Journal of Cultural Economics (2005) 29: 177–190
DOI: 10.1007/s10824-005-1156-5

Modeling Movie Success when 'Nobody Knows Anything': Conditional Stable-Distribution Analysis of Film Returns*

W. DAVID WALLS

Department of Economics and The Van Horne Institute, University of Calgary, Canada T2N 1N4; E-mail: wdwalls@ucalgary.ca

Abstract. In this paper we apply a recently-developed statistical model that explicitly accounts for the extreme uncertainty surrounding film returns. The conditional distribution of box-office returns is analyzed using the stable distribution regression model. The regression coefficients in this model represent what is known about the correlates of film success while at the same time permitting the variance of film success at the box office to be infinite. The empirical analysis shows that the conditional distribution of film returns has infinite variance, and this invalidates statistical inferences from the often-applied least-squares regression model. The estimates of the stable regression confirm some earlier results on the statistics of the movie business and the analysis demonstrates how to model box-office success in the movie business where "nobody knows anything."

Key words: motion picture success, Pareto-Lévy stable distribution, nobody knows principle

1. Introduction

There is a large and growing literature on the economics of the motion-picture industry, much of it focusing on empirical analysis of the attributes and distribution of financially successful films.[1] The most recent empirical research in this line has found that the unconditional distribution of film returns follows a non-Gaussian stable distribution with infinite variance.[2] We find in this paper that the conditional distribution of film returns—conditioned on production budget, opening screens, "star" actors and directors, genre, rating, and time of release—also follows a stable distribution with infinite variance. The infinite variance finding for the conditional distribution of film returns corresponds to William Goldman's (1983) classic statement that in the movie business "nobody knows anything." Goldman's statement has been refined and restated by Richard Caves as the *nobody knows principle*: "That is, producers and executives know a great deal about what has succeeded

*This research was supported by a generous grant from the Committee on Research and Conference Grants of the University of Hong Kong. An earlier version of this paper was presented at the Far Eastern Meeting of the Econometric Society, Seoul, July 2004. I would like to thank Art De Vany, Rob Oxoby, the editors, and two anonymous referees for helpful comments on earlier versions of this paper.

commercially in the past and constantly seek to extrapolate that knowledge to new projects. But their ability to predict at an early stage the commercial success of a new film project is almost nonexistent" (Caves, 2000, p. 371).

Markets for motion pictures and other forms of popular entertainment have demand processes characterized by recursive feedback. Consumers of films discover what they like and dislike, and this information is spread through word-of-mouth and other media, affecting the consumption decisions of potential viewers. The dynamic demand process results in "heavy tails" in the distribution of revenues across products.[3] In earlier work on the movie business, De Vany and Walls (2002a) model the conditional distribution of box-picture revenue using standard regression models that do not account for the infinite variance property. De Vany and Walls (2004) then model the *unconditional* distribution of motion-picture profits using the general stable distribution, capturing the heavy Paretian tails as well as the central portion of the distribution. They reject the Gaussian model because motion-picture revenues, returns, and profit all have infinite variance. This paper refines and extends my earlier analyses with De Vany by modeling the *conditional stable distribution* of motion-picture outcomes: In the framework of a linear regression model we explicitly account for the stable distribution of the endogenous variable while simultaneously estimating the regression coefficients and the characteristic exponent of the stable distribution.

Modeling the conditional distribution of motion-picture returns permits us to examine directly whether or not the non-Gaussian stable distribution of returns results from the aggregation of movies with quantifiably different attributes: genres, ratings, productions budgets, movie stars. In our empirical analysis we find evidence that the distribution of returns conditional on a movie's attributes has infinite variance, thereby invalidating statistical inferences that would be made from a least-squares regression model. Moreover, the stable regression estimates differ statistically from those obtained from the least-squares estimator, and these differences are of large practical significance: returns to production budgets are substantially larger (0.81 versus 0.71) and returns to "stars" substantially lower (103% versus 138%) than one would estimate using an improperly specified least-squares model.[4] We also evaluate some robust alternatives to least squares and find that Huber (1964) regression provides a very good approximation to stable regression while trimmed least squares is substantially inferior to least squares.

2. The Stable Distribution Model

The stable distribution was introduced into finance to explain the "heavy tails" of asset returns as compared to the Normal or Gaussian distribution (Mandelbrot, 1963a, 1963b; Fama, 1963, 1965). The distribution is called "stable" because it is invariant under convolution. Statisticians sometimes call it "Lévy-stable" in honor of the French mathematician Paul Lévy who derived the conditions for a family of distributions to be stable. In finance it is often referred to as "stable Paretian" because the tails of a non-normal stable distribution follow a power law like the Pareto distribution (Bergstrom, 1952).

The stable distribution is in the domain of attraction of sums of independent and identically distributed random variables. In plain language, this means that the stable distribution is based on a more general version of the central limit theorem than the version supporting the Gaussian distribution. In fact, the familiar Gaussian distribution—on which much of modern portfolio theory is based—is the special case of the stable distribution when the variance is finite.[5] The stable distribution model was largely ignored in economics and finance for some thirty years, with alternatives such as mixture distributions and the student-*t* distribution being proposed to explain the heavy tails in financial data without using a distribution characterized by infinite variance.[6] Recently there has been a resurgence of interest in the stable distribution in finance, including applications to modeling asset returns, foreign exchange rates, interest rate and commodity price movements, and real estate returns (Rachev and Mittnik, 2000; McCulloch, 1996).

The stable distribution is important in theory because it is based on a more general form of the central limit theorem. It is important in practice because it can account for the extreme uncertainty associated with physical and social phenomena. In the application to the movie business in this paper, the stable distribution is the exact statistical model used to capture what is known about movie success when "nobody knows anything." Fortunately, the recent theoretical interest in non-Gaussian stable distributions is complemented by advances in statistical computation that have produced fast numerical approximations for use in applied work.[7]

2.1. THE UNCONDITIONAL STABLE DISTRIBUTION

The stable distribution cannot be expressed generally as a probability distribution function. Instead it is expressed in the form of a moment generating function, $X \sim \mathbf{S}(\alpha, \beta, \gamma, \delta)$, with four key parameters:[8] The index of stability α has a range of $0 < \alpha \leq 2$ and the variance of the stable distribution is infinite when $\alpha < 2$. The skewness coefficient β has a range of $-1 \leq \beta \leq 1$, where the sign indicates the direction of skewness. The scale parameter $\gamma > 0$ expands or contracts the distribution about the location parameter δ. All non-Gaussian stable distributions have tails that are heavier than the tails of a Gaussian distribution. When dealing with data containing extreme values that are too large to have been drawn from a Gaussian distribution, the more general stable distribution is the logical candidate due to its heavier tails.[9]

The stable distribution function nests several well-known distributions. When $\beta = 0$, the stable distribution becomes symmetric and is referred to as the *symmetric stable* distribution. The stable distribution is known as the Gaussian distribution when $\alpha = 2$, the Cauchy when $\alpha = 1$ and $\beta = 0$, and the Lévy when $\alpha = 0.5$ and $\beta = \pm 1$. As the characteristic exponent α approaches 2, the skewness coefficient β has less impact on the shape of the distribution; when $\alpha = 2$ the distribution has only two parameters, location and scale, corresponding to the mean and variance of the Gaussian distribution.

2.2. CONDITIONAL STABLE DISTRIBUTION ANALYSIS

Blattberg and Sargent (1971) appear to be the first economists to develop the basic regression model with non-Gaussian stable disturbances. They derive an estimator for regression coefficients conditional on the value of the index of stability $\alpha \leq 2$ and show in a Monte Carlo simulation that their stable regression estimator is superior to the ordinary least squares estimator. More recently, McCulloch (1998a) derived the maximum likelihood estimator for the stable regression model in which the index of stability α and the regression coefficients are estimated jointly.[10] The stable regression model has the familiar form of a linear regression

$$y_i = \beta_0 + \sum_{j=1}^{k} \beta_{ij} x_i + \epsilon_i \tag{1}$$

where the βs are the coefficients to be estimated, the xs are the regressors, but the random disturbance term is assumed to follow a symmetric stable distribution with median zero, $\epsilon_i \sim \boldsymbol{S}(\alpha, 0, \gamma, 0)$.[11] Estimation of the stable regression model results in an estimate of the regression coefficient βs as well as an estimate of the characteristic exponent α.[12] When the characteristic exponent $\alpha < 2$, the random term will follow an infinite variance stable distribution, invalidating all hypothesis tests from the least-squares model.

When the characteristic exponent $1 < \alpha < 2$, the least-squares estimator of the regression coefficients will be centered on γ, but least squares is inefficient relative to maximum likelihood stable regression because it does not account for the heavy tails of non-Gaussian stable distributions.[13] Another way of stating this is that least squares places too much weight on the outlying observations because they are so improbable under the Gaussian distribution.[14] In this sense, the stable maximum likelihood estimator can be thought of as a robust estimator in that it is less sensitive to outliers than is least squares. Because the characteristic exponent α is estimated jointly with the regression coefficients, the data determine the optimal divergence from the least-squares weights attached to each observation.

3. Data Description and Estimation Results

The sample of data is drawn from the population of movies released in the United States and Canada from 1985 to 1996, inclusive. These are the same data analyzed by De Vany and Walls (1999) that were obtained from ACNielson EDI, Inc.'s historical database. The EDI data are compiled from the North American distributor-reported box-office figures and are widely regarded as the standard industry source for published information on motion picture theatrical revenues.[15] From the EDI

Table I. Box-office revenue, negative cost, and opening screens.

Variable	Mean	Std Dev	Min	Max
Box-office revenue	17.2 million	26.9 million	1304	245 million
Negative cost	11.9 million	10.3 million	4801	114 million
Opening screens	844	761	1	3012

Data Source: ACNielson EDI, Inc.

Table II. Composition of sample by sequel, stars, genre, and rating.

Dummy variable	Films	Percentage
Sequel	169	8.50
Star actor/director	326	16.39
Genre		
Action	224	11.26
Adventure	55	2.77
Animated	40	2.01
Black comedy	26	1.31
Comedy	418	21.02
Documentary	8	0.40
Drama	587	29.51
Fantasy	33	1.66
Horror	69	3.47
Musical	32	1.61
Romantic comedy	132	6.64
Sci-Fi	41	2.06
Suspense	140	7.04
Western	15	0.75
Rating category		
G	58	2.92
PG	392	19.71
PG-13	497	24.99
R	1042	52.39

Data source: ACNielson EDI, Inc.

database, we selected all films for which data on the variables of interest were available. The resulting sample of complete cases contained 1989 movies.[16] Table I provides descriptive statistics on box-office revenue, opening screens and the *negative cost*—the cost of producing the final original "negative" of the movie from which the "prints" shown at cinemas are made.[17] Table II provides a tabulation of the sample by a film's attributes for genre, sequel, rating category, and presence of a star actor or director.[18]

We quantify the distribution of motion-picture revenue conditional on Negative Cost, Opening Screens, whether or not the movie is a Sequel (or prequel), whether or not the director or the actors are Stars, the Genre, the Rating category, and the Year of release in the form of a log-linear regression

$$\begin{aligned}\ln \text{Revenue}_i = \beta_0 + \beta_1 \ln \text{Negative Cost}_i + \beta_2 \ln \text{Screens}_i \\ + \beta_3 \text{Sequel}_i + \beta_4 \text{Star}_i + \Gamma[\text{Genre, Rating, Year}]_i' + \mu_i \qquad (2)\end{aligned}$$

where i indexes individual movies, Star and Sequel are dummy variables equal to unity when a movie contains a star or is a sequel, respectively, and zero otherwise, and Γ is a vector of coefficients conformable to the sets of explanatory variables indicating particular genres, ratings, and years of release.[19] This basic regression equation has been used by previous researchers including Smith and Smith (1986), Prag and Cassavant (1994), Litman and Ahn (1998), Ravid (1999), and De Vany and Walls (2002a). We use this log-linear specification for two reasons: 1) use of this equation makes our results comparable to the results obtained by previous researchers, and 2) on a more technical level, De Vany and Walls (2002a) estimate the optimal exponent in a Box-Cox (1964) transformation of Revenue and find statistical evidence in support of modeling the logarithm of box-office revenue.[20]

Least squares and stable regression estimates of the regression parameters are presented in Table III.[21] In the least-squares regression the characteristic exponent is $\alpha = 2$ by construction. In the stable regression α is a parameter to be estimated and our maximum likelihood estimate is $\hat{\alpha} = 1.8436$ with an estimated standard error of 0.0419. Clearly we can reject the hypothesis that the random disturbance follows a Gaussian distribution (the hypothesis that $\alpha = 2$) in favor of the alternative that the disturbance follows a non-Gaussian stable distribution with infinite variance.[22] In Figure 1 the fitted Gaussian distribution of residuals from the least-squares estimation is plotted along with the empirical density of the residuals as approximated by the Epanechnikov kernel.[23] The density plots show that the empirical distribution has heavier tails and a higher more concentrated peak compared to the fitted Gaussian distribution, and these attributes of the empirical distribution are captured in our estimate of the characteristic exponent of 1.84 (which is statistically less than 2).

Since we have demonstrated that the residuals are non-Gaussian, we will now compare the stable estimates with those obtained from the standard least-squares estimation. We shall discuss the individual regression coefficients displayed in Table III in their order of appearance in the regression equation:

- Negative Cost: This regression coefficient represents the elasticity of Revenue with respect to Negative Cost. The least-squares estimate of this elasticity is 0.708 while the stable estimate is 0.809. The difference between these two estimates is 0.101 which is more than twice as large as the estimated standard error of 0.050.[24]

Table III. Least squares and stable regression estimates.

Variable	L-S estimates[a] Coeff	L-S estimates[a] Std Err	Stable estimates[b] Coeff	Stable estimates[b] Std Err
Constant	2.463	0.787	1.236	0.830
Log negative cost	0.708	0.046	0.809	0.050
Log opening screens	0.350	0.017	0.313	0.018
Sequel	0.403	0.303	0.437	0.284
Star	0.869	0.103	0.708	0.089
Genre				
Action	−0.258	0.298	−0.163	0.283
Adventure	−0.264	0.348	−0.196	0.337
Animated	0.259	0.409	0.276	0.390
Black comedy	−0.020	0.415	0.023	0.393
Comedy	0.112	0.287	0.168	0.272
Documentary	0.418	0.619	0.501	0.560
Drama	0.205	0.286	0.251	0.272
Fantasy	0.362	0.388	0.334	0.364
Horror	0.198	0.339	0.291	0.318
Romantic comedy	0.136	0.308	0.197	0.295
Sci−Fi	−0.161	0.369	−0.086	0.350
Suspense	−0.458	0.311	−0.390	0.296
Western	0.134	0.490	0.097	0.463
Rating category				
G	0.627	0.273	0.517	0.260
PG	0.182	0.107	0.187	0.103
R	0.069	0.091	0.046	0.087
Year of release				
1986	−0.361	0.228	−0.346	0.210
1987	−0.376	0.225	−0.342	0.208
1988	−0.685	0.221	−0.590	0.207
1989	−1.264	0.215	−1.150	0.203
1990	−0.781	0.221	−0.691	0.206
1991	−0.481	0.221	−0.445	0.204
1992	−0.648	0.226	−0.619	0.209
1993	−0.461	0.230	−0.482	0.214
1994	−0.508	0.233	−0.546	0.216
1995	−0.612	0.228	−0.567	0.213
1996	−0.690	0.224	−0.705	0.208

[a]The characteristic exponent $\alpha = 2$ by constraint.
[b]The characteristic exponent $\hat{\alpha} = 1.8436$ with an estimated standard error of 0.0419. The Gaussian distribution is clearly rejected.

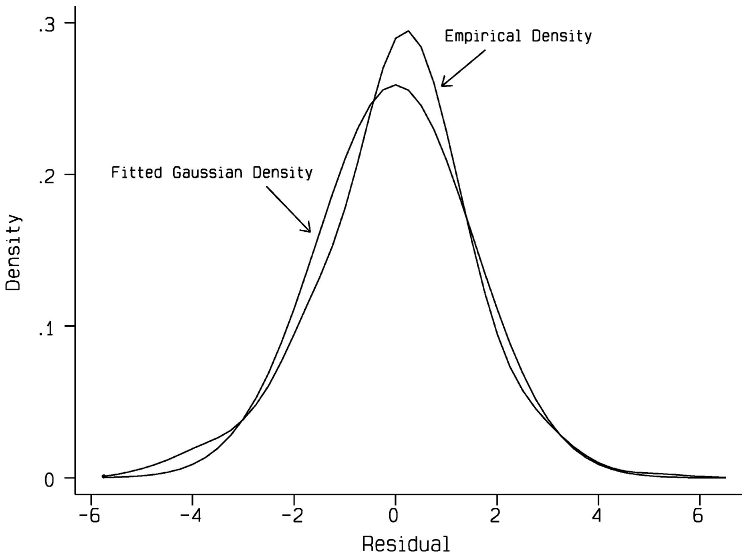

Figure 1. Empirical and Fitted Gaussian Distributions of Regression Residuals. Note: The empirical density is a plot of the kernel density estimate obtained using the Epanechnikov kernel.

- Opening Screens: This regression coefficient represents the elasticity of Revenue with respect to the number of cinema screens on which a motion-picture makes its debut. Least-squares provides an estimate of 0.350. The stable estimate is 0.330 with a standard error of 0.018. The stable estimate is smaller by about one standard error, so the estimates are not statistically different.
- Sequel: The coefficients on the dummy variable Sequel are 0.403 and 0.437, respectively, in the least squares and stable regressions. With an estimated standard error of 0.284, we conclude that these estimates are not statistically different.
- Stars: The dummy variable Stars has a coefficient of 0.869 in the least-squares regression and 0.708 in the stable regression, with an estimated standard error of 0.089. The difference between these two values is about 1.81 standard errors, which is statistically significant at a marginal significance level of about 0.08.
- Genre: None of the individual genre classifications are individually significant in either regression, but in both regressions the genres are significant as a group.
- Rating: The Rating dummy variables show the change in Revenue relative to the omitted category of PG-13. In both regressions we find that G-rated movies have statistically higher revenues at the 5% level, and that PG-rated movies have significantly higher revenues at the 10% level. Revenues of R-rated movies are statistically no different from PG-13 in both regressions.[25]
- Year of Release: In both regressions we find the same basic pattern of movies earning higher revenues in some years than others, with the returns in all years lower than the base year 1985.

We have shown that the coefficient on Star is statistically larger in the least-squares estimation than in the stable regression estimation. But what would be the practical value of knowing this and having the estimates from the stable regression model? To interpret dummy variables in log-linear regression we must subtract 1 from the exponentiated coefficient on the dummy variable. The coefficient on Star in the least-squares regression results in a value of $\exp(0.869) - 1 = 1.3845$ or an increase of some 138 percent. Compare this to the estimated value of a Star in the stable regression of $\exp(0.708) - 1 = 1.0299$ or 103 percent. The difference between these two estimates—35 percentage points—confirms the "curse of the superstar" found by De Vany and Walls (2004). When using the Gaussian model (least squares is equivalent to maximum likelihood in the Gaussian model) if a Star is paid the expected increase in revenue associated with his or her performance in a movie then the movie will almost always lose money. The conditional stable-distribution analysis in this paper permits us to quantify the magnitude of the decision error made when a research analyst ignores the statistics of the movie business and mechanically applies least-squares regression.

We noted earlier that the stable regression model can be thought of as a robust estimator in that it weights extreme observations less heavily than does least squares. For completeness, we have included estimates using two alternative estimators that are also robust to outlying observations but computationally much simpler than stable regression. First, we report results of a bounded influence regression where the observations are reweighted using criteria suggested by Huber (1964) and Mosteller and Tukey (1977).[26] Second, we report the results of trimmed least squares which is least squares applied to the central 9 deciles of the data.

The results of the Huber regression, reported in the first two columns of Table IV, are much closer to the stable estimates. Indeed, the coefficients on Negative Cost, Opening Screens, Sequel and Star differ only at the second decimal place and beyond, and in each case the difference is substantially less than one standard error. The coefficient estimates on individual Genre, Rating, and Year dummy variables do differ, but in these cases the difference is about one standard error and so not statistically different. Also of importance is that the estimated standard errors in the Huber regression are close to those in the stable regression. Overall, the Huber regression provides a close approximation to the stable regression with the exception of the constant term.

The trimmed least-squares estimator performs poorly and for some coefficients (Negative Cost and Star) provides estimates that are farther in error than least squares. The extreme weighting function of trimmed least-squares assigns a zero weight to observations that are discarded. One important problem with the trimmed least-squares estimator is that the influential observations in the original regression may influence the estimated coefficients so much that the residuals associated with those observations do not appear as outliers. In this case the discarded observations are really from the central part of the distribution and the outlying observations are

Table IV. Estimates from alternative robust estimators.

	Huber[a]		Trimmed L-S [b]	
Variable	Coeff	Std Err	Coeff	Std Err
Constant	0.884	0.751	−1.158	0.913
Log negative cost	0.811	0.044	0.947	0.055
Log opening screens	0.323	0.016	0.330	0.018
Sequel	0.497	0.289	0.419	0.297
Star	0.705	0.099	0.854	0.112
Genre				
Action	−0.066	0.285	−0.234	0.292
Adventure	−0.081	0.332	−0.357	0.341
Animated	0.313	0.391	0.129	0.405
Black comedy	0.075	0.397	−0.029	0.440
Comedy	0.239	0.274	0.082	0.279
Documentary	0.552	0.591	0.706	0.601
Drama	0.325	0.273	0.194	0.278
Fantasy	0.349	0.371	0.369	0.396
Horror	0.381	0.324	0.357	0.333
Romantic comedy	0.265	0.294	0.114	0.301
Sci−Fi	0.017	0.353	−0.189	0.372
Suspense	−0.287	0.297	−0.482	0.304
Western	0.110	0.467	0.175	0.499
Rating category				
G	0.408	0.261	0.722	0.272
PG	0.192	0.102	0.204	0.108
R	0.033	0.087	0.073	0.093
Year of release				
1986	−0.343	0.217	−0.490	0.234
1987	−0.344	0.215	−0.448	0.231
1988	−0.522	0.211	−0.722	0.228
1989	−1.046	0.205	−1.256	. 0 224
1990	−0.642	0.211	−0.849	0.229
1991	−0.424	0.211	−0.609	0.228
1992	−0.606	0.216	−0.767	0.234
1993	−0.507	0.220	−0.580	0.238
1994	−0.570	0.222	−0.580	0.242
1995	−0.537	0.218	−0.736	0.239
1996	−0.724	0.214	−0.814	0.234

[a]Robust regression where the observations are reweighted using first the criterion of Huber (1964) and then the biweight criterion of Mosteller and Tukey (1977).
[b]Least squares is applied to the entire data set and the outlying observations in the upper and lower 5% are discarded (trimmed). Least squares is then applied to the remaining 90% of the original sample.

retained, exacerbating the problem. This may explain the poor performance of the trimmed least-squares estimator in our application.

4. Conclusions

Even though "nobody knows anything" when it comes to predicting the financial success of films, much is known about the attributes of financially successful films and we can quantify the systematic component of box-office revenue while accounting for infinite variance. Recent advances in statistical computation make it feasible to estimate a regression model with stable-distributed random disturbances using standard maximum likelihood techniques. The stable regression model is particularly well suited to empirical analysis of the entertainment industries where financial success is characterized by extreme uncertainty and where we are interested in analyzing conditional distributions. In our analysis, we show the mistakes of statistical inference that could be made by ignoring the infinite variance property of film returns and applying the usual least-squares estimator: In particular, the estimated stable regression coefficients differ statistically from those obtained from least squares, and the differences are of large practical significance regarding the returns to production cost and "star" talent. In circumstances where estimation of the stable regression model is inconvenient, applied researchers may use bounded influence regression, which in our application provides a good approximation to stable regression.

Notes

1. See, for example, Albert (1998, 1999), Litman (1983) Litman and Ahn (1998), Litman and Kohl (1989), Prag and Cassavant, Ravid (1999,2003), Sedgwick and Pokorny (1999), Smith and Smith (1986), and Wallace, Seigerman, and Holbrook (1993).
2. In this paper we are modeling the success of *individual* films. Hand (2002) finds that annual cinema admissions aggregated across all films in the United Kingdom can be modeled using standard time-series methods.
3. De Vany and Walls (1996) model motion-picture demand as a Bose-Einstein process and find that it converges asymptotically to a Pareto distribution.
4. It is well known that least squares is the maximum likelihood estimator when the random disturbance follows a Gaussian distribution. For this reason, and because least squares is the estimator used by most applied researchers, we shall refer to least squares as representing the assumption of a Gaussian distribution for the random disturbance.
5. See Samorodnitsky and Taqqu (1994) and Zolotarev (1986) for detailed mathematical proofs.
6. Estimators based on other distributions for heavy-tailed data—such as the student-t—do not account for infinite variance, and are not in the domain of attraction of sums of independent and identically distributed random variables. However, from a practical perspective, a student-t distribution with low degrees of freedom may provide a similar weighting to that of the symmetric-stable distribution. Zellner (1976) provides a complete development of a regression model with Student-t disturbances.
7. In particular, McCulloch's (1998b) numerical approximation of the symmetric stable density is at the heart of the computation in this paper.

8. The moment generating function—also called the characteristic function—is the Fourier transform of the probability density function. See Nolan (1998) for the mathematical expression of the moment generating function. For brevity it is not reproduced here.
9. Other distributions could also be used to model heavy tails—such as the student-t with its heavier-than-Gaussian tails—but these alternatives are arbitrary in that they are not limiting distributions so one cannot appeal to the central limit theorem in their application.
10. The material in this section follows closely the exposition and notation of McCulloch (1998a). See Judge et al. (1985, pp. 825–826) for an overview of econometric models with infinite variance.
11. Most empirical applications of the stable distribution in economics and finance assume symmetry due to the lack of a fast numerical routine to approximate the density of the general stable distribution. General stable regression can be done at high cost. In the application of this paper, discussed below, we find that the empirical distribution of the random disturbance is consistent with symmetry.
12. In the actual estimation, α is constrained to be less than or equal to 2. When the estimated value of α is 2, the stable regression model is identical to least-squares regression. Estimated values of α less than 2 indicate divergence from least squares.
13. In the case of non-Gaussian stable disturbances where $1 < \alpha < 2$, least squares converges to γ at the rate $n^{1/\alpha-1}$ as compared to the rate $n^{-1/2}$ of the stable maximum likelihood estimator. When $\alpha < 1$, the mean does not exist so least squares does not converge on γ at all.
14. In fact, McCulloch (1998a) shows that the first-order conditions for symmetric stable maximum likelihood are precisely the same as for weighted least squares with the appropriate weighting function.
15. The EDI figures are cited and republished by many major industry publications including *Daily Variety* and *Weekly Variety*.
16. A more detailed description and cross tabulation of the entire sample of EDI data is contained in De Vany and Walls (1999).
17. The largest-grossing movies in our sample include *Batman, The Lion King, Home Alone, Forrest Gump, and Jurassic Park.* The largest-budget films in the sample include *Space Jam, Eraser, True Lies, Terminator 2: Judgment Day, and Waterworld*. It is interesting to note that *not one* of the five most costly movies earned the highest revenues.
18. We use the same definition of 'star' used by De Vany and Walls (1999): An actor or director appearing on *Premier*'s annual listing of the hundred most powerful people in Hollywood or on James Ulmer's list of A and A+ actors was considered to be a star in our empirical analysis.
19. The omitted categories for the genre, rating, and year dummy variables are musical, PG-13, and 1985, respectively.
20. The true model is unknown and unknowable, but statistical inferences on the regression coefficients do presume the correct model specification. The specification employed in this paper benefits from the cumulative research of others. Still, there is no guarantee that it is correct.
21. The symmetric stable regression model was estimated in Gauss version 3.2 using code written by McCulloch (1997) and available electronically from the Gauss source code archive at The American University.
22. Because the random terms have a non-Gaussian stable distribution, the inferences of earlier studies based on least-squares estimation are invalid. Only the De Vany and Walls (2003a) study employed robust estimators that are approximately valid when dealing with heavily tailed data.
23. The empirical density of residuals is insensitive to the particular kernel used. The Gaussian kernel results in a density plot nearly indistinguishable from that obtained with the Epanechnikov kernel.
24. For hypothesis testing we use the estimated standard error from the stable regression. Recall that the estimated standard errors from the least-squares regression are not meaningful when the characteristic exponent $\alpha < 2$.

25. These results confirm the main findings of De Vany and Walls (2002b) that are based on the Pareto distribution.
26. The bounded influence regression reported in Table IV was estimated using the robust regression routine programmed into Stata for Unix version 7 (Stata Corporation, 2001, pp. 155–156). In short, the observations are reweighted using the Huber (1964) criterion until convergence, and then these are used as starting values for the biweight criterion of Mosteller and Tukey (1977).

References

Albert, S. (1998) "Movie Stars and the Distribution of Financially Successful Films in the Motion Picture Industry." *Journal of Cultural Economics* 22: 249–270.

Albert, S. (1999) "Reply: Movie Stars and the Distribution of Financially Successful Films in the Motion Picture Industry." *Journal of Cultural Economics* 23: 325–329.

Bergstrom, H. (1952) "On Some Expansions of Stable Distribution Functions." *Arkiv fur Mathematik* 2: 375–378.

Blattberg, R. and Sargent, T. (1971) "Regression with non-Gaussian Stable Disturbances Some Sampling Results." *Econometrica* 39(3): 501–510.

Box, G. and Cox, D. (1964) "An Analysis of Transformations." *Journal of the Royal Statistical Society* B 26: 211–243.

Brosen, B.W. and Prekel, P.V. (1993) "Linear Regression with Stably Distributed Residuals." *Communications in Statisics Theory and Methods* 22: 659–667.

Caves, R.E. (2000) *Creative Industries: Contracts between Art and Commerce*. Harvard University Press, Cambridge.

De Vany, A.S. and Walls, W.D. (1996) "Bose-Einstein Dynamics and Adaptive Contracting in the Motion Picture Industry." *The Economic Journal* 439(106): 1493–1514.

De Vany, A.S. and Walls, W.D. (1999) "Uncertainty in the Movie Industry: Does Star Power Reduce the Terror of the Box Office?" *Journal of Cultural Economics* 23(4): 285–318.

De Vany, A.S. and Walls, W.D. (2002a) "Big Budgets, Movie Stars, and Wide Releases Empirical Analysis of the Blockbuster Strategy." *In Proceedings of the XIX Latin American Meeting of the Econometric Society*, São Paulo, Brazil.

De Vany, A.S. and Walls, W.D. (2002b) "Does Hollywood Make too Many R-rated Movies? Risk, Stochastic Dominance, and the Illusion of Expectation." *Journal of Business* 75(3): 425–451.

De Vany, A.S. and Walls, W.D. (2004) "Motion Picture profit, the Stable Paretian Hypothesis, and the Curse of the Superstar." *Journal of Economic Dynamics and Control* 28(6): 1035–1057.

Fama, E. (1963) "Mandelbrot and the Stable Paretian Hypothesis." *Journal of Business* 36(4): 420–429.

Fama, E. (1965) "The Behavior of Stock Market Prices." *Journal of Business* 38(1): 34–105.

Goldman, W. (1983) *Adventures in the Screen Trade*. Warner Books, New York.

Halvorsen, R. and Palmquist, R. (1980) "The Interpretation of Dummy Variables in Semilogarithmic Equations." *American Economic Review* 70(3): 474–475.

Hand, C. (2002) "The Distribution and Predictability of Cinema Admissions." *Journal of Cultural Economics* 26: 53–64.

Huber, P.J. (1964) "Robust Estimation of a Location Parameter." *Annals of Mathematical Statistics* 35: 73–101.

Judge, G. Griffiths, W. Hill, R. Lutkepohl, H. and Lee, T. (1985) *The Theory and Practice of Econometrics*. Wiley, New York, second edition.

Litman, B.R. (1983) "Predicting the Success of Theatrical Movies: An Empirical Study." *Journal of Popular Culture* 16: 159–175.

Litman, B.R. and Ahn, H. (1998) "Predicting Financial Success of Motion Pictures: The Early '90s Experience", in *The Motion Picture Mega-Industry*. Allyn and Bacon, Needham Heights, Massachusetts, chapter 10, pages 172–197.

Litman, B.R. and Kohl, L.S. (1989) "Predicting Financial Success of Motion Pictures: The '80s experience." *Journal of Media Economics* 2: 35–50.

Mandelbrot, B. (1963a) "New Methods in Statistical Economics". Journal of Political Economy 71: 421–440.

Mandelbrot, B. (1963b) "The Variation of Certain Speculative Prices." Journal of Business 36: 394–419.

McCulloch, J.H. (1996) "Financial Applications of Stable Distributions", in Maddala G.S. and Rao C.R. (eds.), *Statistical Methods in Finance*, volume 14 of *Handbook of Statistics*. North-Holland, New York, pp. 393–425.

McCulloch, J.H. (1997) "Symmetric Stable Linear Regression Computer Code." Gauss Source Code Archive, The American University, Washington DC.

McCulloch, J.H. (1998a) "Linear Regression with Stable Disturbances," in Adler, R.J. Feldman, R.E. and Taqqu, M.S. (eds.), *A Practical Guide to Heavy Tails Statistical Techniques and Applications*. Birkhäuser, Berlin, pp. 359–378.

McCulloch, J.H. (1998b) "Numerical Approximation of the Symmetric Stable Distribution and Density," in Adler R.J. Feldman R.E. and Taqqu M.S. (eds.), *A Practical Guide to Heavy Tails Statistical Techniques and Applications*. Birkhäuser, Berlin, pp. 489–499.

Mosteller, F. and Tukey, J.W. (1977) *Data Analysis and Regression*. Addison-Wesley, Reading, MA.

Nolan, J.P. (1998) "Univariate Stable Distributions Parameterizations and Software," in Adler, R.J., Feldman, R.E. and Taqqu, M.S. (eds.), *A Practical Guide to Heavy Tails Statistical Techniques and Applications*. Birkhäuser, Berlin, pp. 527–533.

Prag, J. and Cassavant, J. (1994) "An Empirical Study of Determinants of Revenues and Marketing Expenditures in the Motion Picture Industry." *Journal of Cultural Economics* 18(3): 217–35.

Rachev, S. and Mittnik, S. (2000) *Stable Paretian Models in Finance*. John Wiley & Sons, New York.

Ravid, S.A. (1999) "Information, Blockbusters and stars: A study of the film industry." *Journal of Business* 72: 463–486.

Ravid, S.A. (2003) "Are They All Crazy or Just Risk Averse? Some Movie Puzzles and Possible Solutions", in Ginsburgh V. ed., *Economics of the Arts and Culture*. Contributions to Economic Analysis No. 260. Elsevier Science, Amsterdam.

Ruppert, D. and Carroll, J. (1980) "Trimmed Least Squares Estimation in the Linear Model." *Journal of the American Statistical Association* 75: 828–838.

Samorodnitsky, G. and Taqqu, M.S. (1994) *Stable Non-Gaussian Random Processes*. Chapman and Hall, New York.

Sedgwick, J. and Pokorny, M. (1999) "Comment Movie Stars and the Distribution of Financially Successful Films in the Motion Picture Industry." *Journal of Cultural Economics* 23: 319–323.

Smith, S.P. and Smith, V.K. (1986) "Successful Movies: A Preliminary Empirical Analysis." *Applied Economics*, 18(5): 501–507.

Stata Corporation (2001) *Stata Reference Manual*, release 7, volume 3. Stata Press, College Station, TX.

Wallace, W.T., Seigerman, A. and Holbrook, M.B. (1993) "The Role of Actors and Actresses in the Success of Films: How Much is a Movie Star Worth?" *Journal of Cultural Economics* 17(1): 1–24.

Zellner, A. (1976) "Bayesian and non-Bayesian Analysis of the Regression Model with Multivariate Student-t error terms." *Journal of the American Statistical Association* 71: 400–405.

Zolotarev, V. M. (1986) *One-Dimensional Stable Distributions*, volume 65 of *American Mathematical Society Translations of Mathematics Monographs*. American Mathematical Society, Providence. (Translation of the original 1983 Russian edition.).