Firms, Destinations, and Aggregate Fluctuations*

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Abstract

This paper provides a forensic account of the role of individual firms in generating aggregate fluctuations using data covering the universe of French firms for the period 1990–2007. We derive a theoretically-founded set of estimating equations that decompose firms' annual sales growth rate into different components. 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: (i) when the firm size distribution is fat-tailed, idiosyncratic shocks to large firms contribute to aggregate fluctuations (Gabaix, 2011), and (ii) sizable aggregate volatility can arise from idiosyncratic shocks due to input-output linkages across the economy (Acemoglu et al., 2012). We find that firm linkages are approximately twice as important as granularity 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; Horvath, 1998, 2000; Dupor, 1999; Foerster et al., 2011; Carvalho and Gabaix, 2010, among many others). The role of 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 aggregate fluctuations. Acemoglu et al. (2012) develop a network model in which idiosyncratic shocks to a single firm or sector can have sizable aggregate effects if it is strongly interconnected with other firms/sectors in the economy, regardless of the size distribution. However, there is currently little empirical evidence to complement these theoretical contributions.

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 estimate the empirical model suggested by theory using a panel regression in which the unit of observation is the annual firm-destination growth rate of sales. The firm-specific component accounts for the overwhelming majority (98.7%) of the sales variability across firms in the firm-destination panel regressions.[1] In addition, about half of the variation in the firm-specific component is explained by variation in that component across destinations, which is interpreted as demand shocks in our conceptual framework.

The procedure yields estimates of the time series of the macroeconomic, sectoral, and firm-specific shocks for each destination served by each firm. We use the estimated 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 do contribute substantially to aggregate fluctuations. Their contribution is roughly similar in magnitude to the combined effect of all sectoral and macroeconomic shocks. To investigate whether exports differ systematically from domestic sales, we then carry out the aggregate volatility decomposition for domestic and export sales separately.[2] The firm-specific component contributes more to the volatility of exports, compared to overall sales, in both the whole economy 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.

We evaluate two explanations for the positive overall contribution of firm-specific shocks. The first, due to Gabaix (2011), is that firm-specific idiosyncratic volatility does not average out because of the presence of very large firms. We refer to this as the "granularity" hypothesis. The second, due to Acemoglu et al. (2012), is that idiosyncratic shocks contribute to aggregate fluctuations because input-output linkages generate comovement between firms. We refer to this as the "linkages" hypothesis.[3] The overall contribution of firm-specific shocks to aggregate volatility can be

[1]This number is based on the ratio of the residual sum of squares to the total sum of squares in our regressions. Using the same metric, Castro et al. (2011) find that idiosyncratic risk accounts for about 90% of the overall uncertainty faced by firms in the U.S. Census Longitudinal Business Database.

[2]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. As Canals et al. (2007) point out, international trade is very granular, both at the firm- and sector-destination level.

[3]Note that in Acemoglu et al. (2012), the structural shocks are uncorrelated but generate positive

decomposed additively into two terms that capture these two mechanisms. Though both channels matter quantitatively, about two-thirds of the contribution of firm-specific shocks to the aggregate variance is accounted for by the "linkages" effect – the covariances of the firm-specific components of the growth rate of sales.

We then exploit cross-sectoral heterogeneity to provide further evidence on the "granularity" and "linkages" mechanisms. We compare the covariances of the firm-specific shocks aggregated at the sector level to a measure of sectoral linkages taken from the Input-Output Tables.[4] We find that sectors with stronger input-output linkages tend to exhibit significantly greater correlation of firm-specific shocks – direct evidence for the linkages hypothesis. We also relate each sector's contribution to aggregate volatility to the "granularity" of the sector. Gabaix (2011) shows that granular fluctuations in the economy will be more pronounced the larger is the Herfindahl index of firm sales – a common measure of concentration. Confirming this result, we find that industries such as transport, petroleum, and motor vehicles, which are more concentrated than the average sector, contribute more significantly to aggregate volatility, whereas the contribution of less concentrated sectors such as metal products or publishing is comparatively smaller. In summary, we find direct corroboration in the data for the mechanisms behind both the "granularity" and the "linkages" hypotheses. Sectors that are i) populated by firms that are more interconnected with the rest of the economy, and ii) more concentrated contribute a disproportionate share of aggregate volatility relative to what we would expect in a "symmetric" economy.

We establish robustness of the results in a number of dimensions. First, in the model and the baseline estimation, 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 of our framework. In an alternative estimation approach, we thus allow for the impact of sector-destination shocks on the growth rate of sales to vary by firm size. Second, it may be that at yearly frequency firm sales and export data feature a fair amount of measurement error. To reduce the impact of measurement error, we aggregate the data over time and use three-year growth rates (opposed to annual

covariances in firm sales.

[4]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.

ones) in our regressions and calculations. Overall, the results are robust to these alternative approaches.

This paper contributes to the literatures on the micro underpinnings of aggregate fluctuations, and on the impact of firm-level volatility. The literature on the micro sources of aggregate fluctuations has traditionally focused on shocks at the sectoral level, and emphasized input-output linkages between the sectors (see, e.g., Long and Plosser, 1983; Jovanovic, 1987; Stockman, 1988; Horvath, 1998, 2000; Dupor, 1999; Foerster et al., 2011; Carvalho and Gabaix, 2010, among many others). The role of individual firms in driving aggregate fluctuations, by contrast, had not received much attention until very recently. Gabaix (2011) 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 (2011) extend this model to a multi-country framework, and argue that it can help rationalize cross-country differences in the magnitude of aggregate fluctuations. Our work is also related to the large literature on firm level volatility (see, among many others, Comín and Philippon, 2006; Davis et al., 2007; Castro et al., 2011; Thesmar and Thoenig, 2011; Moscarini and Postel-Vinay, 2011; Lee and Mukoyama, 2012). 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 are the first to incorporate the international dimension and show that it is important for reliable estimation of shocks. Finally, our estimate of the full variance-covariance matrix at the firm and destination level enables 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 empirical specification. In the model, firm sales growth in each market can be decomposed 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 estimation and aggregation results. Section 5 concludes.

2 Theoretical Framework

Total aggregate sales X_t by all French firms to all destinations 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.[5] The growth rate of aggregate sales is then defined simply as $\gamma_{At} = \ln X_t - \ln X_{t-1}$, 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 by the difficulty of measuring the extensive margin reliably. 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, supporting our choice to restrict attention to the intensive margin.[6]

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 consider a multi-sector heterogeneous firms model in the spirit of Melitz (2003) and Eaton et al. (2011a). There are N countries indexed by n, and J sectors indexed by j. In country n, consumer within-period utility is Cobb-Douglas in the sectors $1, ..., J$:

$$U_{nt} = \prod_{j=1}^{J} \left(C_{nt}^{j}\right)^{\alpha_{nt}^{j}}, \tag{1}$$

where C_{nt}^{j} is consumption of sector j in country n at time t, and α_{nt}^{j} is a time-varying demand shock for sector j in country n (as in Eaton et al., 2011b). The Cobb-

[5] 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 and each destination.

[6] 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.

Douglas functional form for the utility function leads to the well-known property that expenditure on sector j is a fraction α_{nt}^j of the total expenditure in the economy: $Y_{nt}^j = \alpha_{nt}^j Y_{nt}$, where Y_{nt} is aggregate expenditure in country n at time t, and Y_{nt}^j is the expenditure in sector j.

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

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

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

Sector j in the producing country (d=France) is populated by I_{dt}^j firms. Each of these firms sells a unique CES variety, and thus has some market power. Firms also differ in productivity, with each firm characterized by a time-varying 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_{dt}^j. 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:

$$x_{fnt} = \omega_{fnt} \frac{\alpha_{nt}^j Y_{nt}}{\left(P_{nt}^j\right)^{1-\theta}} \left(\frac{\theta}{\theta - 1} \tau_{nd}^j c_{dt}^j a_{fdt} \right)^{1-\theta}, \tag{3}$$

where τ_{nd}^j is the iceberg cost of selling from France to country n in sector j, and we normalize $\tau_{dd}^j = 1$. This equation assumes that (i) τ_{nd}^j is sector-specific but does not vary over time (though that assumption can easily be relaxed, in which case the time variation in τ_{nd}^j will be absorbed in the demand shock), and (ii) the cost bundle c_{dt}^j and the marginal cost a_{fdt} may vary over time, but are not destination-specific.

2.2 Empirical Model of Sales Decomposition

Sales to a single destination then admit the exact decomposition into macroeconomic, sectoral, and firm-specific components. In log differences/growth rates, equation (3) becomes

$$\gamma_{fnt} = \delta_{nt} + \delta_{jnt} + \varepsilon_{fnt}, \tag{4}$$

where γ_{fnt} is the growth rate of sales of firm f in sector j to market n, $\delta_{nt} = \Delta\log Y_{nt}$ is the aggregate ("macroeconomic") shock to the destination demand (to France if $n = d$), $\delta_{jnt} = \Delta\log\alpha^j_{nt} + (1-\theta)(\Delta\log c^j_{dt} - \Delta\log P^j_{nt})$ captures the sectoral (country n-specific) demand and cost shocks; $\varepsilon_{fnt} = \Delta\log\omega_{fnt} + (1-\theta)\Delta\log a_{fdt}$ is the firm-specific demand and cost shock.

Equation (4) can be applied to the domestic French market and to every foreign market, and can be estimated using data on domestic sales and destination-specific exports, respectively.

Our estimation strategy relies on fixed effects to identify the contribution of destination and sector-destination shocks to the growth rate of individual sales. The firm-destination component ε_{fnt} – referred to simply as the *firm-specific* component from now on – is then the residual of the regression. 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. However, this estimation strategy does not let us identify all the shocks. 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, the macroeconomic shock and all of the sectoral shocks cannot be estimated separately in the linear regression framework. Instead, what can be estimated is a conflation of the macroeconomic shock with a shock to an individual "reference" sector, and the sectoral shocks in all other sectors expressed relative to the reference sector.[7] However, since we are ultimately interested in the firm-specific component and its contribution to aggregate fluctuations, this does not pose a problem. 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 impact our estimates of firm-specific shocks, or their impact on the aggregate economy. In what follows, we estimate a set of sector-destination shocks, denoted by $\tilde{\delta}_{jnt}$, that are sector- and market-specific and encompass the macroeconomic and sectoral shocks of the theoretical model (δ_{nt} and δ_{jnt}). We then use these estimates to extract the firm-specific component of individual growth rates (ε_{fnt}). The estimating equation thus becomes

$$\gamma_{fnt} = \tilde{\delta}_{jnt} + \varepsilon_{fnt}. \tag{5}$$

[7] Specifically, for any given market n at time t the full set of sector-destination effects will span the country effect. Therefore, to identify the country effect, a sector effect would have to be dropped. Changing this "reference" sector can affect the estimates of δ_{nt} and δ_{jnt} as well as their variance.

In our theoretical framework, the firm-specific shock, $\varepsilon_{fnt} = \Delta \log \omega_{fnt} + (1 - \theta)\Delta \log a_{fdt}$, can be further decomposed into the common and the market-specific components using the following second-stage estimation:

$$\varepsilon_{fnt} = \varepsilon^1_{ft} + \varepsilon^2_{fnt}, \tag{6}$$

where ε^1_{ft} is a firm-time effect that captures the firm-specific shock common to all destinations: $\varepsilon^1_{ft} = (1-\theta)\Delta \log a_{fdt}$, and ε^2_{fnt} is the residual that captures the destination-specific demand shock: $\varepsilon^2_{fnt} = \Delta \log \omega_{fnt}$.[8]

The two-step approach of (i) running (5), and (ii) taking the resulting estimates, and running (6) leads to a comprehensive set of estimates of shocks that are affecting firms.

2.3 Model Extensions and Estimation Implications

The sales equation (3) is straightforward to estimate. However, the structure of the motivating model might ignore potentially important effects, which in turn may lead to a misleading interpretation of the results. Specifically, there are two important issues that may lead to specification errors in the main regression equation (5).

First, the model laid out above exhibits a unitary elascitity of firm sales with respect to aggregate and sectoral shocks. 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, which would lead to bias in the estimation, and therefore confound firm-specific shocks with heterogeneous responses to more aggregate shocks in the error terms ε_{fnt}. There are several theoretical channels that would deliver a heterogeneous response. One example is a model laid out in Appendix B, in which variable markups imply the size of the firm affects its reaction to different shocks. Di Giovanni and Levchenko (2011) show that the impact of this channel on aggregate volatility is small. However, as a robustness check we carry out alternative estimations in which we interact firm size with the sector-destination effect in the following augmented regression:

$$\gamma_{fnt} = \tilde{\delta}_{jnt} + \tilde{\tilde{\delta}}_{jnt} \times Size_{fnt} + \beta Size_{fnt} + \varepsilon_{fnt}, \tag{7}$$

[8]Specifically, we can estimate ε^1_{ft} as the time t average of ε_{fnt} for each firm that serves multiple destinations (including the domestic market).

where $Size_{fnt}$ is either log sales, or a dummy variable indicating which quintile of the sales distribution firm fn sales fall into.[9]

Second, the firm-specific shocks ε_{fnt} need not be purely idiosyncratic as in Gabaix (2011). For example, these shocks may covary among firms if their activity is interconnected, for instance through input-output linkages (e.g., Acemoglu et al., 2012; Foerster et al., 2011), or other potential firm interactions. To illustrate this possibility, Appendix C 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 measure the importance of these channels, 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.

2.4 Aggregate Volatility

We next use the estimated firm-specific and sector-destination components to calculate their contributions to aggregate fluctuations. The growth rate of aggregate sales to all destinations between $t-1$ and t, γ_{At}, can be written as:

$$\gamma_{At} = \sum_{j,n} w_{jnt-1} \tilde{\delta}_{jnt} + \sum_{f,n} w_{fnt-1} \varepsilon_{fnt}, \tag{8}$$

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.

The variance decomposition of aggregate sales growth is based on the standard deviation of aggregate output growth between 1991 and 2007, which by definition is equal to the square root of

$$\sigma_A^2 = \frac{1}{T-1} \sum_{t=1991}^{2007} (\gamma_{At} - \bar{\gamma}_A)^2, \tag{9}$$

[9] Interacting fixed effects in order to control for potential unobserved heterogeneous effects follows a long tradition in labor economics. See Firpo et al. (2011) for an exhaustive survey on decomposition methods. Following the accepted practice in this literature, our preferred specification captures size differences using quintile dummies, since that allows for greater (non-parametric) flexibility in the estimation.

where $\bar{\gamma}_A \equiv \frac{1}{T}\sum_{t=1991}^{2007}\gamma_{At}$ is the mean growth rate over the sample period. Taking the variance of the right-hand side of (8), the variance of the aggregate volatility σ_A^2 can be *exactly* written as the sum of the variances and covariances of the aggregated shocks:

$$\sigma_A^2 = \sigma_{JN}^2 + \sigma_F^2 + COV, \tag{10}$$

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

While equation (10) represents an exact decomposition of the time-series aggregate variance (9), it is inconvenient for our purposes because it conflates the variances of shocks $\tilde{\delta}_{jnt}$ and ε_{fnt} with movements of the shares w_{jnt-1} and w_{fnt-1} over time. Since we would like to isolate the contribution of the variances of $\tilde{\delta}_{jnt}$ and ε_{fnt} to aggregate volatility, it will be more illuminating to express aggregate variance as a summation of variances and covariances of the shocks themselves (rather than of the shocks-cum-shares):

$$\begin{aligned}\sigma_{At}^2 &= \sum_{g,m}\sum_{f,n} w_{fnt-1}w_{gmt-1}\text{Cov}\left(\gamma_{fnt},\gamma_{gmt}\right)\\ &= \sigma_{JNt}^2 + \sigma_{Ft}^2 + COV_t,\end{aligned} \tag{11}$$

where

$$\sigma_{JNt}^2 = \sum_{k,m}\sum_{j,n} w_{jnt-1}w_{kmt-1}\text{Cov}\left(\tilde{\delta}_{jnt},\tilde{\delta}_{kmt}\right) \qquad \text{(Sector-Destination Volatility)}$$

$$\sigma_{Ft}^2 = \sum_{g,m}\sum_{f,n} w_{fnt-1}w_{gmt-1}\text{Cov}\left(\varepsilon_{fnt},\varepsilon_{gmt}\right) \qquad \text{(Firm-Specific Volatility)}$$

$COV_t =$ the sum of the covariances of the shocks from different levels of aggregation.

Comparing (10) to (11), it is clear that the latter takes the shares w_{jnt-1} and w_{fnt-1} out of the Var/Cov operator, treating these shares in effect as constant (non-random) *at a point in time*. This approach has been adopted in the literature to disentangle the volatilities of the shares from those of the shocks (e.g., Carvalho and Gabaix, 2010; Gabaix, 2011).[10] Note that because (11) is well-defined under the weights from

[10] 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 (10) and (11)

any period in our dataset, σ^2_{At} can be calculated in each individual year. Below we report our estimates of σ^2_{At} in each year, although what ultimately matters for our bottom line is some sense of the average σ^2_{At} over the whole period.

The first term in (11) measures the volatility of sector-destination shocks, which affect all firms within or across sectors for a particular destination market. It is driven by the volatility of the sector-destination shocks ($\text{Var}(\tilde{\delta}_{jnt})$) and their covariance across countries and sectors ($\text{Cov}(\tilde{\delta}_{jnt}, \tilde{\delta}_{kmt})$). 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_{jnt-1}). Thus, French shocks have a larger impact on aggregate volatility than shocks affecting French firms's sales to, say, Japan. Likewise, a country specializing in highly volatile sectors is likely to display large aggregate fluctuations (Koren and Tenreyro, 2007; di Giovanni and Levchenko, 2012). 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 (11), σ^2_{Ft}, measures the contribution of firms to aggregate fluctuations. As in Gabaix (2011), the firm-specific contribution to aggregate volatility is likely to be larger, everything else equal, if the distribution of sales across firms is more dispersed. 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 the firm-specific component of aggregate fluctuations. Section 4.3 discusses in more detail the microeconomic underpinnings of σ^2_{Ft}, both in theory and in our data.

We follow the convention in the literature and use the standard deviation as our

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

measure of volatility. Therefore, when discussing contributions to aggregate volatility we will present the results in terms of *relative standard deviations*, such as σ_{Ft}/σ_{At}.

3 Data Description

The analysis is performed on firm-level data containing 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 1992–1993 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. Both datasets can be merged together thanks to a unique *firm* identifier, called SIREN. We do not have any information at the *plant* level, however.

The first dataset, collected by the fiscal administration, gives balance-sheet information contained in the firms' tax forms. For those firms, 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 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).[11]

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 these data are complicated to harmonize with the rest of the sample. In 2007, those firms represent less than 4% of total sales and about 11% of total employment. Therefore, our sample represents the bulk of the aggregate French economy.

The BRN sample covers 1,577,039 firms undertaking activities in 52 NAF sectors.[12]

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

[12] "NAF", Nomenclature d'Activités Française, is the French industrial classification. Our analysis considers the level of aggregation with 60 sectors. This corresponds to the ISIC (Revision 3) nomenclature with two digits. Before running the regression, we merge together some sectors in order for

This represents around 30% of industrial and service firms but more than 90% of aggregate sales.[13] Of those firms, 208,596 belong to the manufacturing industry (22 NAF industries), which accounts for around 30% of aggregate sales. The dataset provides us with a detailed description of the firms' balance sheets, namely their total, domestic, and export sales, their value added, as well as many components of their costs including the wages they pay, the primary material they buy, and so on.

The information collected by the tax authorities is combined with firm-level export data provided to us by the French customs authorities. This database gives the (free on board) value each French firm exports to each of its destinations over a given fiscal year.[14] Merging these bilateral export flows with the balance sheets completes the dataset with information about the participation of firms in international markets and the geographical distribution of their foreign sales. In our sample, 18% of all firms (and 42% of manufacturing firms) export at some point in time. In merging together the customs and balance-sheet data, we had to make a number of decisions: i) we drop observations on firms that appear in the customs but do not appear in the BRN file (some of these firms may produce farming goods, which are not in the balance-sheet data); ii) 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 customs data are the most reliable source of exporting

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 1990–1992 are converted into the NAF classification using a correspondence table.

[13] 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.

[14] 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 fill 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 do not know *ex-ante* that they don't need to, or because they delegate the customs-related tasks to a third party (e.g., a transport firm) that systematically fills the customs form.

information, we assume that those firms are non-exporters; iii) even when the firm is present in both the customs and the BRN data, the value of export sales is never 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.

Our procedure involves fitting an empirical model on the sales growth rates of firms to individual markets, and retaining the residuals as the firm-specific shocks. One concern with this procedure is that in the data 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, the set of individual growth rates we obtain has a great deal of dispersion. In fact there are a number of reasons for the data to display important outliers. For instance, the BRN file does not provide any information on firms whose accounts are controlled by the fiscal administration 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 the year(s) the firm is controlled. Also, firms that change their organizational structure in a given year, grouping activities together in different entities 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, disappeared from the fiscal files as a consequence.

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. This data cleaning procedure produces a sample of firms whose total sales and export sales mimic aggregate activity quite well. Indeed, the growth rate of total sales in the final sample 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). Third, we repeat the analysis on 3-year growth rates instead of annual growth rate as one of the robustness checks, which helps average 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.

Table 1 presents summary statistics for firm-level growth rates for the whole economy and the manufacturing sector, respectively. Growth rates tend to be higher for the average firm and more dispersed across all firms in the manufacturing sector, but overall there is not a large difference between firms in the manufacturing sector relative to all firms in the economy.

The analysis in the paper is carried out on 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 employment (e.g. Moscarini and Postel-Vinay, 2011). 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. Thus, we cannot replicate our results using either employment or value added instead of sales. However, we can 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.

The top panel of Table A2 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 sales share, at nearly 37% of the total. While the stantard 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 robustness of the results, all of the analysis in the paper is carried out both on the whole economy and on the manufacturing sector.

The bottom panel of Table A2 presents the mean standard deviations of firm-destination growth rates by size quintile, as well as among the top 100 and top 10 firm-destination sales. Volatility decreases in firm-destination size, with a difference of 0.09 in the standard deviation between the top and bottom quintiles of the firm size (sales) distribution. Note that these summary statistics are with respect to firm-destination sales observations rather than firm sales. Even breaking down into destinations, the distribution is quite fat-tailed. The top 10 firm-destination entries account for 7.64% of total sales in the economy, and the top 100 firm-destinations account for 21.93% of total sales.

4 Empirical Results

4.1 Regression Results

Before assessing the impact of firm-specific shocks on aggregate volatility, we present the importance of the different components for 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, respectively.

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.[15] Examining the bottom two panels, it is clear that the importance of the firm-specific component holds for both domestic and export sales.

Whether the firm-specific shocks are common to all destination markets served by the firm or destination-specific is less well understood. Furthermore, looking at the

[15] A variance decomposition of the regression estimates for 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).

data through the lens of the model in Section 2, this decomposition is informative of whether supply or demand shocks are driving firms' sales growth. Table 4 presents the results of extracting the common firm component from destination-specific effects as in equation (6), for both the whole economy and the manufacturing sector.[16] The motivating theoretical model in Section 2 helps interpret this exercise. Since the firm's marginal cost of serving each market (modulo iceberg trade costs) is the same, the component of the firm-specific shock that is common to all destinations can be interpreted as a productivity shock. The destination-specific component of the firm shock is in turn interpreted as a demand shock.

Results are similar in the two samples. For the whole economy, the destination-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 that 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.[17]

4.2 The Aggregate Impact of Firm-Specific Shocks

It is unsurprising that most of the variation in the growth rate of sales is accounted for by firm-specific shocks. This in itself 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 2.4.

Table 5 presents the results using the volatility definition in equation (11), and takes the average of the standard deviation and relative standard deviations over the

[16] 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.

[17] This result is consistent the findings of Eaton et al. (2011a) who fit a 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 to explain aggregate exports.

sample period. The results for the whole economy are in the first two columns, and for the manufacturing sector in the next two columns.[18]

First, 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 0.76 compared 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 0.67. The bottom panels of Table 5 check the results on domestic sales to France only as well as export sales. 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 even more granular than overall sales (Canals et al., 2007).

The results for the manufacturing sector largely mimic those of the whole economy. The relative standard deviation of the firm-specific component of aggregate sales is 0.63 of the actual sales volatility. In this sample, the firm-specific component is slightly less important for aggregate fluctuations than the sector-destination shocks, which have a relative standard deviation of 0.74. The bottom panels of Table 5 check the results on domestic sales to France only as well as export sales. Once again, they show that firms contribute more to aggregate fluctuations for exports than for domestic sales.

Figure 3 presents the plots of σ_{At} and its main components: firm-specific (σ_{Ft}), and sector-destination (σ_{JNt}) for the whole economy and the manufacturing sector. The first notable feature of these plots is how the firm-specific component comoves with the aggregate over-time, whereas the standard deviation of sector-destination shocks is nearly constant over time. Recalling how the different components are calculated from

[18] Overall, the estimated standard deviations of aggregate sales and firm-specific volatility match up both qualitatively and quantitatively if we use the decomposition (10) instead ($\sigma_A = 0.021$ and 0.026, and $\sigma_F = 0.009$ and 0.012 for the whole economy and the manufacturing sector, respectively), though the firm-specific contribution is smaller using the definition (10) (the relative standard deviations, $\frac{\sigma_F}{\sigma_A} = 0.45$ and 0.46 for the whole economy and the manufacturing sector, respectively). However, as discussed in footnote 10, this is to be expected. We therefore use the decomposition in (11) as our baseline when reporting the results.

(11), 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.[19] These shares do not change dramatically at the sector×country level. More interestingly, the firm-specific shocks increase in importance over the sample. For the whole economy, the relative standard deviation of the firm-specific to total sales is 0.39 in 1991, peaking at 1.00 in 1998, before falling to 0.85 in 2007. For the manufacturing sector, the contribution of firms to aggregate fluctuations increases almost monotonically, from 0.43 in 1991 to 0.78 in 2007. These results are a first glimpse of the importance of large firms and firm linkages on aggregate fluctuations. We discuss further what drives these results in Section 4.3.

Before turning to the mechanisms behind the contribution of individual firms to aggregate volatility, we perform several robustness checks on the importance of firm-specific shocks. First, we run the regression specification (7) to control for potential heterogeneous impacts of sector-destination shocks at the firm-destination level. The top two panels of Table A3 present the results obtained under alternative proxies for firms size. The top panel uses a size quintile dummy variable to capture possible heterogeneity of impact of country/sector shocks on firm by size. The specification in the middle panel uses log sales as the size variable. Finally, the bottom panel in Table A3 presents results when estimating the baseline regression (5) on three-year average firm-destination growth rates, instead of yearly growth rates.

Overall, the qualitative results do not change. The contributions of firm-specific relative shocks to aggregate sales volatility are still sizeable in both specifications based on (7). We take this as suggestive evidence that our results are robust to allowing for firm-destinations sales growth to react heterogeneously to macroeconomic and sectoral shocks. Finally, the results are robust to time aggregation.[20]

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

[19]It is possible that a change in the composition of firms or sectors/destinations each period could also drive the results, but this effect is largely absent for the contribution of the sector×country level shocks.

[20]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.

disentangle the economic mechanisms at work. Recalling the definition of aggregate firm-specific volatility from Section 2.4:

$$\sigma_{Ft}^2 = \sum_{g,m} \sum_{f,n} w_{gmt-1} w_{fnt-1} \mathrm{Cov}(\varepsilon_{gmt}, \varepsilon_{fnt}),$$

we decompose it into the contribution of individual variances and comovements between firms:

$$\sigma_{Ft}^2 = \underbrace{\sum_{f,n} w_{fnt-1}^2 \mathrm{Var}(\varepsilon_{fnt})}_{GRAN} + \underbrace{\sum_{g \neq f, m \neq n} \sum_{f,n} w_{gmt-1} w_{fnt-1} \mathrm{Cov}(\varepsilon_{gmt}, \varepsilon_{fnt})}_{LINK}. \tag{12}$$

This decomposition emphasizes two potential mechanisms through which idiosyncratic shocks to the growth rate of individual firms' sales may lead to a large variance of the firm-specific component: (i) the variance of individual shocks, labeled $GRAN$, and (ii) the covariance of shocks across firms, labelled $LINK$.

The predominant tradition in macroeconomics has been to assume that the $GRAN$ 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 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.[21] 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, respectively. The $LINK$ component explains the majority of total firm-specific volatility: $\sqrt{LINK}/\sigma_{Ft}$ is approximately 90% on average over the sample period for both the whole economy and the manufacturing sector. However, it

[21] 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.

is apparent from the figures that the $GRAN$ component rises in importance, and after 2000 its contribution to the total averages about 45%. After 2005, its contribution is about the same as of the $LINK$ component.

4.3.1 The Contribution of Granularity

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., $\mathrm{Cov}(\varepsilon_{gmt}, \varepsilon_{fnt}) = 0 \ \forall \ (g, m) \neq (f, n)$) and across markets within a firm ($\mathrm{Cov}(\varepsilon_{fmt}, \varepsilon_{fnt}) = 0, m \neq n$), and the variance of shocks is identical across firms ($\mathrm{Var}(\varepsilon_{fnt}) = \sigma^2 \ \forall \ f, n$). Under these assumptions, aggregate firm-specific volatility (12) is

$$\sigma_{Ft}^2 = \sigma^2 \sum_{f,n} w_{fnt-1}^2 = \sigma^2 \times Herf_{t-1}, \tag{13}$$

where $Herf_{t-1} = \sum_{f,n} w_{fnt-1}^2$ 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 firms are instead symmetric in size ($w_{fnt-1} = 1/N_{t-1}$ where N_{t-1} is the number of firms in the economy), $\sigma_{Ft} = \sigma/\sqrt{N_{t-1}}$ 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 aggregate volatility due to firm-specific shocks under the assumption that all firms and markets are of equal weight (i.e., $w_{fnt-1} = 1/N_{t-1} \ \forall \ (f, n)$). 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 aggregate standard deviation implied by equal weights is 0.00034, or 15 times smaller than the average $\sqrt{GRAN}$ component, which is equal to 0.0053. For the manufacturing sector, the standard deviation implied by equal weights is 0.00081, almost 10 times smaller than the $\sqrt{GRAN}$ component of 0.0061. 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 granularity. To do so, we decompose the $GRAN$ component in equation (12) into sectors, where sector j's $GRAN$ component is defined as $GRAN^j \equiv \sum_{(f,n)\in j} w_{fnt-1}^2 \mathrm{Var}(\varepsilon_{fnt})$, and $GRAN = \sum_{j=1}^{J} GRAN^j$. Again, if $\mathrm{Var}(\varepsilon_{fnt}) = \sigma^2 \; \forall \; (f,n)$, we would expect that more concentrated sectors would display larger volatilities.[22] Figure 5 evaluates this prediction, by plotting (the square root of) $GRAN^j$ against the (square root of the) mean sectoral Herfindahl index for the whole economy and the manufacturing sector. In Figure 5, $GRAN^j$ 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. As expected the correlation is positive – sectors with higher sales concentration display a larger variance, which is consistent with granularity. The correlation is lower for the whole economy (0.57) than for the manufacturing sector (0.72). 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 A2). This heterogeneity in firm-level volatilities counteracts the impact of sales concentration, thus reducing the overall size of the $GRAN$ 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 follows from Acemoglu et al. (2012), and is captured by the covariance terms $LINK$ in (12). Acemoglu et al. present a network model in which 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.

[22] 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 A2 – the correlation between the standard deviations of the actual growth rates and the firm-specific shocks is 0.996 across sectors.

Appendix C 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-ouput 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

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

where θ is the elasticity of substitution, $(1-\alpha_f)$ 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 $\mathrm{Var}(a_{gmt})$ 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, $(1-\alpha_f)\rho_{fg}$. 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.[23]

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-Ouput (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. $\alpha_f = \alpha^i \ \forall \ f \in i$) and that all firms within a sector interact with the same input providers (i.e. $\rho_{fg} = \rho^{ij} \ \forall \ f \in i, \ g \in j$), 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 across sectors can then be related to the magnitude of covariances of firms within a sector. We expect the weighted sum of covariances to be higher for sector pairs that display stronger IO linkages.[24]

Figure 6 examines this hypothesis. We decompose the $LINK$ component in equation (12) across sector pairs, where the $LINK$ term specific to the pair (i, j) is

[23]This is ruled out in the setting of Appendix C 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.

[24]See Appendix C for details.

defined as $LINK^{ij} \equiv \sum_{(f,n)\in i} \sum_{(g,m)\in j} w_{fnt-1} w_{gmt-1} \text{Cov}(\varepsilon_{fnt}, \varepsilon_{gmt})$, and $LINK = \sum_{i=1}^{J} \sum_{j=1}^{J} LINK^{ij}$. We then correlate the (square root of) those terms to the mean intensity of IO linkages between sectors i and j. $LINK^{ij}$ 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 $0.5 \times [(1-\alpha^i)\rho^{ij} + (1-\alpha^j)\rho^{ji}]$, where α^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).[25] The relationship is marginally more pronounced for the manufacturing sector, with a correlation coefficient of 0.49 compared to 0.39 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.

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 (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

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

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 the aggregate sales growth. We interpret this as evidence for the relevance of firm-level shocks for aggregate fluctuations. Second, roughly two thirds of this variation can be explained by firm linkages, and one third by granularity.

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Table 1. Firm-Level Growth Rates: Summary Statistics

	Whole Economy			*Manufacturing Sector*		
	Mean	St. Dev.	Obs.	Mean	St. Dev.	Obs.
1991	0.0474	0.2645	440,522	0.0462	0.3063	120,061
1992	0.0337	0.2627	456,301	0.0415	0.3067	125,985
1993	0.0139	0.2616	398,510	0.0180	0.3056	105,605
1994	0.0433	0.2669	430,029	0.0641	0.3110	112,640
1995	0.0459	0.2620	537,846	0.0706	0.3069	140,943
1996	0.0302	0.2583	551,923	0.0407	0.3007	145,192
1997	0.0388	0.2579	588,362	0.0582	0.3024	152,009
1998	0.0569	0.2615	609,656	0.0695	0.3041	155,960
1999	0.0520	0.2589	617,191	0.0522	0.3023	156,990
2000	0.0684	0.2623	620,821	0.0778	0.3072	155,553
2001	0.0603	0.2590	610,967	0.0627	0.3057	153,277
2002	0.0407	0.2544	629,390	0.0355	0.3007	153,953
2003	0.0368	0.2541	650,009	0.0339	0.2976	154,518
2004	0.0486	0.2565	659,113	0.0534	0.3002	153,037
2005	0.0468	0.2576	671,130	0.0499	0.3004	151,767
2006	0.0546	0.2597	688,136	0.0639	0.3014	150,603
2007	0.0559	0.2635	696,987	0.0711	0.3030	147,924
Mean	0.0455	0.2601		0.0535	0.3037	

Notes: This table presents the summary statistics for the whole economy and our sample of manufacturing firms over 1991–2007.

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	9,856,889	0.0467	0.2601	1.0000
Firm-Specific	9,856,889	0.0000	0.2583	0.9934
Sector-Destination	16,235	0.0762	0.1259	0.1145
	II. Domestic Sales			
	(1)	(2)	(3)	(4)
	Obs.	Mean	St. Dev.	Correlation
Actual	8,031,451	0.0410	0.2266	1.0000
Firm-Specific	8,031,451	0.0000	0.2255	0.9954
Sector-Destination	595	0.0453	0.0304	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	0.9930
Sector-Destination	15,640	0.0774	0.1279	0.1185

Notes: This table presents the average growth rate, standard deviations, and correlations with the actual, for the two (non-aggregated) components of firm-destination-level growth: Firm-Specific, and Sector-Destination level, over 1991–2007. These estimates are obtained by running the regression in equation (5).

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

	(1)	(2)	(3)	(4)
I. Total Sales				
	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	0.0741	0.0968	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: This table presents the average growth rate, standard deviations, and correlations with the actual, for the two (non-aggregated) components of firm-destination-level growth: Firm-Specific, and Sector-Destination level, over 1991–2007. These estimates are obtained by running the regression in equation (5).

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: This table presents the average growth rates, standard deviations, and correlation coefficients, for the two components of (non-aggregated) firm-specific shocks: the common and destination-specific components, over 1991–2007. These estimates are obtained by running the regressions in equation (6).

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

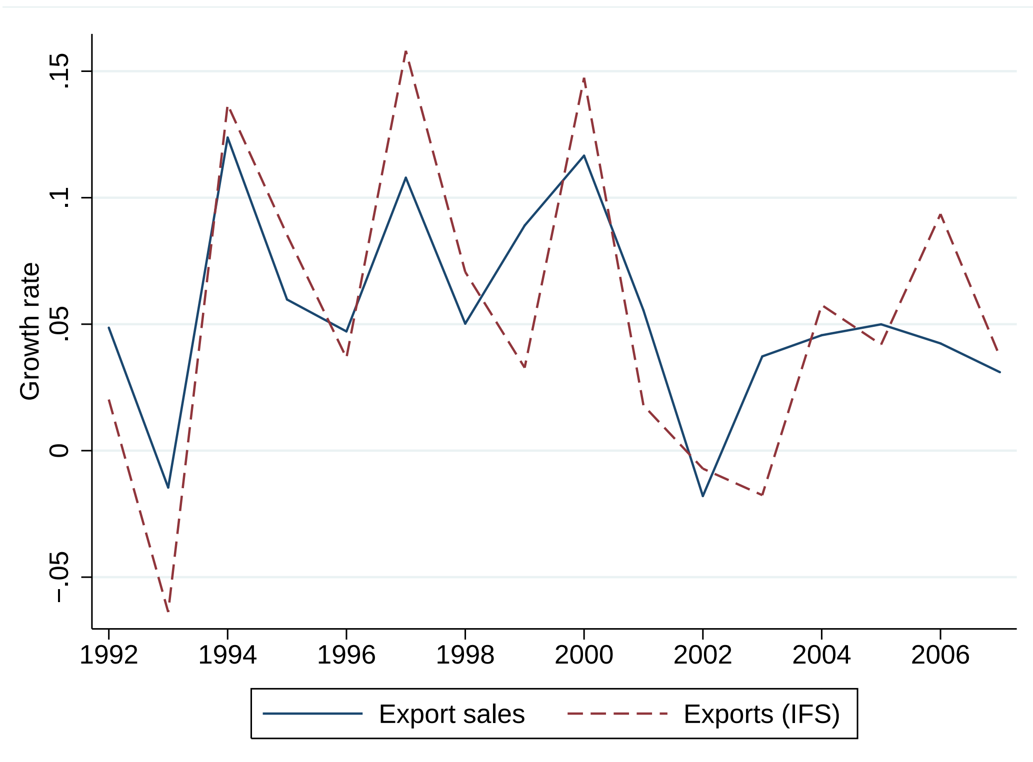
	Whole Economy		*Manufacturing Sector*	
I. Total Sales				
	(1)	(2)	(3)	(4)
	St. Dev.	Relative SD	St. Dev.	Relative SD
Actual	0.0214	1.0000	0.0261	1.0000
Firm-Specific	0.0164	0.7584	0.0165	0.6266
Sector-Destination	0.0137	0.6663	0.0189	0.7394
II. Domestic Sales				
	Whole Economy		*Manufacturing Sector*	
	(1)	(2)	(3)	(4)
	St. Dev.	Relative SD	St. Dev.	Relative SD
Actual	0.0185	1.0000	0.0195	1.0000
Firm-Specific	0.0139	0.7441	0.0114	0.5778
Sector-Destination	0.0127	0.7148	0.0157	0.8186
III. Export Sales				
	Whole Economy		*Manufacturing Sector*	
	(1)	(2)	(3)	(4)
	St. Dev.	Relative SD	St. Dev.	Relative SD
Actual	0.0037	1.0000	0.0086	1.0000
Firm-Specific	0.0029	0.7874	0.0062	0.7224
Sector-Destination	0.0016	0.4475	0.0041	0.4909

Notes: This table presents the standard deviations, in absolute and relative terms with respect to the actual, for the two components of aggregate growth: firm-specific and sector-destination, over 1991–2007. These estimates are obtained from the aggregation equation (11), using regression results from estimating equation (5). The estimates are averaged over the sample period: $\frac{1}{T}\sum_{t=1991}^{2007}\sigma_{At}$, $\frac{1}{T}\sum_{t=1991}^{2007}\sigma_{Ft}$, $\frac{1}{T}\sum_{t=1991}^{2007}\sigma_{JNt}$; $\frac{1}{T}\sum_{t=1991}^{2007}\frac{\sigma_{Ft}}{\sigma_{At}}$, $\frac{1}{T}\sum_{t=1991}^{2007}\frac{\sigma_{JNt}}{\sigma_{At}}$.

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

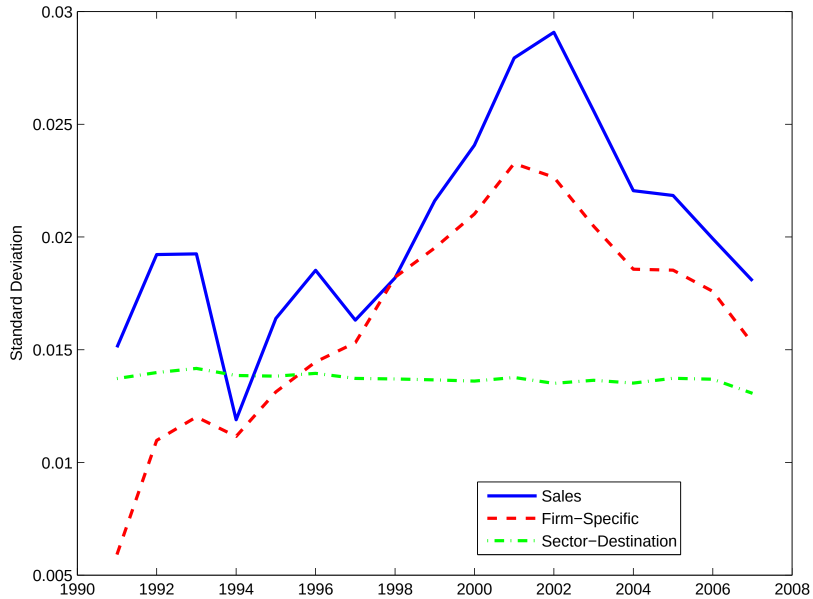
Notes: This figure presents the time series of the growth rates of total sales, before-tax value added, in our data and GDP sourced from the IMF International Financial Statistics.

Figure 2. Growth of Aggregate Exports

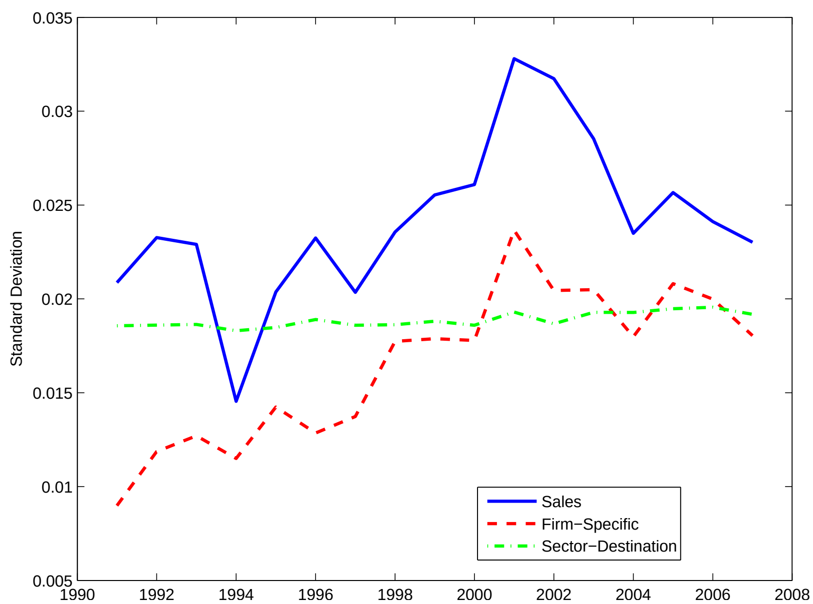


Notes: This figure presents the time series of the growth rates of total exports in our data and total French exports sourced from the IMF International Financial Statistics.

Figure 3. Volatility of Sales Growth and its Components



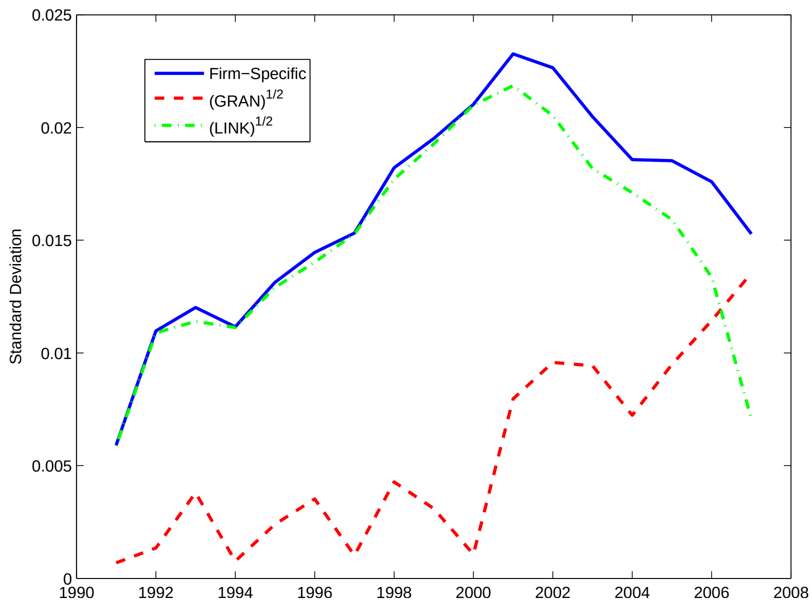
(a) Whole Economy



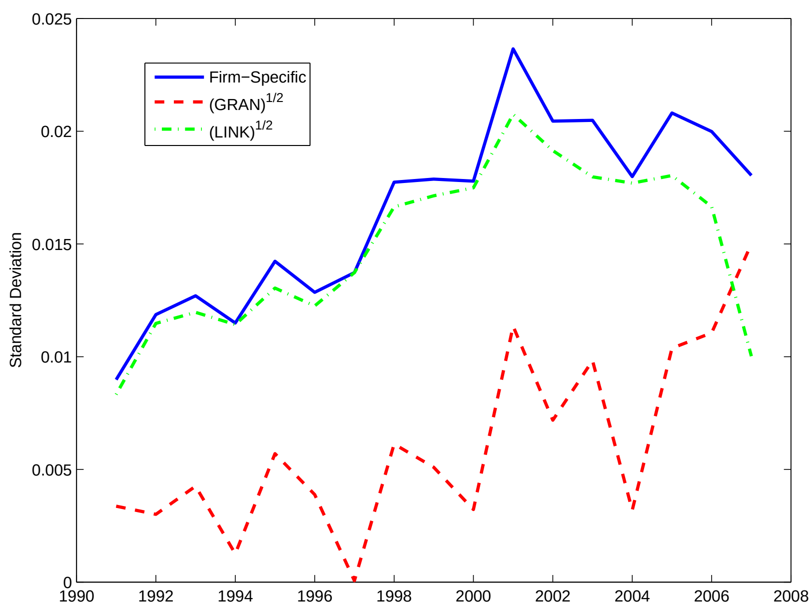
(b) Manufacturing Sector

Notes: This figure presents the time-varying volatilities computed using the aggregation formula (11).

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



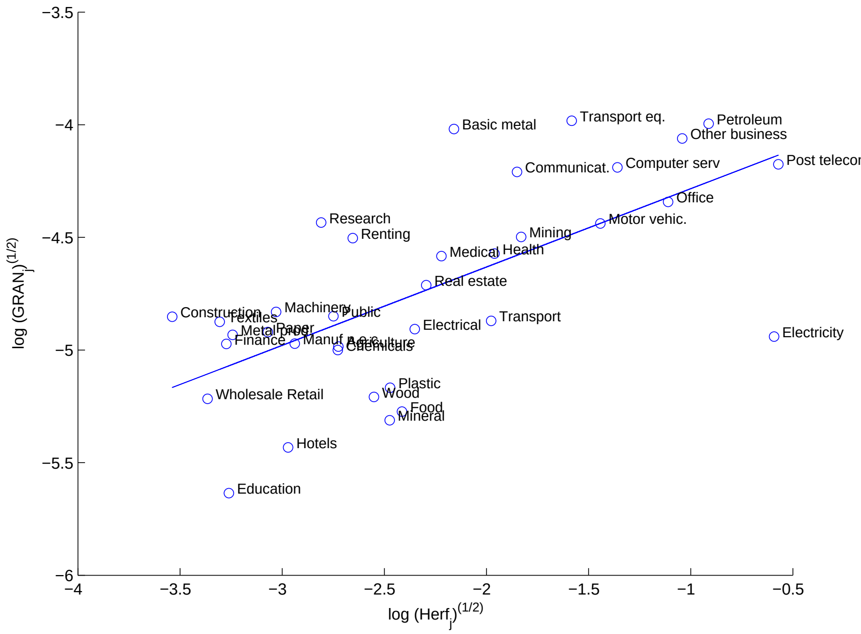
(a) Whole Economy



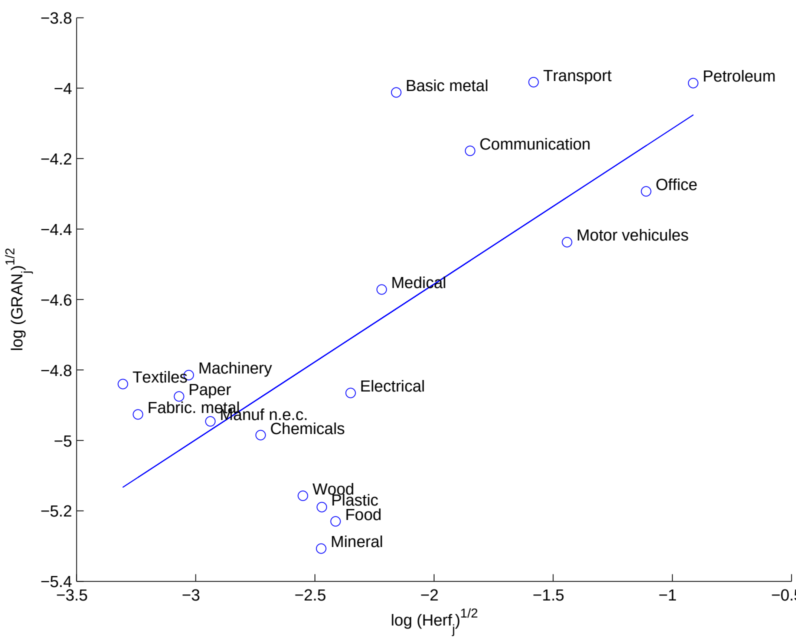
(b) Manufacturing Sector

Notes: Decomposition of the Firm-Specific aggregate variance into two component that measure the contribution of firm-specific variances ($\sqrt{GRAN}$), and of covariance across firms ($\sqrt{LINK}$). The decomposition is based on equation (12).

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



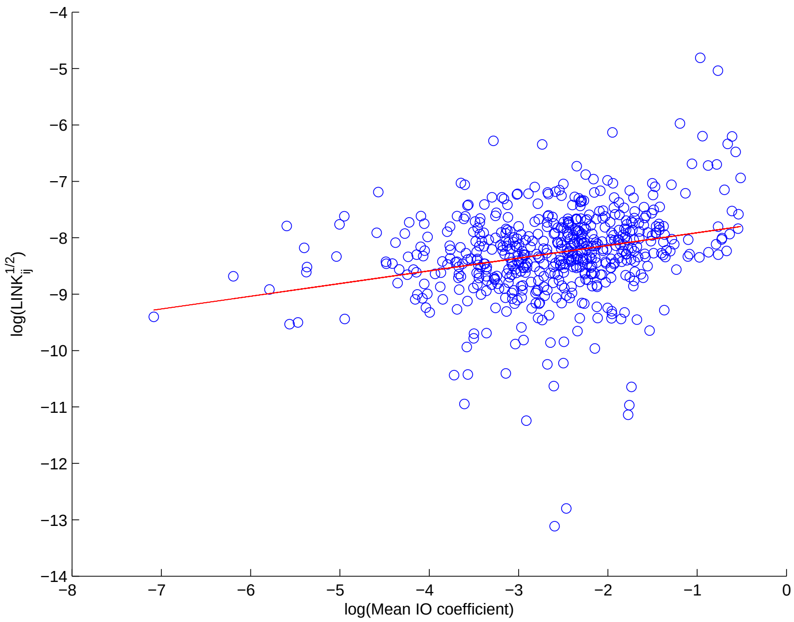
(a) Whole Economy



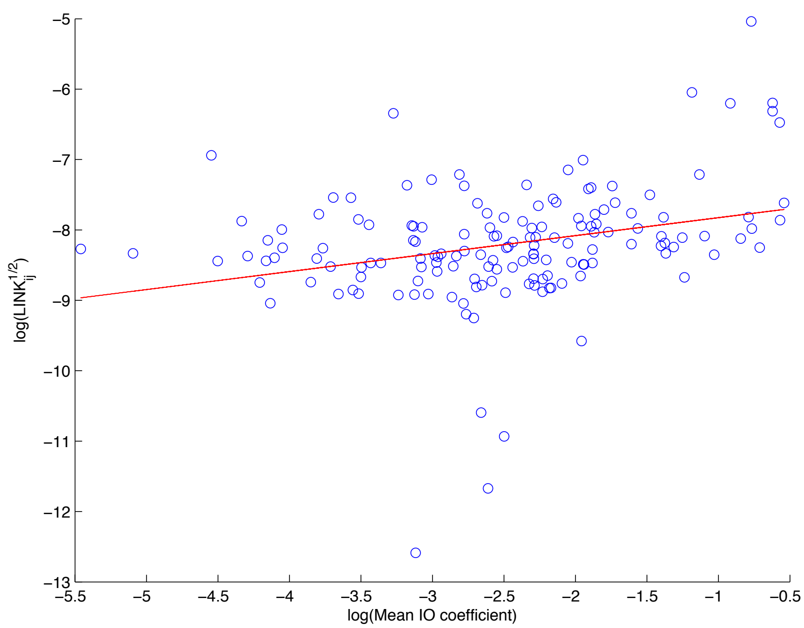
(b) Manufacturing Sector

Notes: This figure plots the correlation of the mean individual volatility ($\sqrt{GRAN}$ component) against the square root of the mean Herfindahl index. The correlation between $\sqrt{GRAN}$ and $\sqrt{Herf}$ is 0.57 for the whole economy and 0.72 for the manufacturing sector. The plot is log-log.

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 correlation of the sum of bilateral covariance terms across sectors ($\sqrt{LINK^{ij}}$) against the mean IO linkage (share of intermediate inputs in total costs times the share of the upstream sector in intermediate consumption). The correlation between the covariances and the IO linkages is 0.38 for the whole economy and 0.47 for the manufacturing sector. The plot is log-log.

APPENDICES
(NOT FOR PUBLICATION)

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 growth rate of total sales can be manipulated to obtain an (exact) decomposition into intensive and extensive components:

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

where $I_{t/t-1}$ is the set of firm×destination pairs active in both t and $t-1$ (the intensive sub-sample of firms×destinations in year t) and $\lambda_{t,t}$ ($\lambda_{t,t-1}$) 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.[26] 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:

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

where $g_{\lambda t} \equiv \ln \lambda_{t,t}/\lambda_{t,t-1}$ is the extensive margin component of equation (A.1) and

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

σ^2_λ is its variance, σ^2_A is the variance of the intensive margin growth rate γ_{At}, and $\mathrm{Cov}(\gamma_{At}, g_{\lambda t})$ is the covariance between the two.

The intensive margin growth rate γ_{At} and the intensive margin variance σ^2_A are the objects of the analysis in the main text. Inclusive of entry and exit, the volatility of total sales $\tilde{\sigma}^2_A$ is the sum of three components: i) the volatility of output produced by incumbent firms – the intensive margin, ii) the 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.[27] 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.[28]

Table A1 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 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

[27] 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.

[28] 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 4.2).

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.[29]

Appendix B 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 aggregate/sectoral shocks. The model serves to motivate the alternative empirical model (7), in which aggregate/sectoral shocks affect firm sales differently depending on firm size. 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:

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

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

$$p_{fnt} = \tilde{p}_{fnt} \tau_{ndt}^{j} + \eta_{ndt}^{j},$$

where $\tilde{p}_{fnt}$ is the producer price, τ_{ndt}^{j} the multiplicative variable trade cost, and η_{ndt}^{j} the additive variable trade cost.[30] Both τ_{ndt}^{j} and η_{ndt}^{j} are assumed to be the same for

[29] These results are available upon request.

[30] The additive cost η_{ndt}^{j} 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.

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:

$$\tilde{p}_{fnt} = \frac{\theta}{\theta - 1} m_{fnt} a_{fdt} c^j_{dt},$$

where

$$m_{fnt} \equiv 1 + \frac{\eta^j_{ndt}}{\theta \tau^j_{ndt} a_{fdt} c^j_{dt}},$$

is the variable component of markups. Importantly, this component is affected by sectoral cost movements (changes in c^j_{dt}) as well as changes in variable trade costs (τ^j_{ndt} and η^j_{ndt}). 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:

$$\begin{aligned} x_{fnt} &= \tilde{p}_{fnt} C_{fnt} \\ &= \omega_{fnt} \frac{\alpha^j_{nt} Y_{nt}}{\left(P^j_{nt}\right)^{1-\theta}} \left(\frac{\theta}{\theta - 1} \tau^j_{ndt} c^j_{dt} a_{fdt} \right)^{1-\theta} \left(\frac{m_{fnt}}{\tau^j_{ndt}} \right)^{1-\theta} \left(\frac{p_{fnt}}{\tilde{p}_{fnt}} \right)^{-\theta}. \end{aligned} \tag{B.1}$$

If we were to use (B.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

$$\begin{aligned}
&\frac{d\ln x_{fnt}}{d\ln c^j_{dt}} = (1-\theta) + (1-\theta)\frac{d\ln m_{fnt}}{d\ln c^j_{dt}} - \theta\frac{d\ln\left(\frac{\tilde{p}_{fnt}}{p_{fnt}}\right)}{d\ln c^j_{dt}}\\
\text{where}\quad &\frac{d\ln m_{fnt}}{d\ln c^j_{dt}} = \frac{-\eta^j_{ndt}}{\theta\tau^j_{ndt}a_{fnt}c^j_{dt} + \eta^j_{ndt}} \in [-1,0]\\
\text{and}\quad &\frac{d\ln\left(\frac{\tilde{p}_{fnt}}{p_{fnt}}\right)}{d\ln c^j_{dt}} = \frac{-\eta^j_{ndt}}{p_{fnt}}\left(1+\frac{d\ln m_{fnt}}{d\ln c^j_{dt}}\right) < 0
\end{aligned}$$

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 $\tilde{\delta}_{jnt}$ 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 estimate equation (7) that interacts the sector-destination effect with measures of firm size, which proxies for firms' productivity. Following the model laid out in this section, the interaction term is intended to capture the larger markup adjustment of the more productive firms in response to sector-destination shocks.[31]

Appendix C 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

[31] The theoretical model implies heterogeneity in the response of firms to sector-destination shocks that is linear in firm productivity. To estimate a more flexible and less parametric empirical model, we also use the quintiles of size interacted with the sector-destination shock.

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:

$$x_{fnt} = \omega_{fnt} \frac{\alpha^j_{nt} Y_{nt}}{(P^j_{nt})^{1-\theta}} \left(\frac{\theta}{\theta - 1} \tau^j_{nd} c_{fdt} a_{fdt} \right)^{1-\theta},$$

where

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

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 α_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:

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

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

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

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

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

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., will have a larger impact. This is what the first term of (C.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 (C.1) and (C.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:

$$LINK = \sum_{g \neq f, m \neq n} \sum_{f,n} w_{gmt-1} w_{fnt-1} \text{Cov}(\varepsilon_{gmt}, \varepsilon_{fnt}) = \sum_i \sum_j LINK^{ij}, \text{ where}$$
$$LINK^{ij} = \sum_{g,m \in j} \sum_{f,n \in i} w_{gmt-1} w_{fnt-1} \text{Cov}(\varepsilon_{gmt}, \varepsilon_{fnt}),$$

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

Assume that i) individual volatilities are homogeneous across firms: $\text{Var}(a_{fdt}) = \sigma^2 \; \forall \; f$; ii) the IO coefficients are homogeneous between firms within a sector: $(1 - \alpha_f) = (1 - \alpha^i) \; \forall \; f \in i$ 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

$$LINK^{ij} = w_{jmt-1} w_{int-1} \sigma^2 (1-\theta)^2 \left[\underbrace{(1-\alpha^j)\rho^{ji} + (1-\alpha^i)\rho^{ij}}_{\text{First-order}} + \underbrace{\sum_k (1-\alpha^i)(1-\alpha^j)\rho^{ik}\rho^{jk}}_{\text{Second-order}} \right].$$

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

Table A1. Intensive and Extensive Margins and Aggregate Volatility

	Whole Economy		*Manufacturing Sector*	
	(1)	(2)	(3)	(4)
	St. Dev.	Relative SD	St. Dev.	Relative SD
Actual	0.0305	1.0000	0.0309	1.0000
Intensive	0.0256	0.8413	0.0260	0.8429
Extensive	0.0199	0.6525	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 A2. Firm-Level Volatility by Sector and Firm Size

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				

II. Firm-Destination Sales Volatility by Firm-Destination Size

Size	0-20% Pctile	21-40% Pctile	41-60% Pctile	61-80% Pctile	81-100% Pctile	Top 100	Top 10
St. Dev.	0.2835	0.2206	0.2009	0.1914	0.1939	0.1362	0.1269

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

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

	Quintiles of Firm Size			
	Whole Economy		*Manufacturing Sector*	
	(1)	(2)	(3)	(4)
	St. Dev.	Relative SD	St. Dev.	Relative SD
Actual	0.0299	1.0000	0.0321	1.0000
Firm-Specific	0.0170	0.5721	0.0168	0.5273
Sector-Destination	0.0129	0.4495	0.0165	0.5233
	Log Size			
	Whole Economy		*Manufacturing Sector*	
	(1)	(2)	(3)	(4)
	St. Dev.	Relative SD	St. Dev.	Relative SD
Actual	0.0363	1.0000	0.0342	1.0000
Firm-Specific	0.0210	0.5794	0.0186	0.5467
Sector-Destination	0.0162	0.4630	0.0162	0.4820
	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
Sector-Destination	0.0111	0.4701	0.0162	0.5905

Notes: This table presents the standard deviations, in absolute and relative terms with respect to the actual for the two components of aggregate growth: firm-specific and sector-destination, over 1991–2007. The estimates for the first two panels are obtained from the aggregation equation (11), using regression results from estimating equation (7). The estimates are averaged over the sample period: $\frac{1}{T}\sum_{t=1991}^{2007}\sigma_{At}$, $\frac{1}{T}\sum_{t=1991}^{2007}\sigma_{Ft}$, $\frac{1}{T}\sum_{t=1991}^{2007}\sigma_{JNt}$; $\frac{1}{T}\sum_{t=1991}^{2007}\frac{\sigma_{Ft}}{\sigma_{At}}$, $\frac{1}{T}\sum_{t=1991}^{2007}\frac{\sigma_{JNt}}{\sigma_{At}}$. The last panel uses the baseline estimation, 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.