THE SURPRISING SYMMETRY OF GROSS JOB FLOWS

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ABSTRACT

A large literature attempts to explain the asymmetric behavior of job destruction and job creation over the business cycle. This paper contends that much of this asymmetry is spurious. Analyzing gross flows in relation to the net flow virtually eliminates cyclical asymmetry in annual data and substantially reduces it in quarterly data. To the extent that gross flows are symmetric, there is a fundamental identification problem in moving between gross flows and the net flow that is reminiscent of the earlier empirical literature on sectoral shifts.

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1. Introduction

For some time now macroeconomic research has focused on gross job flows (job creation and destruction) in hopes of learning why the net growth rate of employment fluctuates so much. Early papers in this literature found that job destruction is more volatile over time than job creation, suggesting that there is useful information in gross flows that is unavailable in the net flow alone. Students of the business cycle have taken up the challenge of explaining this asymmetry by modelling frictions in factor markets that give rise to smooth creation and volatile destruction. This research program has begun to effect the way many economists view the costs (and potential benefits) of recessions. For example, in the most recent edition of their macroeconomics textbook, Robert Hall and John Taylor note that the large amount of labor reallocation typical of downturns may be the "silver lining to the storm clouds of recession."[1]

Because early research in the gross–flow literature used US manufacturing data from the 1970s and 1980s, its authors cautioned that their findings may not necessarily generalize to other sectors, time periods, or countries. In fact, job destruction does not appear especially volatile in other data. Foote (1997), using firm–level employment data from Michigan's unemployment insurance system, finds that job creation, not destruction, is the more volatile gross flow in most non–manufacturing industries over the 11 years of his sample. He suggests that positive trend growth rates in non–manufacturing sectors, interacting with labor adjustment costs, may explain why creation is so volatile outside of manufacturing. Unfortunately, a simple (S,s) model cannot explain the *strength* of the positive relationship between trend employment growth and the relative volatility of job creation observed in the Michigan data. Similarly, Boeri (1996) finds that job destruction is not especially volatile in European data, and also suggests that the high *variance* of destruction in US manufacturing may be related to the high *mean* of destruction in that sector.

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[1] Hall and Taylor (1997), p. 136. If one defines labor reallocation as the sum of job creation and job destruction, then reallocation will covary negatively with the net employment growth rate if the variance of job destruction is larger than the variance of job creation.

This paper takes a step back from the research on gross job flows to ask whether a representative–agent framework can help reconcile the behavior of manufacturing and non–manufacturing data as well as clear up some other puzzles in the literature. We start by thinking about gross flows in an economy with a single representative firm. We then ask the data to tell us whether the intuition from such an economy is useful for understanding gross flows in the real world. It turns out that the representative–firm case is not as irrelevant as previously believed. This insight leads to a surprising result: Job creation and destruction are not so asymmetric after all.

The paper proceeds as follows. Section 2 outlines the main ideas with some simple graphs and Section 3 motivates a regression to explore these ideas. Section 4 presents some empirical results using annual data, while Section 5 presents results that use quarterly data. Section 6 evaluates alternative explanations for the empirical findings and links the paper to an earlier criticism of the sectoral shifts literature made by Abraham and Katz (1986). Finally, Section 7 concludes and offers directions for future research.

2. The Relationship Between the Net Flow and Gross Flows

The now–standard definitions of job creation and job destruction rates for industry j at time period t, originally due to Davis and Haltiwanger (1990), are

$$POS_{jt} = \frac{1}{X_{jt}} \sum_i (E_{ijt} - E_{ij,t-1})^+$$

$$NEG_{jt} = \frac{1}{X_{jt}} \sum_i |(E_{ijt} - E_{ij,t-1})^-|,$$

where $(E_{ijt} - E_{ij,t-1})^+$ is firm i's positive change in employment (equal to zero if the firm does not increase employment), $|(E_{ijt} - E_{ij,t-1})^-|$ is the absolute value of a firm's negative change, and X_{jt} is the size of the sector, defined as the average employment in sector j over periods $t-1$ and t. Suppressing the j and t subscripts for clarity, note that the net flow is simply the difference of the gross flows:

$$NET = POS - NEG.$$

For an industry with only one firm, there is an exact, deterministic relationship between the two gross flows and the net flow, summarized in Figure 1. For positive net growth rates, NEG is zero and $POS = NET$. For negative growth rates, POS is zero and $NEG = -NET$. We will refer to this situation as the representative firm (RF) case.[2] Graphically,

[2] Careful readers will note that the assumption of a single representative firm does not rule out the possibility of simultaneous job creation and destruction at that firm or plant. Typically, however, data on gross flows is built up from net employment changes at individual firms or plants.

if we plot POS and NEG on the vertical axis and NET on the horizontal axis, as in Figure 1, the POS line will sit atop the horizontal axis for negative net growth rates, intersect the origin, and rise with a slope of 1 for positive net growth rates. NEG is plotted analogously, with a slope of -1 in the region of negative net growth rates. Note that at least one gross flow must be zero at all times in the RF case. Both POS and NEG are zero in the special case of $NET = 0$.

Once we relax the RF assumption, then we allow gross flows to be simultaneously positive and lose the exact, deterministic relationship between the net flow and the two gross flows. In fact, a graph of gross flows against the net flow has only two restrictions. First, NEG and POS must not fall below zero, and second, the vertical distance between the NEG and POS lines must be equal to the net growth rate. However, one restriction that proves very helpful in understanding real–world data is to assume that NEG and POS are negatively correlated. Unlike the finding on the relative variances of creation and destruction, this finding is replicated easily in datasets generated by a variety of industries and sample periods. One implication of a negative correlation between POS and NEG is that POS will covary positively with NET, while NEG covaries negatively. This simple fact has important implications for how to think about gross flows, because it means that the RF case may be more useful than previously believed.

Consider an industry with simultaneously positive but negatively correlated gross flows, as in Figure 2. Note that at $NET = 0$, gross flows are equal to one another. Even in the non–RF case, the two gross flows must still intersect at the vertical axis, though not necessarily at the origin. Note also that the restriction of negatively correlated gross flows forces the intuition of the RF case to assert itself at strongly positive and strongly negative net growth rates. For example, at strongly positive growth rates, POS is virtually equal to NET while NEG is virtually zero, similar to the RF case.

What can prevent the tyranny of the RF case from determining the behavior of gross job flows? Note that the distance AB in Figure 2 provides an upper bound for NEG at positive net growth rates, just as it provides an upper bound for POS at negative net growth rates. An unspoken assumption in all previous research on gross flows is that the distance AB is large enough so that the RF case is not worth thinking about. In fact, a separate stylized fact to emerge from early work on gross job flows (aside from the assertion concerning the high volatility of destruction) goes back to the original paper by Leonard (1987): Gross flows are large relative to net flows. In order to rule out the RF case, however, gross flows must be large relative to *extreme* values of the net flow, not just the *average* value of the net flow. Moreover, it is not the unconditional expectation of the gross flow that must be large, it is the expected value of the gross flow *conditional* on a net growth rate of zero. This conditional expectation, after all, is just the distance AB from Figure 2. If this distance is small relative to extreme values of the net growth rate, then one of the gross flows will bump up against its zero constraint (providing, of course, that the gross flows are negatively correlated). The RF case then becomes relevant.

Figure 3 portrays our graph with two important features. First, the distance AB is large relative to extreme values of the net flow, and second, the net growth rate is solely determined by the rate of job destruction. Note that we have drawn the distance AB to be large enough so that the relationships between NET and POS and between NET and NEG are *linear*. The POS relationship is linear because job creation does not vary over the business cycle. The NEG relationship is linear because the distance AB is large enough (and relevant movements in the net growth rate are small enough) so that NEG never bumps up against the horizontal axis at positive growth rates. The fact that both relationships are linear at the same time is no accident. If one relationship is linear, then the other must be linear as well, because $NET = POS - NEG$. Note also that in this graph, it makes perfect sense to use the relative variances of job creation and destruction as an index of gross–flow asymmetry over the cycle. No matter what the distribution of actual net growth rates, NEG will vary more than POS, and thus the cyclical importance of NEG relative to POS will be revealed. Though drawn only once to my knowledge in any previous paper, this "linear" graph summarizes the conventional wisdom on gross job flows.[3]

Though a simple comparison of the variances of POS and NEG is appropriate for the linear world of Figure 3, it is inappropriate for the nonlinear world of Figure 2. This is because the sample variances of POS and NEG in Figure 2 will depend on the distribution of net growth rates. For example, if most growth rates are negative, then POS will trace out the flat part of its curve, and NEG will trace out the steep part of its curve. The variance of POS will therefore be smaller than that of NEG, but this comparison will tell us more about the density of net growth rates than about any asymmetry in the cyclical behavior of gross job flows. In light of this problem, I develop a simple alternative measure of asymmetry between job destruction and job creation that is more flexible than the comparison of raw gross–flow variances. This measure will be based on regressions of either POS or NEG on the net growth rate and (to pick up the non–linearity) the *square* of the net growth rate. It turns out that these regressions will provide compelling evidence that the non–linear model of Figure 2 describes the world better than the conventional, linear model of Figure 3. These results, in turn, suggest that arguments for asymmetry based on simple comparisons of the variances of creation and destruction are fundamentally flawed, as is the use of simple creation and destruction variances to calibrate specific models of the business cycle.

[3] In one of his original paper on monetary rules, John Taylor (1994) uses a graph similar to Figure 3 (with GDP on the horizontal axis) to contend that absent any non–linearities in the POS or NEG relationships, GDP volatility does not necessarily enhance reallocation and productivity growth.

3. A Regression Framework

To interpret regressions of POS and NEG on the net flow and its square, it is helpful to sketch out a simple stochastic model of gross and net job flows. We will start with a linear model to gain intuition, then modify the model to address non–linearities in the spirit of Figure 2. The model is built around "fundamental" (but unobservable) values of NET, POS, and NEG, which are denoted with stars. Conceptually, the stochastic process begins with a draw of the fundamental net growth rate, NET^*, which has constant mean μ:

$$NET^* = \mu + \epsilon_{NET^*}, \tag{1}$$

where ϵ_{NET^*} is a random variable. To bring about NET^*, fundamental gross flows are determined as follows:

$$POS^* = \alpha + \beta_{POS} NET^* \qquad \beta_{POS} \in (0,1) \tag{2}$$

$$NEG^* = \alpha + \beta_{NEG} NET^* \qquad \beta_{NEG} = \beta_{POS} - 1 \in (-1,0) \tag{3}$$

Because $\beta_{POS} - \beta_{NEG} = 1$, it must be the case that $POS^* - NEG^* = NET^*$. The parameter α is the empirical counterpart of the distance AB in Figures 2 and 3, representing the value of both gross flows when the net growth rate is zero. A large negative value for β_{NEG} and a small positive one for β_{POS} signifies that job destruction is the most important adjustment margin for NET^* over the cycle. A value of .50 for β_{POS} and –.50 for β_{NEG} represents perfect symmetry.

At this point, there are three series (POS^*, NEG^*, and NET^*) but only one source of stochastic variation (ϵ_{NET^*}). Were POS^* and NEG^* the actual gross flows that we observe, there would be a deterministic relationship between them, but we do not observe this in the data. Therefore, to convert POS^* and NEG^* into observable (unstarred) values, we add sources of independent variation to POS^* and NEG^*:

$$POS = POS^* + \epsilon_{POS} \tag{4}$$

$$NEG = NEG^* + \epsilon_{NEG}, \tag{5}$$

where the correlations of the random variables ϵ_{POS} and ϵ_{NEG} with each other and with POS^* and NEG^* are left unspecified for now. Finally, subtract destruction from creation to get the observed net growth rate

$$NET = POS - NEG = NET^* + \epsilon_{POS} - \epsilon_{NEG}. \tag{6}$$

Deriving a regression equation

Ideally, we would like to find β_{POS} and β_{NEG} by examining POS^*, NEG^*, and NET^* directly. Since these flows are unobservable, we estimate β_{POS} and β_{NEG} from regressions of POS or NEG on NET. These estimates will be biased by the independent sources of variation in POS and NEG, ϵ_{POS} and ϵ_{NEG}, which will feed back to the observed net growth rate. Consider a regression of POS on NET:

$$\begin{aligned} POS &= \alpha + \beta_{POS}NET^* + \epsilon_{POS} \\ &= \alpha + \beta_{POS}(NET - \epsilon_{POS} + \epsilon_{NEG}) + \epsilon_{POS} \\ &= \alpha + \beta_{POS}NET + (1 - \beta_{POS})\epsilon_{POS} + \beta_{POS}\epsilon_{NEG}, \end{aligned}$$

or

$$POS = \alpha + \beta_{POS}NET + \xi_{POS}, \tag{7}$$

where $\xi_{POS} = ([1 - \beta_{POS}]\epsilon_{POS} + \beta_{POS}\epsilon_{NEG})$.[4] If ϵ_{POS} and ϵ_{NEG} are uncorrelated with POS^* and NEG^*, but potentially correlated with each other, then they generate "measurement error" in (7).[5] The expected value of $\widehat{\beta_{POS}}$ becomes

$$E(\widehat{\beta_{POS}}) = \frac{\beta_{POS}V(\epsilon_{NET^*}) + Var(\epsilon_{POS}) - Cov(\epsilon_{POS}, \epsilon_{NEG})}{V(\epsilon_{NET^*}) + Var(\epsilon_{POS}) + Var(\epsilon_{NEG}) - 2 \cdot Cov(\epsilon_{POS}, \epsilon_{NEG})}. \tag{8}$$

Similar steps reveal that the expected value of $\widehat{\beta_{NEG}}$ in a regression of NEG on NET is

$$E(\widehat{\beta_{NEG}}) = \frac{\beta_{NEG}V(\epsilon_{NET^*}) - Var(\epsilon_{NEG}) + Cov(\epsilon_{POS}, \epsilon_{NEG})}{V(\epsilon_{NET^*}) + Var(\epsilon_{POS}) + Var(\epsilon_{NEG}) - 2 \cdot Cov(\epsilon_{POS}, \epsilon_{NEG})}. \tag{9}$$

Note that even though we do not observe the fundamental flows, it still must be the case that $\widehat{\beta_{POS}} - \widehat{\beta_{NEG}} = 1$, just as $\beta_{POS} - \beta_{NEG} = 1$.[6] Yet the estimates are biased in a direction that depends on the relative variances of ϵ_{POS} and ϵ_{NEG}. Also, bias in the estimates of β_{POS} and β_{NEG} via ϵ_{POS} and ϵ_{NEG} is less worrisome as the variance of ϵ_{NET^*} becomes large relative to ϵ_{POS} and ϵ_{NEG}. Another consequence of small variances of ϵ_{POS} and ϵ_{NEG} is that we are increasingly likely to observe a negative covariance between POS and NEG as these variances diminish. This is because a negative correlation is "hard–wired" into POS^* and NEG^* via the opposite signs of β_{POS} and β_{NEG}, and this correlation emerges as the independent sources of variation in the gross flows diminish.

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[4] Similarly,

$$NEG = \alpha + \beta_{NEG}NET + \xi_{NEG},$$

where $\xi_{NEG} = ([1 + \beta_{NEG}]\epsilon_{NEG} - \beta_{NEG}\epsilon_{POS})$.

[5] I take up the issue of a possible correlation between POS^* and ϵ_{POS} or NEG^* and ϵ_{NEG} below.

[6] There is one (very unlikely) case in which bias does not appear: when $\epsilon_{POS} = \epsilon_{NEG}$. Then any innovation in ϵ_{POS} is matched by an equal innovation in ϵ_{NEG}, so that both ϵ_{POS} and ϵ_{NEG} are uncorrelated with NET.

Investigating non–linearities with a quadratic regression

As yet, no non–linearities have been introduced in the model; we have described a model appropriate for the linear world of Figure 3. To make the model appropriate for the non–linear world of Figure 2, rewrite (2) and (3) to

$$POS^* = \alpha + \beta_{POS} NET^* + \gamma NETSQ^* \tag{2'}$$

and

$$NEG^* = \alpha + \beta_{NEG} NET^* + \gamma NETSQ^* \tag{3'}$$

where $NETSQ^* = (NET^*)^2$. The non–linear coefficient (γ) is the same in both equations and enters with the same sign, which preserves the relation $POS^* - NEG^* = NET^*$ as long as $\beta_{POS} - \beta_{NEG} = 1$. Figure 2 suggests that the value of γ will be positive, as the POS line becomes steeper as the net growth rate increases, while the NEG line becomes flatter.

Just as we might hope to estimate β_{POS} with a regression of POS on NET, we might also hope to estimate both β_{POS} and γ with a regression of POS on NET and $NETSQ$. As noted above, the accuracy of these estimates will depend on the variation in NET^* relative to that in ϵ_{POS} and ϵ_{NEG}. If this variation is strong enough, it may be possible to notice a change in $\widehat{\beta_{POS}}$ when $NETSQ$ is added to the right–hand–side of a regression of POS on NET.

In addition to the sign of γ, the direction of this change in $\widehat{\beta_{POS}}$ will depend on the sample correlation of NET and $NETSQ$. If γ is positive, a negative correlation between NET and $NETSQ$ (which may exist in a declining industry, or in an industry where employment drops suddenly and rises slowly) would bias down the estimate of β_{POS} if $NETSQ$ is omitted. In the language of Figure 2, the negative correlation between NET and $NETSQ$ would be associated with a sample that traces out the flat portion of the POS curve. A linear regression would erroneously extrapolate the sample flatness of POS over all portions of the graph, with the implication that job destruction is always and everywhere the most important margin of adjustment. Adding flexibility to the POS line by inserting $NETSQ$ in the regression allows us to change our estimate of the slope of the POS line as the net growth rate changes.

Should we expect the addition of $NETSQ$ to change our estimate of β_{POS} even if non–linearities of the type displayed in Figure 2 are unimportant? We know from the stochastic model outlined above that estimates of β_{POS} are likely to be biased due to the independent sources of variation in the gross flows (ϵ_{POS} and ϵ_{NEG}) that feed back to the net growth rate. However, *as long as these sources of variation enter linearly*, entering $NETSQ$ should not lead to spurious changes in β_{POS}. This finding is illustrated in Table 1, where I report densities of regression estimates from simulated data, generated by (1)–(6).

Sensitivity analysis is performed by varying the values of γ, the size of the variation in ϵ_{POS} and ϵ_{NEG} relative to NET^*, and β_{POS}. For all of the simulations, I choose a negative value of μ in order to bring about a negative correlation between NET and $NETSQ$. Moreover, variance in the independent sources of variation (ϵ_{POS} and ϵ_{NEG}) are always set equal to one another for simplicity.[7] Because real–world sample sizes are often small, I choose an N of 17 for each regression, and repeat the regression 10,000 times for each unique collection of true parameters. In addition to the mean and standard deviation of $\widehat{\beta_{POS}}$ for both the linear and quadratic regressions, I report the fraction of regressions for which the t–statistic for γ in the quadratic regression is greater than 2 or less than –2. All random variables are distributed normally.

The first six rows of Table 1 show that if $\gamma = 0$, adding $NETSQ$ to the regression should not be expected to change our estimate of β_{POS}. In rows 1, 3, and 5, the true value of β_{POS} is equal to .5, and this is the estimate given by β_{POS} in both the linear and quadratic regressions. The estimates center on the value of .5 exactly because there is no non–linearity in the model ($\gamma = 0$) and because the variances of ϵ_{POS} and ϵ_{NEG} are equal.[8] Rows 2, 4, and 6 use a true value of β_{POS} equal to .2. Parameter estimates in these rows, however, are closer to .5, because the equal variation in ϵ_{POS} and ϵ_{NEG} biases the estimates toward .5.[9] More importantly, though, the central tendency of these estimates does not change when $NETSQ$ is entered. Looking down rows 1 through 6, it does not appear that adding $NETSQ$ to the regression would spuriously support non–linearities when none exist, no matter what the true value of β_{POS}.

Estimates of β_{POS} do change in the lower six rows of the table, where $\gamma > 0$, provided that variation in NET^* is large relative to variation in ϵ_{POS} and ϵ_{NEG}. Rows 7, 9, and 11 show that estimates of β_{POS} are biased down from their true value of .50, because the regression samples trace out the flat portion of the POS curve. Adding $NETSQ$ increases the estimates, as long as variation in NET^* is large, though estimates do not generally move all the way to .50. Estimates of β_{POS} are also increased with the addition of $NETSQ$ when the true value of $\beta_{POS} = .20$, which is the case in rows 8, 10, and 12. Because of the equal variances of ϵ_{POS} and ϵ_{NEG}, however, removal of the downward bias arising from the correlation between NET and $NETSQ$ moves the coefficients closer to .50 and farther

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7 There is also no correlation between ϵ_{POS} and ϵ_{NEG}. Adding a negative correlation had no effect on the message of Table 1. Neither did making the variance of ϵ_{NEG} larger than that of ϵ_{POS}.

8 As can be seen from (8), equal variances of ϵ_{POS} and ϵ_{NEG} tend to bias the estimate of β_{POS} toward .5, which happens to be the true value of β_{POS} in rows 1, 3, and 5. Hence, the central tendence of estimates is .50.

9 Note that this bias is more severe the higher is the variation in ϵ_{POS} and ϵ_{NEG} relative to variation in NET^*. In row 4, where the variance of ϵ_{POS} and ϵ_{NEG} are both three times the variance of NET^*, the estimate of β_{POS} is centered quite close to .5 (.46). In row 6, where the magnitude of variance is reversed, the estimate is centered closer to the true value.

away from the true value of $\beta_{POS} = .20$.

This movement away from the true value of β_{POS} in rows 8, 10, and 12 highlights the difficulty of estimating β_{POS} without knowledge of the fundamental flows. We may find that our estimate of β_{POS} changes after adding $NETSQ$, but we should remember that this estimate is still biased away from its true value, in a direction that depends on the relative variances of ϵ_{POS} and ϵ_{NEG}. For example, if we find that our estimate of β_{POS} rises to something close to .50 after adding $NETSQ$, this may be caused by a true value of β_{POS} that is lower than .50, combined with a variance of ϵ_{POS} that is larger than that of ϵ_{NEG}. This would still be a surprising result, however, since most previous models implicitly contend that there is no dependence of gross job flows on any fundamental net growth rate, and that the independent sources of variation in the gross flows are all that matter. Moreover, because these models seek to explain a large variance of destruction, they contend that independent variation in destruction is more volatile, not less volatile, than independent variation in creation.

4. Empirical Results using Annual Data

Manufacturing vs. services

Before examining coefficient estimates explicitly, it is helpful to run some ocular regressions using graphs constructed along the lines of Figures 1–3. Figure 4 graphs annual values of POS and NEG against NET for US manufacturing from 1973–1988. These data were constructed by Davis, Haltiwanger and Schuh using the Census Bureau's Longitudinal Research Database (LRD).[10] The top two panels plot POS and NEG against NET along with linear regression lines, while the bottom two panels plot the flows with quadratic regression lines. Simple inspection of the top two panels indicates that POS and NEG are negatively correlated and that the linear regression line for NEG is steeper than the linear regression line for POS. However, it is clear from the bottom two panels that the quadratic lines give a better fit. These inferences are verified in Table 2, where various correlations and parameter estimates using the annual LRD flows are presented. I report the parameter estimates from the regression of POS on NET and $NETSQ$ only, because regressions of NEG on NET give the same estimates of α, γ, and the residuals. Moreover, as was the case for the linear regression, one can show that the estimate of β_{NEG} from the quadratic regression equals the quadratic estimate of β_{POS} minus 1 as well. The only interesting

[10] See Davis, Haltiwanger and Schuh (1996) for details on the construction of job creation and destruction measures from the LRD. Thanks are due to John Haltiwanger for supplying gross flows from the LRD via his anonymous ftp site.

extra information from the NEG regression is the adjusted R^2.[11] Table 2 shows that the correlation between POS and NEG in annual manufacturing data is strongly negative (–.75) as is the correlation between NET and $NETSQ$ (–.61). The estimate of β_{POS} from the linear regression is only .39, suggesting asymmetry, but this estimate rises sharply to .47 (near the "symmetric" value of .50) when $NETSQ$ is entered. Moreover, the estimate of γ enters with a t–statistic of more than 2.5, even though there are only 16 annual observations available.

Table 3 uses annual Michigan UI data to confirm these results. Unlike the LRD, these data are on the firm–level, rather than the plant–level, and are annual averages of employment, not point–in–time data.[12] The Michigan data allows us to see whether sectors with *positive* correlations between NET and $NETSQ$ generate estimates of β_{POS} that fall, rather than rise, when $NETSQ$ is entered. This is generally the case. Perhaps the best example of this is Michigan's services industry, where the correlation between NET and $NETSQ$ is strongly positive (.94) and where $\widehat{\beta_{POS}}$ from the linear regression is much larger than .50. Adding $NETSQ$, however, reduces the estimate of β_{POS} to near .50. Additionally, the quadratic services regression provides an estimate of γ that enters with a t–statistic of more than 5, even though there are only 10 observations in the Michigan sample period. The estimate of β_{POS} from the quadratic services regression (.45) turns out to be quite close to the corresponding estimate from Michigan manufacturing (.47), which is in turn exactly the same as the estimate using the LRD (Table 2). Looking at all nine sectors in the Michigan data, point estimates of γ are always positive and are significant at conventional levels in four of the nine sectors (agriculture, mining, manufacturing and services). Addition of $NETSQ$ brings the estimate of β_{POS} closer to .5 in all sectors except agriculture, mining, and construction. For these sectors, however, the linear estimate ranges from .43 to .55, so it is hard to interpret these results as compelling evidence against symmetry.[13]

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[11] Though the standard error of the estimate must be the same in the two regressions, because the residuals are identical, R^2 also depends on the raw variances of POS and NEG, which are usually different.

[12] Because virtually every employer must report employment to the state employment office, the Michigan data cover almost every employer in the state. The LRD, by contrast, is generated mostly by a probability–based sample of individual manufacturing plants (the Annual Survey of Manufactures) along with the Census of Manufactures, which is taken every five years. A main advantage of using the LRD is the ease of linking plants from year–to–year across changes in legal ownership, which is more difficult with UI data. Advantages of using UI data lie in its wider coverage and its inclusion of comparable data on manufacturing and non–manufacturing employment. See Foote (1997) for an extended comparison of the LRD and the Michigan UI data.

[13] Additionally, agriculture and mining are the two smallest sectors in the Michigan data. Services, manufacturing, and retail trade are the largest.

Young and old manufacturing plants

In addition to resolving the manufacturing vs. non–manufacturing puzzle in the behavior of gross job flows, our framework is also helpful in addressing purported differences in gross flows generated by young and old manufacturing plants from the LRD. Table 4 reports results using gross flows for young plants (0 to about 10 years old) and mature plants (older than 10 years).[14] The linear estimate of β_{POS} for young plants is exactly .50 while the linear estimate for mature plants is much smaller (.33). However, young and old plants also differ in their correlations between NET and $NETSQ$, which is positive for young plants (.48) and strongly negative for older plants (–.85). These correlations suggest that the addition of $NETSQ$ should lower the estimate of β_{POS} for young plants and raise it for old ones, and it does. The estimate of β_{POS} for young plants drops to .47 in the quadratic regression, while the estimate for old plants rises to .44.

Note that the estimate of γ is statistically significant for old plants (with a t–statistic of about 2), while it is insignificant for young plants. The explanation for this difference may center on the large differences in $\widehat{\alpha}$ across the two age classes. Recall that $\widehat{\alpha}$ is our estimate of the distance AB in Figures 2 and 3. A larger value of AB makes it less likely that the "zero constraint" for POS and NEG will bind, so that non–linearities in the relationship between the gross flows and the net flow are less likely to arise. Estimates in Table 4 suggest that the distance AB is about twice as large for young plants than for old ones. This is not surprising, since Davis, Haltiwanger and Schuh (1996) have shown that reallocation rates for younger plants are generally larger than rates for older plants.[15] Because the distance AB is relatively large for young plants, we would expect non–linearities there to be less important. The empirical implication is that adding $NETSQ$ changes the estimate of β_{POS} for young plants relatively little while the change for old plants is more substantial.

Disaggregated data from the LRD and the Michigan data

As we move to the investigation of gross flows in two– and four–digit SIC classifications, we would expect that non–linearities would be just as important, since the assumption of a representative firm becomes even more compelling the lower the level of aggregation. This hypothesis is supported by both the Michigan data and the LRD. Because of space limitations, I present results from the disaggregated data with histograms, rather than with tables of actual parameter estimates. Figure 5 presents results using the

[14] The line dividing old from young plants is usually about 10 years, but varies over time due to data limitations in the LRD. The flows for young plants in Table 4 are actually employment–share weighted averages of rates for the youngest two age classifications (plants less than one year old and plants from one to about 10 years old).

[15] The estimate of α can be thought of as an index of reallocation intensity at a net growth rate of zero.

20 two–digit manufacturing sectors in the LRD. The upper left histogram graphs estimates of β_{POS} from linear regressions. This density is centered well to the left of .5 because 18 of the 20 two–digit sectors display negative correlations between NET and $NETSQ$. The upper right panel presents the estimates of β_{POS} from the quadratic regressions. The central tendency of the density moves to the right, approximating .5.[16] The lower two panels present results relevant to the estimate of γ. The lower left panel shows that a large majority of γ estimates are positive, and the lower right panel shows that even though there are only 16 annual observations in the LRD, many of these estimates of γ generate t–statistics of two or more. Figure 6 presents results from 447 four–digit LRD sectors.[17] The message is the same as in the previous figure: The central tendency of the β_{POS} estimates moves to the right when $NETSQ$ is entered, and the point estimate for γ is usually positive and often significant.

Support for the non–linear model is also found in the 70 two–digit Michigan industries, which generate results displayed in Figure 7. Here, however, the density of β_{POS} estimates does not shift to the right across the top two panels, because (unlike manufacturing data) there is no preponderance of negative correlations between NET and $NETSQ$ in the Michigan data.[18] However, the bottom two panels show that the estimates of γ in the two–digit data are generally positive, and that a non–trivial portion of these estimates are significant at conventional levels, even with only 10 observations.

5. Empirical Results Using Quarterly Data from the LRD

Using quarterly rather than annual data also lessens apparent asymmetries between the volatility of creation and destruction, but estimates of β_{POS} from the quadratic regressions generally do not approach symmetry as closely as they do with annual data. The top two panels of Figure 8 present POS and NEG graphed against NET, along with implied quadratic regressions lines. As was the case with annual data presented in Figure 4, there also appears to be a non–linear relationship between NET and the two gross flows. The bottom two panels present spline regressions rather than quadratic ones, with a linear slope change allowed at zero. The POS line becomes steeper and the NEG line becomes flatter as we move leftward from negative to positive net growth rates, as is the case (more smoothly) in the quadratic panels above. Figures 9a (quadratic) and Figures 9b (spline) plot the fitted values of POS and NEG against each other to facilitate comparisons.

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[16] The actual means of the two densities are .39 (linear) and .48 (quadratic).

[17] Because of the 1987 change in SIC designations, the sample period for the four–digit data ends in 1986. The SIC change does not significantly affect two–digit data.

[18] The mean of β_{POS} estimates is .55 in both the linear and quadratic regressions.

Unlike the case with annual data, however, allowing the responsiveness of POS to NET to vary across different net growth rates does not bring us to virtual symmetry. Table 5 shows that the estimate of β_{POS} rises from .29 to .38 with the addition of $NETSQ$, but this value is still more than two standard errors away from .50. (The estimate of γ is positive with a t–statistic of about 2.5.) There are several possible reasons for this finding. One is that previously suggested explanations for why job destruction is excessively volatile work well on the quarterly level, but not the annual level. For example, if it takes a shorter time to destroy existing job matches than to create new ones, which is the fundamental mechanism in Mortensen and Pissarides (1994), then perhaps these asymmetries are only strong enough to emerge in quarterly data. A similar case could be made for other explanations of excessive job destruction volatility, such as that of Caballero and Hammour (1996), which focuses on the nature of specific investments in firm–worker relationships.

However, there is also an explanation for robust destruction volatility in quarterly data in terms of the model of this paper. Recall from Figures 2 and 3 and from the discussion of old and young plants that the likelihood of non–linearities depends in large part on expected gross flows at a net growth rate of zero (the distance AB, as measured by the parameter α). The regression at the top of Table 5 constrains α and γ to be the same for all quarters, which could obscure evidence for non–linearities if these parameters differ across quarters. The middle portion of Table 5 estimates the linear and quadratic regressions for each quarter separately and suggests that α and γ do differ across quarters. Most importantly, the estimate of α is much larger for the first quarter than for other quarters. Part of this difference could be due to true seasonal patterns in reallocation. Another part may stem from the fact that the quarterly LRD is generated from answers to annual surveys, so that recorded job flows in the first quarter vary systematically from job flows in other quarters.[19] In any event, removing the first quarter from the quarterly sample, as is done in the bottom part of Table 5, results in a quadratic estimate of β_{POS} of .47, which is identical to both the annual estimate in Table 2 and to the estimate for the first quarter alone in the middle part of Table 5. Moreover, in the regression that excludes the first quarter, the estimate of γ enters with a t–statistic of more than 4, while this estimate is not significant in the regression that uses first–quarter data alone. This is consonant with a relatively high value of AB in the first quarter.

One must be careful in interpreting these quarterly results as rock–hard endorsements of symmetry. Since 1972, the quarter with the largest employment decline was the first quarter of 1975. Treating the first quarter differently may therefore be using this important cyclical variation incorrectly. Moreover, the seasonal pattern of job creation and destruction

[19] See the technical appendix to Davis, Haltiwanger and Schuh for more details of the uniqueness of the first quarter in the quarterly LRD.

may be linked to the business cycle in an important way.[20] In any case, the least that can be said with regards to quarterly data is that evidence of asymmetry in destruction and creation flows is substantially weakened when non–linearities are taken into account. Truly compelling arguments for complete symmetry must await the collection of additional quarterly data from other industries or time periods.

Figures 10 and 11 repeat the earlier disaggregated analysis by two– and four–digit SIC classification. (All quarters are included in all regressions.) Like the annual data, addition of $NETSQ$ moves the density of β_{POS} estimates to the right, as is evident in the top two panels of Figures 10. All 20 estimates of γ are positive and significant at conventional levels; the statistical significance results from the larger number of observations in the quarterly data. The message is basically the same for the 447 four–digit industries that generate Figure 11, though some estimates of γ have t–statistics less than 2.

6. Intepretation of Results

Other potential non–linearities

Though the empirical results of this paper seem strong, they are only as useful as the identifying assumptions underpinning them. The key identifying assumption of the paper is that the effect of NET^* on POS^* and NEG^* is non–linear, while the independent sources of variation in POS and NEG (ϵ_{POS} and ϵ_{NEG}) enter linearly. Are there good reasons to believe that these independent sources of variation are non–linearly related to the underlying net growth rate? For example, rewrite (5) to

$$NEG = \alpha + \beta_{NEG} NET^* + (\theta_N NETSQ^* + \tilde{\epsilon}_{NEG}), \tag{5'}$$

where ϵ_{NEG} has been redefined to equal $(\theta_N NETSQ^* + \tilde{\epsilon}_{NEG})$. One explanation for such a non–linear correlation summarized by θ_N could be a "reallocation timing effect" in the spirit of Davis and Haltiwanger (1990). If aggregate activity is extremely low, then agents may decide to intertemporally optimize by reorganizing the economy and destroying large numbers of jobs. If this effect kicks in only at strongly negative values of NET^*, then the slope of the NEG line could become much steeper at strongly negative net growth rates. The result would be a non–linearity in the relationship between NEG and NET that is picked up by $NETSQ$ in our regressions. The problem with this explanation is that Figures 4 and 8 give no evidence that non–linearities are important for NEG only at strongly negative values of NET. Specifically, the lower two panels of Figure 8, which present fitted lines from spline regressions, do not suggest that the non–linearity arises

[20] See the work of Jeffrey Miron on this point.

only at strongly negative growth rates. If anything, they suggest that the non–linearity is appropriate at zero, as it would be in the truly representative agent world of Figure 1. While inferring a break in the slope of any collection of data points is tricky, it does not appear from these two panels that the break in the slope of the NEG points is in the wrong place.

Perhaps even more compelling evidence against unforeseen non–linearities comes from examining sectors with generally positive growth rates, such as Michigan services (Table 3). One may think that industry–level congestion effects in job creation of the type described by Caballero and Hammour (1994) may put a ceiling on the job creation rate. For example, a rising supply price of capital goods may prevent the economy from creating a large number of jobs all at once. The problem here is that this non–linearity goes the wrong way — rather than flattening out at strongly positive net growth rates, estimates from Michigan services suggest that the POS line gets steeper. In short, non–linearities in both POS and NEG are well explained by the representative agent framework, which is not the case with non–linearities based on other explanations in the literature.

Revenge of the representative agent

If the motivation for this paper starts with the representative agent – who was not exactly scarce in pre–gross–flow macroeconomics – why have the ideas of this paper taken so long to surface? One explanation may be that the large size of gross flows surprised many economists when these flows were first calculated. Before the seminal papers of Leonard (1987) and Davis and Haltiwanger (1990), economists knew that a huge number of workers regularly flowed in and out of employment, unemployment, and out–of–the–labor–force status. But no one could foresee the large extent to which these worker flows were generated by a constantly changing set of job opportunities. The finding that job flows are an important source of worker flows will undoubtedly be a lasting contribution of gross–flow research. However, as this paper has shown, it is not obvious that gross flows are large enough to make the representative agent completely irrelevant.

Another reason for the lack of any representative agent modelling in gross flow research could stem from the way in which densities of micro–level employment growth rates have been analyzed. Researchers with access to micro–level data often compute these densities to study their shapes. Virtually all research suggests that these densities have fat tails and spikes at zero, as firms or plants make large positive or negative employment changes or none at all. A particularly interesting characteristic of these densities is how they change shape over the business cycle. In recessions, the mean of the density falls, but this is generally not accomplished by a shift of the entire density to the left. Rather, the mean falls due to a disproportionate swelling of the (fat) left tail. Simply put, recessions occur as the percentage of firms making big employment cuts goes up. Yet even in recessions, there are still firms that either increase employment or hold it steady. As recessions were discovered to be anything but equal opportunity destroyers, the attempt to explain why employment fell at some firms and not others took center stage.

However, even though aggregate employment declines are accomplished by dramatic increases in job destruction, it does not automatically follow that employment *increases* will be accomplished by dramatic *decreases* in job destruction. Consider a heuristic micro-level growth rate density, pictured in Figure 12. This simplified density has just three bins, a destruction bin (populated by firms which cut employment by 25 percent), a zero bin (populated by firms which make no changes in employment), and a creation bin (populated by firms which increase employment by 25 percent). The placement and shape of the bins is meant to capture the "fat tail" nature of real–world employment–change densities. In recessions, the shift to the left in the mean of the density is not accomplished by leftward shifts in each of the three bins, but rather by a swelling of the destruction bin. Observing this behavior in an industry in which employment declines are relatively frequent (such as US manufacturing) could lead one to place inordinate emphasis on job destruction as the most important margin of adjustment. Yet consider what must happen if employment is going to jump sharply. For job destruction to remain the most important margin of adjustment, the size of this bin must shrink by a large amount, but mathematically, it cannot shrink below zero. A good indicator of whether the destruction bin is generally large enough to accommodate big increases in employment is the size of the bin at a net growth rate of zero, when both the creation and destruction bins are the same size.[21] This size, of course, is related to the distance AB in Figures 2 and 3. If the two bins at $NET = 0$ are small relative to the increases in NET that must be accommodated, then the creation bin must also be used to increase employment, and job creation takes its place as important adjustment margin over the business cycle.

The Abraham and Katz critique revisited

It is also helpful to place this paper in the long literature on sectoral shifts as a potential source of aggregate fluctuations. In a famous paper, Lilien (1982) noted that growth rates of one–digit sectors such as manufacturing and services moved farther apart from one another in recessions, and suggested that shifts in labor demand among one–digit sectors could be a key forcing variable in aggregate fluctuations. In an equally famous paper, Abraham and Katz (1986) pointed out that an alternative explanation for increased dispersion in industry–level growth rates in recessions is the difference in cyclical sensitivities between declining industries (such as manufacturing) and growing ones (such as

[21] Of course, the bins will be the same size at $NET = 0$ only if they are placed the same distance away from zero, but this is meant to be a heuristic discussion.

services). Since manufacturing generally resides on the left tail of the industry–level growth rate density, and since manufacturing employment is more sensitive to the business cycle, recessions may simply knock manufacturing even farther to left of the density relative to services, increasing dispersion. Abraham and Katz concluded that there was a fundamental identification problem when determining causality between reallocation intensity (measured by dispersion in industry–level growth rates) and recessions (measured by the mean of the industry–level growth–rate density). One needs to bring other information to the matter before being sure that reallocation causes recession, rather than the other way around.

This paper shows that a similar identification problem between reallocation and recession may exist in the study of gross flows. Consider a model which delivers asymmetric behavior in the net employment growth rate due to frictions in product markets (rather than factor markets), with sharp decreases in employment followed by relatively small increases. Perhaps the simplest model that does so is characterized by output equalling real balances, prices that adjust slowly over time, and sharp drops in nominal balances due to decisions of the monetary authority. This model would generate a negative correlation between NET and $NETSQ$. In the non–linear world of Figure 2, such a model would make job destruction appear to be the most important margin of adjustment over the business cycle, even though job destruction was not "causing" the business cycle in any fundamental sense. Conversely, consider one of the many models in the gross–flow literature, based on reallocation frictions or other phenomena, that operate via factor markets. These models are designed to generate highly variable destruction, and in those models job destruction is a true "driving force" in the economy. To the extent that gross flows are symmetric, however, product–market models and factor–market models are observationally equivalent, in that they can both generate a high raw variance of job destruction, depending on the correlation of NET and $NETSQ$. In short, the simple availability of job flow data does not necessarily mean that the most important friction in the economy is located in factor markets rather than product markets.

7. Conclusion

The results of this paper suggest that purported asymmetries in the cyclical behavior of job creation and destruction may be overstated because of important but previously ignored non–linearities in the effect of the net flow on gross flows. This simple finding, motivated by a mathematical tautology appropriate for a representative agent, explains why the high volatility of job destruction in US manufacturing has been hard to replicate elsewhere. It reconciles the behavior of gross flows in services and manufacturing and in old and young manufacturing plants, at least on the annual level. Results also suggest an explanation for why trend employment growth is related to the cyclicality of creation relative to destruction.[22] Finally, accounting for non–linearities substantially reduces asymmetries in quarterly manufacturing data, though evidence for complete symmetry there is weaker.

As for future empirical research, it would be very useful to obtain high–frequency job flows for non–manufacturing sectors in order to determine whether evidence for remaining asymmetries in the quarterly LRD is corroborated elsewhere. Regarding theory, this paper has suggested that models with frictions outside of labor markets may be quite consonant with the cyclical behavior of gross job flows, as long as they generate the "right" correlation between NET and $NETSQ$. Whether these models can do better than factor–market models in explaining the entire constellation of business–cycle facts must be resolved by future research.

[22] The link between trend growth and the relative volatility of creation lies in the correlation between NET and $NETSQ$, which is likely to be positive in sectors when trend employment growth is positive.

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Table 1: Simulation Results

	True Parameters				Estimates from Linear Regression	Estimates from Quadratic Regression	
Row	μ	γ	$\frac{V(\epsilon_{POS})}{V(NET^*)}$	β_{POS}	$E(\widehat{\beta_{POS}})$	$E(\widehat{\beta_{POS}})$	% of "large" t-stats for $\widehat{\gamma}$
1	-.01	.00	1.00	.50	.50 (.11)	.50 (.19)	.0637
2				.20	.40 (.12)	.40 (.20)	.0626
3			3.00	.50	.50 (.13)	.50 (.21)	.0634
4				.20	.46 (.13)	.45 (.22)	.0685
5			0.33	.50	.50 (.08)	.50 (.16)	.0661
6				.20	.32 (.09)	.32 (.17)	.0654
7		.10	1.00	.50	.43 (.12)	.46 (.19)	.0742
8				.20	.33 (.13)	.35 (.22)	.0746
9			3.00	.50	.47 (.12)	.47 (.20)	.0624
10				.20	.43 (.13)	.43 (.22)	.0630
11			0.33	.50	.38 (.10)	.45 (.16)	.1527
12				.20	.20 (.12)	.27 (.19)	.1323

The data generating mechanism is described by equations (1) through (6) of the text:

$$\begin{aligned} NET^* &= \mu + \epsilon_{NET^*}. \\ POS^* &= \alpha + \beta_{POS} NET^* + \gamma (NET^*)^2 \\ NEG^* &= \alpha + \beta_{NEG} NET^* + \gamma (NET^*)^2 \\ POS &= POS^* + \epsilon_{POS} \\ NEG &= NEG^* + \epsilon_{NEG} \\ NET &= POS - NEG \end{aligned}$$

where $\beta_{NEG} = \beta_{POS} - 1$ and $\alpha = 10$. There is no correlation between ϵ_{POS} and ϵ_{NEG}, nor between either of these variables and NET^*. The variances of ϵ_{POS} and ϵ_{NEG} are equal. The linear regression is

$$POS = \alpha + \beta_{POS} NET + \xi_{POS}$$

while the quadratic regression is

$$POS = \alpha + \beta_{POS} NET + \gamma NETSQ + \xi_{POS}.$$

Each regression sample consists of 17 observations and is replicated 10,000 times. Standard deviations of the sampling distributions appear in parentheses. "Large" t–statistics for γ are those which are greater than 2 or less than –2.

Table 2: Results Using One–Digit Annual Data from LRD (1972–1988)

$N = 16$	*Correlations*		*Regression Results*				
Sector	*POS* & *NEG*	*NET* & *NETSQ*	$\hat{\alpha}$	$\widehat{\beta_{POS}}$	$\hat{\gamma}$	$\overline{R^2}_{POS}$	$\overline{R^2}_{NEG}$
Manufacturing	−.75	−.61	9.56 (.24)	.39 (.05)		.81	.91
			9.12 (.26)	.47 (.05)	.023 (.009)	.86	.94

All regression statistics are taken from a regressions of *POS* on *NET* or of *POS* on *NET* and *NETSQ*, except for $\overline{R^2}_{NEG}$, which is taken from regressions with *NEG* on the left–hand–side.

Table 3: Results Using One–Digit Annual Data from Michigan UI Dataset (1978-1988)

$N = 10$	*Correlations*		*Regression Results*				
Sector	*POS* & *NEG*	*NET* & *NETSQ*	$\hat{\alpha}$	$\widehat{\beta_{POS}}$	$\hat{\gamma}$	$\overline{R^2}_{POS}$	$\overline{R^2}_{NEG}$
Agriculture	−.67	.84	15.14 (.42)	.43 (.08)		.77	.86
			14.91 (.33)	.19 (.11)	.041 (.016)	.87	.92
Mining	−.25	−.75	12.55 (1.25)	.45 (.14)		.52	.63
			10.26 (1.22)	.76 (.15)	.033 (.012)	.75	.80
Construction	−.74	−.42	18.54 (.65)	.55 (.07)		.88	.83
			17.67 (1.11)	.58 (.08)	.009 (.010)	.88	.83
Manufacturing	−.68	−.68	6.94 (.48)	.33 (.07)		.71	.91
			6.43 (.38)	.47 (.07)	.017 (.006)	.85	.95
Trans & Comm	−.02	.23	7.61 (.43)	.73 (.15)		.71	.18
			7.33 (.64)	.71 (.16)	.036 (.058)	.69	.12
Wholesale Trade	−.57	.36	9.93 (.36)	.58 (.09)		.82	.70
			9.41 (.47)	.53 (.09)	.039 (.025)	.84	.74
Retail Trade	−.84	.68	10.52 (.18)	.62 (.05)		.95	.87
			10.13 (.33)	.56 (.06)	.035 (.026)	.95	.88
FIRE	−.42	.88	6.20 (.28)	.81 (.08)		.92	.35
			6.11 (.32)	.71 (.18)	.025 (.039)	.91	.30
Services	−.78	.94	12.08 (.29)	.77 (.05)		.97	.73
			12.36 (.15)	.45 (.07)	.031 (.006)	.99	.94

Table 4: Results Using One–Digit Annual Data from LRD (1972–1988) Separated by Age of Plant

$N = 16$	*Correlations*		*Regression Results*				
Sector	*POS* & *NEG*	*NET* & *NETSQ*	$\hat{\alpha}$	$\widehat{\beta_{POS}}$	$\hat{\gamma}$	$\overline{R^2}_{POS}$	$\overline{R^2}_{NEG}$
Manufacturing: Young Plants	–.36	.48	15.40 (.65)	.50 (.09)		.65	.66
			15.09 (.87)	.47 (.11)	.008 (.015)	.63	.66
Manufacturing: Mature Plants	–.80	–.85	7.72 (.20)	.33 (.04)		.82	.95
			7.58 (.19)	.44 (.07)	.017 (.008)	.85	.95

NOTE: Because of data limitations, the dividing line between young and old plants changes slightly from year to year in the LRD. The line generally falls at about 10 years of age. The flows for young plants are actually employment–share weighted averages of rates for the youngest two age classifications, plants less than one year old and plants from one to about 10 years old.

Table 5: Results Using One–Digit Quarterly Data from LRD (1972–1988)

	Correlations		*Regression Results*				
Quarter	*POS* & *NEG*	*NET* & *NETSQ*	$\hat{\alpha}$	$\widehat{\beta_{POS}}$	$\hat{\gamma}$	$\overline{R^2}_{POS}$	$\overline{R^2}_{NEG}$
All (N=67)	–.36	–.71	5.30 (.08)	.29 (.04)		.47	.85
			5.18 (.09)	.38 (.05)	.031 (.012)	.52	.86
Q1 only (N=16)	–.73	–.90	5.61 (.14)	.32 (.05)		.75	.93
			5.67 (.47)	.47 (.10)	.023 (.015)	.78	.94
Q2 only (N=17)	–.20	–.69	5.16 (.18)	.26 (.09)		.32	.81
			4.63 (.22)	.48 (.10)	.132 (.041)	.58	.88
Q3 only (N=17)	–.05	.49	5.15 (.19)	.47 (.12)		.46	.53
			4.71 (.18)	.28 (.10)	.235 (.061)	.72	.76
Q4 only (N=17)	–.21	–.82	5.19 (.16)	.29 (.09)		.35	.79
			4.95 (.17)	.55 (.14)	.110 (.047)	.50	.84
Excluding Q1 (N=51)	–.20	–.56	5.21 (.10)	.32 (.05)		.41	.76
			4.84 (.11)	.47 (.05)	.110 (.022)	.60	.84

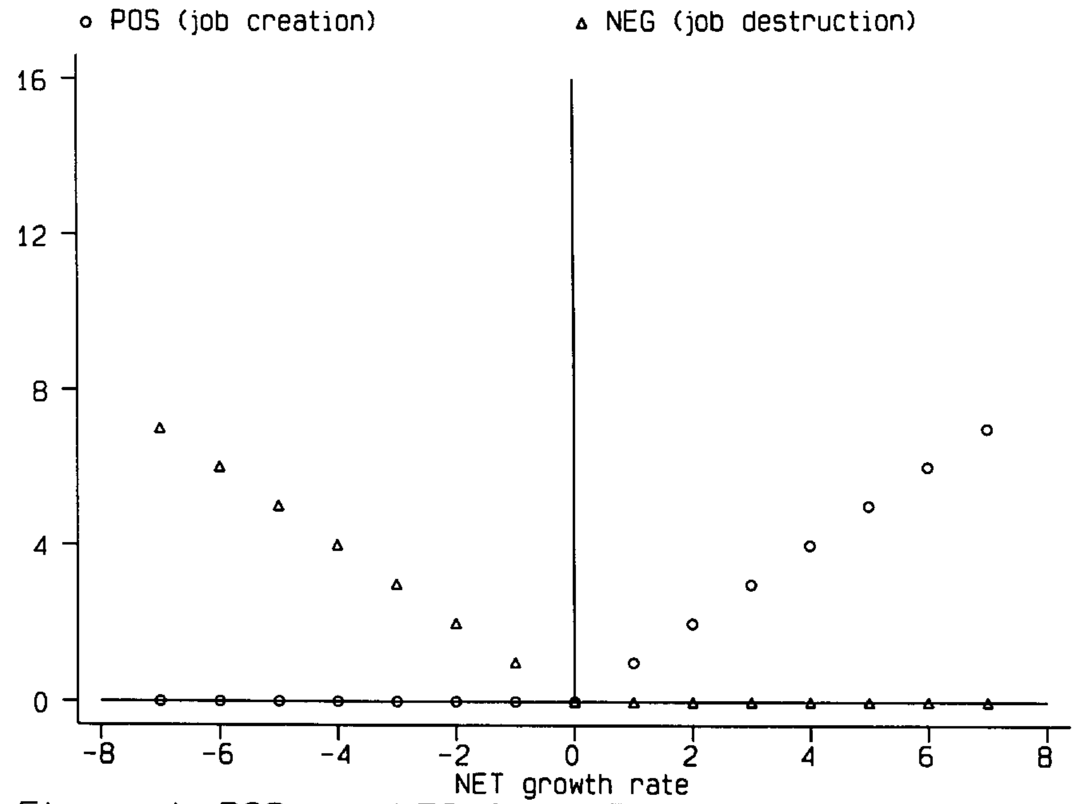

Figure 1: POS and NEG for a Representative Firm

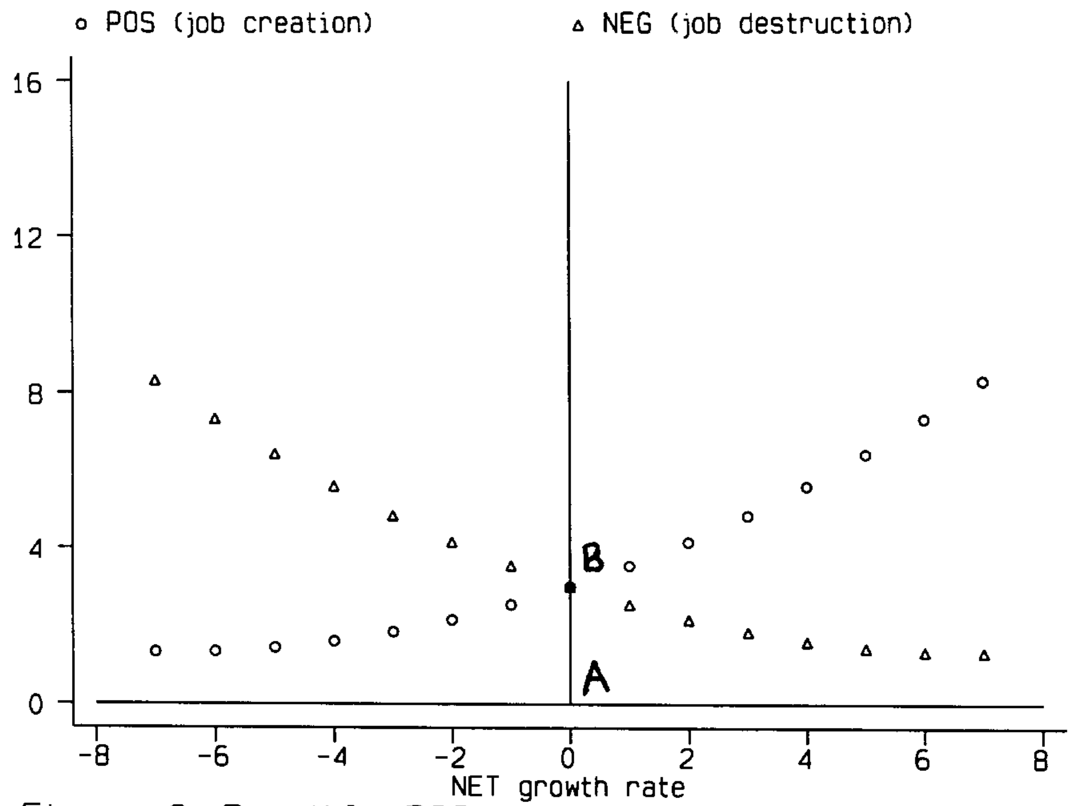

Figure 2: Possible POS and NEG for non RF-case

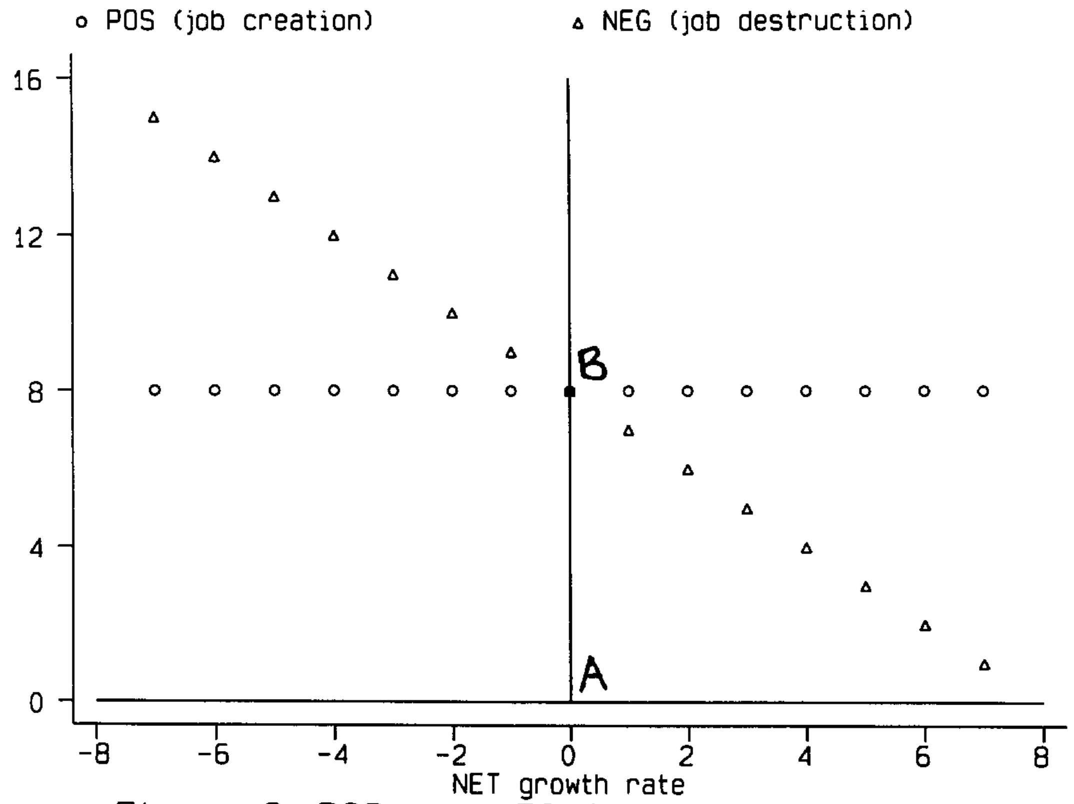

Figure 3: POS and NEG for Linear Case

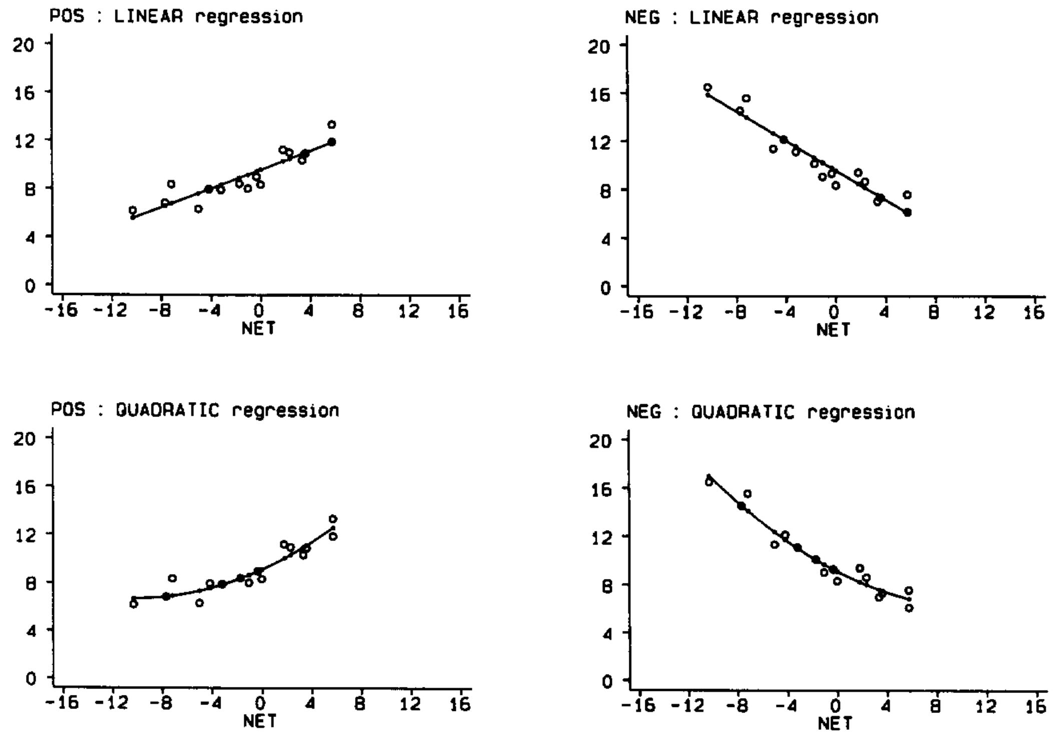

Fig 4: Fitted values for POS and NEG in Annual LRD

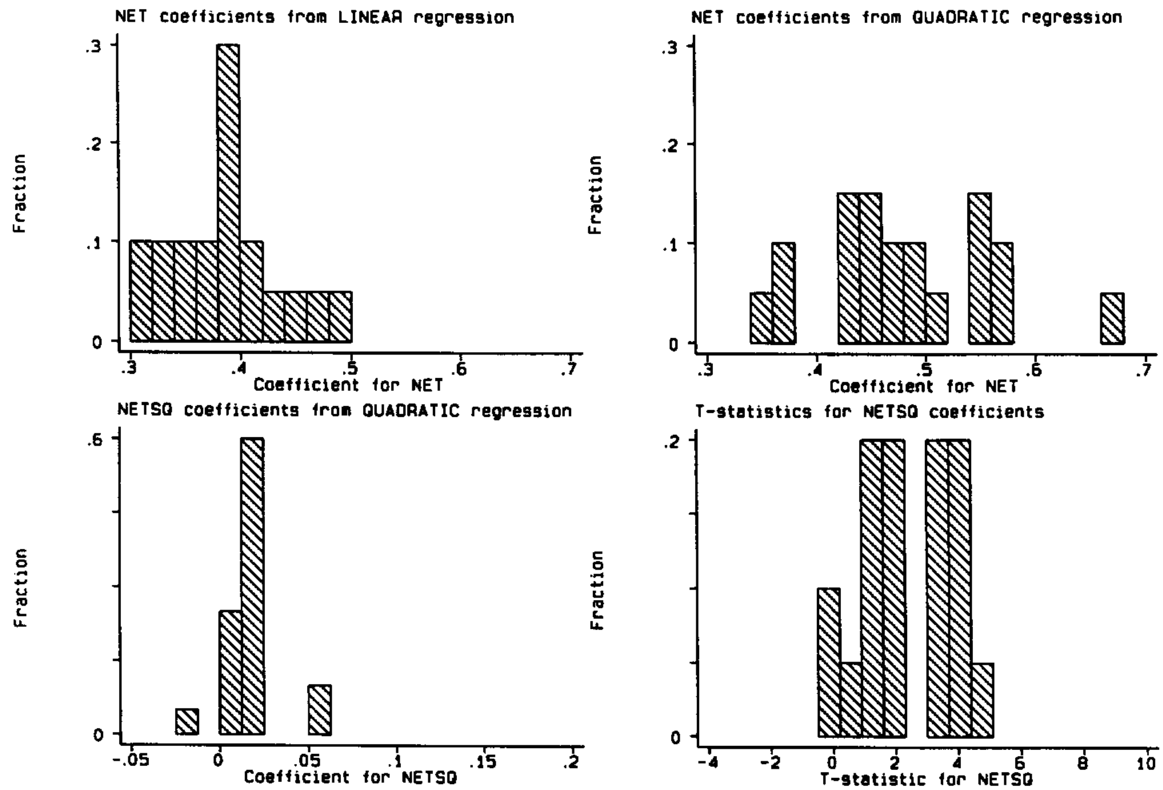

Fig 5: Summary of Results from 2-digit Annual LRD

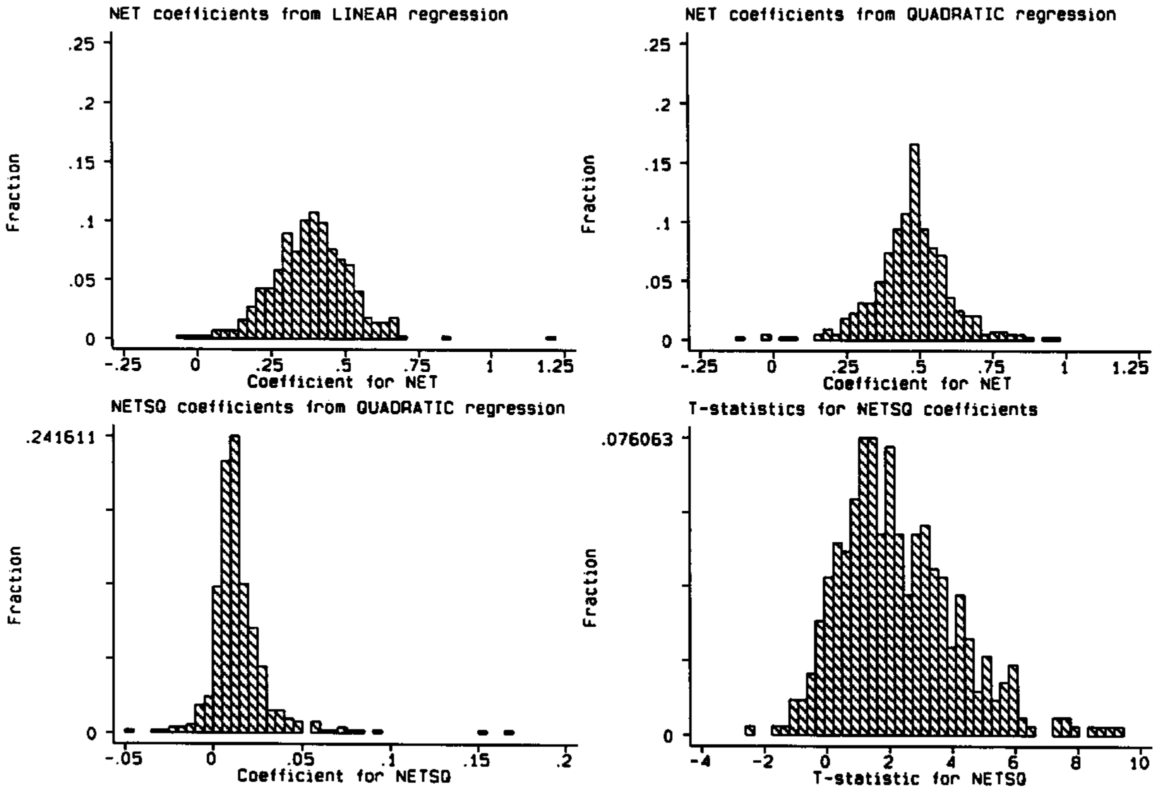

Fig 6: Summary of Results from 4-digit Annual LRD

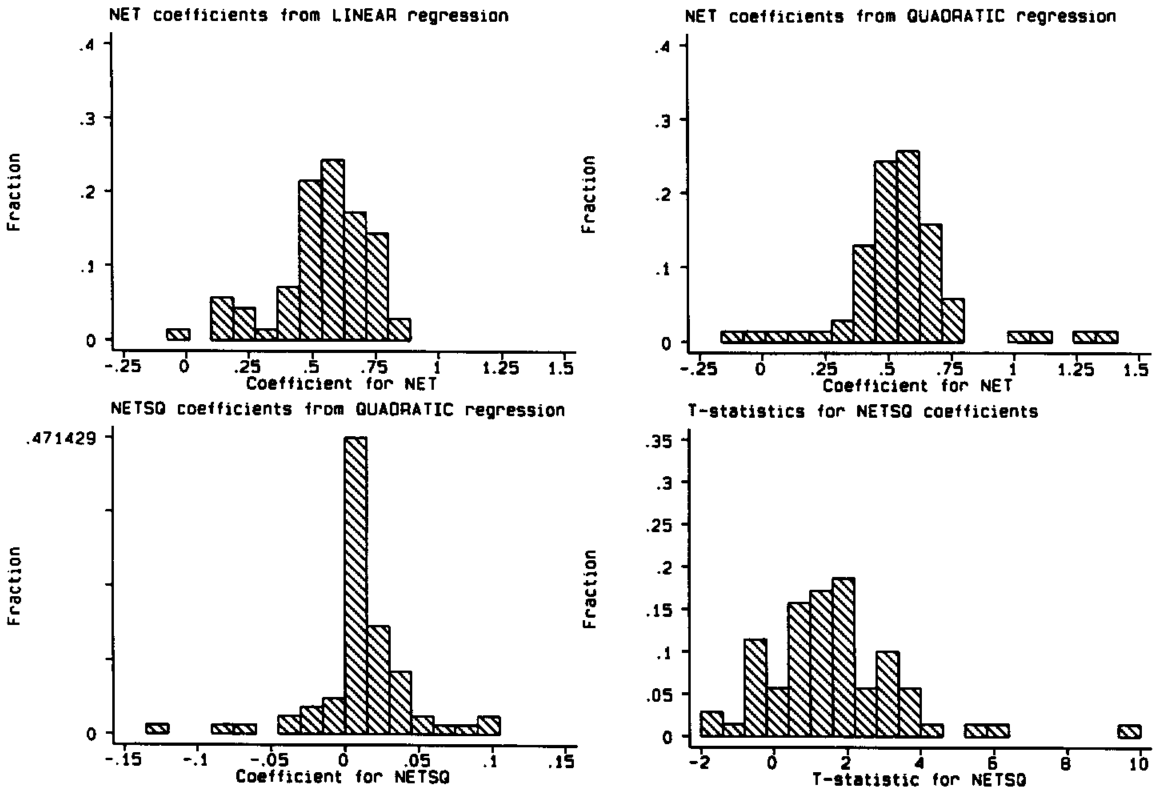

Fig 7: Results from 2-digit Annual Michigan UI data

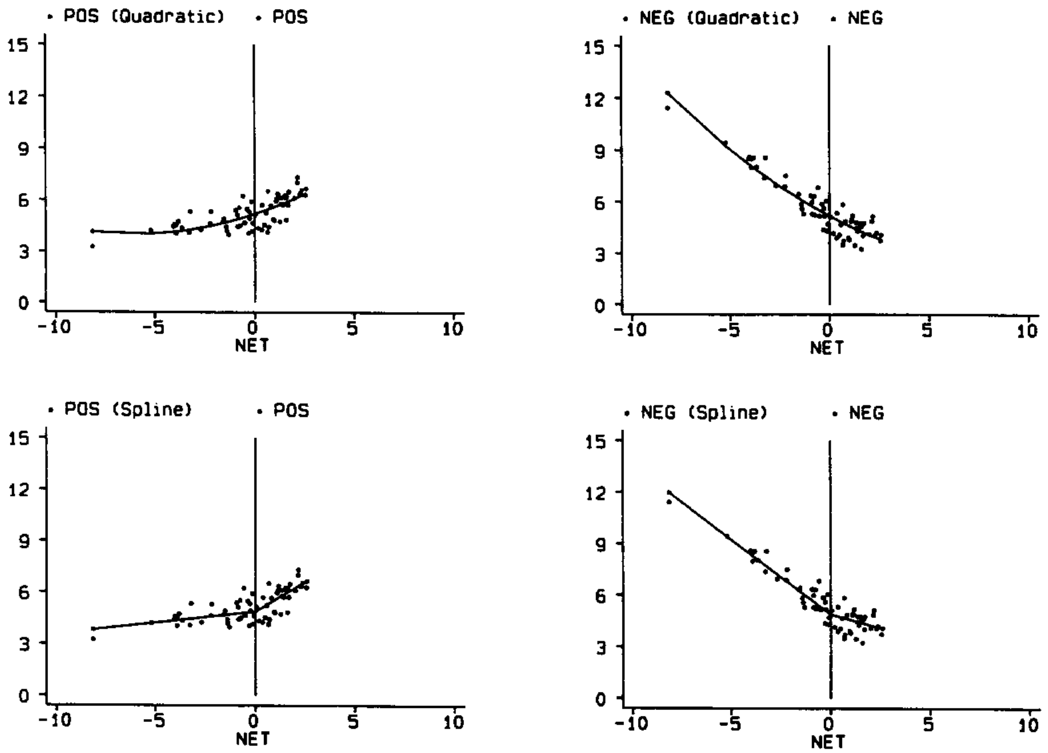

Figure 8: Quarterly POS and NEG from LRD

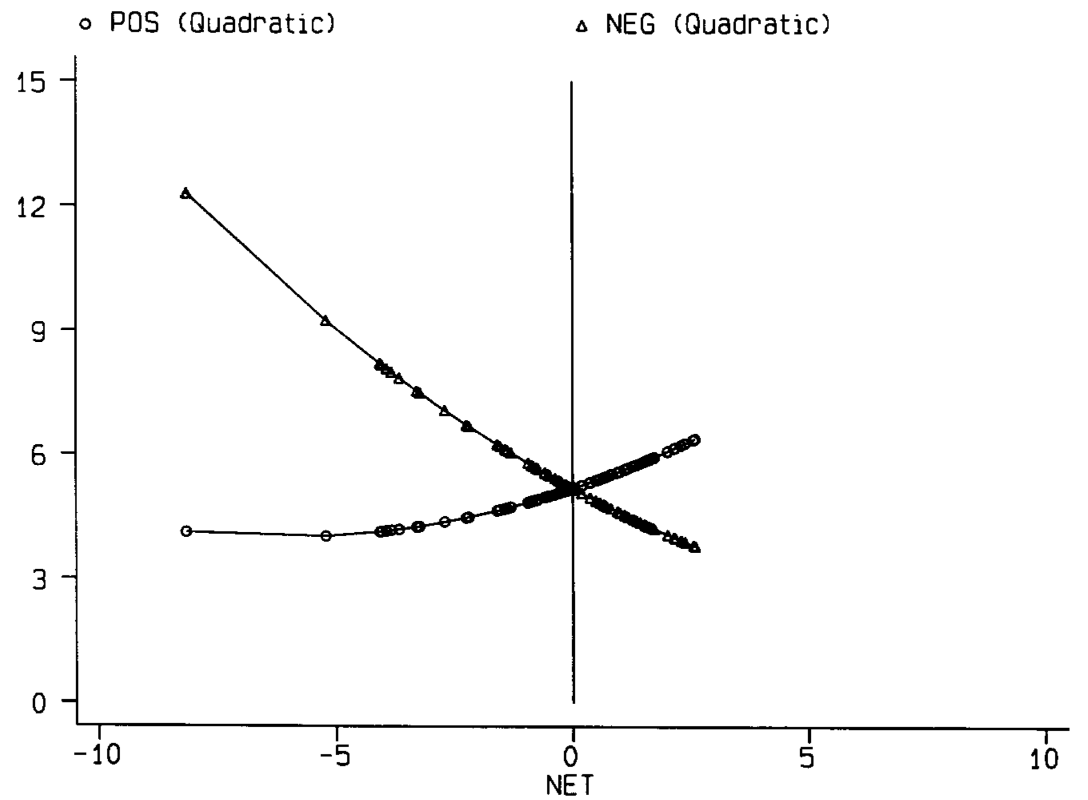

Figure 9a: Implied Quadratic Lines (Quarterly LRD)

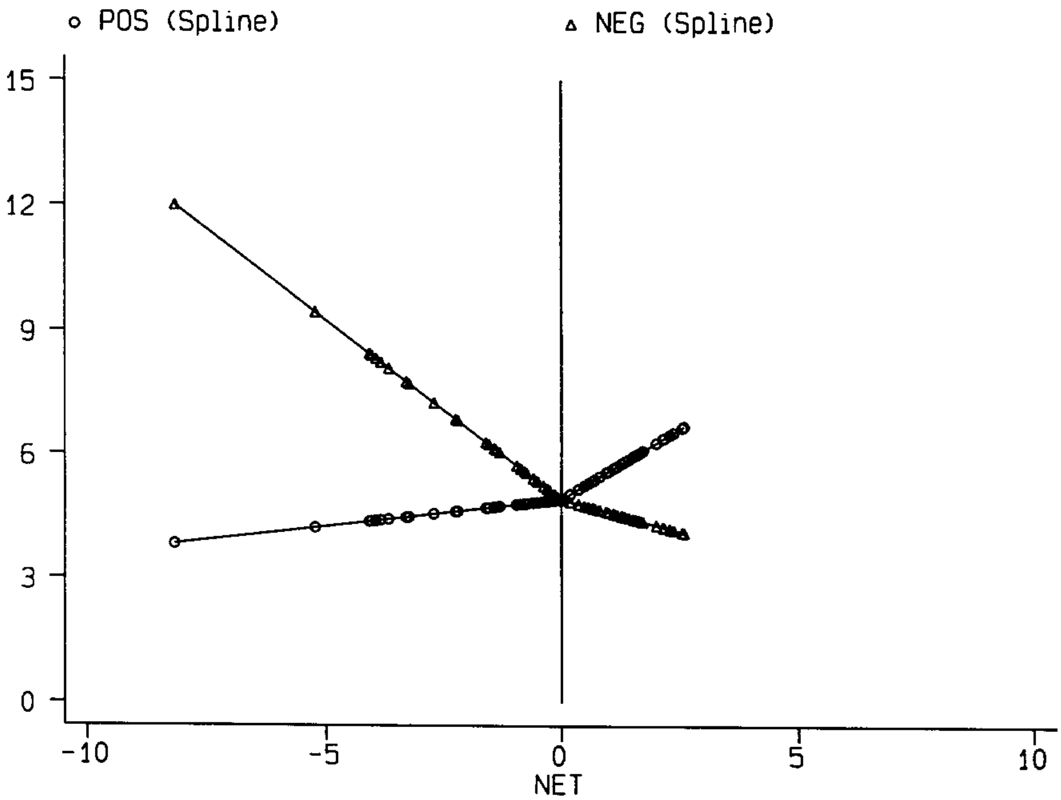

Figure 9b: Implied Spline Lines (Quarterly LRD)

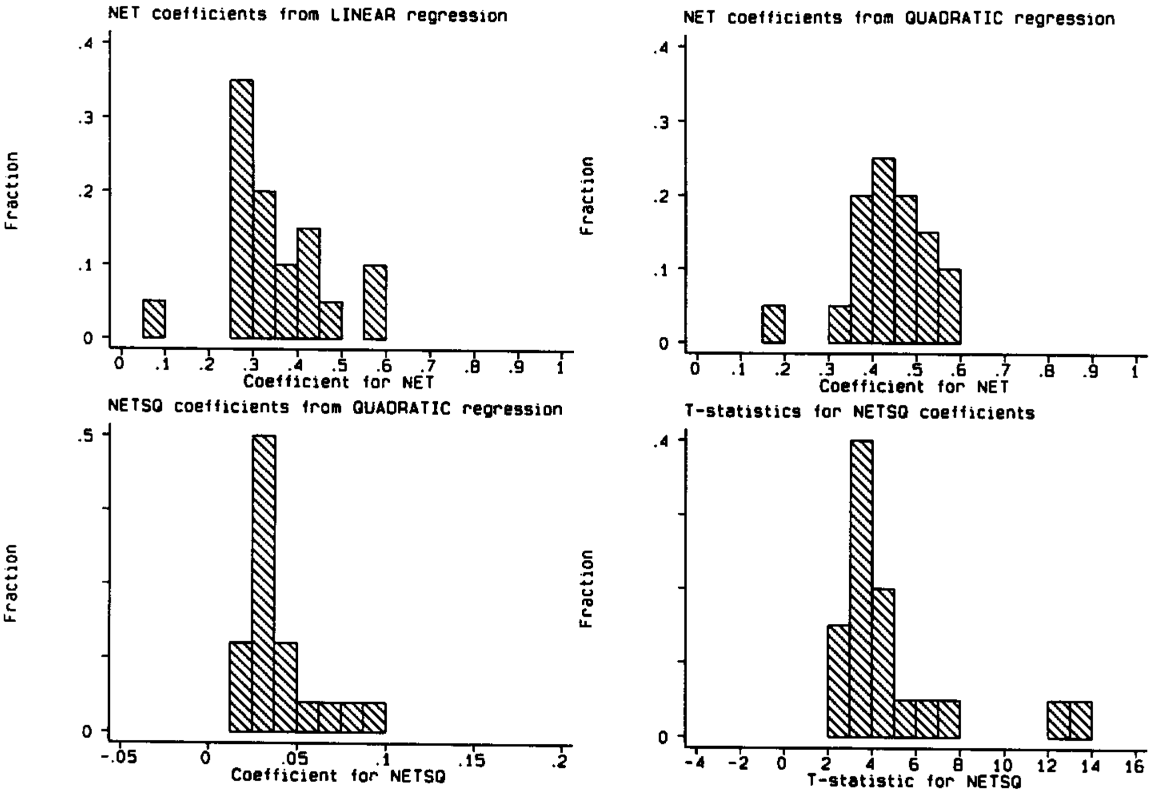

Fig 10: Summary of Results from 2-digit Quarterly LRD

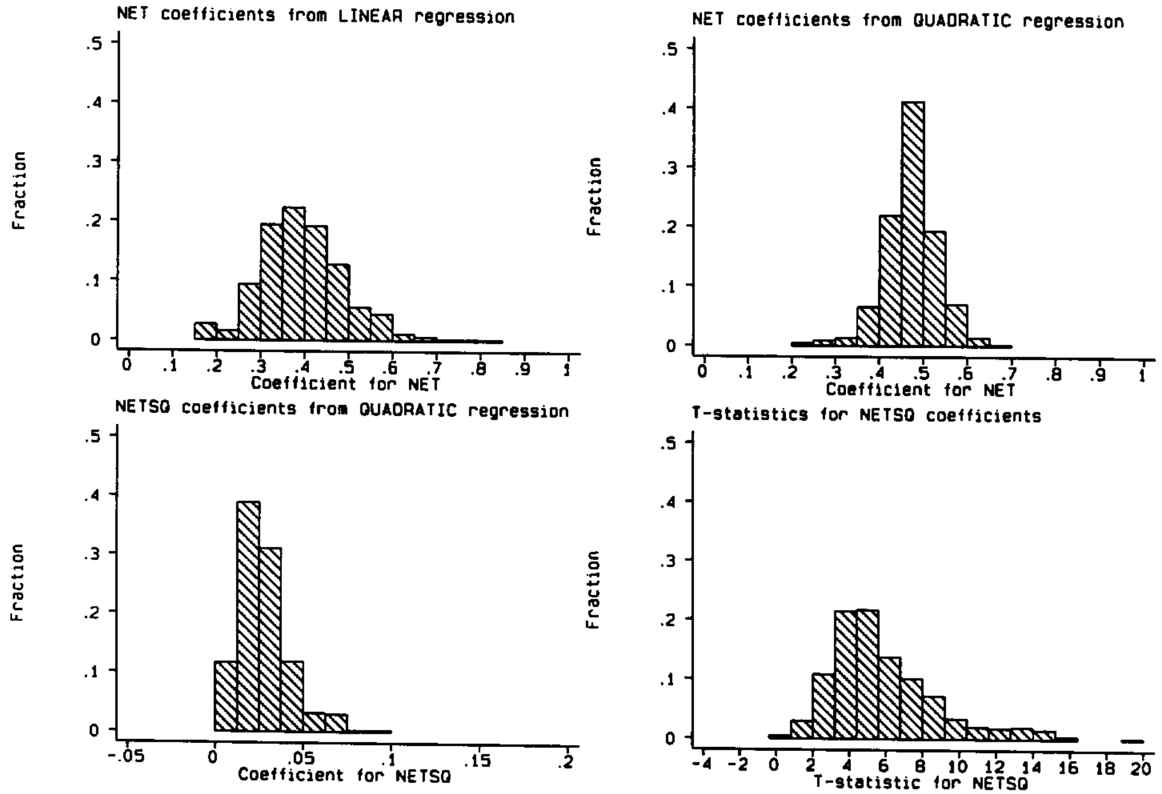

Fig 11: Summary of Results from 4-digit Quarterly LRD

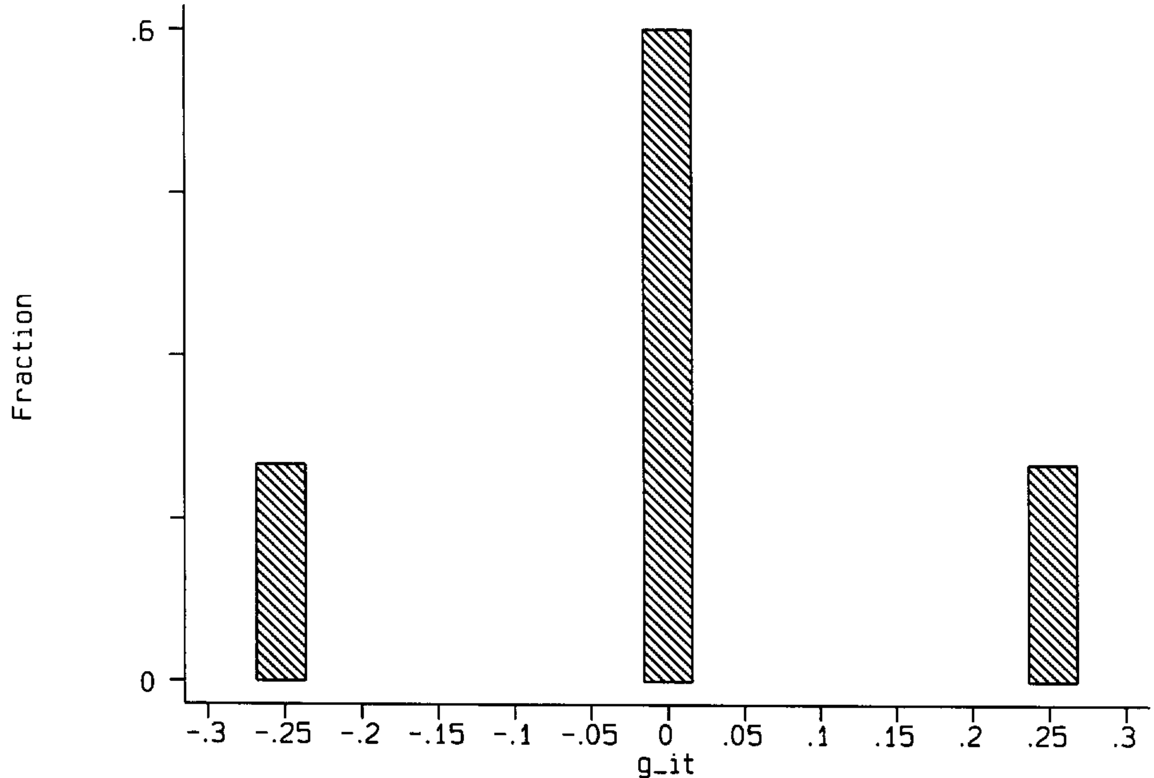

Figure 12: Heuristic Growth--Rate Density