On the measurement of US firms' fixed operating costs

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Abstract

The objective of this study is to estimate the fixed operating costs of American firms using a novel measure that considers firms' flexibility. In the sample, fixed operating costs account for 15.5% of the firm's sales. The results show a significant level of heterogeneity across sectors of economic activity and firm size. In particular, it is found that the fixed operating costs to sales ratio is typically higher in smaller firms and service-related industries. This result is connected to the cost structure of firms in each sector. A negative correlation between the fixed operating costs to sales ratio and the share of COGS in total operating costs is found, as well as positive correlations between this ratio and the shares of SG&A expenses and depreciation and amortization. Lastly, the impact of the COVID-19 pandemic in this measure of fixed operating costs is studied. It is found that whenever the pandemic years are excluded from the regression, the fixed operating costs to sales ratios obtained are lower, on average, for the same dataset of firms and years.

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Resumo

O objetivo deste estudo é estimar os custos operacionais fixos de empresas americanas utilizando uma nova medida que tem em consideração a flexibilidade da empresa. Na amostra, os custos operacionais fixos representam 15.5% das vendas da empresa. Os resultados evidenciam um nível significativo de heterogeneidade por setor de atividade económica e pelo tamanho da empresa. Em particular, conclui-se que o rácio de custos operacionais fixos para vendas é tipicamente maior em empresas mais pequenas e em indústrias relacionadas com os serviços. Este resultado está ligado à estrutura de custos das empresas em cada setor. Existe uma correlação negativa entre o rácio de custos operacionais fixos para vendas e o peso dos Custos de Bens Vendidos, assim como correlações positivas entre este rácio e os pesos de Despesas com Vendas, Gerais e Administrativas e depreciação e amortização. Por fim, o impacto da pandemia de COVID-19 nesta medida de custos operacionais fixos é estudado. Conclui-se que quando os anos de pandemia são excluídos da regressão, os rácios de custos operacionais fixos para vendas obtidos são menores, em média, para a mesma amostra de empresas e anos.

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1. Introduction

Is it possible to accurately estimate a firm's fixed costs? Looking at a firm's financial statements does not provide a lot of help in distinguishing between the costs that are fixed and those that are variable. The reason is that accounting standards do not require firms to make that distinction. Consequently, it becomes necessary to find other ways of estimating a firm's cost structure. The aim of this study is to estimate the operating component of fixed costs for American companies and analyze its variation across industries and size. This is done using the QFC methodology introduced by Gu *et al.* (2018). Additionally, the impact of the COVID-19 pandemic in the measure of fixed operating costs used throughout the study is analyzed.

Firstly, it is crucial to define what a fixed cost is. Typically, fixed costs are defined as those costs that are independent of the level of goods or services provided by a business. In other words, they remain the same no matter what the firm produces. The most common examples of fixed costs are rents, depreciation, insurance contracts, salaries and interest expenses paid on the company's debt. A distinction must be made between the fixed costs that are related to the firm's operations (fixed operating costs) and those that are associated with the firm's financing activities (financial fixed costs). From the examples of fixed costs presented previously, only interest expenses would be considered financial fixed costs, while all the other examples are fixed operating costs. In this study, however, fixed costs are viewed as those that are too costly to avoid. The rationale behind this view is that firms can have fixed costs that are adjustable at a relatively low cost in a short period of time, and could choose to do so in the event of an adverse shock. This view on fixed costs is similar to the one presented by Félix *et al.* (2021) and Gu *et al.* (2018).

Fixed costs have many implications for companies and investors alike. Although having a relatively higher ratio of fixed to variable costs can increase the predictability of a firm's expenses, it also takes away some flexibility for the firm. The literature on this topic documents that fixed costs magnify the impact of shocks in firm income. In other words, higher fixed costs imply that cash flows are more sensitive to sales. On the one hand, if sales are high, profitability will increase because the increased sales are not associated with significantly higher costs. On the other hand, if the firm faces a negative shock in sales, its profitability will decrease as fixed costs remain and only the variable costs are decreased. All in all, high operating leverage requires revenues to keep up, or else profits will decline. Financial leverage works much in the same way at amplifying the effects of an adverse shock to a company. Naturally, these leverage mechanisms and the consequences they can have are very relevant for investors as well. In the presence of a significant amount of leverage, investors require higher returns to invest in the firm, thus increasing the risk premium and the cost of debt (see, for example, Ayres and Blank 2017).

The importance of fixed costs and leverage mechanisms has been present in financial literature for a long time. Interest expenses, for example, are an integral part of the Trade-off theory of capital structure, which claims that corporate leverage is determined by weighing the benefits of interest tax shields against the costs of bankruptcy and is still a dominant theory of capital structure nowadays. A firm's debt and interest payments also serve as inputs for credit risk models attempting to predict default probabilities and boundaries (see, for example, Leland 1994). Further discussion on the importance of fixed costs in the literature is available in Section 2.

More recently, the dire economic context triggered by the pandemic in 2020 highlighted the relevance of measuring fixed operating costs. The consequences were immediate for firms. Bloom *et al.* (2021) report an average drop of 29% in sales of small American businesses in the second quarter of 2020. At the same time, Bartik *et al.* (2020) found that three quarters of the respondents only had enough cash to last 2 months or less. Naturally, in situations such as the one experienced in 2020, a firm's fixed operating costs are decisive for its ability to weather the crisis or not. Actively monitoring the firm's fixed operating costs can prove very useful for managers in case a similar scenario occurs in the future.

The rest of this study is organized as follows. In Section 2, previous literature on operating leverage and its measurement is presented. Section 3 introduces the data used and its treatment and Section 4 describes the operating cost structure of American publicly traded firms, breaking down its components by firm size and sector of economic activity. The construction of the QFC measure is explained in Section 5. Section 6 reports the empirical results obtained in the estimation, and Section 7 checks the validity of the measure by comparing it to other measures of operating leverage. Section 8 assesses the impact of the COVID-19 pandemic and Section 9 concludes.

2. Literature Review

As mentioned previously, and despite not being as widely addressed in the literature as financial leverage, operating leverage plays a very important role in several fields of finance, from equity risk to capital structure decisions, among others.

Regarding the relationship between operating leverage and capital structure, several studies have documented the substitution effect between financial and operating leverage and their effect on the firm's optimal capital structure. For instance, Chen *et al.* (2019) document that operating decisions have a causal effect in a firm's debt level. The intuition is that a higher level of capital investment (i.e., higher operating leverage) increases the firm's probability of default when in distress, and this effect more than offsets the higher recovery rates when in default. Consequently, anticipating the possibility of distress, managers will choose a lower level of financial leverage. Kahl *et al.* (2019) also confirm the negative relationship between financial and operating leverage and add another possible explanation. They conclude that an important reason why high fixed cost firms follow more conservative financial policies is their desire to sustain investment when sales are low. Reinartz and Schmid (2016) find that firms with higher production flexibility (i.e., lower operating leverage) rely more on debt financing (i.e., higher financial leverage). The authors observe that production flexibility affects financial leverage via lower expected costs of financial distress and higher present value of tax shields and that the relative importance of each channel is dependent on the firm's profitability.

In what concerns the link between operating leverage and equity risk and returns, Lev (1974) concludes that as operating leverage increases, the higher will be the overall and systematic risk of the stock. This result has important practical implications for both investors and managers. For managers, it is relevant because they can expect the stock riskiness to increase if operating leverage increases, which can have negative effects on the shareholders' value. For investors, it may help in the estimation of the firm's stock risk given expected changes in its operating leverage. For example, knowing that a firm will experience a significant change in operating leverage, an investor would not base the estimation of the stock's riskiness exclusively in historical data, as it would be inadequate. Mandelker and Rhee (1984) find that the degrees of operating and financial leverage magnify the risk of a firm's stock and that the two types of leverage are correlated and explain a large portion of the variation in beta.

Testing the hypothesis that production costs are as important as debt in levering the exposure of a firm's stock to underlying risks, Novy-Marx (2011) shows that firms with levered assets earn significantly higher average returns than firms with unlevered assets when operating leverage is considered (and not financial leverage). In the same study, it is demonstrated that operating leverage helps explain why the value premium[1] is strong within industries, but weak across industries, assisting investors in the definition of trading strategies that are more profitable. Along the same lines, Garcia-Feijóo and Jorgensen (2010) find that the degree of operating leverage is positively associated with book-to-market ratios in the cross-section, with stock returns and with the firm's beta.

Turning to the link between operating leverage and labor markets, several economists study a particular form of operating leverage that is induced by labor factors, called labor leverage. Labor leverage has implications in several dimensions for a firm, from its risk and expected returns to its profitability. For instance, firms in high-mobility industries such as manufacturing, in which workers have more flexibility to move to other industries due to the portability of their skills, are more exposed to labor flows and their potential impact in the firm's systematic risk, amplifying the risk of owning capital for shareholders (Donangelo, 2014). Chen *et al.* (2011) show that labor unions tend to reduce a firm's operating flexibility by making wages stickier and layoffs costlier, which ultimately increases its systematic risk and cost of equity. Favilukis and Lin (2016) explore how wage rigidity (i.e., infrequent wage resetting) induces a form of operating leverage that makes profits and dividends riskier to shareholders, contributing to the explanation of asset pricing. Petrosky-Nadeau *et al.* (2018) present another channel from which labor induced leverage is generated. In their study, they find that search and matching frictions in the job market actively contribute to the decrease of profitability in times of recession. Amid all these complementary drivers of labor leverage, Donangelo *et al.* (2019) present the labor share (i.e., the ratio between a firm's labor expenses and its value added) as a significant measure in explaining cross-sectional differences in expected returns. Additionally, the paper confirms the hypothesis that the sensitivity of operating profits increases with labor leverage. Finally, Donangelo (2021) also shows that labor leverage explains roughly 50% of the value premium.

[1] The value premium refers to the greater risk-adjusted returns of value stocks (those with high book-to-market ratios) over growth stocks (those with low book-to-market ratios).

More recently, literature on how operating leverage relates to credit risk has shown the importance of the former for the latter. When wages are rigid, there is an increase in labor induced operating leverage (labor leverage) that increases the firm's credit risk because wage payments are senior to interest payments and make them riskier (Favilukis *et al.*, 2020). Furthermore, the authors find that labor markets play an important role in driving aggregate and cross-sectional variation in credit risk. Chou *et al.* (2019) find that a firm's cost structure (its ratio of fixed to variable costs) contains relevant information for the estimation of its credit risk that adds to the data on past volatility and performance. More specifically, since cash obligations are more concerning for debtholders than non-cash expenses (e.g., depreciation), the authors capture only the cash component of operating leverage and conclude that as it increases, so do the bond yield spreads. Ayres and Blank (2017) also show that operating leverage has an economically significant role in credit markets and the cost of debt. More precisely, the authors find that operating leverage affects corporate bond spreads and that firms with higher operating leverage have significantly lower credit ratings.

Having established the importance that operating leverage has in several dimensions of a firm's reality, it is crucial to understand how economists measure it in practice. The most traditional and prominent measure used in the literature and by analysts alike is the Degree of Operating Leverage (DOL). In this study, the DOL is obtained following the methodology proposed by Garcia-Feijóo and Jorgensen (2010), based on the techniques originally proposed by Mandelker and Rhee (1984) and O'Brien and Vanderheiden (1987). This approach uses a time-series regression of Earnings Before Interest and Taxes (EBIT) on a firm's sales. Alternatively, Ferri and Jones (1979) estimate the DOL as the percentage change of earnings before interest and taxes (EBIT) as a proportion of the percentage change in sales. The authors also propose an additional proxy for operating leverage, the ratio of net fixed assets to total fixed assets. Kahl *et al.* (2019) propose estimating operating leverage through the sensitivity of operating costs to changes in sales. The rationale is that firms with a higher proportion of fixed costs to total operating costs will show a lower sensitivity to changes in sales. An advantage of this technique is that it is unaffected by factors unrelated to the firm's cost structure, such as profit margins, unlike EBIT-based measures such as the DOL. Finally, Gu *et al.* (2018) add to the literature by introducing the Inflexibility measure, defined as the firm's historical range of operating costs over sales scaled by the volatility of the logarithm of changes in sales over assets. The rationale behind it is that firms with higher adjustment costs (i.e., operating leverage) will take longer to adjust to changes in profitability, thus being less flexible.

Regarding the actual measurement of fixed operating costs, one common technique is to set them equal to SG&A costs. This is often done in structural credit risk models as the one by Eisdorfer *et al.* (2019). SG&A are the expenses incurred by the company in its daily business operations that cannot be directly attributed to making a product or delivering a service. Examples include the salaries paid to the marketing or human resources teams, office supplies, rents and utilities, among others. The reason that SG&A is used as proxy for fixed operating costs is the fact that these costs are typically stickier, meaning that they are slower to adjust in the event of decreased activity for the firm compared to an equivalent increase in activity. Anderson *et al.* (2003) find that, on average, SG&A increase by 0.55% per 1% increase in sales but decrease only by 0.35% per 1% decrease in sales. Similarly, Chen *et al.* (2019) find that, on average, firms adjust their COGS by 0.86% and their SG&A expenses by 0.41% in response to a 1% decrease in sales revenue, supporting the assumption that the SG&A costs are a good proxy for fixed operating costs. One of the biggest advantages of using SG&A as a proxy for fixed operating costs is the fact that it is widely available in a firm's income statement. Nevertheless, it does have a few drawbacks. Anderson *et al.* (2007) find that SG&A costs are not necessarily indicative of managerial efficiency due to managers' expectations of future firm performance, for example. Managers may decide to maintain excess resources during periods of reduced demand because they expect the slowdown to be temporary. In this scenario, the proportion of SG&A to sales would increase, although it does not reflect management's ability to control costs.

Gu *et al.* (2018) estimate fixed operating costs through the QFC (Quasi-Fixed Costs) measure. In their model, QFC are estimated as next period's expected costs even if sales were zero. One advantage of this technique is that it incorporates firm flexibility in the measurement of fixed operating costs. The methodology behind its construction is explained in Section 5.

3. Sample, data cleaning and variables

The sample is constructed using all publicly traded US-based firms available in the Compustat database from 2001 to 2021. All firm-year observations are required to have both positive sales and operating costs. Since operating costs are computed as the sum of SG&A expenses (Compustat item XSGA), depreciations and amortizations (Compustat item DP) and COGS (Compustat item COGS), observations that have negative or missing values for these three variables are excluded from the analysis. Further notes on data cleaning are given in the sections in which they are relevant. These requirements allow the estimation of the QFC measure for each firm-year observation in the 2001-2021 period. This period is chosen for two main reasons. Firstly, it should be long enough to capture the persistence of operating costs and their sensitivity to changes in sales. Secondly, it is crucial to have data for the years 2020 and 2021 in order to assess the impact of the COVID-19 pandemic on the estimates obtained.

Additionally, CRSP data is used for the construction of the $Firm\ Age$ variable. The construction of all relevant variables used is described in Appendix 1.

4. The structure of operating costs for American firms

This section discusses the structure of operating costs for publicly traded US firms. A firm's operating costs are those that are associated with the normal day-to-day activities of running a business. These can be broken down into three main categories: Depreciation and Amortization (D&A), Cost of Goods Sold (COGS) and Selling, General and Administrative expenses (SG&A). By nature, these three categories are very different in terms of flexibility for the management of a firm.

Depreciation and Amortization is a non-cashflow component that is linked to the decline in value of both tangible assets (such as buildings, vehicles, machines, etc.) and intangible assets (such as patents, trademarks, etc.), over their useful life, thus matching the cost of these assets with the revenue they generate.

Cost of Goods Sold represents all those costs that can be directly attributable to the production of goods or delivery of services, such as the cost of the materials and labor. Unlike some other databases, Compustat does not possess a specific item for labor expenses. Therefore, these costs are split between SG&A (if they are not directly associated to sales) and COGS (if they are directly associated to sales).

Selling, General and Administrative Expenses refers to nearly all the business costs that are not directly linked to the production of a good or the delivery of a service. For example, this item includes rents, utilities, office supplies, advertising expenses and salaries of back-office employees, among other costs.

Figure 1 shows the decomposition of the weights that each of these three categories have in the total operating costs for each sector of economic activity. The average shares of COGS, SG&A and Depreciation and Amortization across all sectors are 60%, 32% and 8%, respectively.

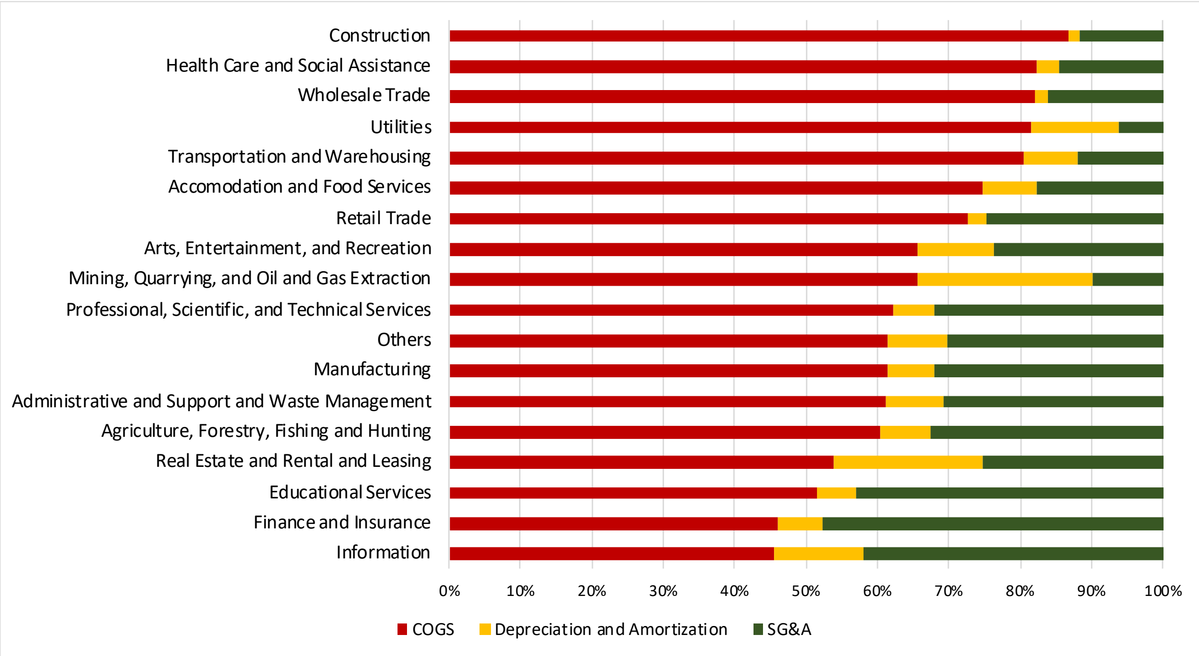

Figure 1. Operating costs decomposition by sector of economic activity

Notes: The shares of each type of cost are computed at the firm level and then aggregated at the sector level using the gross profit as weight. The sectors of economic activity are based on the North American Industry Classification System (for further information, see Appendix 1).

A first look at the figure indicates that COGS is the most important expense in almost all sectors. However, its importance varies greatly between them. Among the sectors with the highest COGS are Construction (87%), Health Care and Social Assistance (84%) and Wholesale Trade (82%). On the other end, it is less relevant in service-related industries such as Information (46%), Finance and Insurance (46%) and Educational Services (52%), where SG&A represents a considerable share of operating costs as well.

For the most part, there is trade-off between the share of COGS and the share of SG&A in the total operating costs of a firm (i.e., on average, the higher the share of COGS the lower the share of SG&A and vice-versa). This trade-off between COGS and SG&A is only slightly disrupted in capital-intensive industries, where the predominance of fixed assets such as property, plant and equipment leads to a lot of wear and tear and consequently, a higher share of depreciation in the total operating costs. For instance, the sectors with the highest percentages of Depreciation and Amortization are Mining, Quarrying, and Oil and Gas Extraction (24%), Real Estate and Rental and Leasing (21%) and Utilities (12%). Additionally, the Information sector also presents a comparatively high share of Depreciation and Amortization (12%) due in large part to the higher amount of intangible assets (and resultant amortization).

Figure 2 reports the decomposition of the weights of the three categories of operating costs by firm size. Based on this figure, there is not a clear relation between firm size and the share of COGS on total operating costs. Large and Medium cap firms are the ones that have the highest shares of COGS in their operating cost structure. On the other end, Micro and Mega cap firms have the lowest shares of COGS and the highest shares of SG&A expenses. Despite the differences in the shares of each category of costs, it is not possible to conclude that a firm's operating cost structure is directly linked to its size.

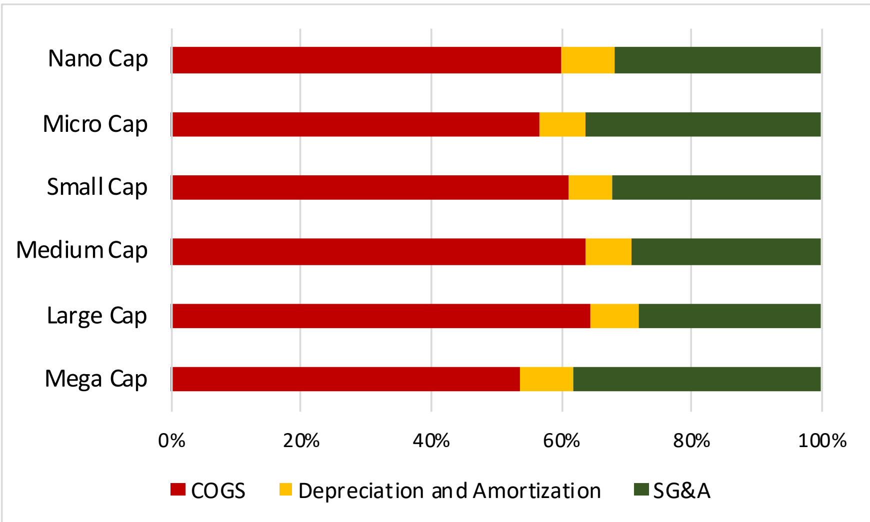

Figure 2. Operating costs decomposition by firm size

Notes: The shares of each type of cost are computed at the firm level and then aggregated at the firm size level using the gross profit as weight. Firm size is based on market capitalization for each firm-year observation (for further information, see Appendix 1).

5. Construction of the Quasi-Fixed Costs (QFC) measure

The operating leverage measure used in this study closely follows the methodology proposed by Félix *et al.* (2021). It is based on the technique used by Gu *et al.* (2018), although with some small adjustments. Firstly, Gu *et al.* (2018) estimate the QFC measure using quarterly data, whereas in this study and in Félix *et al.* (2021) the estimation is made with annual data. Secondly, the slope coefficients estimated with this adjusted methodology are not obtained at the firm level, but rather at the industry level. In this setup, a firm's fixed operating costs are those that are not easily adjustable in a short period of time and do not move with contemporaneous sales. The baseline specification to be estimated is the following[2]:

$$OpCosts_{i,t} = a_i + b_j OpCosts_{i,t-1} + c_j Sales_{i,t} + d_j Sales_{i,t-1} + \varepsilon_{i,t} \tag{1}$$

where $OpCosts_{i,t}$ corresponds to firm i's operating costs in year t. The independent variables on the right-hand side correspond to firm i's previous year operating costs ($OpCosts_{i,t-1}$), contemporaneous sales ($Sales_{i,t}$) and previous year sales ($Sales_{i,t-1}$). a_i is the firm fixed effect and $\varepsilon_{i,t}$ is the error term. The slope coefficients b_j, c_j and d_j are estimated at the industry level j using a linear regression model with one-interacted high-dimensional fixed effect, as proposed by Guimarães and Portugal (2010). In this case, the high-dimensional fixed effect used to estimate the three slope coefficients is the North American Industry Classification System (NAICS) code j. Unlike the three slope coefficients, the a_i coefficient is estimated at the firm level.

With the inclusion of contemporaneous sales and the previous year sales variables in the regression, it is possible to differentiate between the influence that each of them has on a firm's operating costs, allowing for a more accurate estimation of the impact of shocks in output.

[2] The sample is restricted to firms with at least 5 years of observations. The minimum number of observations per industry j is set at 20. The industry j is based on the North American Industry Classification System. In the end, the estimation includes 511 industries. The slope coefficients and the QFC to sales ratio are winsorized at the 1st and 99th percentiles.

After estimating the coefficients of regression (1), the predicted fixed costs next period are obtained through the following expression:

$$QFC_{i,t} = a_i + b_j OpCosts_{i,t-1} + d_j Sales_{i,t-1} \tag{2}$$

As indicated in equation (2), the QFC measure is obtained by summing the intercept coefficient to the contribution of the two lagged variables. It corresponds to the predicted operating costs in the next period assuming that sales are zero.

6. Empirical Results

This section presents the results obtained in the estimation of the QFC measure. The quasi-fixed operating costs estimated are reported as a percentage of previous year's sales for comparability purposes. Figure 3 exhibits the estimated QFC. The distribution reinforces the heterogeneity of this measure across firms[3].

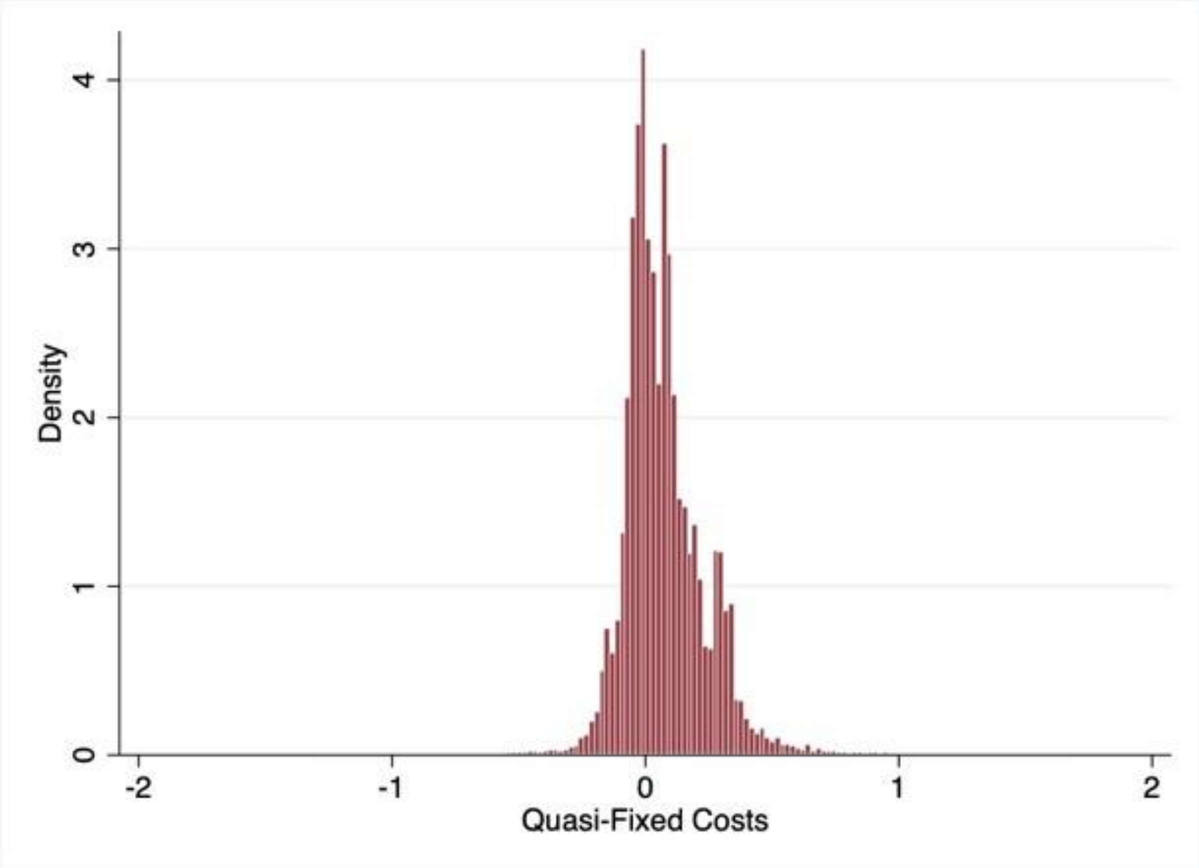

Figure 3. Distribution of estimated Quasi-Fixed Costs

Notes: estimated QFC scaled by one year lagged sales, weighted by the firm's gross profit.

Table 1 reports the main summary statistics of the estimated QFC. In the end, 46 484 non-negative estimates are obtained with average fixed operating costs of 15.5% of the firm's sales. This result is in line with the one obtained by Félix *et al.* (2021), who estimate an average value of 15% for Portuguese firms in the period from 2006 to 2018. A point worth noting is that the median is only 11.1%, roughly a four percentage point decrease when compared to the average value. This indicates the presence of firm-year observations with very high values of QFC, even though many firms present comparatively low values.

[3] Negative estimates of QFC account for roughly 30% of observations and may be due to measurement error.

	N	Mean	St. Dev.	Q1	Q2	Q3
$QFC_t/Sales_{t-1}$	46 484	0.155	0.164	0.056	0.111	0.221

Table 1. Summary statistics of the QFC to sales ratio

Notes: estimated QFC scaled by one-year lagged sales, weighted by the firm's gross profit. The sampling period goes from 2001 to 2021. The sample is restricted to firms with non-negative values of QFC to sales ratio. N represents the number of observations, while Q1, Q2 and Q3 represent the first quartile, median, and third quartile, respectively.

Next, the estimated QFC by firm size are reported in Table 2. It is possible to infer that, generally, the bigger the firm, the smaller its operating leverage. The mean QFC for Nano Cap firms (34.2%) is more than double that of Large Cap firms (15.2%). This result is hardly surprising when economies of scale are considered. Economic theory posts that there are cost advantages when a firm scales up its production, leading to a decrease in the average cost per unit. Fixed costs are diluted as output increases, explaining why smaller firms would have a higher ratio of QFC to sales. Another possible reason, related to the previous one, is that smaller firms are generally younger than bigger firms. In 2019, the average age of a Nano Cap firm was 23 years, compared to 48 years for a Mega Cap firm. This may help explain why, on average, these smaller firms do not have the production capacity of bigger firms and consequently have a higher proportion of fixed costs.

Market Capitalization	N	Mean	St. Dev.	Q1	Q2	Q3	Firm Age (2019)
Nano Cap	3960	0.342	0.656	0.081	0.170	0.340	23 years
Micro Cap	9879	0.298	0.448	0.087	0.186	0.349	21 years
Small Cap	14644	0.187	0.306	0.057	0.121	0.233	22 years
Medium Cap	11195	0.160	0.199	0.048	0.100	0.212	28 years
Large Cap	6375	0.149	0.152	0.039	0.107	0.224	35 years
Mega Cap	431	0.152	0.107	0.076	0.116	0.218	48 years
TOTAL	**46 484**	**0.155**	**0.164**	**0.056**	**0.111**	**0.221**	**25 years**

Table 2. Summary statistics of the QFC to sales ratio by firm size

Notes: estimated QFC scaled by one-year lagged sales, weighted by the firm's gross profit. The sampling period goes from 2001 to 2021. The sample is restricted to firms with non-negative values of QFC to sales ratio. N represents the number of observations, while Q1, Q2 and Q3 represent the first quartile, median, and third quartile, respectively. Firm size is based on market capitalization for each firm-year observation (for further information, see Table A1 in the appendix). Firm age is the number of years (plus one) since the company first appeared in CRSP or Compustat, in 2019 (for further information, see Appendix 1).

Understanding how this measure of operating leverage behaves across industries also proves helpful. Table 3 reports the estimated fixed operating costs by sector of economic activity.

The first conclusion to be drawn is that these estimates are not homogeneous across sectors. For example, the three sectors with the highest QFC to sales ratio (excluding Others) are Information (24.6%), Arts, Entertainment and Recreation (23.2%) and Professional, Scientific and Technical Services (18.3%) while the three sectors with the lowest QFC to sales ratio were Retail Trade (9,2%), Agriculture, Forestry, Fishing and Hunting (5,4%) and Wholesale Trade (4,0%).

Sector of economic activity	N	Mean	St. Dev.	Q1	Q2	Q3
Information	4125	0.246	0.232	0.085	0.252	0.343
Arts, Entertainment, and Recreation	384	0.232	0.213	0.124	0.195	0.292
Others	548	0.197	0.079	0.155	0.195	0.234
Professional, Scientific, and Technical Services	2326	0.183	0.199	0.085	0.166	0.234
Accommodation and Food Services	1261	0.163	0.106	0.080	0.156	0.233
Manufacturing	17577	0.163	0.144	0.064	0.129	0.252
Health Care and Social Assistance	694	0.149	0.159	0.101	0.142	0.175
Mining, Quarrying, and Oil and Gas Extraction	1833	0.148	0.277	0.026	0.092	0.196
Construction	706	0.144	0.078	0.076	0.175	0.192
Utilities	117	0.138	0.313	0.054	0.069	0.079
Transportation and Warehousing	658	0.124	0.120	0.032	0.091	0.192
Educational Services	278	0.122	0.141	0.065	0.091	0.142
Real Estate and Rental and Leasing	1080	0.110	0.119	0.074	0.093	0.116
Finance and Insurance	10099	0.103	0.133	0.038	0.080	0.131
Administrative and Support and Waste Management	894	0.097	0.113	0.025	0.054	0.157
Retail Trade	2396	0.092	0.069	0.060	0.080	0.110
Agriculture, Forestry, Fishing and Hunting	93	0.054	0.033	0.048	0.052	0.059
Wholesale Trade	1415	0.040	0.082	0.008	0.027	0.048
TOTAL	**46 484**	**0.155**	**0.164**	**0.056**	**0.111**	**0.221**

Table 3. Summary statistics of the QFC to sales ratio by sector of economic activity

Notes: estimated QFC scaled by one-year lagged sales, weighted by the firm's gross profit. The sampling period goes from 2001 to 2021. The sample is restricted to firms with non-negative values of QFC to sales ratio. N represents the number of observations, while Q1, Q2 and Q3 represent the first quartile, median, and third quartile, respectively. The sectors of economic activity are based on the North American Industry Classification System (for further information, see Appendix 1).

Naturally, these results are explained by the cost structure of a typical firm in each sector. For instance, one can think of the differences between a newspaper company, in the Information sector, and a wholesaler, in the Wholesale Trade sector. In the event of a sharp decline in sales, it is easier for the wholesaler to cut costs because its cost structure is more oriented towards COGS, which adjusts more rapidly than SG&A, for example. On the other hand, the newspaper company will have a harder time cutting its costs because its cost structure is stickier, with an increased weight of SG&A expenses. In the end, this indicates that the wholesaler probably has a lower QFC to sales ratio compared to the newspaper company. In practice, this is what happens, on average. Figure 1 reports that COGS represents only 46% of total operating costs in the Information sector, compared with 82% for firms in the Wholesale Trade sector, while SG&A expenses represent 42% of total operating costs for firms in the Information sector and only 16% for firms in the Wholesale Trade sector. Meanwhile, the average estimated QFC ratio is only 4% in the Wholesale Trade sector, compared to 24.6% in the Information sector.

In fact, this relationship between the shares of COGS and SG&A in the cost structure and the QFC is very relevant across sectors. Table 4 reports the correlations between the estimated QFC to sales ratio and the shares of COGS, SG&A and D&A for each sector. It is found that sectors with a higher QFC to sales ratio present a higher share of SG&A costs and a lower share of COGS in their cost structure. This relationship is true for most sectors of economic activity. Overall, the correlations between the firm's QFC to sales ratio and the proportions of COGS, SG&A costs and D&A in total operating costs are -0.298, 0.261 and 0.188, respectively. These results are in accordance with the initial intuition. In particular, they highlight a significant negative relationship between the share of COGS and the QFC to sales ratio and a significant positive relationship between the share of SG&A and the QFC to sales ratio.

Sector of economic activity	Share of COGS	Share of SG&A	Share of D&A
Manufacturing	-0.280***	0.210***	0.364***
Information	-0.372***	0.438***	-0.270***
Finance and Insurance	0.077***	-0.070***	-0.051***
Construction	-0.206***	0.368***	-0.369***
Utilities	-0.305***	0.049	0.421***
Agriculture, Forestry, Fishing and Hunting	0.009	-0.024	0.056
Mining, Quarrying, and Oil and Gas Extraction	-0.256***	0.271***	0.203***
Wholesale Trade	-0.385***	0.307***	0.536***
Retail Trade	-0.379***	0.378***	0.292***
Transportation and Warehousing	-0.123***	0.015	0.153***
Real Estate and Rental and Leasing	-0.147***	0.118***	0.046
Professional, Scientific, and Technical Services	-0.146***	0.127***	0.125***
Administrative and Support and Waste Management	-0.716***	0.713***	0.254***
Educational Services	-0.339***	0.351***	-0.202***
Health Care and Social Assistance	-0.438***	0.435***	-0.038
Arts, Entertainment, and Recreation	0.041	-0.155***	0.231***
Accommodation and Food Services	-0.286***	0.207***	0.364***
Others	0.411***	-0.402***	-0.376***
TOTAL	**-0.298*** **	**0.261*** **	**0.188*** **

Table 4. Correlations between the QFC to sales ratio and the shares of COGS, SG&A and D&A

Notes: ***, **, * indicate statistical significance at the 1%, 5%, and 10% level, respectively. The computation of the correlations between the QFC to sales ratio and the shares of COGS, SG&A and D&A uses the gross profit as weights.

7. Robustness tests

In this section, the estimates obtained for the QFC measure are compared to other measures of operating leverage presented in section 2, namely the Cost Structure (Kahl *et al.* 2019), the regression-based DOL used by Garcia-Feijóo and Jorgensen (2010), the static methodology of DOL proposed by Ferri and Jones (1979), the Inflexibility measure (Gu *et al.* 2018) and finally the SG&A to assets ratio (Chen *et al*. 2019). Subsections 7.1 to 7.5 present the methodologies employed to obtain the respective measures of operating leverage, as well as the main summary statistics for each one of them. Subsection 7.6 reports the comparison between these measures and the QFC measure.

7.1 Cost Structure

In their paper, Kahl *et al.* (2019) introduce a measure of operating leverage that directly reflects the importance of fixed operating costs in a firm's cost structure. This measure is based on the estimation of the sensitivity of operating costs to changes in the firm's sales. The intuition behind it is that a firm that has a higher ratio of fixed to total operating costs will not respond as much to changes in sales.

The methodology used starts with the generation of *ex ante* expectations of operating costs and sales using the geometric growth rate over the previous two years:

$$E[Sales_{i,t}] = Sales_{i,t-1}\left(\frac{Sales_{i,t-1}}{Sales_{i,t-3}}\right)^{1/2} \tag{3}$$

$$E[OpCosts_{i,t}] = OpCosts_{i,t-1}\left(\frac{OpCosts_{i,t-1}}{OpCosts_{i,t-3}}\right)^{1/2} \tag{4}$$

Next, innovations in growth rates are computed as follows:

$$\mu_{i,t}^{Sales} = \left(Sales_{i,t} - E\left[Sales_{i,t}\right]\right)/Sales_{i,t-1} \tag{5}$$

$$\mu_{i,t}^{OpCosts} = \left(OpCosts_{i,t} - E\left[OpCosts_{i,t}\right]\right)/OpCosts_{i,t-1} \tag{6}$$

Lastly, the following regression is run using seven years of innovations:

$$\mu_{i,t}^{OpCosts} = Cost\ Structure_{i,t} \times \mu_{i,t}^{Sales} + \epsilon_{i,t}, t \ \in \ [-7,0] \tag{7}$$

Sales and operating costs are winsorized at the 1st and 99th percentiles. The Cost Structure measure is also winsorized at the 1st and 99th percentiles to remove the influence of outliers. Observations with an estimated Cost Structure below zero are excluded from the analysis. Table 5 reports the main summary statistics obtained:

	N	Mean	St. Dev.	Q1	Q2	Q3
$Cost\ Structure$	49 154	0.86	0.28	0.71	0.91	1.01

Table 5. Summary statistics of the $\boldsymbol{Cost\ Structure}$ measure

Notes: Estimates of $Cost\ Structure$ obtained according to the methodology in Kahl *et al*. (2019). Estimates presented for the period from 2001 to 2021. Negative estimates of $Cost\ Structure$ are not included.

7.2 Inflexibility Measure

In accordance with the methodology presented by Gu *et al.* (2018), the Inflexibility ($INFLEX$) measure is also computed. This measure of operating leverage is a proxy for the width of a firm's inaction region. The rationale is that firms with less operating flexibility will wait longer before adjusting its costs in response to changes in profitability. $INFLEX$ is computed as follows:

$$INFLEX_{i,t} = \frac{max_{i,0,t}\left(\frac{OpCosts}{Sales}\right) - min_{i,0,t}\left(\frac{OpCosts}{Sales}\right)}{std_{i,0,t}\left(\Delta log\left(\frac{Sales}{Assets}\right)\right)} \tag{8}$$

The numerator corresponds to the range of the firm's operating costs over sales in the period from year 0 until year t, and the denominator is the standard deviation of the annual growth rate of sales over total assets in the period from year 0 until year t. Year 0 is the firm's beginning year in the data. Operating costs, sales and assets, as well as the $INFLEX$ measure itself, are winsorized at the 1st and 99th percentiles. Table 6 reports the main summary statistics obtained:

	N	Mean	St. Dev.	Q1	Q2	Q3
$INFLEX$	82 876	2.59	4.71	0.61	1.20	2.42

Table 6. Summary statistics of the $INFLEX$ measure

Notes: Estimates of $INFLEX$ obtained according to the methodology in Gu *et al.* (2018). Estimates presented for the period from 2001 to 2021.

7.3 Regression-based DOL

Garcia-Feijóo and Jorgensen (2010) propose estimating the DOL through a two-step time-series regression approach, based on the methodology first introduced by Mandelker and Rhee (1984). In the first step, they run the following regressions using 5-year rolling windows:

$$log\ (EBIT_t) = log(EBIT_0) + \beta_{EBIT}t + \mu_{t,EBIT} \tag{9}$$

$$log\ (Sales_t) = log(Sales_0) + \beta_{Sales}t + \mu_{t,Sales} \tag{10}$$

Here, $EBIT_0$ and $Sales_0$ correspond to the beginning values of EBIT and sales in the data, respectively. The time trend removes the effect from EBIT and sales growth during the 5-year window. $\mu_{t,EBIT}$ and $\mu_{t,Sales}$ are the error terms. A transformation is used in order to compute the logarithm for negative values of EBIT (Ljungqvist and Wilhelm, 2005). In particular, the logs are computed as $ln\ (1 + EBIT)\ if\ EBIT \geq 0$ and $-ln\ (1 - EBIT)\ if\ EBIT \leq 0$.

In the second step, they use the errors terms ($\mu_{t,EBIT}$ and $\mu_{t,Sales}$) to run a second regression:

$$\mu_{t,EBIT} = DOL^{regression} \times \mu_{t,Sales} + \epsilon_t \tag{11}$$

$DOL^{regression}$ thus measures the average sensitivity of the percentage deviation of EBIT from its trend relative to the percentage deviation of sales from its trend. Sales and operating costs, as well as the $DOL^{regression}$ measure itself, are winsorized at the 1st and 99th percentiles. Table 7 reports the main summary statistics obtained:

	N	Mean	St. Dev.	Q1	Q2	Q3
$DOL^{regression}$	50 968	2.18	2.58	0.74	1.28	2.48

Table 7. Summary statistics of the $DOL^{regression}$ measure

Notes: Estimates of $DOL^{regression}$ obtained according to the methodology in Garcia-Feijóo and Jorgensen (2010). $DOL^{regression}$ is measured in absolute value. Estimates presented for the period from 2001 to 2021.

7.4 Static DOL

Ferri and Jones (1979) estimate the DOL as the percentage change of EBIT over the percentage change of Sales, in a given year. Specifically:

$$DOL_t^{static} = \frac{(EBIT_t - EBIT_{t-1})/EBIT_{t-1}}{(Sales_t - Sales_{t-1})/Sales_{t-1}} \tag{12}$$

Sales and EBIT, as well as the DOL^{static} measure itself, are winsorized at the 1st and 99th percentiles. Table 8 reports the main summary statistics obtained:

	N	Mean	St. Dev.	Q1	Q2	Q3
DOL^{static}	54 274	9.92	28.32	1.09	2.35	6.27

Table 8. Summary of statistics of DOL^{static} measure

Notes: Estimates of DOL^{static} obtained according to the methodology in Ferri and Jones (1979). Estimates presented for the period from 2001 to 2021. Negative estimates of DOL^{static} are not included.

7.5 SG&A to assets ratio

As mentioned previously, setting fixed operating costs equal to SG&A expenses is a common technique in the literature. Consequently, it is also computed for purposes of comparison to the QFC measure. The $SGA - to - assets$ ratio is computed as in Chen *et al.* (2019). Specifically:

$$SGA - to - assets_t = SGA_t / Assets_{t-1} \tag{13}$$

SG&A, assets, as well as the $SGA - to - assets$ measure itself, are winsorized at the 1st and 99th percentiles. Table 9 reports the main summary statistics obtained:

	N	Mean	St. Dev.	Q1	Q2	Q3
$SGA - to - assets$	85 405	0.34	0.41	0.07	0.22	0.46

Table 9. Summary statistics of the $SGA - to - assets$ measure

Notes: Estimates of $SGA - to - assets$ obtained according to the methodology in Chen *et al.* (2019). Estimates presented for the period 2001 to 2021.

7.6 Comparison

The robustness of the QFC measure is tested by comparing its estimates to the results obtained with the measures of operating leverage presented above. The correlations between QFC and these measures are presented in Table 10. Since the number of estimates obtained for each measure is different, the table reports the number of firm-year observations used in the computation of each correlation.

	$\boldsymbol{Cost\ Structure}$	$\boldsymbol{INFLEX}$	$\boldsymbol{DOL^{regression}}$	$\boldsymbol{DOL^{static}}$	$\boldsymbol{SGA - to - assets}$
Correlation Coefficient	-0.035***	0.160***	0.036***	0.016***	0.094***
N	29 678	44 944	30 383	44845	28974

Table 10. Correlations between the QFC to sales ratio and other measures of operating leverage

Notes: ***, **, * indicate statistical significance at the 1%, 5%, and 10% level, respectively. The computation of the correlations between the QFC to sales ratio and the other measures of operating leverage uses the gross profit as weights.

QFC has a positive correlation with every measure of operating leverage except for the $Cost\ Structure$. These results are reassuring in the sense that the sign of the correlations is in accordance with the initial intuition. On the one hand, since firms with higher operating leverage are expected to have lower values of $Cost\ Structure$, the relationship between this measure and the QFC to sales ratio is expected to be negative. On the other hand, higher values in the other four measures suggest a higher level of operating leverage in the firm, just like in the QFC measure. Therefore, the positive correlations obtained are appropriate. The results are consistent with the idea that the QFC to sales ratio is indicative of a higher level of operating leverage (and less flexibility).

Figure 3 plots the QFC to sales ratio against each of the operating leverage measures used. The positive slopes in the fit line for every plot except for the $Cost\ Structure$ measure confirm the signs of the correlations presented in Table 10.

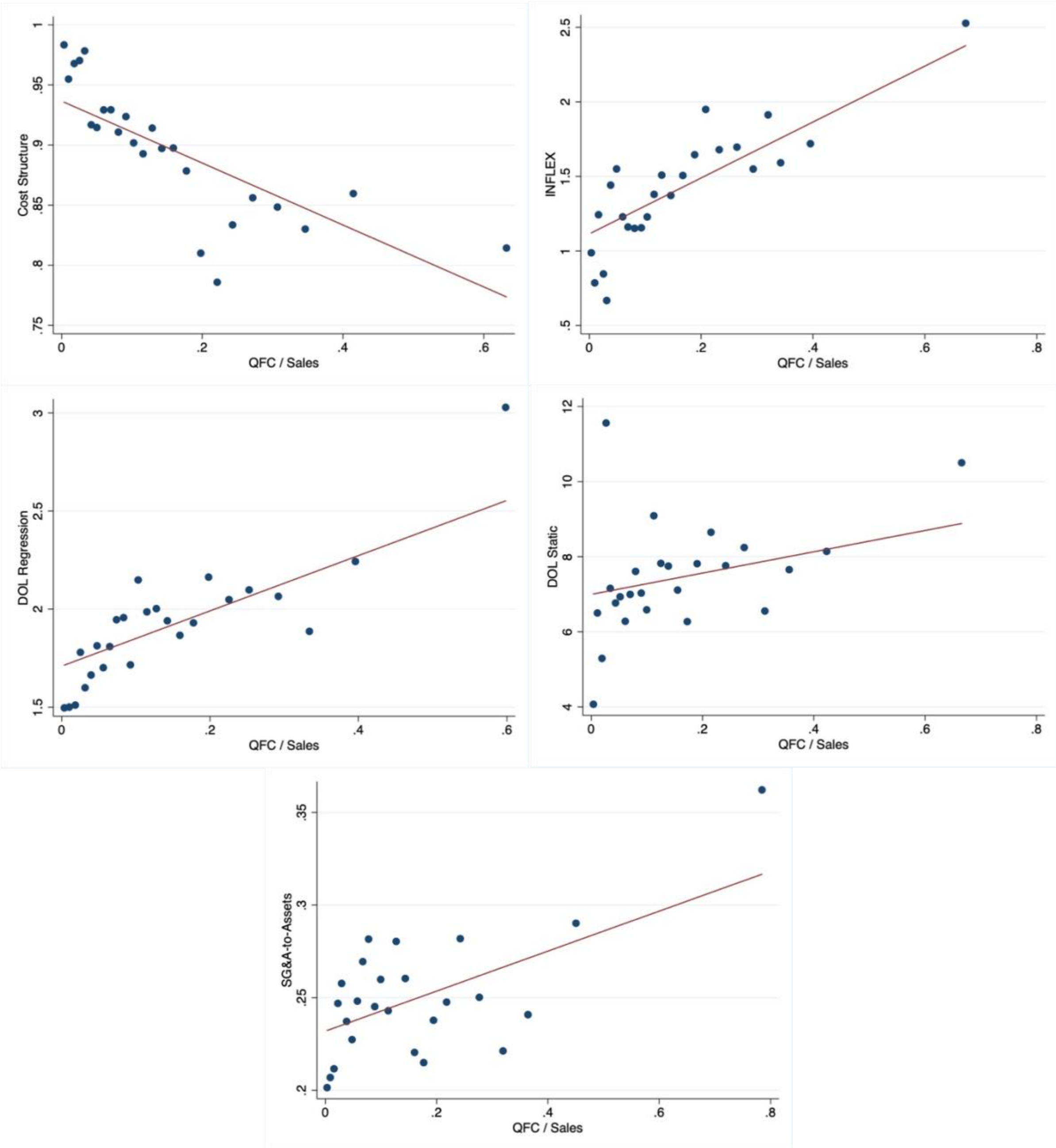

Figure 4. Scatter plots between the QFC to sales ratio and other measures of operating leverage

Notes: The scatter plots use bins to ease the visualization of the data. Only non-negative values are included in the plots. The bins are computed using the gross profit as weights.

8. The impact of COVID-19

Considering the very sharp impact that the pandemic had on firms' sales[4], it is relevant to analyze whether the inclusion of the years 2020 and 2021 has any impact on the fixed operating costs estimates. To test this hypothesis, the methodology explained in Section 5 is once again employed, the only difference being the exclusion of the years 2020 and 2021 in the estimation. Hereinafter, this new model (without 2020 and 2021 data) is called the *Pre-Covid Model*, whereas the previous model is called the *Full Model*. The QFC to sales ratio is once again estimated in the *Pre-Covid Model*[5]. For comparability purposes, Table 11, Table 13, and Table 14 present the results obtained with *Pre-Covid Model* as well as with the *Full Model*. In this section, the results of the *Full Model* are obtained using the regression coefficients estimated in Section 6, only now they are used to compute QFC for the same firm-year observations as the *Pre-Covid Model*. Using this approach, a meaningful comparison between the two models is obtained. The results are presented in Table 11.

	N	**Mean**			**St. Dev.**	**Q1**	**Q2**	**Q3**
		Full Model	*Pre-Covid Model*	Change				
$QFC_t/Sales_{t-1}$	39 041	0.160	0.133	-2.7 pp	0.169	0.035	0.089	0.185

Table 11. Summary statistics of the QFC to sales ratio using the *Pre-Covid Model*

Notes: estimated QFC scaled by one-year lagged sales, weighted by the firm's gross profit. The sampling period goes from 2001 to 2019. The sample is restricted to firms with non-negative values of QFC to sales ratio. N represents the number of observations, while Q1, Q2 and Q3 represent the first quartile, median, and third quartile, respectively. Change is computed as *Pre-Covid Model* - *Full Model*. Values in red correspond to negative changes and values in green correspond to positive changes.

The average value of the QFC to sales ratio using the *Pre-Covid Model* is 13.3%, which corresponds to a 2.7 percentage point (pp) decrease compared to the *Full Model*. Table 12 compares the new coefficients with the ones estimated considering the *Full Model*. The average firm level intercept a_i decreases substantially in the *Pre-Covid Model*. There is a marginal difference in the b_j coefficient, which decreases from 0.63 in the *Full Model* to 0.62 in the *Pre-Covid Model*. This means that operating costs become less persistent. The increase from 0.71 to 0.75 in the c_j coefficient indicates a higher sensitivity to contemporaneous sales

[4] For instance, Bloom et al. (2021) find that, on average, sales of small American firms were down 29% in the second quarter of 2020.
[5] Negative estimates of QFC account for roughly 35% of observations and may be due to measurement error.

in the *Pre-Covid Model*, while the decrease from -0.40 to -0.43 in the d_j coefficient suggests that the estimation of a firm's fixed operating costs is also more sensitive to lagged sales. All things considered, the lower estimated a_i, b_j and d_j coefficients in the *Pre-Covid Mo*del lead to a lower estimated average value of the QFC ratio (the c_j coefficient is not relevant for the computation of the QFC ratio). Additionally, once sales are higher than operating costs for the most part, the 0.03 change in the d_j coefficient has a greater impact than the -0.01 change in the b_j coefficient for the computation of the QFC ratio in the *Pre-Covid Model*.

	Full Model	***Pre-Covid Model***
a_i	645.57	450.50
b_j	0.63	0.62
c_j	0.71	0.75
d_j	-0.40	-0.43

Table 12. Comparison of estimated coefficients between the *Pre-Covid Model* and the *Full Model*

Notes: The average values of the estimated coefficients are computed using the gross profit as weight.

As in the *Full Model*, the estimated QFC are also analyzed by firm size and by sector of economic activity. The results are reported in Table 13 and Table 14, respectively. Once again, the results presented in Table 13 indicate that, on average, smaller firms have higher values in the QFC to sales ratio. Nano Cap firms report a value of 33.9%, compared to the much lower 11.0% reported by Mega Cap firms or the 14.2% reported by Large Cap firms. In what the change between the two models is concerned, it is not possible to establish a trend according to the firm size. For instance, the change in the estimated QFC to sales ratio amounts to -3.1 pp for Micro Cap firms but has a positive value of 0.8 pp for Nano Cap firms. Nevertheless, the COVID-19 pandemic contributes to higher estimated QFC for firms of all sizes except Nano Cap firms, on average.

Market Capitalization	N	Mean			St. Dev.	Q1	Q2	Q3
		Full Model	*Pre-Covid Model*	Change				
Nano Cap	3695	0.331	0.339	0.8 pp	0.768	0.068	0.150	0.285
Micro Cap	8496	0.308	0.277	-3.1 pp	0.535	0.058	0.140	0.301
Small Cap	12253	0.201	0.176	-2.5 pp	0.318	0.046	0.100	0.214
Medium Cap	9518	0.168	0.138	-3.0 pp	0.201	0.034	0.075	0.173
Large Cap	4784	0.162	0.142	-2.0 pp	0.149	0.034	0.099	0.210
Mega Cap	295	0.143	0.110	-3.3 pp	0.096	0.033	0.081	0.157
TOTAL	**39 041**	**0.160**	**0.133**	**-2.7 pp**	**0.169**	**0.035**	**0.089**	**0.185**

Table 13. Summary statistics of the QFC to sales ratio by firm size using the *Pre-Covid Model*

Notes: estimated QFC scaled by one-year lagged sales, weighted by the firm's gross profit. The sampling period goes from 2001 to 2019. The sample is restricted to firms with non-negative values of QFC to sales ratio. N represents the number of observations, while Q1, Q2 and Q3 represent the first quartile, median, and third quartile, respectively. Change is computed as *Pre-Covid Model - Full Model*. Values in red correspond to negative changes and values in green correspond to positive changes.

Regarding the impact across sectors of economic activity, it is possible to conclude that it is not homogeneous. It is well known that industries such as hospitality or retail trade were severely affected by the restrictions imposed across the world. In the survey they conducted for small American firms in 2020, Bloom et al. (2021) find that the five sectors most affected by the pandemic, in terms of sales, were Travel, Arts, Clothes, Retail and Food. The results reported in Table 14 are in accordance with these findings. Among the sectors with the biggest change between the two models are Arts, Entertainment, and Recreation with a -6.3 pp decrease in the average QFC to sales ratio, Accommodation and Food Services with a -11.5 pp decrease in the ratio, and Retail Trade with a -3.0 pp decrease in the ratio. Other sectors with above average decreases in the QFC to sales ratio include Finance and Insurance, Real Estate and Rental and Leasing, and Information. On the other end, the results indicate that the pandemic years have less impact on fixed costs estimates in sectors such as Professional, Scientific and Technical Services, Transportation and Warehousing and Agriculture, Forestry, Fishing and Hunting. With the exception of the Educational Services sector, all sectors of economic activity present a higher value in their estimated QFC ratio using the *Full Model.*

Sector of economic activity	N	Mean			St. Dev.	Q1	Q2	Q3
		Full Model	*Pre-Covid Model*	Change				
Educational Services	329	0.116	0.196	8.0 pp	0.137	0.103	0.138	0.239
Professional, Scientific, and Technical Services	2194	0.195	0.192	-0.3 pp	0.250	0.094	0.179	0.229
Others	505	0.195	0.188	-0.7 pp	0.078	0.153	0.193	0.220
Information	3937	0.226	0.168	-5.8 pp	0.217	0.036	0.113	0.229
Manufacturing	15209	0.174	0.160	-1.4 pp	0.157	0.059	0.112	0.246
Arts, Entertainment, and Recreation	274	0.220	0.157	-6.3 pp	0.104	0.070	0.137	0.220
Mining, Quarrying, and Oil and Gas Extraction	1633	0.155	0.151	-0.4 pp	0.313	0.032	0.099	0.190
Construction	661	0.144	0.140	-0.4 pp	0.063	0.076	0.167	0.181
Utilities	116	0.135	0.128	-0.7 pp	0.286	0.053	0.067	0.078
Transportation and Warehousing	540	0.127	0.127	-0.0 pp	0.114	0.043	0.103	0.200
Health Care and Social Assistance	774	0.137	0.107	-1.0 pp	0.270	0.038	0.048	0.123
Real Estate and Rental and Leasing	863	0.127	0.096	-3.1 pp	0.157	0.038	0.068	0.116
Finance and Insurance	6716	0.141	0.088	-5.3 pp	0.141	0.027	0.054	0.128
Accommodation and Food Services	935	0.189	0.074	-11.5 pp	0.064	0.040	0.067	0.099
Retail Trade	2405	0.096	0.066	-3.0 pp	0.081	0.019	0.035	0.093
Agriculture, Forestry, Fishing and Hunting	72	0.062	0.059	-0.3 pp	0.062	0.036	0.067	0.072
Administrative and Support and Waste Management	774	0.060	0.044	-1.6 pp	0.077	0.014	0.032	0.052
Wholesale Trade	1104	0.046	0.038	-0.8 pp	0.110	0.011	0.021	0.040
TOTAL	**39 041**	**0.160**	**0.133**	**-2.7 pp**	**0.169**	**0.035**	**0.089**	**0.185**

Table 14. Summary statistics of the QFC to sales ratio by sector of economic activity using the *Pre-Covid Model*

Notes: estimated QFC scaled by one-year lagged sales, weighted by the firm's gross profit. The sampling period goes from 2001 to 2019. The sample is restricted to firms with non-negative values of QFC to sales ratio. N represents the number of observations, while Q1, Q2 and Q3 represent the first quartile, median, and third quartile, respectively. Change is computed as *Pre-Covid Model - Full Model*. Values in red correspond to negative changes and values in green correspond to positive changes.

Table 15 reports the comparison of the average estimated coefficients of the two models between the *Pre-Covid Model* and the *Full Model* by sector od economic activity. The results evidence the significant variation of the coefficients in some sectors, such as Information, Real Estate and Rental and Leasing or Accommodation and Food Services, among others. Naturally, the differences in the coefficients help explain the variations in the QFC to sales ratios between the models. For example, in the Accommodation and Food Services sector, which is one of the most affected industries, the change in the d_j coefficient is once again very relevant. The coefficients obtained with the *Full Model* mostly lead to higher estimates of QFC, suggesting that the COVID-19 pandemic indeed impacts the estimation of this measure of operating leverage.

Sector of economic activity	Change		
	b_j	c_j	d_j
Information	-0.12	0.08	0.01
Arts, Entertainment, and Recreation	0.06	0.04	-0.11
Others	-0.01	0.00	0.00
Professional, Scientific, and Technical Services	-0.01	0.01	0.01
Accommodation and Food Services	-0.03	0.13	-0.10
Manufacturing	0.01	0.02	-0.03
Health Care and Social Assistance	-0.08	0.11	-0.01
Mining, Quarrying, and Oil and Gas Extraction	0.06	0.00	-0.06
Construction	0.04	0.03	-0.03
Utilities	0.00	0.00	0.00
Transportation and Warehousing	-0.05	-0.01	0.06
Educational Services	-0.17	-0.11	0.24
Real Estate and Rental and Leasing	0.22	0.04	-0.22
Finance and Insurance	-0.03	0.04	-0.03
Administrative and Support and Waste Management	0.06	0.03	-0.10
Retail Trade	0.02	0.03	-0.05
Agriculture, Forestry, Fishing and Hunting	-0.02	0.26	0.00
Wholesale Trade	-0.10	0.00	0.09
TOTAL	**-0.01**	**0.04**	**-0.03**

Table 15. Change of estimated coefficients between the *Pre-Covid Model* and the *Full Model* by sector of economic activity

Notes: The average values of the estimated coefficients are computed using the gross profit as weight. Change is computed as *Pre-Covid Model - Full Model*.

A possible reason for the increase in the QFC to sales ratio observed with the *Full Model* is the expected duration of the pandemic. Adjusting the firm operating structure is a burdensome task. Therefore, if firms expect the negative economic shock triggered by the pandemic to be only temporary, they will be more reluctant to adjust their cost structure. In this scenario, managers may consider that the disutility from reducing costs outweighs the disutility induced by a negative temporary shock in output. In contrast, if managers take the shock as permanent, it is possible that they adjust their cost structure more drastically leading to lower fixed costs estimates. This downsize may lead to the cut of costs that in general would be considered as fixed costs. Bartik et al. (2020) conduct a survey of more than 5800 small businesses and find that, in April 2020, more than 90% of firms expected the pandemic to end by January 2021. This means that the vast majority of businesses expected the shock to last approximately 9 months or less. This finding may help explaining why the estimated QFC measure is higher using the *Full Model*. Finally, the record-breaking $2 trillion CARES Act signed into law on March 27th 2020 can also play a role in the explanation. This stimulus bill's objective was to curb the impact of the economic downturn and support small and large businesses, households, health providers, and others. When asked about the CARES Act and the impact of the loans and grants included in their businesses, 72% of respondents said they had interest in taking up the program and reported improved probabilities of being open by December 2020 and improved projections for their employment level by December 2020 (Bartik et al. 2020). The expectation of a limited and temporary shock coupled with the perceived benefits of the relief program introduced by the US government may have led firms to not adjust their costs dramatically, resulting in increases of the QFC measure estimated.

9. Conclusion

In this study, fixed operating costs for American publicly traded firms are estimated. Using a measure of operating leverage that takes the firm's management flexibility into account, it is found that average fixed operating costs account for 15.5% of sales. Furthermore, these results are heterogeneous across firm size and across sectors of economic activity. Concerning the differences by firm size, it is found that smaller firms have higher estimated values of fixed operating costs than bigger firms. Regarding the differences across sectors, it is found that service-related sectors typically present higher values for the QFC measure.

An interesting relation between the estimated QFC and the shares of the components of operating costs (COGS, SG&A expenses, and Depreciation and Amortization) in the firm's operating cost structure is also evidenced. In particular, there is a significant negative correlation between QFC and the share of COGS and a significant positive correlation between QFC and the share of SG&A. These findings confirm the initial intuition that SG&A is generally stickier than COGS and consequently leads to higher levels of operating leverage.

The QFC measure is also tested against other measures of operating leverage proposed in the literature. The results prove that it is economically and statistically significant as an alternative method of estimating operating leverage.

Finally, the impact of the COVID-19 pandemic on fixed costs estimates is analyzed using a model that excludes data from 2020 and 2021. The main conclusion drawn is that the estimated QFC are higher when these two years are used in the estimation. In addition to the variations in the estimated coefficients, this result may also be explained by the expected duration of the pandemic as well as by the relief programs promoted by the US government. The second main conclusion is that the industries that usually come to mind when thinking about the impact of COVID-19 (e.g., retail trade, restaurants, accommodation, and entertainment) are among the ones that experience a higher increase in their estimated QFC.

Overall, these findings support the idea that the QFC measure can be used as a valid measure of operating leverage, with implications for firm managers, investors, credit risk models and also government officials. Nevertheless, the analysis performed still leaves some questions unanswered. For instance, it would be interesting to understand the optimal period (i.e., number of years) to use in the estimation of the QFC measure.

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Appendix

Appendix 1. Relevant variables

Variable	Description
Operating Costs	Cost of Goods Sold (Compustat item COGS) + Selling, General and Administrative expenses (Compustat item XSGA) + Depreciation and Amortization (Compustat item DP)
Firm Size	Firm size is defined according to the market capitalization (Compustat item PRCC x Compustat item CSHO) of each firm-year observation. For all years in the sample, six bins are constructed. The bins correspond to the following categories: Mega Cap; Large Cap; Medium Cap; Small Cap; Micro Cap; Nano Cap. The bin boundaries used for 2021 are the following: Mega Cap > $200 Billion $10 Billion < Large Cap < $200 Billion $2 Billion < Medium Cap < $10 Billion $300 Million < Small Cap < $2 Billion $50 Million < Micro Cap < $300 Million Nano Cap < $50 Million For the preceding years (2001-2020), the bin boundaries are adjusted using the yearly growth rates of the S&P500 market capitalization in those years.
Sector of economic activity	The sectors of operating activity are obtained using the two-digit North American Industry Classification System (NAICS) code. The sector corresponds to the two leftmost numbers of the code. For instance, the code 441221 corresponds to the industry Motorcycle, ATV, and Personal Watercraft Dealers. The two leftmost numbers in the code are 44, which corresponds to the Retail Trade sector.
Firm Age	Firm age is the number of years (plus one) since the company first appeared in CRSP or Compustat, in 2019. The two databases are merged using the PERMCO code, which is a unique company level identifier.