with variance $\sigma^2_{JN\tau}$. Finally, when $\boldsymbol{\psi_t} = \begin{pmatrix}\cdots & \varepsilon_{fnt} & \cdots & \cdots & \delta_{jnt} & \cdots\end{pmatrix}'$ is the stacked vector of δ_{jnt} and ε_{fnt} and $\mathbf{w} = \begin{pmatrix}\cdots & w_{fn\tau-1} & \cdots & \cdots & w_{jn\tau-1} & \cdots\end{pmatrix}'$ is the stacked vector of $w_{fn\tau-1}$'s and $w_{jn\tau-1}$'s, then $Z_t = \gamma_{At|\tau}$.

This appendix states a set of sufficient conditions on the properties of the vector-valued stochastic process $\boldsymbol{\psi_t}$ and the weights vector $\mathbf{w}$ such that Z_t is stationary and the sample variance of Z_t for $t = 1, ..., T$ is a well-behaved estimator of the true variance of Z_t. Applying these conditions to the three cases above separately yields a statement of the sufficient conditions under which the sample variance of T realizations of $\gamma_{At|\tau}$ is a well-behaved estimator of $\sigma^2_{A\tau}$, and similarly for the estimators of $\sigma^2_{F\tau}$ and $\sigma^2_{JN\tau}$.

Definition 1 *A sequence $(Z_t)_{t\in\mathbb{N}}$ of random variables is called* ***α-mixing*** *if*

$$\alpha(m) = sup\left\{\alpha\left((Z_1, ..., Z_k), (Z_j)_{j\geq k+m}\right)|k \in \mathbb{N}\right\} \xrightarrow{m\to\infty} 0 \tag{C.1}$$

where α is the strong mixing coefficient defined as

$$\alpha(Z, X) = \sup_{\substack{A\in\sigma(Z)\\ B\in\sigma(X)}} |P(A \cap B) - P(A)P(B)|, \tag{C.2}$$

where $\sigma(Z)$ is the σ-field defined by Z.

Lemma 1 *Let $\boldsymbol{\psi_t}$ be a vector-valued jointly stationary and α-mixing stochastic process of dimension $F \times 1$ with mean $\boldsymbol{\mu}$ and variance $\boldsymbol{\Omega}$. Denote by $Z_t \equiv \mathbf{w}'\boldsymbol{\psi_t}$ the scalar-valued process that corresponds to the weighted sum of the individual elements of $\boldsymbol{\psi_t}$. Then,*

1. *Z_t is a stationary, α-mixing process with mean μ_Z and variance σ_Z^2.*

2. *If Z_t satisfies $E|Z_t|^8 < \infty$ and $\alpha(T) = O(T^{-3})$,[31] then the sample variance*

$$s_Z^2 = \frac{1}{T-1}\sum_{t=1}^{T}(Z_t - \bar{Z}_t)^2, \tag{C.3}$$

where $\bar{Z}_t = \frac{1}{T}\sum_{t=1}^{T} Z_t$ is the sample mean, is a consistent estimator of the variance σ_Z^2 of Z_t, with a limiting distribution characterized by

$$\sqrt{T}(s_Z^2 - \sigma_Z^2) \xrightarrow{d} N(0, \xi^2), \tag{C.4}$$

where

$$\xi^2 = Var\left[(Z_t - \mu_Z)^2\right] + 2\sum_{k=1}^{\infty} Cov\left[(Z_t - \mu_Z)^2, (Z_{t+k} - \mu_Z)^2\right]. \tag{C.5}$$

Proof: The function $Z(\mathbf{x}) = \mathbf{w}'\mathbf{x}$ is measurable since $\mathbf{w}$ is known and not time-varying. Theorem 1.1 in Durrett (2005, p. 333) combined with joint stationarity of $\boldsymbol{\psi_t}$ delivers the result that $Z_t = Z(\boldsymbol{\psi_t}) = \mathbf{w}'\boldsymbol{\psi_t}$ is stationary (a measurable function of a stationary process is itself stationary). Similarly, Theorem 3.49 in White (2001, p. 50) combined with the assumption that $\boldsymbol{\psi_t}$ is α-mixing of size $-a$ delivers the result that Z_t is also α-mixing of size $-a$ (a measurable function of an α-mixing process is itself α-mixing). This proves the

[31] The statement of these conditions can be made more general. Namely, the proposition holds if $\exists\ \nu > 0$ and $\exists\ \phi > 0$ such that $E|Z_t|^{\max\{\phi,2(2+\nu)\}} < \infty$ and $\alpha(T) = O(T^{-\rho})$ for $\rho > \frac{3\phi\nu+\nu+5\phi+2}{2\phi\nu}$. This more general statement of the conditions captures the tradeoff between the number of finite moments and the degree of time dependence: one can allow for more time dependence (lower ρ) if one assumes existence of higher order finite moments, and vice versa.

first claim. The second claim follows directly from Theorem 1.8 of Dehling and Wendler (2010, p. 128), since Z_t satisfies all the conditions required in that theorem and it is easily verified that the $U-$statistic corresponding to the sample variance satisfies the moment and continuity conditions of that theorem. ■

C.3 Standard Errors

As is customary, in our empirical implementation we will compute the confidence intervals based on the empirical counterpart of (C.5):

$$\hat{\xi}^2 = \frac{1}{T-1}\sum_{t=1}^{T}\left[(Z_t - \bar{Z}_t)^2 - s_Z^2\right]^2 + 2\sum_{k=1}^{T-2}\frac{1}{T-k-1}\sum_{t=1}^{T-k}\left[(Z_t - \bar{Z}_t)^2 - s_Z^2\right]\left[(Z_{t+k} - \bar{Z}_t)^2 - s_Z^2\right] \tag{C.6}$$

For large k, the object $\sum_{t=1}^{T-k}\left[(Z_t - \bar{Z}_t)^2 - s_Z^2\right]\left[(Z_{t+k} - \bar{Z}_t)^2 - s_Z^2\right]$ cannot be precisely estimated. Thus, we cut the number of maximum allowable lags to $q \ll T-2$ and use the HAC estimator that downweights more distant covariances (Newey and West, 1987):

$$\begin{aligned}\hat{\xi}^2_{HAC} = & \frac{1}{T-1}\sum_{t=1}^{T}\left[(Z_t - \bar{Z}_t)^2 - s_Z^2\right]^2 + \\ & 2\sum_{k=1}^{q}\left[1 - \frac{k}{q+1}\right]\frac{1}{T-k-1}\sum_{t=1}^{T-k}\left[(Z_t - \bar{Z}_t)^2 - s_Z^2\right]\left[(Z_{t+k} - \bar{Z}_t)^2 - s_Z^2\right]\end{aligned} \tag{C.7}$$

Following Andrews (1991), we choose q as a function of sample size according to the following rule of thumb:

$$q + 1 \approx 0.75T^{1/3}$$

For us, with $T = 17$, this amounts to $q + 1 \approx 2$, so we only use the covariance for one lag. We are interested in the standard error of s_Z^2, which is obtained by dividing $\hat{\xi}^2_{HAC}$ by $\sqrt{T}$. Finally, the figures and tables in the main text report the results expressed in terms of the standard deviation s_Z. We use the delta method to obtain the standard error of the standard deviation.

Appendix D Detailed Data Description

The sales data, as well as additional variables, come from the balance sheet information collected from firms' tax forms. The French tax system distinguishes three different regimes, the "normal" regime (called BRN for *Bénéfice Réel Normal*), the "simplified" regime (called RSI for *Régime Simplifié d'Imposition*) that is restricted to smaller firms, and the "micro-BIC" regime for entrepreneurs. The amount of information that has to be provided to the fiscal administration is more limited in the RSI than in the BRN regime, and even more so for "micro-BIC" firms. Under some conditions, firms can choose their tax regime. An individual entrepreneur can thus decide to enroll in the "micro-BIC" regime if its annual sales are below 80,300 euros. Likewise, a firm can choose to participate in the RSI rather than the BRN regime if its annual sales are below 766,000 euros (231,000 euros in services).[32]

Throughout the exercise, "micro-BIC" and "RSI" firms are excluded. We do not have enough information for "micro-BIC" firms. We also exclude "RSI" firms, both because their weight in annual sales is negligible and because it is difficult to harmonize these data with the rest of the sample. In 2007, those firms represented less than 4% of total sales and about 11% of total employment. Thus, our sample represents the bulk of the aggregate French economy.

The BRN dataset contains detailed information on the firms' balance sheets, including total, domestic, and export sales, value added, as well as many cost items including the wage bill, materials expenditures, and so on, as well as NAF sectors in which the firm operates.[33] This represents around 30% of industrial and service firms but more than 90% of aggregate sales.[34] We do not have any information at the plant level, however.

The information collected by the tax authorities is combined with the firm-level export data for each foreign destination market from the French customs authorities. The datasets can be merged using a unique firm identifier, called SIREN. In merging together the customs and balance sheet data, we had to make a number of adjustments. First, we drop observations for firms that appear in the customs but do not appear in the BRN data (some of these firms may produce farming goods, which are not in the balance sheet data). Second, a number of firms declare positive exports to the tax authorities but are not in the customs files. Since our procedure exploits the bilateral dimension of exports, and the

[32]Those thresholds are for 2010. They are adjusted over time, but marginally so.

[33]"NAF", *Nomenclature d'Activités Française*, is the French industrial classification. Our baseline analysis considers the level of aggregation with 60 sectors. This corresponds to the 2-digit ISIC (Revision 3) nomenclature. We merge together some sectors in order for our nomenclature to be consistent with the one used in the input-output tables. Namely, we merge agriculture, forestry and fishing (NAF 1, 2 and 5), all mining and quarrying activities (NAF 10 to 14), tobacco and other food industries (NAF 15 and 16), textile, wearing apparel and leather (NAF 17, 18 and 19), paper products and publishing (NAF 21 and 22), manufacturing n.e.c and recycling (NAF 36 and 37), all activities related to electricity gas and water (NAF 40 and 41), wholesale and retail trade (NAF 50, 51 and 52), transport and storage activities (NAF 60 to 63) and all community, social and personal services (NAF 90 to 93). We also drop NAF sectors 95 (domestic services), and 99 (activities outside France). The NAF nomenclature has been created in 1993, as a replacement for the "NES" (Nomenclature Economique de Synthèse). Data for 1990–92 are converted into the NAF classification using a correspondence table.

[34]We drop the banking sector because of important restructuring at the beginning of the 2000s that artificially adds a large amount of volatility to the dataset. This sector represents less than 4% of total sales in 1990 but more than 25% by the end of the period.

customs data are the most reliable source of exporting information, we assume that those firms are non-exporters. Third, in a small fraction (6.6%) of exporter-year observations present in both the customs and the BRN data, the value of export sales is not the same in the two databases. We thus use the customs data to compute the share of each destination market in total firm exports and apply these shares to export sales provided in the BRN file.

The customs data are quasi-exhaustive. There is a declaration threshold of 1,000 euros for annual exports to any given destination. Below the threshold, the customs declaration is not compulsory. Since 1993, intra-EU trade is no longer liable for any tariff, and as a consequence firms are no longer required to submit the regular customs form. A new form has however been created that tracks intra-EU trade. Unfortunately, the declaration threshold for this kind of trade flows in much higher, around 150,000 euros per year. A number of firms continue declaring intra-EU export flows below the threshold however, either because they don't know ex ante that they will not reach the 150,000 Euro limit in a given fiscal year, because they apply the same customs procedure for all export markets they serve, or because they delegate the customs-related tasks to a third party (e.g., a transport firm) that systematically fills out the customs form. Below-cutoff exports missing from customs data can potentially create two problems (i) some export sales might be counted as domestic, affecting the computation of domestic shocks; and (ii) some export sales that occur in reality (a subset of those below 150,000 euros) are missing from our data, affecting the computation of export shocks. We use the information contained in the tax forms to both deal with this problem and assess its extent. On the tax form, the firms report their total exports. Thus, we can conjecture that firms that do not appear in customs data but report positive exports on their tax forms are those for whom exports (by destination) fall below the customs cutoff. We address problem (i) by calculating the firm's domestic sales as the difference between their reported total sales and their exports reported on the tax form. In this way, we do not "contaminate" domestic sales with erroneously classified exports. Below, we report our main results for domestic sales only, and they are robust. For problem (ii), this fix is not available. We can judge how many exports we are missing by comparing exports declared on tax forms to exports declared to customs. It appears that the problem is relatively minor. In 10% of firm-year observations, the tax form reports exports but the customs data do not. These observations account for 7% of overall exports. On average, the total exports reported in the tax form but missing from customs (413,000 euros per year) are an order of magnitude smaller than average exports in the whole sample, which are 3,056,000.

Our approach involves working with the sales growth rates of firms to individual markets. One concern with these data is that firm sales could be measured with error, and thus the volatility of firm-specific shocks we estimate may simply be the variance of the measurement error. As is typical of micro data, there is a great deal of dispersion in the set of individual growth rates we obtain. There are a number of reasons for which the data may contain outliers. For instance, the BRN file does not provide any information on firms undergoing a *controle fiscal* – i.e. a tax audit – during a given year. For these firms, the "sales" variable is either zero or missing, which results in either extreme growth rates or artificial exits and re-entries around those years.[35] Also, firms can change their organizational structure in a given year, grouping activities together in different entities, which can result in a number of large "exits." In a number of cases, firms decided to create new holding companies that pooled together the charges and benefits of all firms comprising the group. The members of those groups, that before filed separate tax forms, would then disappear from the fiscal files.

While measurement error is by construction impossible to rule out, we believe that our results are not unduly driven by it for a number of reasons. First, the French data we are working with are high quality, coming from tax and customs records. These are the data underlying the national accounts for France. Second, in order for extreme observations not to introduce noise in the estimation and aggregation exercise, we apply a trimming procedure. Namely, we drop the individual growth rates in which sales are either double or half their previous year's value. Third, we repeat the analysis on 3-year growth rates instead of annual growth rates as one of the robustness checks, a procedure that should help average out year-to-year measurement error. The fact that 3-year growth rates continue to produce a significant firm component for aggregate fluctuations suggests that the main results in the paper are not driven by measurement error.

[35] The audit of the firm's tax statements is over the period going back 3 years, and up to 10 years if fraud is detected. This is relevant for us because this process often lasts for many months, and during the year the company is in *controle fiscal*, there is no "regular" BRN declaration which may result in missing data values for certain firm-years, even for big companies. Unfortunately, we do not have data on which firm-years are under *controle fiscal.*

Appendix E A Simple Model of Input-Output Linkages at the Firm Level

This appendix presents a simple extension of the baseline model of Section 2 to illustrate how interconnections between firms can generate positive correlation in the estimated firm-specific shocks. We model the interconnection through input-output linkages.

Suppose that the sales of a firm are given by (3), but the cost of the input bundle is now firm- rather than sector-specific:

$$x_{fnt} = \omega_{fnt} \frac{\varphi_{jnt} Y_{nt}}{(P_{jnt})^{1-\theta}} \left(\frac{\theta}{\theta - 1} \kappa_{jnd} c_{fdt} a_{fdt} \right)^{1-\theta},$$

where

$$c_{fdt} = A h_{dt}^{\lambda_f} \prod_{g \in \Xi_{fdt}} p_{gdt}^{(1-\lambda_f)\rho_{fg}}, \quad \sum_g \rho_{fg} = 1.$$

This specification assumes that the cost of firm f's input bundle c_{fdt} has a Cobb-Douglas form in labor, paid the equilibrium wage h_{dt}, and the set Ξ_{fdt} of inputs bought from the firm's input providers at their equilibrium price p_{gdt}. The parameter λ_f measures the share of labor in the firm's cost function, and ρ_{fg} is the share of spending on inputs produced by firm g in the total intermediate input spending by firm f. Finally, A is a constant that depends on the parameters of the production function.

Productivity shocks to an input provider g have a direct effect on its sales: $d \ln x_{gmt} / d \ln a_{gmt} = 1 - \theta$. Because of input-output linkages, they also transmit to firm f with the following elasticity:

$$\frac{d \ln x_{fnt}}{d \ln a_{gmt}} = (1-\theta)(1-\lambda_f)\rho_{fg}.$$

Intuitively, a positive productivity shock decreases the upstream firm's output price and thus the downstream firm's input cost, positively affecting its sales. This transmission of shocks via the IO linkage implies that the sales growth rates of firms f and g exhibit positive comovement.

In particular, if idiosyncratic firm-specific productivity shocks are the only source of shocks in the economy, the covariance of the firm-specific sales growth components between any two firms f and g is

$$\begin{aligned}\text{Cov}\left(\varepsilon_{fnt}, \varepsilon_{gmt}\right) = (1-\theta)^2 \Bigg[& \underbrace{(1-\lambda_g)\rho_{gf}\text{Var}(a_{fdt})}_{\text{Propagation from } f \text{ to } g} + \underbrace{(1-\lambda_f)\rho_{fg}\text{Var}(a_{gdt})}_{\text{Propagation from } g \text{ to } f} \\ & + \underbrace{\sum_{h\in\Xi_{fdt}\cap\Xi_{gdt}} (1-\lambda_f)(1-\lambda_g)\rho_{fh}\rho_{gh}\text{Var}(a_{hdt})}_{\text{Propagation through common input providers}} \Bigg].\end{aligned} \tag{E.1}$$

Summing over all firms connected to f and assuming that the variance of shocks is homogeneous over firms ($\text{Var}(a_{fnt}) = \sigma^2 \ \forall \ f, n$), one can recover the contribution of a single firm to the overall linkage factor (neglecting the impact of weights):

$$\begin{aligned}\sum_{g,m} \text{Cov}(\varepsilon_{fnt}, \varepsilon_{gmt}) = (1-\theta)^2\sigma^2 \Bigg[& \underbrace{\sum_g (1-\lambda_g)\rho_{gf}}_{\text{Weighted out-degree } d_f} + (1-\lambda_f) \\ & + (1-\lambda_f) \underbrace{\sum_{g,m} \sum_{h\in\Xi_{fdt}\cap\Xi_{gdt}} (1-\lambda_g)\rho_{fh}\rho_{gh}}_{\text{Second-order degree } q_f} \Bigg].\end{aligned} \tag{E.2}$$

As in Acemoglu et al. (2012), the impact of one single firm on the aggregate volatility depends on how connected it is to the rest of the economy. Shocks affecting a firm that provides inputs to a large number of downstream players, i.e., that has a large "weighted out-degree" d_f in the words of Acemoglu et al. (2012), will have a larger impact. This is what the first term of (E.2) captures. The second term accounts for the fact that firms that use more inputs will fluctuate more as a result of productivity shocks affecting their input providers. Finally, the third term captures "second-order connections" as denoted by Acemoglu et al. (2012) – namely the fact that common input suppliers magnify the propagation of shocks across firms.

Ideally, one would like to investigate the role of firm-level linkages in aggregate fluctuations using the insights of (E.1) and (E.2). Using these equations, it is possible to correlate the magnitude of covariances at the firm-level to appropriate measures of linkages. Unfortunately, such firm-level measures of IO linkages are not available for France. Instead, we use sectoral data on IO linkages as a proxy for the intensity of production networks. The implicit assumption is that those sectoral measures of IO linkages are a good proxy for the magnitude of interconnections between firms belonging to those sectors. Since the information is available at the level of each sector pair, we need to correlate them with measures of the $LINK$ term that are also defined by sector pair.

Recall the definition of the $LINK$ term and write it as the sum over all sector pairs in the economy:

$$LINK_\tau = \sum_{g\neq f, m\neq n} \sum_{f,n} w_{gm\tau-1} w_{fn\tau-1} \mathrm{Cov}(\varepsilon_{gmt}, \varepsilon_{fnt}) = \sum_i \sum_j LINK_{ij\tau}, \text{ where}$$

$$LINK_{ij\tau} = \sum_{g,m\in j} \sum_{f,n\in i} w_{gm\tau-1} w_{fn\tau-1} \mathrm{Cov}(\varepsilon_{gmt}, \varepsilon_{fnt}),$$

and $\mathrm{Cov}(\varepsilon_{gmt}, \varepsilon_{fnt})$ is defined by (E.1).

Assume that i) individual volatilities are homogeneous across firms: $\mathrm{Var}(a_{fdt}) = \sigma^2 \ \forall \ f$; ii) the IO coefficients are homogeneous between firms within a sector: $(1-\lambda_f) = (1-\lambda_i) \ \forall \ f \in i$ and $\rho_{fg} = \rho_{ij} \ \forall \ f \in i, g \in j$, and iii) $\Xi_{fdt} \cap \Xi_{gdt}$ is homogeneous between firms within a sector pair. Then the $LINK$ term becomes

$$LINK_{ij\tau} = w_{jm\tau-1} w_{in\tau-1} \sigma^2 (1-\theta)^2 \left[\underbrace{(1-\lambda_j)\rho^{ji} + (1-\lambda_i)\rho_{ij}}_{\text{First-order}} + \underbrace{\sum_k (1-\lambda_i)(1-\lambda_j)\rho^{ik}\rho^{jk}}_{\text{Second-order}} \right].$$

This expression thus motivates our approach in Section 4.3.2 of looking for a relationship between the $LINK_\tau$ term and the strength of IO linkages between the sectors.

Appendix F Heterogeneous Response to Shocks at the Firm Level

This appendix develops a variant of the model in Section 2 with variable markups. In this more general framework, firms react heterogeneously to common shocks. When this is the case, the firm-specific effect in the baseline estimation would capture not only the impact on firm sales of idiosyncratic shocks but also the heterogeneous response of the firm to sector-destination shocks. The model serves to motivate the alternative empirical model (12), in which sector-destination shocks affect firm sales differently depending on firm characteristics. The main results are robust to this alternative conceptual framework and empirical model.

Consider the model in Section 2 that has Cobb-Douglas preferences over sectors and CES preferences over varieties within a sector. As before, each firm faces the following demand in market n:

$$C_{fnt} = \left(\frac{p_{fnt}}{P_{jnt}}\right)^{-\theta} \omega_{fnt} \frac{\varphi_{jnt} Y_{nt}}{P_{jnt}},$$

where variables are defined in Section 2, and p_{fnt} is the consumer price of firm f's product in market n.

The baseline model assumes the standard "iceberg" multiplicative cost of delivering one unit of the good to market n. Suppose instead, following Berman et al. (2012), that the variable trade cost has two components, one multiplicative and one additive. The consumer price in market n is then

$$p_{fnt} = \tilde{p}_{fnt} \kappa_{jndt} + \eta_{jndt},$$

where $\tilde{p}_{fnt}$ is the producer price, κ_{jndt} the multiplicative variable trade cost, and η_{jndt} the additive variable trade cost.[36] Both κ_{jndt} and η_{jndt} are assumed to be the same for all firms within a sector selling goods to the same destination market.

A per-unit component of variable trade cost implies that, even under CES preferences, individual markups are not homogeneous across firms. Namely, profit maximization leads to the following producer price:

$$\tilde{p}_{fnt} = \frac{\theta}{\theta - 1} m_{fnt} a_{fdt} c_{jdt},$$

where

$$m_{fnt} \equiv 1 + \frac{\eta_{jndt}}{\theta \kappa_{jndt} a_{fdt} c_{jdt}},$$

is the variable component of markups. Importantly, this component is affected by sectoral cost movements (changes in c_{jdt}) as well as changes in variable trade costs (κ_{jndt} and η_{jndt}). Moreover, the elasticity of m_{fnt} with respect to sector-destination shocks is heterogeneous across firms, and depends on the individual productivity level (a_{fdt}). Identical shocks can thus have different effects on firms sales growth.

Conditional on selling to market n, (f.o.b.) sales by a French firm f (i.e., residing in country d) to market n in period t are thus given by:

$$\begin{aligned} x_{fnt} &= \tilde{p}_{fnt} C_{fnt} \\ &= \omega_{fnt} \frac{\varphi_{jnt} Y_{nt}}{(P_{jnt})^{1-\theta}} \left(\frac{\theta}{\theta - 1} \kappa_{jndt} c_{jdt} a_{fdt}\right)^{1-\theta} \left(\frac{m_{fnt}}{\kappa_{jndt}}\right)^{1-\theta} \left(\frac{p_{fnt}}{\tilde{p}_{fnt}}\right)^{-\theta}. \end{aligned} \tag{F.1}$$

[36]The additive cost η_{jndt} can either be thought of as a distribution cost or a per-unit transportation cost. When thinking of it as a distribution cost, it makes sense to assume this cost is paid using foreign labor. This does not change the main results, but introduces an additional source of sector-destination shocks since the optimal markup then depends on the destination market's wage.

If we were to use (F.1) to write a decomposition of firm sales growth as a function of country, sector-destination and firm-destination shocks as in (4):

$$\gamma_{fnt} = \delta_{nt} + \delta_{jnt} + \varepsilon_{fnt},$$

the firm-specific component would now be

$$\varepsilon_{fnt} = \Delta \log \omega_{fnt} + (1-\theta)\Delta \log a_{fdt} + (1-\theta)\Delta \log m_{fnt} - \theta \Delta \log \left(\frac{\tilde{p}_{fnt}}{p_{fnt}} \right),$$

The first two terms are firm-specific by construction, as before. However, the last two terms, $(1-\theta)\Delta \log m_{fnt} - \theta \Delta \log \left(\frac{\tilde{p}_{fnt}}{p_{fnt}} \right)$, depend on sectoral shocks (and on the macro shocks if the distribution cost is paid in foreign labor). These terms capture firms' heterogeneous response to common shocks.

In particular, the impact of a sectoral cost shock on the firm-level sales is

$$\begin{aligned}
&\frac{d \ln x_{fnt}}{d \ln c_{jdt}} = (1-\theta) + (1-\theta)\frac{d \ln m_{fnt}}{d \ln c_{jdt}} - \theta \frac{d \ln \left(\frac{\tilde{p}_{fnt}}{p_{fnt}} \right)}{d \ln c_{jdt}} \\
\text{where} \quad &\frac{d \ln m_{fnt}}{d \ln c_{jdt}} = \frac{-\eta_{jndt}}{\theta \kappa_{jndt} a_{fnt} c_{jdt} + \eta_{jndt}} \in [-1, 0] \\
\text{and} \quad &\frac{d \ln \left(\frac{\tilde{p}_{fnt}}{p_{fnt}} \right)}{d \ln c_{jdt}} = \frac{-\eta_{jndt}}{p_{fnt}} \left(1 + \frac{d \ln m_{fnt}}{d \ln c_{jdt}} \right) < 0
\end{aligned}$$

The first term captures the direct effect of the shock on the firm's marginal cost, which is homogeneous across firms and captured in the δ_{jnt} term of equation (5). The second term, which would be captured in ε_{fnt}, reflects the response of the firm's markup to the shock. When the cost of the input bundle increases, firms reduce their optimal markup, more so the more productive they are. This markup adjustment tends to attenuate the effect of the sectoral shock on sales of the more productive firms. Finally, the third term captures the adjustment in the ratio of the consumer to the producer prices. The combined effect of the cost shock and the markup adjustment on this ratio further attenuates the direct impact of the sectoral shock.

From an econometric point of view, endogenous markup adjustments would induce a negative correlation between the sector-destination fixed effects and the residual term of equation (5). To control for this bias, we thus implement equation (12) that interacts the sector-destination effect with a number of measures, many of which can be thought of as proxies for firm productivity. Following the model laid out in this section, these interaction terms are intended to capture the larger markup adjustment of the more productive firms in response to sector-destination shocks.

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