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A Survival Analysis of the Contraction Phases of Business Cycles in Industrial Countries

Summary: This study tried to determine whether systematic changes have taken place in the size (amplitude) and duration (length) of business cycle phases in industrial countries over the past half century and to analyze, by using two parametric duration models, mainly, Gompertz and Weibull models, the possible effects of some macroeconomic variables, such as labor productivity growth, inflation, real interest rate, openness, oil prices, and gross saving rate, on the duration of the contraction phases of business cycles. The reference turning point chronology elaborated by the OECD for 23 industrial countries for the post-1956 period was used. The sample included 258 expansions and 267 contraction spells. The widespread belief that the length of expansions has, on average, become longer and that of contractions has become shorter over time was not supported in our sample. There is sufficient evidence of monotonically increasing hazard rates for both contraction and expansion durations; i.e., the spells are positively duration-dependent. Regarding the impacts of covariates on the hazard rate of contractions, the saving rate, openness, productivity growth, and size (depth) were found to have significant positive impacts, whereas the real interest rates have a negative effect. Inflation, oil prices, and length of previous expansion period have no significant impact on contraction durations.

Key words: Survival analysis, Duration models, Business cycles, Recessions, Industrial countries, Factors driving business cycles.

JEL: C41, E32, F44.

In the business cycle literature, there is a widespread idea that both the size (depth and severity) and duration (length) of business cycle phases have changed over time. Specifically, the duration of expansions is believed to have become longer, and the duration and size of contractions shorter, in the post-WWII (World War II) era in developed countries (Thomas Dalsgaard, Jorgen Elmeskov, and Cyn-Young Park 2002; James H. Stock and Mark W. Watson 2002; César Calderon and J. Rodrigo Fuentes 2014). The idea of shortening recessions and lengthening expansions is mainly based on US data: the National Bureau of Economic Research (NBER) estimated the average length of recessions (expansions) as 21.6, 18.2, and 11.1 months (26.6, 35.0, and 58.4 months) for the periods 1854-1919, 1919-1945, and 1945-2009, respectively (NBER Business Cycle Dating Committee). Contrary to this obvious trend in the NBER data, Christina D. Romer (1992) argued that the NBER dating methods were not consistent before and after WWII; after making the necessary corrections in the methodology, she concluded that the US recessions, on average, did not become shorter, less severe, or less persistent over time. By redating the annual peaks and troughs for the entire period of 1796-1914 by using the single metric of annual industrial production index, Joseph H. Davis (2005) also found no discernible differences in the frequency and duration of industrial cycles among the pre-Civil War, Civil-War-to-WWI (World War I), and post-WWII periods.

The objective of this study was twofold. First, it aimed to determine whether systematic changes have taken place in the size (amplitude) and duration (length) of business cycle phases in industrial countries over the past half century. Second, similarly to Vitor Castro (2010), it tried to analyze the possible effects of some macroeconomic variables, such as labor productivity growth, inflation, real interest rate, openness, oil prices, and gross saving rate, on the duration of the contraction phases of business cycles, by using some parametric duration (namely, the Gompertz and Weibull) models and the Organisation for Economic Co-operation and Development (OECD) turning point chronology data for the post-1956 period. Admittedly, the list of exogenous variables that drive national and international business cycles is very long, including fiscal and monetary policy shocks, exchange rates, terms of trade, and changes in technologies and preferences, among others. Difficulties in collecting data prevented us from including all variables in our model.

In contrast to the United States (US), the other industrial economies do not have long business cycle chronologies that would allow a detailed assessment of the idea of changing cycle durations over time. We tried to increase the sample size (number of cycle phases) by including all industrial countries for which the cycle chronology data issued by the OECD are available. The following 23 countries were thus included in this study: Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Japan, Luxemburg, the Netherlands, New Zealand, Norway, Portugal, South Africa, Spain, Sweden, Switzerland, the United Kingdom, and the US. To ensure that the sample would be as homogeneous as possible, emerging market economies were excluded. Calderon and Fuentes (2014) previously showed that the business cycles phases in emerging markets were significantly different from those in industrial economies.

The rest of the study is organized as follows: Section 1 summarizes the related literature. Section 2 discusses whether the size (amplitude) and duration (length) of contraction phases have changed over time. Section 3 tackles model selection problems and presents the regression results obtained from two parametric duration models (Weibull and Gompertz). Finally, Section 4 provides the conclusion.

1. Literature Survey

Regarding the weakening of recessions, Stock and Watson (2002) focused on the considerable decline in cyclical volatility in the US economy, comparing the periods of 1960-1983 and 1984-2001. According to their calculations, 20-30% of the moderation in volatility was attributable to improved policy, and another 20-30% was due to good luck in the form of productivity and commodity price shocks.

In a comprehensive paper, Dalsgaard, Elmeskov, and Park (2002) argued that the amplitude of business cycles has fallen in many OECD countries over the past three or four decades because of some policy and structural changes, such as the shift toward a more service-based economy, stability-oriented macroeconomic policies, improvements in inventory (stock-building) management, increasing openness to trade, a surge in intra-firm and intra-industry trade, intensified financial deepening, monetary policies aimed at low inflation, increasing focus on fiscal stabilizers and fiscal consolidation, and ongoing reforms and structural changes in the labor and product markets, among others. They concluded that output fluctuations have diminished since 1960, with a particularly strong tendency from the early 1990s, mainly reflecting a reduced role of stock building and more stable private consumption. Calderon and Fuentes (2014) documented the properties of business cycles in 71 countries (23 industrial and 48 emerging market economies) for the period 1970-2012 and found that recessions became less costly during the globalization period (1985-2007) for both groups of countries. They argued that this finding reflects the institutional changes made during the Great Moderation.

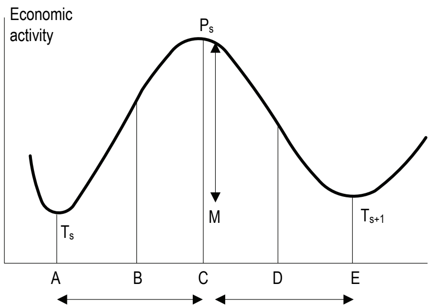
There are four main types of modeling in the business cycle literature: dynamic stochastic general equilibrium (DSGE) (e.g., David K. Backus, Patrick J. Kehoe, and Finn E. Kydland 1992; Backus and Mario J. Crucini 2000; Frank Smets and Rafael Wouters 2007; Alejandro Justiniano and Giorgio E. Primiceri 2008), structural VAR (e.g., Robert G. King et al. 1991; Jordi Gali 1999; Stock and Watson 2005; Jonas D. M. Fisher 2006), dynamic factor (e.g., Watson 1991; M. Ayhan Kose, Christhoper Otrok, and Charles H. Whiteman 2008; Crucini, Kose, and Otrok 2011), and Markov regime switching models [(Salih N. Neftçi 1982; James D. Hamilton 1989; Frédérique Bec, Othman Bouabdallah, and Laurent Ferrara 2015), in Turkey Hüseyin Taştan and Nuri Yildirim 2008; Sumru Altuğ and Melike Bildirici 2010] are employed to study the cycles dating, contribution of particular macroeconomic variables in driving business cycles and to quantify comovements among macroeconomic variables. Besides these four approaches, parametric discrete-time duration models are also suitable tools for the study of business cycle dynamics. By using the turning point chronology elaborated by the Economic Cycle Research Institute (ECRI) for 13 industrial countries and the related covariates in a discrete-time duration model, Castro (2010) found that interest rate spread, stock market price index, duration of previous expansion, private investment, and oil prices have significant impacts on business cycle phases.

There is a wide literature on business cycle synchronization and comovements showing the existence of common (global) business cycles for some groups of economies. For example, Ioanna Konstantakopouloua and Efthymios G. Tsionas (2014) found two distinct cycles in OECD countries: a euro-area cycle that includes the business cycles of European economies and a world cycle that includes the busines cycles of the US, the UK, and Canada. Sebastian-Florian Enea, Silvia Palaşcǎ, and Claudiu Tiganǎş (2015) argued that globalization and trade channels lead to the globalization of business cycles. They distinguished three common cycles: one for European countries, one for the American continent, and one for Asian economies.

2. Some Remarks on the Business Cycles Phases Derived from the Data

2.1 Definition of Business Cycle Phases

Figure 1 presents the two phases of a typical business cycle: expansion and contraction. A business cycle has two main characteristics: size (amplitude) and duration (length). The size (amplitude) of a contraction phase is the vertical distance (indicated as P_sM in Figure 1) between peak P_s and the next trough T_{s+1} (s denotes the phase index), i.e., the absolute sum of positive and negative amplitudes. It indicates the maximum drop in the level of economic activity measured by the GDP or other variables during the contraction phase. Along the contraction duration from P_s to T_{s+1}, the positive amplitude represents a declining growth rate that is still positive, whereas the negative amplitude shows an absolute shrinking of the economy, i.e., a negative growth rate.



Notes: T_s: s^{th} trough; P_s: s^{th} peak; *AC*: expansion (*AB*: recovery, *BC*: prosperity); *CE*: contraction (*CD*: recession, *DE*: depression); P_sM: amplitude (size) of the contraction phase *CE*; *AE*: length (duration) of the full business cycle.

Source: Author's own drawing.

Figure 1 Phases of a Business Cycle

The duration of the cycle is the length from peak to trough for contraction (*CE*) and from trough to peak for expansion (*AC*) episodes. Although the NBER uses the terms contraction and recession interchangeably, some economists prefer to use the terms recession and depression for the first (*CD*) and the second (*DE*) half of the contraction phase, respectively. The NBER defines the business cycle phases as follows: "A recession is a period between a peak and a trough, and an expansion is a period between a trough and a peak. During a recession, a significant decline in economic activity spreads across the economy and can last from a few months to more than a year. Similarly, during an expansion, economic activity rises substantially, spreads across the economy, and usually lasts for several years" (NBER 2013).

2.2 Business Cycle Turning Point Data

We used the reference turning points of the OECD composite leading indicators (CLI) system, which is based on the "growth cycle", i.e., the deviation-from-trend series approach (see, OECD 2013).

The OECD determines business cycle turning points by using the rules established by the NBER, known as the Bry and Boschan methodology. The main reference series used in the OECD CLI system is the monthly de-trended indices of industrial production (IIP) covering all industry sectors excluding construction (OECD 2011). This study includes all turning point chronologies since January 1956 (1956M01) for all industrial countries for which the data were available; however, developing countries are excluded due to the short span of their IIP time series.

Table 1 Summary Statistics of the Business Cycle Durations in 23 Industrial Countries, 1956M01-2011M03

	Expansions	Contractions
No. of observations (N)	258	267
Mean (months)	27.4	22.7
Median (months)	23	21
Minimum (months)	9	7
Maximum (months)	72	67
Standard deviation	13.4	10.2
Skewness	0.98	0.95
Kurtosis	3.51	3.71

Source: Author's own calculations.

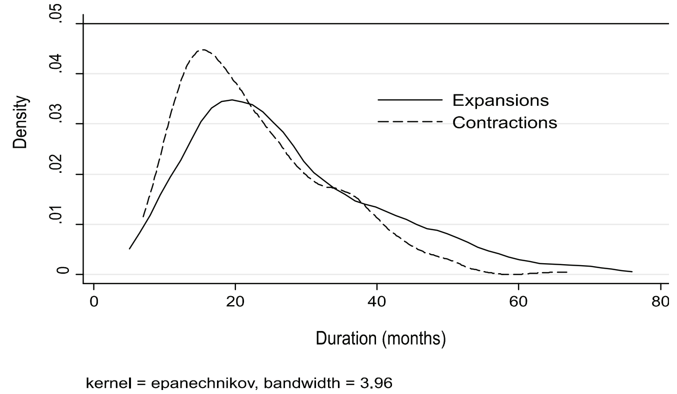
Although the monthly IIP series from 1960 onward are available for the majority of developed countries, such data rarely exist for the pre-1980 period for emerging markets. The sample includes the above-mentioned 23 developed countries for which the business cycle turning point chronology data of the OECD are available. The turning point data go back to 1956M01 for a few countries but are available only for the post-1960 period for the majority of countries. Only 8 contraction episodes out of a total of 267 belong to the pre-1960 period.

Table 1 above presents the summary statistics on the duration of business cycle phases in the 23 industrial countries for the period 1956M01-2011M03. The average duration is 27.4 months for 258 expansion spells and 22.7 months for 267 contraction spells.

2.3 Expansions Last Longer than Contractions on Average

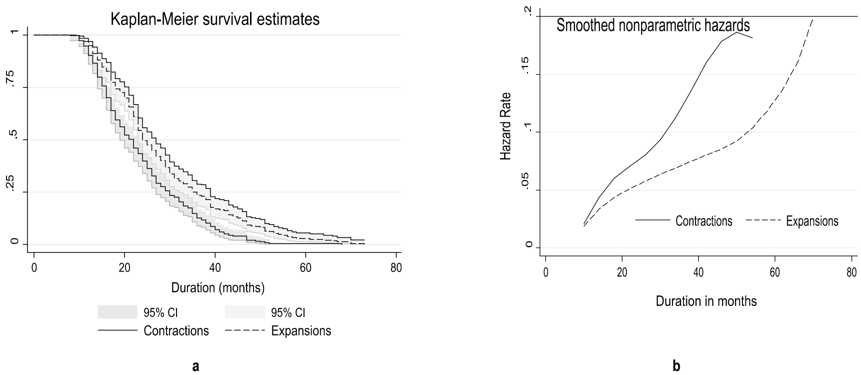
In the business cycle literature, it is accepted as a stylized fact that, on average, expansions last longer than contractions. Both the NBER data on US business cycles and the calculations for other industrial and emerging market economies (e.g., Calderon and Fuentes 2014) verify this fact. As indicated in the summary statistics and kernel density distributions of the phase durations (shown in Table 1 and Figure 2, respectively), our data also support this conviction.

The durations of both phases are right-skewed, as is often the case with duration data with non-Gaussian distributions. The mean and median durations are 27.4 and 23 months, respectively, for 258 expansion spells, and 22.7 and 21.0 months for 267 contraction spells. The *t* test strongly rejected the null hypothesis of equality of means between expansions and contractions (p = 0.0168); the Wilcoxon-Mann-Whitney test rejected the equality of medians (p = 0.0456).



Source: Author's own estimates.

Figure 2 Kernel Density Estimates of the Business Cycle Durations in 23 Industrial Countries, 1956M01-2011M03



Notes: Log-rank test of equality of survivor functions: $\chi^2(1) = 19.10$, $p = 0.000$. Smoothed (lowess) nonparametric hazard estimates are obtained from the life tables of the spells given in Table 6 in Appendix.

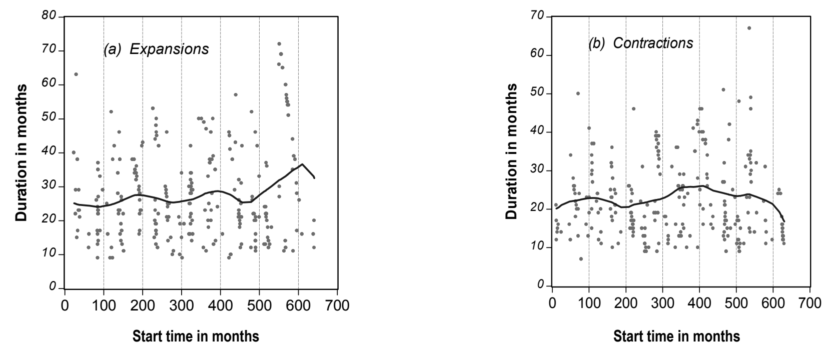
Source: Author's own estimates.

Figure 3 (a) Kaplan-Meier Estimation of the Survivor Functions and (b) Nonparametric Hazard Rates for Expansion and Contraction Spells in 23 Industrial Countries, 1956M01-2011M03

The survivor functions shown in Figure 3*a* also depict this distinction between the two phases of business cycles. All tests for equality of survivor functions (log-rank, Wilcoxon and Tarone-Ware) strongly rejected the null (equality) hypothesis. Figure 3*b* presents the nonparametric estimates of the hazard rates obtained from the life tables of the spells. The exit rate from contraction is substantially greater than that from expansion over all ranges of duration time.

2.4 Did the Duration (Length) of Business Cycle Phases Change over Time?

There is a widespread belief that the length of expansions of business cycles in developed countries has become longer, and that of contractions shorter, over the past half century (Dalsgaard, Elmeskov, and Park 2002; Stock and Watson 2002; Calderon and Fuentes 2014). As previously mentioned, this idea is based mainly on the NBER turning point chronology data for US business cycles and was not supported in our sample of 258 expansion spells in 23 industrial countries. Figure 4*a* and 4*b* present the scatter diagrams of the phase durations against their start time (month) and a kernel fit applied to the data. There is no statistically significant trend in expansion duration if we exclude very long-lasting expansion episodes in the first half of the 2000 years. The slope coefficient of a linear regression fitted to the 227 expansion spells that took place during the 1956-2000 period has a t-value of -0.57 (p = 0.566). As shown in Table 2, the mean and median values of expansion over those decades sorted by start time showed no trend. The mean value of expansion was 24-25 months for the 1960s and 1990s, 27-28 months for the 1970s and 1980s, and 42 months for the first half of the 2000 years.



Notes: The curves in the graphs represent the kernel fit (Epanechnikov; h = 92.550 and 92.850, respectively).

Source: Author's own estimates.

Figure 4 Scatter Diagrams of (*a*) Expansion and (*b*) Contraction Durations against Their Start Time in Months (1956M01-2011M01)

Similarly, our contraction data do not support the idea of shortening recessions. As indicated in Figure 4*b* and Table 2, the mean value of contraction spells showed a positive trend in the pre-2005 period. The trend regression fitted to the contraction data for the 1956-2005 period (248 observations) had a positive slope with a t-value of 1.91 (p = 0.057). Only 19 unusually short-lived contraction episodes (average of 15.7 months) with start times (months) that fall in the post-2005 period reversed this upward trend. There were longer contractions in the first half of the 2000s and in the 1980s than in other decades. Hence, the shortening recession duration over time found by the NBER in the US economy is not a general tendency for the rest of the industrialized world. This finding does not mean that the Keynesian stabilization policies and all other anti-cyclical economic measures applied by governments and financial authorities are useless and ineffective. Recessions might be more severe and longer without these policies and measures.

Table 2 Duration of Expansion and Contraction Episodes for Subperiods in 23 Industrial Countries Sorted by Start Time (Months)

Period	Expansions				Contractions			
	N	Mean	Median	SD	N	Mean	Median	SD
1956M01-1969M12	55	24.4	23	11.1	62	22.3	22	8.3
1970s	56	27.6	25.5	11.0	53	20.4	19	9.1
1980s	54	27.1	25	11.3	54	25.9	26	10.7
1990s	61	24.6	22	11.7	52	21.7	18	10.6
2000M01-2005M12	27	42.1	44	20.1	27	28.2	29	13.2
2006M01-2009M12	5	18	16	5.3	19	15.7	15	4.2

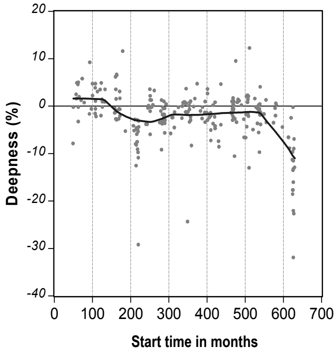
Source: Author's own calculations.

2.5 Did the Size (Amplitude) of Contractions Change over Time?

As mentioned in the introduction, another common opinion on post-WWII business cycles in industrial countries is that, because of some structural and policy changes in the economy, the size (amplitude) of business cycles becomes smaller over time (see, for example, Dalsgaard, Elmeskov, and Park 2002; Stock and Watson 2002). By using the OECD turning point chronology data for the post-1960 period, we calculated the size (amplitude and depth) of the contraction episodes as % change in the monthly IIP series of 19 industrialized countries from the peak to the next trough. Because the OECD turning point chronology does not completely match the turning points of the IIP series, some of the amplitudes calculated seemed to be positive percentage changes. However, although positive, they still provide us with useful information about the amplitude of contractions. For four industrialized countries (Australia, South Africa, New Zealand, and Switzerland) for which the IIP data were not available, the cyclical components of the CLI indices were used.

Figure 5 presents the scatter diagram of the size (amplitude and depth) of the contraction episodes against their start times (months), with a kernel fit. The deepest persistent declines, which caused decreases of more than 10% in the IIP indices during the last half of the century, occur twice: first, during the 1973-1974 oil price shock (between the 208th and 228th months) and, second, during the recent global financial crisis beginning in the first months of the year 2008 (around the 627th month).

The kernel fit, which moved downward around the 1973-1974 shock and the 2008 crisis, showed no clear trend between these two events. The linear trend fitted to the 156 observations for the period 1976M01-2005M12 (from the 240th to 601st months) had an insignificant slope coefficient with $t = 0.2$ ($p = 0.796$). Hence, the idea that business cycle fluctuations have become smaller over time is not supported by our contraction data.



Notes: The solid curve represents the kernel fit (Epanechnikov, *h* = 87.000). Depth: annualized monthly % change in IIP series from the peak to the next trough.

Source: Author's own calculations and estimates.

Figure 5 Scatter Diagram of Contraction Sizes (Depth) against Their Start Times: 19 Industrial Countries for the Period 1960M01 (1st Month) to 2011M12 (624th Month)

3. Impacts of Some Macroeconomic Variables on the Duration of Contractions

In this section, we try to estimate the impacts of some macroeconomic variables, such as labor productivity growth, inflation, real interest rate, openness, oil prices, and gross saving rate, on the duration of contraction episodes, by using parametric duration models, namely, the Gompertz and Weibull models.

3.1 Data on Macroeconomic Variables

Macroeconomic variables for which monthly time series data for industrial countries are available from the OECD and World Bank statistical databases were used in the study. Ideally, all basic macroeconomic variables that might potentially affect economic fluctuations should be included in the model; however, the difficulty of obtaining monthly time series data, especially for earlier decades, limited the number of variables included here. Since the global financial crisis of 2008-2009, many macroeconomic models have been developed to incorporate financial variables, such as credit availability, collaterals, and macroprudential policies, into the business cycle analysis (see Adrian Pagan and Tim Robinson 2014, and references therein). We were unable to include such variables in our model due to the lack of available data. Our variables are defined as follows (Table 3):

Table 3 Description of Variables

Variable	**Description** (the subscript *sj* is read as "during the s^{th} contraction spell of country *j*")
INF_{sj}	Average inflation rate (%)
$OPENNESS_{sj}$	Sum of imports and exports as a percentage of the GDP (%)
GSR_{sj}	Gross saving rate: gross savings as a percentage of the GDP (%)
$LPROD\_PC_{sj}$	Annual percentage change in labor productivity in the total economy
r	Short-term real interest rates (%) corresponding to the contraction spell under consideration

OIL_{sj}	Crude oil prices in 2005 (constant) US dollars
$CONT_{sj}$	Duration (in months) of the contraction spell *sj*
$EXP_{s-1,j}$	Duration (in months) of the (s-1)th expansion preceding the current (sth) contraction spell of country *j*
$SIZE\_HALF_{sj}$	Percentage change in the index of industrial production (IIP_j)* during the first half-time of contraction *sj*

Notes: For four countries (Australia, South Africa, New Zealand, and Switzerland) for which the IIP data were not available, the cyclical components of the composite leading indicator (CLI) indices were used.

Source: Author.

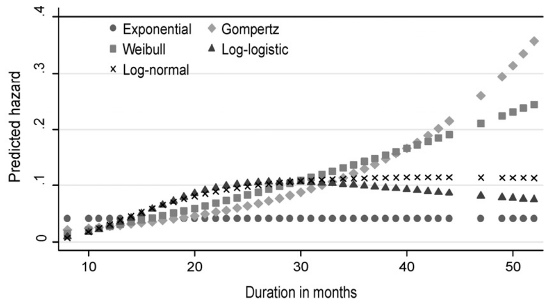
As previously explained, the sample included 23 developed countries for which business cycle turning point chronology data from the OECD were available. The turning point data go back to 1956M01 for a few countries; however, the data exist only for the post-1960 period for the majority of countries. Only 8 contraction episodes out of a total of 267 belong to the pre-1960 period. The data on macroeconomic variables were of annual frequency, with the exception of export and imports (openness), for which monthly data were available. The average values of these time-varying covariates were used for the contraction spells. The value of a macroeconomic variable, for example, x_{sj}, corresponding to the s^{th} contraction spell, $CONT_{sj}$, was calculated as the weighted average of the years covered by the duration of this spell, with the number of months expended in each year as weights. For example, suppose that the s^{th} spell lasted 20 months, of which 11 months belong to the year $t-1$ and the remaining 9 months belong to the year t. Then, x_{sj} is calculated as a weighted average as: $(11\ x_{t-1} + 9x_t)/20$.

3.2 Parametric Duration Models

Duration models are appropriate statistical techniques for analyzing the impacts of various covariates (explanatory variables) on the hazard (transition) rate (see Nicholas Kiefer 1988; A. Colin Cameron and Prain K. Trivedi 2005, Chapter 17; Hans-Peter Blossfeld, Katrin Golsch, and Götz Rohwer 2007, Chapter 4 and 7). Depending on the distribution of the durations, we mainly have three types of parametric duration models for studying the hazard rate, herein, the exit rate from a contraction/expansion phase. These are (i) models with a constant hazard rate; (ii) models with a monotonically changing (increasing/decreasing) hazard rate; and (iii) models with a non-monotonic, U-shaped (inverse U-shaped) hazard rate.

The exponential model has a time-constant hazard rate (γ) and thus assumes the duration independence of the data. Hence, it is not suitable for modeling the duration of business cycle phases. Such phases are widely accepted to have positive duration dependence (see Francis X. Diebold and Glenn D. Rudebusch 1990; Daniel E. Sichel 1991; Ram Mudambi and Larry W. Taylor 1995) i.e., the probability of a contraction/expansion phase ending increases as the phase becomes longer. Thus, the longer the phase, the more likely it is to complete its duration. In the case of duration dependence, the Weibull and Gompertz models with monotonically increasing/decreasing hazard functions are suitable tools. If a non-monotonic, bell-shaped (U- or inverse U-shaped) hazard rate is assumed, then log-logistic and log-normal models would be appropriate.

Figure 6 presents the hazard functions estimated by five parametric duration models for our contraction spells data. The exponential model predicts the time-constant exit rate from a contraction phase (γ) to be 0.0422, which corresponds to a mean survival time of 23.7 months (= 1/0.0422), one month longer than the actual average (22.7 months). The monotonically increasing hazard functions estimated by the Weibull and Gompertz models intersect at around the 40th month of the duration. The log-logistic model predicts a $\cap$- shaped hazard function that reaches its maximum at around the 30th month of the duration, whereas the log-normal model estimates a hazard function that first increases up to around the 35th month and then becomes flat.



Source: Author's own estimates.

Figure 6 Hazard Rates for the Contraction Spells Predicted by the Parametric Duration Models without Covariates

3.2.1 Model Selection

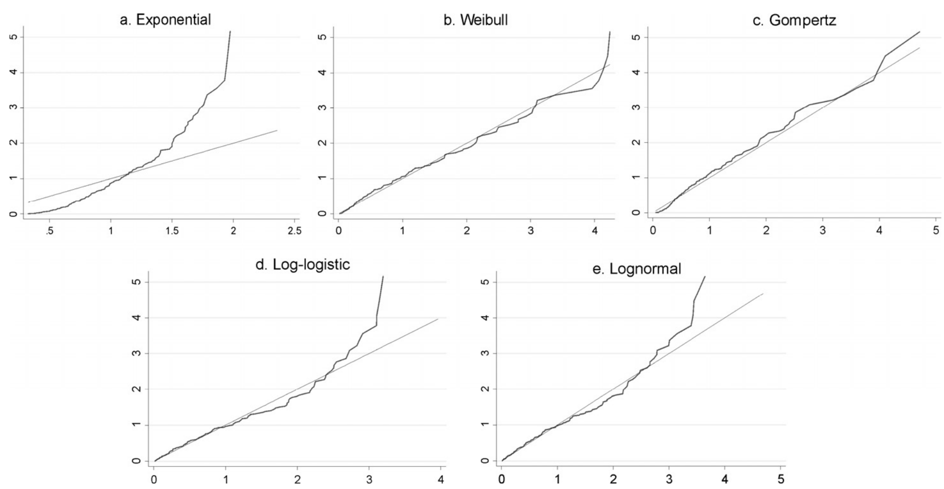
The estimates of the shape parameter α in the Weibull and Gompertz models for our data provide evidence of duration dependence. The Weibull model without covariates predicts the duration dependence parameter $\hat{\alpha}$ to be 2.47, which is statistically greater than 1 (p = 0.000); this points to a monotonically increasing hazard function. Similarly, the shape parameter $\hat{\alpha}$ = 0.0634 is estimated by the Gompertz model without covariates, with a z-value = 14.79 and p = 0.000, indicating positive duration dependence.

Hence, we excluded duration independence, i.e., a constant (flat) hazard function, the exponential model assumption for our business cycle duration data. The appropriate model will have either a monotonically changing (Weibull and Gompertz model) or a non-monotonically changing (log-logistic and log-normal models) hazard rate. The Cox-Snell pseudo-residuals provide some useful information in choosing the correct model.

Cox-Snell Pseudo-Residuals

The theoretical considerations and shape parameter estimates of the Weibull and Gompertz models strongly suggest a changing hazard function for our data; however, the exact shape of the function has yet to be determined. In this regard, a graphical check of the Cox-Snell pseudo-residuals (or generalized residuals) is helpful. Because the dependent variable (hazard rate) is not observable in duration models, the traditional residuals cannot be computed.

David R. Cox and Eleanor J. Snell (1968) suggested a method to compute pseudo-residuals (or generalized residuals) based on cumulative hazard rates (see Blossfeld, Golsch, and Rohwer 2007, p. 222). If the selected model fits the data well, the plot of logarithm of the cumulative hazard of the Cox-Snell residuals against these residuals themselves should be a straight line with a slope of 1 passing through the origin. As shown in Figure 7, the checking of the pseudo-residuals pointed to the Gompertz and Weibull models as the best-fitting models for our data. Hence, we disregarded non-monotonically changing (log-logistic and log-normal) hazard models and chose monotonically changing (Weibull and Gompertz) hazard models. The estimates of these two models are presented in the next section.



Source: Author's own estimates.

Figure 7 Plot of Logarithm of Cumulative Survivor Functions of Cox-Snell Residuals against the Residuals Themselves: Alternative Five Parametric Models

Likelihood Ratio (LR) Test

Because the exponential model is nested in both the Gompertz and Weibull models, we can check, by using a likelihood ratio (LR) test, which of these two models yields a larger improvement compared with the exponential (reference) model. For our contraction duration data, the LR test statistic calculated from the log-likelihood values of the Gompertz and exponential models is significant and equal to 180.2:

$$LR = 2\,(LL_{gomp} - LL_e) = 2\,[-200.3 - (-290.4)] = 180.2 > \chi^2_{df=1}\ (= 6.63 \text{ for } \alpha = 0.01).$$

The LR statistic calculated from the log-likelihood values of the exponential and Weibull models is 251.6, larger than that of the exponential and Gompertz model (180.2). Hence, the LR test showed that although both the Gompertz and Weibull models provide highly significant improvements for our contraction duration data compared with the reference (exponential) model, the improvement attained by the Weibull model is larger.

Spurious or True Duration Dependence?

There are two sources of duration dependence: one is true duration dependence coming from the existing state dependence in the process, and the other is spurious duration dependence due to the presence of unobserved, time-invariant, individual-specific heterogeneity. To take into account this heterogeneity in the error term in the hazard rate models, a gamma mixture model proposed by James W. Vaupel, Kenneth G. Manton, and Eric Stallard (1979) and Nancy B. Tuma (1985) is generally used. In this random effects (frailty) approach, it is assumed that the unobserved constant effects can be represented as the realization of a random variable, identically distributed for all individuals and independent of observed covariates (Blossfeld, Golsch, and Rohwer 2007, p. 256). Random effects are assumed to be gamma-distributed, with a unit mean and variance μ.

Because the Cox-Snell pseudo-residuals and other above-mentioned evidence indicate that the Weibull model is appropriate for our contraction spells data, we used such model with a gamma mixture to consider the possible spurious dependence due to individual heterogeneity. The hazard function of the Weibull model is given as:

$$r(t) = \alpha\gamma^{\alpha}t^{\alpha-1}, \ \ \alpha > 0, \ \gamma > 0, \tag{1}$$

where α and γ are the shape and scale parameters, respectively. This hazard function takes the following form in the Weibull gamma mixture (Blossfeld, Golsch, and Rohwer 2007, p. 261):

$$r(t) = \frac{\alpha\gamma^{\alpha}t^{\alpha-1}}{1+\mu(\gamma t)^{\alpha}}, \tag{2}$$

where μ is the variance of the mixing gamma distribution and is parameterized as $\mu = e^{\delta}$. For our contraction spells data, an insignificant δ of -0.45 (p = 0.513) is estimated, indicating that there is no an extra gain in applying a mixture model. This somewhat provides evidence of the robustness of our Weibull model estimates, which are presented in the next section.

3.3 The Gompertz and Weibull Models with Covariates

3.3.1 The Endogeneity Problem

Because the hazard rate, i.e., the exit rate from a contraction spell, is modeled in the parametric duration models, there is a genuine risk that some of the covariates used to determine the hazard rate are not exogenous but endogenous. The contraction durations and some of these explanatory macroeconomic variables may be determined simultaneously by the same system. Among our six covariates, oil price is exogenous by nature. Being a structural variable, openness may also be considered exogenous with regard to contraction durations; however, more policy-oriented variables, such as real interest rate, inflation, gross saving rate, and productivity growth, can be endogenous. The Hausman test for endogeneity (see Jeffrey M. Wooldridge 2002, Chapter 15) was applied to some of these variables with regard to contraction duration in an OLS framework. The structural model can be written as:

$$CONT_s = \beta_0 + \beta_1 GSR_s + \beta_2 LPROD\_PC_s + \beta_3 r_s + \\ + \beta_4 SIZE_s + \beta_5 OPENNESS_s + \beta_6 OIL_s + u_{s.} \tag{3}$$

We assume that the last two variables (openness and oil prices) are exogenous, whereas the first four variables may be endogenous, i.e., correlated with u_s. To test for exogeneity, we need to estimate the reduced form for the suspected right-side variables in turn, by regressing each of them on all exogenous variables in the structural form and on additional instrumental variables. We used the lagged values of the suspected variables corresponding to the previous cycle phases (i.e., EXP_{s-1} and $CONT_{s-1}$) as instruments. Then, the residuals of these reduced-form regressions ($\hat{v}_{GSR}, \hat{v}_{SIZE}, \hat{v}_r$ and $\hat{v}_{LPROD\_PC}$) are used as regressors in the structural model (3) and checked for individual and joint significance by a t and an F (Wald) test, respectively. The test results showed that among the four suspected variables, only *SIZE* is endogenous; the other three variables (*GSR, LPROD_PC*, and *r*) are exogenous with regard to the contraction duration variable *CONT*. The individual t test and joint F test results are as follows:

H_o: $\hat{v}_{GSR}$ is insignificant in the Equation (3) → $t = -1.07, p = 0.2869$;

H_o: $\hat{v}_r$ is insignificant in the Equation (3) → $t = 0.32, p = 0.7501$;

H_o: $\hat{v}_{LPROD\_PC}$ is insignificant in the Equation (3) → $t = -0.50, p = 0.6184$;

H_o: $\hat{v}_{SIZE}$ is insignificant in the Equation (3) → $t = 2.40, p = 0.0179$.

Joint F tests:

H_o: $\hat{v}_{GSR}$, $\hat{v}_r$, and $\hat{v}_{LPROD\_PC}$ are jointly insignificant in the Equation (3) → $F(3, 122) = 0.61, p = 0.6094$;

H_o: $\hat{v}_{GSR}$, $\hat{v}_r$, $\hat{v}_{LPROD\_PC}$, and $\hat{v}_{SIZE}$ are jointly insignificant in the Equation (3) → $F(4, 121) = 4.12, p = 0.1285$.

To avoid endogeneity, the variable *SIZE* is replaced with *SIZE_HALF*, which denotes the total % change in the IIP during the first half of the contraction spell. Differentiating the time coverages of the two variables, the contraction duration (*CONT*) and amplitude (*SIZE*) alleviate the endogeneity problem. Indeed, the t statistic of the null hypothesis that $\hat{v}_{SIZE\_HALF}$ is insignificant in the Equation (3) is obtained as 1.18 ($p = 0.241$).

3.3.2 Estimation Results

The estimation results for the two models fitted to our contraction duration data with six covariates are shown as β coefficients and hazard ratios, respectively, in Tables 4 and 5. Although our sample includes 267 contraction spells, 8 of these belong to the 1956M01-1959M12 period and the remaining 259 to the post-1960 period; this is due to the empty cells on covariates in the data set. Thus, our sample is reduced to 163 observations and covers only the post-1969M03 period.

The covariates, oil prices, inflation, and duration of the previous expansion (EXP_{s-1}) preceding the current contraction episode ($CONT_s$) are excluded from the models because they are not significant. The idea that the length of the previous phase impacts the current duration was first suggested by Arnold Zellner (1990).

The variables openness and labor productivity growth were included in the models as dummy variables (1/0 for values above/below the sample median); they are not significant otherwise. Because the gross capital formation (*GCF*) ratio and gross saving rate (*GSR*) are closely related both in the statistical (correlation = 0.503) and the economic sense, only one (*GSR*) was used in the models. The explanatory power of savings was greater than that of investment ratio.

As shown in Table 4, the LR test statistics, which compare the full and constant-only (i.e., without covariates) models, were highly significant in both models, indicating that the covariates have an important effect on the contraction durations. The shape parameter $\hat{\alpha} = 0.070 > 0$ in the Gompertz model was significant and positive, and $\hat{\alpha} = 2.547 > 1$ in the Weibull model was significant and greater than 1; both parameters indicate a monotonically increasing hazard rate of moving out of the contraction spell. That is, both models show that the contraction durations, conditional on the covariates, have positive duration (time) dependence, which means that the probability of the spell ending increases as the spell lengthens.

With the exception of the openness dummy variable in the Weibull model, all coefficients have a *p*-value not greater than 0.10; thus, they are significant at conventional levels. Note that the Weibull coefficients (β_W; Table 4, column 2) are not directly comparable with the Gompertz coefficients (β_G) because of the different parameterization used. To make such comparison possible, the values should be multiplied by $-\hat{\alpha}$. The transformed coefficients ($\beta'_W (= -\alpha\beta_W)$; Table 4, column 1) are directly comparable with the Gompertz coefficients (β_G) and are used in the succeeding assessments.

Although it is significant only in the Gompertz model, the dummy variable of openness has a positive coefficient, which means that the hazard (exit) rate is higher (i.e., the contraction duration is shorter) in relatively more open economies (*dummy_openness* = 1) than in the less open economies (*dummy_openness* = 0). We can show this by calculating the mean duration time, i.e., the expected duration *E(T)*, corresponding to the sample averages of the covariates ($\bar{x}_k$, $k = 1,\ldots,6$) by using Equation (4). In the Weibull model, the mean duration time *E(T)* is given as (Janet M. Box-Steffensmeier and Bradford S. Jones 2004, p. 26):

$$E(T)=\frac{\Gamma(1+\frac{1}{\alpha})}{\gamma}, \tag{4}$$

where Γ denotes the gamma function.

The Weibull model with covariates predicts the shape and scale parameters $\hat{\alpha}$ and $\hat{\gamma}$ to be 2.547 and 0.0378 (=$e^{-\bar{x}\beta}$) for $\bar{x}_k$, $k=1,...,6$, respectively, for our contraction data. By using the values in (4), we calculate a mean duration time *E(T)* of 23.5 months, which is very close to the actual sample average of the contraction duration of 22.7 months. By holding all the other covariates at their sample averages and applying values of 0 (less open case) and 1 (more open case) to the openness dummy covariate in the Weibull model, we calculated *E(T)* as 24.7 and 22.6 months, respectively. Thus, the contractions are shorter by 2.1 months in relatively more open economies (i.e., the openness ratio is above the sample median) compared with less open ones. The hazard ratios for the openness dummy are estimated as 1.256 and 1.324 in the Weibull and Gompertz models (Table 5), respectively, indicating that the impact of a change from 0 to 1 in the openness dummy increases the hazard by 25-32% [=100x (hazard ratio -1)] over the baseline hazard.

The covariate *SIZE_HALF* measures the total % change in the IIP during the first half of the contraction spell. Because the coefficient of the covariate *SIZE_HALF* is negative, and *SIZE_HALF* takes negative values during sharp recessions, the impact of the cycle amplitude on the hazard rate will be positive. That is, the depth (severity) of the recession will increase the exit rate from the recession; thus, sharp recessions will last shorter than mild ones. The Weibull model estimates show that an increase of 1 percentage point in depth, *ceteris paribus*, causes recessions to be shorter by 0.7 months. As shown in Figure 5, in the post-1960 period, two sharp recessions took place: the first just after the 1974 oil shock (1974-76), and the second during the 2008 global financial crisis. The average duration of contractions was 17.7 months in the 1974M01-1976M12 period and 15.7 months in the post-2006 period (Table 2).

Gross saving rate (*GSR*), similarly to investment ratio, has two contrasting impacts on contraction durations. On the one hand, the high savings stimulate demand through investments; on the other hand, they curb consumption expenditures, which are crucial for ending recession, in the short run. The net impact will be determined by the larger of these opposing effects. In our models, saving rate has a significant positive impact on the hazard rate. The higher the savings during the contraction period, the more likely that the contraction will be shorter. However, the magnitude of the impact is not considerable. For example, if we increase the gross saving rate by 1 percentage point from its sample average (from 22.93% to 23.93%) while holding all the other covariates at their sample averages, the average contraction duration decreases only by 0.4 months (from 23.5 to 23.1 months).

The labor productivity growth dummy (*dummy_lprod_pc*) has a significant positive impact on the hazard (exit) rate, meaning that a higher productivity growth leads to high exit rates and, hence, shorter contraction durations. Similarly to the openness dummy variable, by applying values of 0 and 1 (below- and above-median

Table 4 Estimated Parameters for Contraction Durations Based on Two Parametric Models with Covariates

Covariates	Weibull model (AFT form[1]); $r(t)=\alpha\gamma^{\alpha}t^{\alpha-1},\ \gamma=e^{-X\beta}$. Transformed coefficients[3]: $\beta_W^{'}=-\alpha\beta_W$	β_W	Std. error	z	p > z	Gompertz model (LRH form[2]); $r(t)=\gamma e^{\alpha t},\ \gamma=e^{X\beta}$. β_G	Std. error	z	p > z
SIZE_HALF	-0.074	0.029	0.008	3.55	0.000	-0.078	0.022	-3.60	0.000
GSR	0.038	-0.015	0.007	-2.19	0.028	0.041	0.018	2.29	0.022
dummy_openness	0.228	-0.089	0.065	-1.38	0.167	0.281	0.168	1.67	0.095
dummy_lprod_pc	0.364	-0.143	0.063	-2.28	0.023	0.400	0.165	2.43	0.015
real int. rate, *r*	-0.058	0.023	0.011	2.17	0.030	-0.050	0.028	-1.77	0.077
Constant		3.733	0.164	22.72	0.000	-5.754	0.502	-11.46	0.000
$\hat{\gamma}(X=\bar{X})^{4}$		0.0378				0.0118			
Shape parameter, $\hat{\alpha}$		2.547	0.151			0.070	0.006	11.35	0.000
ln $\hat{\alpha}$		0.935	0.059	15.75	0.000				
N		163				163			
log likelihood		-98.13				-118.49			
LR test[4]: $\chi^2_{(df=6)}$		26.71			0.000	27.32			0.000

Notes: [1] Accelerated failure time (AFT) form. First, ln *t* is modeled instead of *t*. Here, the hazard rate is given by: $r(t\,|\,x)=r_0(te^{-x'\beta}).e^{x'\beta}$. [2] The log relative-hazard form, which estimates β coefficients as a logarithm of the hazard ratios: β_G=Ln (*hazard ratio*). [3] The Weibull coefficients (β_W; column 2) are not directly comparable with the Gompertz coefficients because of the different parameterization used. To make such comparison possible, the values should be multiplied by -$\hat{\alpha}$. The coefficients [$\beta_W^{'}$ $(=-\alpha\beta_W)$; column 1] are directly comparable with the Gompertz coefficients (β_G). [4] $\hat{\gamma}(X=\bar{X})$ denotes the estimation of the scale parameter γ for the sample averages of the covariates, $\bar{x}_k, k=1,...,5$.

Source: Author's own estimates.

Table 5 Estimated Hazard Ratios for Contraction Durations Based on the Weibull and Gompertz Models with Covariates

Covariates	Weibull model: Hazard ratio	Std. errors	z	p > z	Gompertz model: Hazard ratio[1]	Std. errors	z	p > z
SIZE_HALF	0.928	0.020	-3.47	0.001	0.925	0.020	-3.60	0.000
GSR	1.038	0.018	2.17	0.030	1.042	0.018	2.29	0.022
dummy_openness	1.256	0.208	1.37	0.169	1.324	0.223	1.67	0.095
dummy_lprod_pc	1.439	0.233	2.25	0.025	1.492	0.245	2.43	0.015
real interest rate, *r*	0.943	0.026	-2.15	0.032	0.951	0.027	-1.77	0.077
$\hat{\alpha}$	2.547	0.151			0.070	0.006	11.35	0.000
Log likelihood	-98.13				-118.49			

Notes: The hazard ratio is given as $r(t\,|\,x)/r_0(t,\alpha)=e^{x'\beta}$ in the Gompertz model and as $e^{-\alpha(x'\beta)}$ in the Weibull model. For the sample averages of the covariates ($\bar{x}_k$), the hazard ratio is equal to e^{β} in the Gompertz model and to $e^{-\alpha\beta}$ in the Weibull model.

Source: Author's own estimates.

productivity growth, respectively) to the covariate *dummy_lprod_pc* in the Weibull model while keeping all the other covariates at their sample averages, the expected duration *E(T)* is obtained as 25.2 and 21.8 months, respectively. Thus, contractions are on average shorter by 3.4 months in economies with above-median productivity growth compared with the below-median group. The significant difference in contraction durations between slow and fast productivity growth economies can also be observed from the hazard ratios (Table 5), indicating that changing the value of the dummy variable from 0 to 1 brings about a 44-49% increase in the hazard rate relative to the baseline hazard.

As expected, short-term real interest rate (*r*) has a significant negative impact on the exit rate (i.e., a positive impact on duration). High real interest rates that result from curbing investments and discouraging consumption expenditures lead to longer contraction spells. However, the effect size is rather small. An increase of 1 percentage point in the real interest rate (from a sample average of 2.28% to 3.28%), *ceteris paribus*, leads to an increase of only 0.5 month in the mean duration time (from 23.5 to 24.0 months).

The results of the Gompertz model are similar to the estimates of the Weibull model. Some survival time estimates obtained from the Gompertz model are worth noting. For example, by applying values of 0 and 1 (below-median and above-median productivity growth, respectively) to the covariate *dummy_lprod_pc* in the Gompertz model while keeping all the other covariates at their sample averages, we estimated exit rates of 0.0393 and 0.0587, respectively, for the 20th month (t = 20) of the contraction spell. These rates correspond to survival times of 0.655 and 0.532, respectively. That is, the probability of a contraction event to last beyond 20 months is 12.3% points lower when the labor productivity growth is above the median value than when such growth is below the median.

4. Conclusion

This study tried to determine whether some systematic changes have taken place in the size (amplitude) and duration (length) of business cycle phases in industrial countries over the past half century and to analyze the possible effects of some macroeconomic variables, such as productivity growth, inflation, real interest rate, openness, oil prices, and gross saving rates, on the duration of contraction phases of business cycles, by using two parametric duration (Gompertz and Weibull) models. We used the reference turning point chronology elaborated by the OECD for 23 industrial countries for the post-1956 period. Emerging market economies were excluded from the sample to ensure homogeneity. The sample included 258 expansions and 267 contraction spells. The average and median durations were 27.4 and 23.0 months for expansions, and 22.7 and 21.0 months for contraction spells. The differences between the means and medians of the phases were statistically significant.

The widespread belief that the length of expansions on average has become longer and that of contractions has become shorter over time, which is mainly based on the NBER business cycle chronology for the US economy, was not supported by our duration data. If the unusually long expansion episodes starting in the post-2001 period (27 observations) were excluded from the sample, the expansion durations in the pre-2001 period (227 observations) would not show any significant trend, except for the slope coefficient having a negative sign. The idea of shortening contractions was not supported in our sample either. The trend regression fitted to the contraction data for the 1956-2005 period (248 observations) had a positive slope with a t-value of 1.91 ($p = 0.057$). Only 19 unusually short-lived contraction episodes (average of 15.7 months) with start times (months) that fall in the post-2005 period reversed this upward trend.

Another common opinion on post-WWII business cycles in industrial countries is that, because of some structural and policy changes in the economy, the size (amplitude) of business cycles becomes smaller over time. Whereas this idea may be true in the pre-oil shock period, our sample did not support this notion in the post-1976 era. The linear trend fitted to the 156 observations of contraction amplitude for the 1976-2005 period (the time span between the 1973-1974 oil shock and the 2008 financial turmoil) showed an insignificant slope coefficient with $t = 0.2$ ($p = 0.796$).

There is adequate evidence of the suitability of monotonic hazard models, such as the Weibull and Gompertz models, for our data. These models are used to capture the impacts of some macroeconomic covariates on the exit rate from a recession phase. Both models predicted a monotonically increasing hazard rate for contraction durations; that is, contraction spells are positively time-dependent.

Regarding the impacts of covariates on the hazard rate, the dummy variable of openness had a positive coefficient, meaning that the hazard (exit) rate is higher (i.e., the contraction duration is shorter) in relatively more open economies (dummy = 1) compared with less open economies (dummy = 0). Oil prices and inflation rate were found to be insignificant in both models. The size (severity) of the recession increases the exit rate from recession; thus, sharp recessions last shorter than mild ones. Gross saving rate (*GSR*) had a significant positive impact on the hazard rate, but the magnitude of its effect was small. An increase of 1 percentage point in the saving rate, *ceteris paribus*, leads to a 0.4-month decrease in the mean duration. Although labor productivity growth seemed to be uncorrelated with the durations in a bivariate analysis, its dummy had significant coefficients in our models. Thus, contractions are on average shorter by 3.4 months in economies with above-median productivity growth compared with those in the below-median group.

As expected, short-term real interest rate (r) had a significant negative impact on the exit rate (i.e., a positive impact on duration). High real interest rates due to the curbing of investments lead to longer contraction spells; however, the effect size is small. An increase of 1 percentage point in interest rate, *ceteris paribus*, leads to a 0.5-month increase in the mean duration.

The difficulty of obtaining macroeconomic data, especially qualitative data on economic policies, for the countries included in our sample was a main obstacle in this study. Important variables that were omitted constitute a main source of bias in the statistical inferences. The use of richer data sets will result in more comprehensive studies in the future.

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Appendix

Table 6 Contraction and Expansion Durations: Kaplan-Meier Survivor Functions

Contraction durations						Expansion durations					
Interval (months)		Beginning total (N)	Deaths (N)	Survival	Std. error	Interval (months)		Beginning total (N)	Deaths (N)	Survival	Std. error
6	9	267	1	0.9963	0.0037	9	12	258	15	0.9419	0.0146
9	12	266	13	0.9476	0.0136	12	15	243	27	0.8372	0.023
12	15	253	39	0.8015	0.0244	15	18	216	26	0.7364	0.0274
15	18	214	42	0.6442	0.0293	18	21	190	21	0.655	0.0296
18	21	172	32	0.5243	0.0306	21	24	169	41	0.4961	0.0311
21	24	140	25	0.4307	0.0303	24	27	128	19	0.4225	0.0308
24	27	115	28	0.3258	0.0287	27	30	109	21	0.3411	0.0295
27	30	87	18	0.2584	0.0268	30	33	88	11	0.2984	0.0285
30	33	69	14	0.206	0.0248	33	36	77	14	0.2442	0.0267
33	36	55	14	0.1536	0.0221	36	39	63	15	0.186	0.0242
36	39	41	14	0.1011	0.0185	39	42	48	4	0.1705	0.0234
39	42	27	12	0.0562	0.0141	42	45	44	10	0.1318	0.0211
42	45	15	5	0.0375	0.0116	45	48	34	10	0.093	0.0181
45	48	10	5	0.0187	0.0083	48	51	24	6	0.0698	0.0159
48	51	5	2	0.0112	0.0065	51	54	18	4	0.0543	0.0141
51	54	3	2	0.0037	0.0037	54	57	14	5	0.0349	0.0114
66	69	1	1	0	.	57	60	9	2	0.0271	0.0101
						60	63	7	1	0.0233	0.0094
						63	66	6	2	0.0155	0.0077
						66	69	4	1	0.0116	0.0067
						69	72	3	2	0.0039	0.0039
						72	75	1	1	0	.

Source: Author's own estimates.

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