Internal Capital Markets in the Great Depression*
PRELIMINARY AND INCOMPLETE

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Abstract

Much attention has been focused on understanding the role of external capital markets in deepening and lengthening the Great Depression. This focus has come at the cost of neglecting the role of internal capital markets within a firm. We construct a plant-level dataset from the Census of Manufactures for a select set of industries linked to their parent company. First, we document that plants that are part of multi-plant firms have more volatile monthly employment. Furthermore, we show that multi-plant firms themselves have more monthly volatile employment. We provide evidence that this excess volatility is due to the reallocation of resources inside the firm. In particular, plants that are part of multi-plant firms are more sensitive to shocks to local economic conditions. Finally, we discuss the implications of these results for the magnitude of the Depression and models of internal capital markets.

1 Introduction

Business cycles are granular in nature with much of the change in aggregate output driven by changes in output of the largest firms (Gabaix, 2011). The largest firms are unique in many ways. We focus on one specialty: the existence of internal capital markets. For example, consider the differences between Wal-Mart to a local mom-and-pop convenience store. Now on average, we would expect, on average, that Wal-Mart was more productive than the mom-and-pop (Foster et al., 2008). Wal-Mart also operates thousands of stores all across the country whereas the mom-and-pop is by definition a single store. The existence of these far flung stores for Wal-Mart requires

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headquarters to make crucial decisions on how resources should be allocated spatially between the stores.

We study the role of internal capital markets in the context of the Great Depression. While not quite as granular as the modern US economy, the economy at that time was still dominated by large firms that operated multiple plants across the country. Consider the fact that in the cement industry, the average number of plants the three largest firms operated was more than 10. For the Big Three automobile makers, the average was about 18. So understanding the behavior of these biggest firms has important implications for our understanding fo the Depression as a whole. Furthermore, the Great Depression was a time of unprecedented disruptions in *external* capital markets from rolling bank failures to stock price collapses matched with an unprecedented decline in output. Rightly, then, economists from Friedman and Schwartz (1971) to Bernanke (1983) have attempted to understand the link between these two occurrences. Still to this day, the debate between those who place large portion of the decline on the banking crisis versus those who see the banking crisis as an epiphenomena such as Cole and Ohanian (2000) rages on. However, none of this work has attempted to address the possible connections between shocks to external capital markets and the response of internal ones.

Taking this plant or establishment-level view suggests new questions to be addressed. First, what role did multi-plant firms and their internal capital markets play in mitigating or exacerbating local economic fluctuations and, thereby, contribute or detract from the Depression as a whole? We begin to address this question by constructing a plant-level dataset, which we link into firms, for a select group of industries from the Census of Manufactures taken in 1929, 1931, 1933, and 1935. These industries, discussed in more detail later, span a variety of industry characteristics from capital intensity to who the typical end user is. There are also differences in the extent of multi-plant firms across the industries. These differences allows us to identify the effects of internal capital markets using both between and within industry variation.

The first result we document is that plants that are part of a multi-plant are more volatile than single plant as measured by the monthly variation in employment. Now this is not necessarily surprising if firms have active internal capital markets and engage in winner picking moving resources from unproductive to productive plants. However, the next result we document is more surprising showing that even at the *firm-level*, employment is more volatile for multi-plant (MP) firms compared to single-plant (non-MP) firms. The effects at the plant and firm level are large in magnitude between 8 and 10% of the average volatility. One might have imagined that while individual plants that are part of a multi-plant firm are more volatile, the volatility of the overall employment of the firm would have been less volatile through a diversification effect. This simply does not appear to be the case. Furthermore, we find this pattern holds broadly across industries. Strikingly, it does not hold exactly in the time series. The effect is largest in 1929 and then follows developments in the banking sector with the effect nearly zero by 1933 before recovering in 1935.

The second set of results attempts to address part of this puzzle by studying how local shocks are propagated between different regions through internal capital markets. The excess volatility for plants that are part of multi-plant firms may be due to the fact that they are more sensitive to shocks in their own region and possibly spillovers of shocks in other regions through internal capital markets. We consider local demand shocks (for plants that predominantly sell locally) and banking shocks. This latter shock allows us to address interaction between internal capital markets and shocks to the external capital markets. This is particularly important at this time as the banking system was highly fragmented due to branch banking restrictions within and across states. Internal capital markets can precisely serve as a substitute for these markets.

We then go on to show that shcoks to other plants that are part of a single MP firm located in different areas spillover. In particular, if demand is relatively higher in another region, a plant connected to that region through a particular firm will have lower employment on average. This is similarly the case for discount rates. Finally, we document that MP and non-MP plants do not locate in the same regions. What is more surprising is the fact that MP plants that are part of the same firm tend to locate in areas with similar conditions. Rather than diversifying away the risk faced, MP firms tend to increase this risk. We also find some evidence that this "correlation" declined from 1929. This is suggestive of either a selection effect of which plants are forced to close within a firm or a changing distribution of shocks across regions.

The closest parallel to this work is an attempt to use the shock of the 2007-2009 financial crisis to understand the role of internal capital markets. Matovs and Seru (2013) estimate a structural model finding that internal capital markets act as a substitute for external ones during the crisis. In a related paper using the 2007-2009 crisis, Kuppuswamy and Villalonga (2010) show that the diversity discount falls. They argue that this is the result of improvement in efficiency of internal capital. We reiterate that the two key points of departure from much of the literature in terms of data. First of all, we use the CoM a source that includes the whole universe of plants rather than only the biggest firms as in the Compustat. Second, we focus on geographic diversification rather than "product" diversification. This measure does not suffer from the problem that the firms' themselves report this information. Furthermore, it allows us to more easily identify shocks impacting particular plants in particular areas relative to plants in other regions.

2 Literature Review on Internal Capital Markets

A very good summary of the literature both theoretical and empirical on internal capitals from a corporate finance perspective is in Stein (2003).[1] The theoretical literature stretches back to Gertner et al. (1994), which laid out the costs and benefits from agency point of view of internal versus external credit markets. The benefits of internal capital markets are two-fold. First, there is a diversification benefit to pooling operations when outcomes are not negatively correlated. This can allow small firms to tap wider pools of capital by reducing the risk of the overall operation. Stein (1997) highlighted another possible benefit internal capital markets even if there is no relaxation of credit constraints through "winner-picking."

Internal capital markets are not necessarily unalloyed goods since they tend to introduce less than perfect competition. The "dark side of internal capital markets" was modeled in a paper by Scharfstein and Stein (2000). Here division managers rent seek and attempt to raise their own bargaining power inside the organization. This has the potential to distort resource flows and lead to "socialism" where the weakest divisions receive more resources. The reason for this is that the managers of the weakest divisions have the greatest incentive to engage in rent seeking behavior. Therefore, to stem those activities, the CEO has to shift more resources to that division. A slightly different model of dark side of internal capital markets is developed in Rajan et al. (2000). In both cases, shocks that affect the bargaining power of managers even if they do not directly affect investment opportunities force the headquarters to shift resources, often in deleterious directions for firm value. While the theoretical literature has been developed in a number of different directions, work remains to extend these first generation models to more dynamic settings.

[1] More recent reviews of the literature are in Maksimovic and Phillips (2007) and Maksimovic and Phillips (2013).

The empirical literature, like the theoretical literature, is split over what the effect of internal capital markets is. We first note that almost all of this work has used information on "segments" of firms reported in Compustat as the measure of the size of internal capital markets. There is ample evidence that internal capital markets are active going back to the paper by Lamont (1997) who studied the effect of oil price shocks on non-oil divisions of oil producing companies. More recently, Giroud (2013) have documented the reallocation of resources towards plants that become gain airline routes. In complimentary earlier work, Giroud and Mueller (2012) showed that these plants increased their investment. The combination of the results in these two papers suggested that, first, information frictions matter inside of firms and, second, firms attempt to allocate resources towards productive plants away from less productive ones. While the results in Lamont (1997) were interpreted as reflecting "socialism" in internal markets, more direct evidence for this was given in the paper by Shin and Stulz (1998) using data from Compustat. In addition, Ozbas and Scharfstein (2010) provided evidence for dark side view along the lines of Scharfstein and Stein (2000). They compared Q-sensitivity of investment in stand alone versus diversified segments.

As hinted before, there is other evidence for the salutary effects of internal capital markets. For example, Khanna and Tice (2001): studied diversified retailers in response to entry of Wal-Mart. They showed that diversified firms were able to "pick winners." Interestingly, there is very little evidence that internal capital markets serve to alleviate external capital market frictions. Dimitrov and Tice (2006) compared diversified and focused firms over the business cycle and attempted to relate differences in their behavior to the existence of credit constraints and relaxation of those constraints by diversified plants. The paper is hamstrung by a lack of data on the credit of these firms.

The bright side of internal capital markets view has had to answer the empirical puzzle of the "diversification discount" documented in Lang and Stulz (1994) where "diversified" firms tend to trade at a discount to the value of the various pieces of the firm. Maksimovic and Phillips (2002) provide a neoclassical explanation for this and Gomes and Livdan (2004) calibrate this model and find that it can empirically match a variety of firm-level moments. The problem with nearly all of the empirical literature is the use of segments from the Compustat dataset. Villalonga (2004) shows that using other sources other than Compustat to define diversification leads to very different magnitudes for the size of the diversity discount. The difficulty is that the number of segments is not just that diversification is endogenous but even the report on the number of segments is a choice of the firms.

It is somewhat puzzling but business cycles and corporate finance have remained rather distinct strands in the literature. While macroeconomics has imported many insights from the finance and banking literature, little from corporate finance in the form of internal capital markets has made the jump. At the same, it is, of course, simple enough to introduce something like a business cycle shock into many of the corporate finance models. Yet this has not really been explored even in a partial equilibrium setting. The work on the Great Recession is probably the closest to this. Furthermore, empirical papers that even consider explicitly business cycles are nearly nil, the only example being Dimitrov and Tice (2006) and Hovakimian (2011). We are unware of any fully specified macro model with a serious model of internal capital markets.

3 Model

We first develop a simple neoclassical model to lay out some of the possible effects of internal capital markets. A firm operates two plants A and B in different locations. Each plant operates a decreasing returns to scale production function in labor alone $y_i = A_i L_i^\eta$ with $\eta < 1$. Plants need to have their wage bill wL_i upfront in cash (working capital), which can either be obtained from the headquarters or borrowed in local capital markets. Normalize $w = 1$. Now assume that there are two shocks in each region: a demand shock P_i and credit shock R_i. So that plant in location i maximizes

$$\max_{L_i} P_i L_i^\eta - \frac{R_i L_i}{\omega_i}$$

The term ω_i is chosen by the parent company subject to $\omega_A + \omega_B = 1$ with $\omega_A, \omega_B \geq 0$. One could think of this as the parent firm providing a subsidy to the individual plants by borrowing in the This formulation allows for closed form solutions though similar intuition would hold in levels. For now, there is no conflict between individual plants and headquarters. The plant's problem is the same as the one for the headquarters.

The timing is as follows. Shocks are realized, the parent company sets ω_i, and finally, plants choose levels of output. To solve this, first consider the solution to plant's problem taking as given the "subsidy" from the parent company. It is easy to check then that

$$L_i^* = c\left(\frac{\omega_i P_i}{R_i}\right)^{\frac{1}{1-\eta}}$$

where c is a constant that depends only on η. Let profits be denoted by $\pi(P_i, R_i, \omega_i)$, then the firm maximizes

$$\max_{\omega_A,\omega_B} \sum_i \pi(P_i, R_i, \omega_i) = \sum_i \frac{1}{R_i}\pi(P_i/R_i, \omega_i)$$

Let $d_i = \frac{1}{R_i}\left(\frac{P_i}{R_i}\right)^{\frac{1}{1-\eta}}$, then the firm's problem is

$$d_A \omega_A^{\frac{\eta}{1-\eta}} + d_B(1-\omega_B)^{\frac{\eta}{1-\eta}}$$

The solution for ω_A, given the behavior of the plants, is

$$\omega_A = \frac{b}{1+b}$$

where

$$b = \left(\frac{d_B}{d_A}\right)^{\frac{2\eta-1}{1-\eta}}$$

Given decreasing returns to scale, it is not optimal to go to a corner instead both plants receive a subsidy. It is clear from this expression that by sharing risk, the firm can do better relative to two independent plants since ω_A will only equal 1/2 in special cases. This is not particularly surprising and we have no allusions that this is a serious theory of the firm. Instead we use this setup to drive some empirical predictions and build intuition. What is also important to note is the fact that the firm's problem is not homogeneous of degree 1 in P_i/R_i like each plant's since the firm sums across profits at each plant at the end.

It is easy to see from this that the sensitivity of labor to demand and credit shocks for MP plants $\alpha_D^{MP}, \alpha_R^{MP}$ is higher than that for non-MP plants $\alpha_P^{nMP}, \alpha_R^{nMP}$. We can write for demand shocks and similarly for credit shocks

$$\alpha_D^{MP} = \frac{\partial \log L_i^*}{\partial P_i} = \alpha_D^{nMP} + \frac{\partial \log \omega_i}{\partial P_i}$$

and $\frac{\partial \log \omega_i}{\partial P_i} > 0$. Now the issue will be that for credit shocks, we will find less sensitivity. We suggest in discussing those results that the correct model is one not where the local interest rate matters but where the minimum of interest rates overall regions matters. This would easily generate lower volatility as in the data.

We now calculate the volatility in (log) employment at the plant and firm level for MP and non-MP plants and firms. By definition, volatility at the plant-level σ^P_{nMP} is the same as that at the firm-level for non-MP plants σ^P_{nMP}. Plant volatility σ^P_{MP} is defined analogously. For non-MP plants, volatility is simple to calculate as

$$\sigma^P_{nMP} = \frac{1}{(1-\eta)^2}(Var \log P_i + Var \log R_i + 2Cov(\log P_i, \log R_i))$$

The covariance between $\log P_i$ and $\log R_i$ is taken as parametric and constant across regions. For MP plants, we have

$$\sigma^P_{MP} = \sigma^P_{nMP} + \frac{1}{(1-\eta)^2}\sigma^2_{\log \omega} + \frac{2}{(1-\eta)^2}Cov(\log \omega_i, \log P_i/R_i)$$

Now $Cov(\log \omega_i, \log P_i/R_i) \geq 0$ since $\frac{\partial \log \omega_i}{\partial \log P_i} > 0$ and $\frac{\partial \log \omega_i}{\partial \log R_i} > 0$. It would only be equal to 0 in the case where there is no variation in $\log P_i/R_i$. However, note that even in this case as long as one of the variables has some variance, then $\sigma_{\log \omega} > 0$. The key point is that the firm problem is not homogeneous in P_i/R_i. So in either case, $\sigma^P_{MP} > \sigma^P_{nMP}$

Whether or not this is also holds at the firm-level is a little more subtle since there is a built in degree of negative correlation between the plants. In particular, the key force is the correlation between outcomes in regions A and B. In our empirical exercises, we will define firm volatility as the volatility of the log of total employment. We think this makes the comparison to non-MP firms more transparent as well as aids in interpretation. However, for showing analytically what matters, it easier to study volatility over the sum of log employments.

First consider the volatility for a randomly constructed two plant firm $\sigma^F_{nMP} \equiv Var(\log L_A + \log L_B)$ where L_A, L_B are evaluated given $\omega_A = \omega_B = 1/2$. This would be given by

$$\sigma^F_{nMP} = 2\sigma^P_{nMP} + \frac{1}{(1-\eta)^2}Cov(\log P_A/R_A, \log P_B/R_B)$$

Like the correlation between shocks within a region, the cross-correlation $Cov(\log P_A/R_A, \log P_B/R_B)$ will be taken as given. For MP firms, we have

$$\sigma_{MP}^F = \sigma_{nMP}^F + \frac{2}{(1-\eta)^2} Var \log \omega_A + \frac{4}{(1-\eta)^2} Cov(\log \omega_A, \log P_A/R_A) + \frac{2}{(1-\eta)^2} Cov(\log \omega_A, \log(1-\omega_A))$$

Then $\sigma_{MP}^F \geq \sigma_{nMP}^F$ if and only if

$$Var \log \omega_A + 2Cov(\log \omega_A, \log P_A/R_A) + Cov(\log \omega_A, \log(1-\omega_A)) \geq 0$$

Or

$$1 + \rho_{\omega,P/R} \frac{\sigma_{\log P/R}}{\sigma_{\log \omega}} + \rho_{\omega,1-\omega} \geq 0$$

For this calculation, we have assumed symmetry in the shocks such that $Var \log \omega_A = Var \log \omega_B$ and $Cov(\log \omega_A, \log P_A/R_A) = Cov(\log \omega_B, \log P_B/R_B)$. However, we know that $\rho_{\omega,1-\omega} \geq -1$ and $\rho_{\omega,P/R} \frac{\sigma_{\log P/R}}{\sigma_{\log \omega}} > 0$. So therefore, $\sigma_{MP}^F > \sigma_{nMP}^F$.

4 Data

We collect data from the Census of Manufactures for 11 industries: ice, macaroni, agricultural implements, sugar refining, cement, malt, bone black, cane sugar, automobiles,[2] concrete, and radio. The source as a whole is discussed in greater detail in Ziebarth (2013). This is an incredibly rich source to study the Depression at an unprecedented degree of disaggregation. The important limitations to this data are that it lacks information on investment (or the value of capital) and any information on the financial position of the plants. The first limitation makes the focus of this paper in terms of the outcome variable different than much of the literature. We will focus on monthly employment instead of on investment like much of the modern literature.

While collected ostensibly for other purposes, the industries provide a nice cross-section of the manufacturing sector as a whole. Ice, sugar, and macaroni are consumer, non-durable products while both cement and agricultural implements are capital goods purchased by other businesses. The industries also differ to what extent they sell locally or to national markets. Because of high

[2] This dataset was collected by Bresnahan and Raff (1991) and is available on ICPSR.

shipping costs, both ice and cement plants have limited geographic scope, while the others such as automobiles and radios ship across the country. Furthermore, there are differences in the degree of competition. The tacit collusion in the sugar and cement industries has been suspected by many authors.[3] Finally, the industries differ quite strikingly with regards to the importance of labor in production. The fraction of wages to revenue (gross output), a rough measure of the elasticity of production with respect to labor, ranges from .04 in sugar to .22 in agricultural implements. The diversity of the industries lends credence to the claim that the results reported below apply generally to the manufacturing sector.

We note that the industries differ in their degree of "aggregation." The CoM did not use things like 4 digit SIC codes to organize plants. Instead they had categories that changed over time tending to become more narrowly defined. For example, the radio industry starts out in 1929 as also including phonograph producers before splitting these plants into a separate category. At the same time, the industries of ice, macaroni, cement, sugar refining, malt, bone black, and cane sugar are very narrowly defined with plants tending to make only one product with little differentiation (besides spatial for some). On the other hand, the remaining industries are closer 3 digit SIC codes with many plants producing a variety of products. This is particularly true for agricultural implements where plants make reapers, tractors, thrashers among other things. The concrete industry, while tending to have a particular plant only producing one product, covers all things made with concrete from concrete blocks to statues. Whether or not plants are correctly grouped based on who they compete with or what their production is will not be particularly crucial questions for us.

At this point, it is useful to reiterate what type of internal capital markets we have in mind. Broadly speaking, the literature has not been particularly careful on this matter. In terms of theoretical models, as far as we know, the literature has almost exclusively focused on what we would call "horizontal" internal capital markets. In other words, firms that operate multiple plants all producing the same output for sale in some national market.This should be compared to "vertical" internal capital markets, which have been ignored both theoretically and empirically.[4] Now the

[3]For sugar, see Genesove and Mullin (1998). For cement, see (Chicu et al., 2013) and the FTC's court case in 1931, *FTC v. Cement Institute.*

[4]Empirical work has not even attempted to separate out these different types of segments. We return to this point at the end of the paper arguing that it demands more careful consideration.

empirical literature has tended to reinterpret these models of horizontal internal capital markets as being about firms that have operations in a variety of different markets. Think of Microsoft, for example, that sells Windows, Office, X-Box, and other internet services. Roughly speaking, this, in our view, is a reasonable mapping of the model into the data.[5] For a number of our industries, our empirical setup will be even closer to the theoretical models with plants selling similar products into national or local markets.

Focusing on industries of this form allows for a cleaner interpretation of the results. In horizontally arranged industries, the only reason why shocks to a particular MP plant in one region should spill over to a plant part of the same firm in another region is through the internal capital market. In contrast, assume that we could identify a shock to demand for Windows, because of compatibility issues between Windows and Office, this would induce a demand shock for Office clouding the interpretation of any results. More abstractly, for horizontal internal capital markets, the "treatment" to one plant does not directly affect the "control" plant.

We should be clear that due to data limitations, we are not able to identify plants owned by a particular firm that fall outside the our industries of interest. To a first approximation for the industries we consider, the firms only own plants in the one particular industry. This is not true in the automobile industry where the Big 3 owned not just final assembly plants but plants producing various components from brake pads to interior seating. We discuss this worry in more detail when we discuss the results.

Besides the cement industry where directories from the Cement Institute were employed, we link by hand from the schedules plants into their parent firm using the name of the parent company. This can be a fraught process when firms change their names over the years. The process of linking establishments over time, by way of comparison is much easier since we can use name of the plant as well as the location of the plants. There is no reason to think that the errors are anything but random. That being said, almost surely the errors in the process of matching lead me to underestimate of the fraction of plants that are part of multi-plant firms. The reason for this is that the vast majority of errors are almost surely not matching a plant to the wrong firm but not finding a match at all. This leads to a proliferation of fictitious single plant firms.

[5]It does miss the fact that whereas Windows and Office are not really competitors with each other, a GM auto plant in Detroit is "in competition" with a plant in, say, South Carolina.

5 Empirical Specifications and Results

5.1 Comparing Multi-plant versus Single Plant Firms

First, Table 1 reports some summary statistics for the role of multi-plant firms in their respective industry. The variation between industries is quite remarkable with macaroni with no multi-plant firms to the cement industry where over 60% of the plants are part of a multi-plant operation. What is quite remarkable as well is how skewed the distribution is as the plants that are part of multi-plant operations (MP) produce more of the output relative to their number. For example, in the agricultural implements industry where only 18% of the plants are MP but have over 70% of the revenue. This ratio is greater than 1 in all of the industries considered. This emphasizes the importance of understanding how these firms and plants behave.

Next we compare MP plants to non-MP plants along some other dimensions including size as measured by revenue and employment as well as labor shares of revenue. For all of the results, we report a test for the equality of means where values of the variable are demeaned and scaled by the standard deviation. This aids in comparing the magnitudes across different industries by placing plants on a similar scale. It is useful to note for future reference that the labor inputs variable I will be using only captures wage earners not salaried workers nor anything about labor inputs on the intensive margin of hours worked.

Table 3 reports the differences between MP and non-MP plants in standardized units and the results of the statistical test. There are very sharp differences in the statistical and economic senses when the comparison is in terms of output. Here the MP plants dominate by a real margin with even in the smallest case, the difference reflecting a move from the 47th percentile to the 53rd in cement. For sugar, the difference in size between MP and non-MP plants reflects a move from the 41st percentile of the output distribution to the 59th. Broadly speaking, the same flavor of results hold for wage earners with MP plants having larger work forces, not surprising given they are producing so much more.One could interpret these differences as *prima facie* evidence for internal capital markets alleviating credit frictions and allowing plants that would be constrained to grow bigger. A different interpretation would be that for some reason, MP plants are more productive than non-MP plants and this explains, then, why they are larger as suggested by Foster et al. (2008). There is modern evidence in a paper by Schoar (2002) that finds MP plants or, more precisely, conglomerate firms are more productive on average than stand alone firms, but some of this benefit is dissipated when a stand along chooses to diversify. She does not, however, consider whether this difference in productivity explains any of the size differential as measured by output present in her data as well.

On the other hand, across all the industries, MP plants have smaller ratios of wages to revenue. However, this difference does not appear large in a statistical oor economic sense. That suggests MP plants are not different in terms of the technology being employed relative to non-MP plants in their same industry at least with regards to the role of labor in the production process. At the same time, there is qualitative evidence from various sources that in some particular industries there were differences in technology such as automobiles Bresnahan and Raff (1991) and macaroni Alexander (1997). These papers are silent on whether these technology choices were correlated with MP firms. As a whole, we conclude that differences in size between MP and non-MP plants as measured by output or employment are not due to technological differences.

5.2 Comparing the Volatility of Employment in MP versus non-MP Plants and Firms

We now consider differences between these two types of plants relevant to understanding business cycle fluctuations. In particular, are MP plants more volatile than non-MP plants *controlling* for size? Furthermore, if we aggregate to the level of the firm, are MP firms more volatile again controlling for size? MP plants. Note that size as measured by total revenue is an important control here not only because there are differences in the average size between MP and non-MP plants, but that size appears to be correlated with sensitivity to the business cycle, at least in modern data (Moscarni and Postel-Vinay, 2012). We examine this pattern across industries and over time as well. The latter we think provides some interesting insights into the interaction between external and internal capital markets.

We now introduce some notation to specify the regression. Plant i part of firm j has average log monthly employment in year t of

$$\bar{E}_{ijt} = \frac{1}{12} \sum_{\tau=1}^{12} \log E_{ijt}$$

Its (monthly) standard deviation is denoted by $\bar{\sigma}_{ijt}^{E}$. For firms, we sum over all i that are a member from firm j before applying the log transform. Firm variables are denoted with a tilde. Using the standard deviation of log makes the interpretation of the results more transparent as a one standard deviation shock represents some percentage variation in the employment variable. We report summary statistics for these variables in Table 2 . To be precise, the employment variable is solely wage earners excluding salaried employees.

The regression specification at the plant-level is

$$\sigma_{ijt}^{E} = \alpha_0 + \alpha_1 \bar{E}_{ijt} + \alpha_2 MP_{jt} + \sum_k \sum_t \delta_{kt} Year_t Industry_k + \varepsilon_{ijt}$$

where MP_{jt} is an indicator whether firm j is multi-plant firm and $\sum_k \sum_t \delta_{kt} Year_t Industry_k$ represents a full set of industry-specific time trends. Note that MP_{jt} is not necessarily fixed over time. It may be the case that new plants join a particular firm making an originally single-plant operation a multi-plant operation or vice verse where a multi-plant firm refocuses and becomes a single-plant operation. In principle, this would allow for the possibility of identifying the effects of being part of a multi-plant operation using within plant variation. Unfortunately, the number of plants that this applies to is vanishingly small. Because of this, we cannot control for firm and plant fixed effects separately from the MP indicator. We report heteroskedasticity robust standard errors. Clustering at the firm-level produces only minor changes in the standard errors.

Table 4 reports the results from these regressions. All three regression show that MP plants have more volatile employment counts from month to month. This is consistent across the 3 specifications, which range from including a full set of industry-specific time trends to no fixed effects at all. The magnitude of the effect in our preferred specification taking out industry specific time trends is quite significant being approximately 13% of the average volatility. The results are also robust to the inclusion state fixed effects as well. The overall effect from size of the plant as measured by total revenue is also interesting as there appears to be very little relationship between size and volatility. The coefficient is statistically significant but economically not very meaningful. Finally, the excess volatility for MP plants is relatively common across the industries. Table 5 reports the multiplant effect industry by industry. 5 out of 8 show a strong positive effect and none of the negative coefficients are precisely estimated. Now we make no suggestion that these results should be surprising or not. In our view, any model of active internal capital markets would deliver such a result.

We now turn to the results at the firm-level with results reported in Table 6. As at the plant-level, MP *firms* are consistently more volatile than non-MP firms even after controlling for size. One might have thought that the higher volatility at the plant-level would have been offset by an averaging across a number of different plants that are not highly correlated to get lower volatility at the firm-level. This does not appear to be the case. The effect is reasonably large as well around 8.5% of the average level of volatility. At the firm-level, we do observe a more significant negative pattern between volatility and size besides the case with no fixed effects. This is both in statistical magnitude and economic magnitude where the coefficients are 50% or larger. Table 7 reports the multiplant effect across the industries in the sample. Besides one negative coefficient (that is statistically significant), all the others show a positive relationship. Again the simple "neoclassical" theory outlined above does not necessarily imply anything about volatility at the firm-level since it depends on the correlation of shocks. What we find also interesting is the fact that the relationship between size and volatility is quite variable across industries with an almost equal number of positive and negative effects.

Finally, we turn to the time series pattern of the multiplant effect. Table 8 reports this effect at the plant and firm level for each year of 1929, 1931, 1933, and 1935. The overall effect from the previous regressions is almost completely driven by 1929. The MP effect for 1931 and 1933 are severely attenuated and indistinguishable from 0 in 1933 at both the plant and firm level. We find it highly suggestive that the Depression does begin in earnest until the middle to end of 1929 and the banking panics do not start until 1930, peak in 1933, and are over by 1935. This pattern exactly matches the effects with 1935 showing again a large MP effect. Now this banking pattern is also the pattern for the broader economy. So it is difficult to know whether this is a financial markets effect or a general business cycle effect. One can think of this approach as similar in spirit to both Matovs and Seru (2013) and Kuppuswamy and Villalonga (2010) who exploit the 2008 Financial Crisis as an exogenous shock to external capital markets. The former paper is closer in that they are interested in resource allocation within firms as well. They find that with the costs of external finance increasing, internal capital markets provide a substitute.

Whatever the source of this excess volatility is appears to be exacerbated by the number of plants within a firm. In results not reported here, we find that volatility at the firm or plant-level is strongly increasing in the number of plants.There is some slight evidence for an inverted U-shaped pattern with the firms having the largest number of plants showing lower volatility. This is suggestive evidence that multi-plant firms and their constituent plants are more sensitive to shocks of some sort, but it does not have anything to say about where the source of that volatility is coming from. We now attempt to explain part of this relationship by examining the response of MP plants to local shocks versus non-MP plants.

5.3 Response to Local Shocks in MP versus non-MP Firms and Plants

The previous section documented that MP firms and plants are more volatile in terms of their month-to-month employment counts. We now interrogate why this is by comparing the response to local economic shocks of MP plants versus non-MP plants. We consider two “shocks” at the regional Fed district-level. Because the nature of the diversification we consider is geographic, this is why we focus on shocks disaggregated in this way. Besides the work of Giroud and Mueller (2012) which also focuses on the geographic dimension, all the other work we are aware of looks at conglomerates and attempts to identify shocks affecting one segment or another. We would simply note that this is very difficult given the self-reported and rather vague nature of these segments. While identifying shocks will still be difficult for us, geographic diversification is not open to these other vagaries. One difficulty is the rather broad geographic range of a Federal Reserve region. This will lead to cases where there are MP firms that are completely contained in one district. For these firms, it is impossible to estimate geographic spillovers from other regions. We offer a couple different approaches to handling these plants and firms.

These shocks are the discount rate for the respective regional Fed and a regional “demand shock” as proxied by the retail sales index collected by the Federal Reserve. With regards to the first shock, recall that this was time before authority over discount policy had been centralized at the Federal Reserve Board. This led to variation to be exploited across different regions in the choice of the discount rate by the regional Fed bank. The details regarding the second shock, th retail sales data, are discussed in Park and Richardson (2011). As noted before, not all of these industries sold locally so to what extent this shock is a demand shock matters by industry. We will attempt to control for this by interacting this with industry fixed effects. Finally, we aggregate the data to the quarterly level since this is the frequency of the discount rates.

We will follow the setup of Giroud and Mueller (2012) as close as possible for the sake of comparability. So in particular, the dependent variable will be the "centered" log employment at the plant-level centered by the industry-month median. Abusing notation slightly, denote this by $\log E_{it}$. This makes it transparent that we will not be using industry-specific time trends to identify any effect and the choice of the median is to limit the influence of outliers. For now, we choose to not trim tails of any variable though results are relatively robust to the choice here. Finally, we cluster the standard errors at the firm-year level following precisely the choices in Giroud and Mueller (2012) and then estimate the following specification

$$\log E_{it} = \alpha_1 + \alpha_2 MP_{it} + \alpha_3 R_{it} + \tilde{\alpha}_3 MP_{it} R_{it} + \alpha_4 I_{it} + \tilde{\alpha}_4 MP_{it} * I_{it} + \varepsilon_{it} \tag{1}$$

This equation will be estimated using the within estimator to difference out plant fixed effects. The actual level effect of MP is identified off of plants that change firms. The baseline specification will also include Fed district specific yearly time trends. We also experiment with specifications where we drop all MP firms where all of the plants are located in the same Federal Reserve district. We do this mainly for comparability for some later regressions where we look for spillovers from plants in other districts. This simply cannot be done when all the plants are in the same district. This is one point where more disaggregated data would be very welcome.

Table 9 reports the results of these regressions. We hesitate to use causal language here, but it is clear from the results that employment at MP-plants is more highly correlated with demand shocks as proxied for by the retail sales index and quite substantially so. First, the "demand" shock affects employment in the "correct" direction and though we do not report all of the correlations for all of the industries, they are positive. Apparently, even the plants that sell into broadly national markets are correlated with local demand conditions, this is possibly evidence for reverse causality. We are not that interested in answering that question. Instead the differential correlation is what is of interest. In fact, the correlation ranges The results are broadly consistent across the specifications varying the set of fixed effects.

These results do not appear to hold for the case of the discount rate where the difference between these types of plants is much smaller, and in fact the correlation declines in magnitude. Again the baseline correlation is sensible with the discount rate negatively correlated with employment. So why are MP plants more correlated with local "demand" shocks? Second, why is this only present for demand shocks rather than discount rate shocks? A suggestion for second question is that funds from internal capital markets are being substituted for a decline in credit. Shocks to the discount rate at this time had large effects on wholesalers' ability to finance purchases. The existence of another source of credit from the producers themselves could alleviate that problem and explain why MP plants, at least at the point estimates, look less sensitive to changes in the discount rate than non-MP plants. One can tell a similar story for the demand shocks whereby internal capital markets allow MP plants to expand more rapidly in response to increases in demand and vice versa for declines in demand.

The reason for this is that local financing still played an important role through the financing of working capital for wholesalers. The notes that were generated in the process of funding wholesale purchases were precisely what the regional Federal Reserve banks aimed to discount. It is important to emphasize that these notes were very short-term liabilities usually at most a year as commercial banks were required to basically mark-to-market their loan books ever year. As noted by Richardson and Troost (2009), until 1932, short-term commercial paper was the only asset eligible for rediscount at the discount window. To a lesser extent, banks also played a role in funding working capital for producers to pay wages and buy materials. For our purposes, it does not matter if we think of the firm as operating on the wholesalers and indirectly onto the producers or the producers directly.

The results also still apply when I restrict attention to a slightly different comparison reported in 10. Besides MP firms that span multiple Fed districts, there is a group of firms and plants that are concentrated in one Fed region. One may think that this group is not a fair comparison since for this group, a shock in the local region affects all the plants at the same time independent of any internal capital market effects. Even in this case, the patterns identified before are present with only minor effects on the magnitudes. Now the question is whether this additional correlation is driven by reallocation of resources within the firm or that plants in an MP firm are able to respond more sensitively to demand shocks because of, say, slack borrowing constraints. To answer this, we look for evidence of spillovers of local shocks across plants part of the same MP firm.

5.4 Response to Other Local Economic Shocks in MP vs. non-MP plants

Here we go one step further and examine possible spillover effects of regional shocks to a plant not located in that region but linked through internal capital markets. Start by taking a concrete example.[6] Consider the Alpha Portland Cement Company and two of its constituent plants,[7] one located in Alabama and another located in Illinois. During the Depression, there are region-specific shocks like say the banking panic in Chicago of July 1931, which presumably would affect directly the Alpha plant located in the state of Illinois. What we address here is how that Chicago may propagate all the way to Alabama through the internal capital markets linking this plant in Illinois to the one in Alabama. In particular, it almost is necessary that there be spillovers given the limited effect of discount rates for MP plants.

If all MP firms had solely two plants, this would be relatively simple to operationalize by including the other plant's shock in the regression from before. With multiple plants, we have to decide on how to weight the shocks at the various plants. For the retail index, what we do is for each plant, we construct a revenue-weighted average of the retail index for regions where other plants part of the same firm are located, call this $\tilde{I}_{it}$. To spell this variable out in more detail, let w_{jt}^k denote share of total revenue for firm j at time t from region k. For simplicity, let me suppress the dependence on the firm subscript j. Also denote the rescaled weights excluding region k as

$$\tilde{w}_t^k = \frac{w_t^k}{\sum_{\tilde{k} \neq k} w_t^{\tilde{k}}}.$$

By construction $\sum_{\tilde{k} \neq k} w_t^{\tilde{k}} = 1$. Then for plant i in region k, we calculate

$$\tilde{I}_{it} = \sum_{\tilde{k} \neq k} \tilde{w}_t^k I_t^k$$

We do the same process to construct a weighted-average of discount rates, $\tilde{R}_{it}$. We also consider the minimum discount rate over all regions since if firms could borrow freely, then it would the least costly to borrow in the cheapest region to fund all their operations. One could also consider more flexible approaches where the weights were estimated inside of the model.

[6]Pun intended.

[7]The firm actually has 9 plants total.

For single plant firms or firms with all of its plants in the same Federal Reserve region, both of these variables will be set to 0. There is no particular reason to set this value to 0. It is not literally the case that these plants have an average other discount rate of 0. In some sense, this information is missing. However, we do not want to drop this group of plants since they still provide useful information for identifying effect of own discount rate and retail index. Let $\tilde{M}P_{it}$ be an indicator for the group of plants that do have plants in other regions, then what we will estimate is the interaction between this indicator and the other discount rate and retail index variables. Note that $\tilde{M}P_{it}$ is not exactly the indicator for being a multi-plant firm since it also requires the plants to be located in separate Fed districts. We will also consider some regressions where we only use $\tilde{M}P$ plants.

The basic idea of the regression we estimate is similar in spirit to the specification of Giroud and Mueller (2012), who are also interested in how local shocks spillover. They do not look at the effects of local shocks to economic conditions instead focusing on the plausibly exogenous introduction of an airline route to study the role of information in internal capital markets. So their paper is not interested in business cycles at all and the role of internal capital markets thereof. This comes with the benefit of having causal estimates. Unlike that paper,we are more limited in being able to ascribe a causal interpretation. To be specific, we estimate for plant i at time t

$$\log E_{it} = \alpha_0 + \alpha_1 MP_{it} + \alpha_2 I_{it} + \tilde{\alpha}_2 MP_{it} * I_{it} + \beta_1 MP_{it} * \tilde{I}_{it} + \alpha_3 R_{it} + \tilde{\alpha}_3 MP_{it} * R_{it} + \beta_2 MP_{it} * \tilde{R}_{it} + \varepsilon_{it} \quad (2)$$

Industry by year fixed effects are also included in the regressions. We consider various ways to decompose the error ε_{it} such as estimating firm-level fixed effects. Again by including the $\tilde{M}P_{it}$ terms means that we will not be using the information for non-$\tilde{M}P$ firms to identify the spillover effects. In the regression where we restrict attention to $\tilde{M}P$ plants, then the relevant variables are excluded.

Table 11 reports the results of this regression. We find that a plant in a particular location responds to conditions of plants in other locations that are part of the same firm. In particular, the response is the opposite of the response to a shock in its own region. If demand is relatively high for other plants, employment is lower. Similar results hold for discount rates. This is further evidence the firms are actually shuffling resources across areas in the face of some constraint on the amount of resources at their disposal. In other words, it is not the case that firms "keep their powder dry" whereby they could give more resources to one particular plant without affecting another plant. What is left is to what extent plants within the same firm are located differently than non-MP plants.

5.5 Geographical Clustering of MP Plants

Consider Figure 1, which shows the distribution of plants across Federal Reserve district regions for MP versus non-MP plants. This is not controlling for industry composition, but it would not matter. The picture is clear. MP and non-MP plants are not locating in the same proportions across the regions. As noted earlier, the differences in production technologies as measured by share of labor are not much different across MP and non-MP plants within a firm. So it seems unlikely that the differences in location decisions are driven by some applicability of a particular technology to a particular region.

This leads us to our remaining question if MP plants are not locating in the same areas as non-MP plants, is this driving the differences in volatility? In particular, do MP plants of a particular firm tend to locate in areas with correlated economic conditions? Now if each firm had only two plants, then it would be trivial to calculate the correlation between plans across the cross-section of firms in a given year. However, there are two questions that must be addressed. First, given some firms have more than two plants, how do we calculate its contribution to the "correlation"? Second, one would expect some amount of correlation simply due to the presence of aggregate shocks. But how much exactly should we expect?

We first discuss how we calculate the "correlation" when firms may have more than two plants. Let firm j have n_j plants indexed by i with economic conditions A_{ij}, which have been demeaned by the average at the aggregate level. First the "covariance" is given by [8]

$$Cov = \frac{1}{N} \sum_{j=1}^{N} \sum_{i=1}^{n_j} \sum_{k<i} \frac{A_{ij} A_{kj}}{\binom{n_j}{2}}$$

[8] We thank Alex Poirier for helpful discussions on this topic.

where N is the number of firms. Then we calculate the "correlation" C as

$$C = Cov/\hat{\sigma}_A^2$$

where $\hat{\sigma}_A^2$ is the sample variance of A. Call the realized value of C, C_{MP}. The idea of this measure is to take the product of all possible unique pairs of plants within a firm. However, we do not want to "overcount" the contribution of a particular plant that has many plans. This is why we divide by the number of possible pairs. Note that in the case of two plants per firm this would collapse to the basic correlation formula. We do this calculation industry by industry and year by year. For now, we simply pick a single month for each census year.

The question is what should C_{MP} be compared to. In particular, in the presene of aggregate shocks, this correlation need not be 0 in some baseline.For concreteness, assume that there are L possible locations (Federal Reserve regions for our case). Now we assume that each of these locations may have an idiosyncratic loading ρ_l on some aggregate factor A. Analytically, we write

$$A_l = \rho_l A + \epsilon_l$$

Think of A as fixed in this specification and ρ_l, ϵ_l as the random variables. If one "randomly" constructed firms by drawing locations for where the (exogenous) number of plants would be located, then the correlation in outcomes within firms will be related to the correlation between ρ_l, ϵ_l and the marginal distribution of ϵ_l for the MP and non-MP plants. We emphasize that this is a possibility even if firms are just random pairings of plants.

To address this issue, we take a "dart board" approach similar to Ellison and Glaeser (1997), who are interested in the geographic concentration of industry. We can calculate a baseline"random" correlation by randomly creating firms to match the size distribution of MP firms. We draw the constituent plants by sampling randomly with replacement from two possible marginal distributions: (1) locations of MP plants or (2) locations of non-MP plants. We do this repeatedly and calculate C for each. Call the average value over all of these simulations, C_{nMP}.

Table 12 reports the resutls for the ice industryusing the monthy of July. We think ice is a particularly good industry to examine since a particular plant's demand is quite local. The results are quite striking for retail sales with MP firms tending to strongly locate their plants in areas that have similar demand conditions as measured by retail sales. This correlation is almost one in 1929 and still quite high in the other years. Furthermore, based on the other two columns for the randomly constructed firms, there is no evidence that this correlation is due to aggregate shocks and different marginal distributions of locations for the plants. These correlations are in fact essentially zero. In the bottom half of the table, the same patterns are borne out for region discount rates. We note that there are no values for 1929 since for the regions ice plants are present in, there is no variation in the discount rate. The fact that the sample correlation falls is potentially suggestive that MP firms are shedding plants that are highly correlated with each other (a "risk off" strategy) or simply that the correlation between economic conditions in different regions changed. At the same time, the fact that the baseline correlation shows

6 Conclusion

Big firms matter. They matter in particular for business cycle fluctuations. Take the modern case. Many downturns are driven in purely accounting terms by declines in automobile production. Yet there are only three auto firms that matter. While the industry was more fragmented in 1937 though the Big 3 still dominated, there is evidence that a shock impacting labor costs in automobile industry caused the recession in that year (Hausman, 2011). So understanding business cycles is in many cases not about looking for aggregate shocks but particular shocks to "systemic" firms. At the same time, big firms are not simply small firms scaled up. They different in kind having internal capital markets and incentive problems.

We have made some progress in attempting to understand how these firms differ in their behavior and their role in the Great Depression. We found that MP firms had more volatile employment than non-MP firms. This held true at the plant-level *and* firm-level. We then documented that employment at MP firms was more correlated with local "demand" conditions as proxied by a retail sales index but less so with regional Fed discount rates. We argued that this implicated differences in access to credit as the explanation for this "double difference." In addition, we found that shocks tended to spillover between plants part of the same firm located in different regions. To what extent these differences contributed to the differences in volatility depends on the locations and the underlying distribution of shocks face by MP and non-MP plants. Finally, we showed that plants that are part of MP firms tend to locate in areas with similar economic conditions.

It is useful to emphasize that these results potentially apply more broadly. Here we have emphasized geographic differences and spatial differentiation between production units. However, there is no reason why it only applies in this setting. Much of the modern literature, in fact, has emphasized differences between "segments" in the largest firms. These are not located at different points in physical space but in product spaces. For example, how does Microsoft allocate resources between its XBox segment and its mobile division? Again we have studied the physical aspect not because of some *a priori* belief that it is necessarily more important rather that it is easy to separate firms geographically as well as to identify local shocks. These frictions, however, still almost surely apply to the allocation of resources horizontally across different product lines and vertically in organizations such as automobiles that are vertically integrated.[9] This suggests that it would be potentially quite illuminating to consider how these results apply for an even broader set of industries where these other sources of differentiation play a role.

For future work, it would be interesting to collect data on the financial position of these firms. There is the possibility for the largest firms who were covered by Moody's and were on the NYSE. There is also the possibility of collecting limited financial data for the smallest firms from Dun and Bradstreet. This was a credit rating agency at the time and they reported some estimate of a firm's net worth as well as a subjective credit rating like Moody's and S&P do today. This information would allow for a better sense of how dependent the firms are on external finance and to what extent the structure of a firm's balance sheet affects reallocation between its units.

Another possible extension would be to use the differential behavior of multi plant versus single plant firms in a given region to infer whether particular banking panics are based on insolvency or illiquidity. This is a reoccurring debate in the literature going back to Friedman and Schwartz (1971) through Wicker (1996) and to the present in Calomiris and Mason (2003). All of this work has, not surprisingly, used sources on banks in various degrees of disaggregation to address this question. The idea here would be to do something like the reverse. Instead of attempting to play

[9] Internal capital markets with vertical integration actually present a whole different array of issues as hold-up problems begin to crop up with the producers of crucial inputs to places higher on the production chain. This also links up to the revived literature on the role of intermediate goods in business cycles and economic growth e.g., Jones (2011).

the role of bank examiner, one could use the observed behavior of multi-plant firms in particular region to infer the beliefs of actual economic actors at the time. The intuition would be as follows. If bank failures are driven by illiquidity, then resources should flow into multi-plant firms to take advantage of the high shadow value of funds in that region. If instead bank failures reflect poor fundamentals in the region, then would expect to see multi-plant firms move resources away from that area. We leave this suggestion for future work.

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Industry	Labor Share	Revenue Fraction for MP plants	# of MP Plants	Total Plants
Sugar refining	.0362085	.5299287	36	77
Malt	.0447968	.862410	107	131
Cane Sugar	.0740852	.2391837	47	279
Macaroni	.1130271	0	0	1,271
Boneblack	.1273552	.7120594	42	68
Ice	.1808449	.5277324	5,403	13,592
Cement	.1820524	.6590207	358	580
Concrete	.2118638	.1701925	578	5,733.0
Radio	.2850091	.3540027	82	785.0

Table 1: Summary statistics for labor share and role of multiplant firms in the select set of industries.

Industry	Plant	Firm
1	1.981	1.981
	(0.073)	(0.073)
2	4.693	4.996
	(0.366)	(0.327)
3	6.357	6.547
	(0.137)	(0.131)
4	1.442	1.577
	(0.328)	(0.321)
5	2.803	3.174
	(0.253)	(0.305)
7	2.960	3.220
	(0.108)	(0.091)
8	3.280	3.301
	(0.748)	(0.750)
9	4.882	10.252
	(0.266)	(0.196)
10	1.483	1.466
	(0.238)	(0.227)
11	3.740	3.658
	(0.353)	(0.351)
Total	1.826	1.805
	(0.293)	(0.277)

Table 2: Summary statistics for average log monthly employment and monthly volatility of log employment. The first number for each industry is the average employment and the number below it is the volatility. Note that the firm average need not be larger than plant average because of the log transformation.

	Revenue	Wage Earners	Labor Share
Cement	0.190**	0.190**	-0.0825
	(0.0847)	(0.0845)	(0.0875)
Sugar Refining	0.441*	0.496**	-0.0128
	(0.226)	(0.221)	(0.230)
Ice	0.398***	0.114***	-0.0738***
	(0.0184)	(0.0194)	(0.0162)
Malt	0.235	0.216	0.0376
	(0.197)	(0.208)	(0.146)
Bone Black	0.553**	0.508*	-0.331
	(0.267)	(0.259)	(0.326)
Cane Sugar	0.214	0.390**	0.105
	(0.192)	(0.170)	(0.174)
Concrete	0.606***	0.670***	-0.251***
	(0.0473)	(0.0466)	(0.0391)
Radios	0.949***	1.101***	-0.0335
	(0.116)	(0.117)	(0.0491)

Table 3: Comparing MP plants to non-MP plants. The respective variable is demeaned and scaled by the standard deviation for the respective industry. The table reports the mean difference in the variable between MP and non-MP plants. Both output and wage earners are in terms of logs. The labor fraction is the ratio of total wage bill to total revenue. The data is missing for macaroni since there are no multi-plant firms. Numbers in parenthesis are standard error of the difference. $*$ difference significant at 10%. $**$ difference significant at 5%. $***$ difference significant at 1%.

	Std. Dev. Log Wage Earners		
	(1)	(2)	(3)
Mean Log Wage Earners	-0.00411**	-0.00345**	-0.000947
	(0.00168)	(0.00168)	(0.00128)
Multiplant	0.0374***	0.0366***	0.0623***
	(0.00416)	(0.00419)	(0.00383)
Fixed effects?	Industry * Year	Industry, Year	None
Observations	20253	20253	20253
Adjusted R^2	0.134	0.120	0.012

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4: Comparing volatility of employment at plant-level between MP and non-MP plants. The dependent variable is the standard deviation of log monthly employment with independent variables that include a control for average log size in all specifications. Numbers in parenthesis are robust standard errors. $*$ difference significant at 10%. $**$ difference significant at 5%. $***$ difference significant at 1%.

	Std. Dev. Log Wage Earners									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Mean Log Wage Earners	0.0182***	-0.209***	-0.0777***	-0.0278***	-0.0940***	0.00547	-0.332***	0.00724*	0.0456***	0.0233***
	(0.00234)	(0.0168)	(0.0236)	(0.00238)	(0.0279)	(0.0191)	(0.0210)	(0.00409)	(0.00359)	(0.00495)
Multiplant	-	0.0541***	-0.0232	0.0235***	-0.0559	0.0509	0.0979	-	0.113***	-0.0455
		(0.0203)	(0.0204)	(0.00425)	(0.131)	(0.0349)	(0.0598)		(0.0134)	(0.0433)
Industry	1	2	3	4	5	7	8	9	10	11
Observations	1158	580	77	11253	130	68	276	619	5338	754
Adjusted R^2	0.044	0.452	0.151	0.019	0.191	0.007	0.463	0.034	0.078	0.046

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5: Comparing volatility of employment at plant-level between MP and non-MP plants for each industry. The dependent variable is the standard deviation of log monthly employment with independent variables that include a control for average log size in all specifications. Two industries have no multiplant firms and, hence, no estimate of the effect is reported there. Numbers in parenthesis are robust standard errors. $*$ difference significant at 10%. $**$ difference significant at 5%. $***$ difference significant at 1%.

	Std. Dev. Log Wage Earners		
	(1)	(2)	(3)
Mean Log Wage Earners	-0.00655***	-0.00572***	0.00304*
	(0.00201)	(0.00202)	(0.00169)
Multiplant	0.0236***	0.0219***	0.0407***
	(0.00761)	(0.00766)	(0.00752)
Fixed effects?	Industry * Year	Industry, Year	None
Observations	14818	14818	14818
Adjusted R^2	0.153	0.142	0.002

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6: Comparing volatility of employment at firm-level between MP and non-MP plants. The dependent variable is the standard deviation of log monthly employment with independent variables that include a control for average log size in all specifications. All variables have been aggregated to the firm-level. Two industries have no multiplant firms and, hence, no estimate of the effect is reported there. Numbers in parenthesis are robust standard errors. $*$ difference significant at 10%. $**$ difference significant at 5%. $***$ difference significant at 1%.

Table 7: Comparing volatility of employment at firm-level between MP and non-MP plants by industry. The dependent variable is the standard deviation of log monthly employment with independent variables that include a control for average log size in all specifications. All variables have been aggregated to the firm-level. Two industries have no multiplant firms and, hence, no estimate of the effect is reported there.

	Std. Dev. Log Wage Earners	
	Plant	Firm
	(1)	(2)
Multiplant	0.0612***	0.0577***
	(0.00809)	(0.0136)
(Year=1931)*Multiplant	-0.0264**	-0.0588***
	(0.0117)	(0.0188)
(Year=1933)*Multiplant	-0.0522***	-0.0574***
	(0.0117)	(0.0195)
(Year=1935)*Multiplant	-0.0200*	-0.0273
	(0.0116)	(0.0188)
Observations	20253	14818
Adjusted R^2	0.135	0.153

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 8: Comparing volatility of employment between MP and non-MP plants over time. The dependent variable is the standard deviation of log monthly employment with independent variables that include a control for average log size in all specifications. The first column is at the plant-level while the second is at the firm-level.

	Centered Log Wage Earners		
	(1)	(2)	(3)
Retail Index	0.0607***	0.0745***	0.192***
	(0.0193)	(0.0193)	(0.0201)
(Multiplant=1)*Retail Index	0.0860***	0.0854***	0.0979***
	(0.0166)	(0.0168)	(0.0174)
Discount Rate	-0.112***	-0.112***	-0.0620***
	(0.0120)	(0.0116)	(0.0108)
(Multiplant=1)*Discount Rate	0.0220**	0.0201**	0.0133
	(0.0100)	(0.00999)	(0.0101)
Fixed effects?	Industry * Year	Industry, Year	None
Observations	209596	209596	209596
Adjusted R^2	0.093	0.090	0.067

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 9: Effects of local "demand" and "financial" shocks for MP versus non-MP plants. The dependent variable is the centered log employment where we center by the median industry employment for that month-year. All regressions use the within estimator to difference out plant fixed effects.

	Centered Log Wage Earners		
	(1)	(2)	(3)
Retail Index	0.0582***	0.0752***	0.192***
	(0.0193)	(0.0193)	(0.0201)
(Multiplant=1)*Retail Index	0.0675***	0.0648***	0.0770***
	(0.0206)	(0.0206)	(0.0214)
Discount Rate	-0.0995***	-0.102***	-0.0620***
	(0.0119)	(0.0116)	(0.0108)
(Multiplant=1)*Discount Rate	0.0283**	0.0291**	0.0216*
	(0.0121)	(0.0121)	(0.0121)
Fixed effects?	Industry * Year	Industry, Year	None
Observations	173558	173558	173558
Adjusted R^2	0.054	0.050	0.028

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 10: Effects of local "demand" and "financial" shocks for MP versus non-MP plants. Here we drop firms that have all their plants in one Fed district.

	Centered Log Wage Earners		
	(1)	(2)	(3)
Other Retail Index	-0.0513*	-0.0615**	-0.0747**
	(0.0280)	(0.0280)	(0.0301)
Other Discount Rater	0.0202*	0.0244**	0.0248**
	(0.0111)	(0.0111)	(0.0111)
Retail Index	0.0607***	0.0743***	0.192***
	(0.0193)	(0.0193)	(0.0201)
(Multiplant=1)*Retail Index	0.111***	0.116***	0.135***
	(0.0227)	(0.0228)	(0.0244)
Discount Rate	-0.111***	-0.111***	-0.0620***
	(0.0120)	(0.0116)	(0.0108)
(Multiplant=1)*Discount Rate	0.0113	0.00740	0.000424
	(0.0116)	(0.0115)	(0.0115)
Fixed effects?	Industry * Year	Industry, Year	None
Observations	209596	209596	209596
Adjusted R^2	0.093	0.090	0.067

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 11: Effects of other “demand” and “financial” shocks for MP versus non-MP plants.

Year	C_{MP}	C^1_{nMP}	C^2_{nMP}
Retail sales			
1929	0.98	0.0020	0.0094
1931	0.75	0.0023	0.00055
1933	0.74	0.0018	0.0041
1935	0.74	0.00021	-0.0014
Discount Rates			
1929	-	-	-
1931	0.81	0.0022	0.0044
1933	0.73	0.0012	0.0048
1935	0.63	-0.00034	0.0040

Table 12: "Correlation" of MP ice firms' demand and credit conditions over time C_{MP} relative to two baselines of randomly constructed firms. We redraw samples 500 times and report the average correlation. This is for the month of July. There is no value for 1929 credit conditions because there is no variation in discount rates for ice plants (at least).

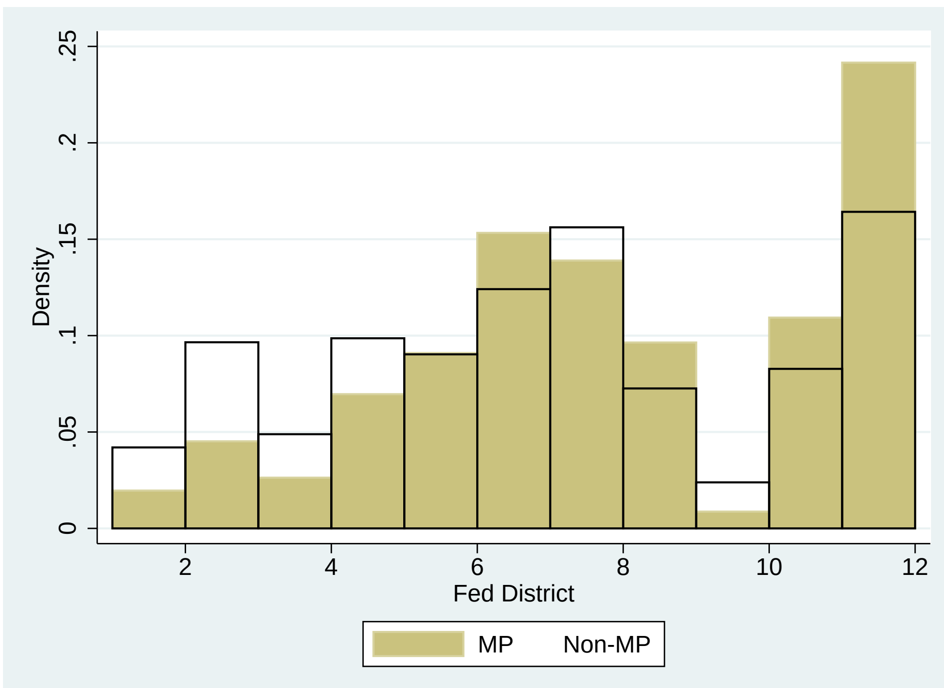

Figure 1: Histogram of plant locations by Federal Reserve District for MP and non-MP plants.