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Quantifying the impact of economic crises on infant mortality in advanced economies

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Policy makers rely on a mix of government spending and tax cuts to address the imbalances in the economy during an economic crisis, by promoting price stability and renewed economic growth. However, little discussion appears to focus explicitly on quantifying the cost of economic crises in terms of human lives, especially the lives of the most vulnerable members of society, infants. Using a statistical approach that is robust to the increases of mortality in outlying years, we quantify the effect that economic crises, periods of prolonged economic recession, have on infant mortality. Moreover, we investigate whether different levels of public spending on health across advanced industrialized democracies can mitigate the impact of crises on infant mortality. We find that economic crises are extremely costly and lead to a more than proportional increase in infant mortality in the short-run. Substantial public spending on health is required in order to limit their impact.

I. Introduction

Policy makers rely on a mix of government spending and tax cuts to address the imbalances in the economy during an economic crisis, by promoting price stability and renewed economic growth. However, little discussion appears to focus explicitly on the costs of economic crises in terms of human lives, especially the lives of the most vulnerable members of society, infants. Standard models for mortality including the statistical tool proposed by Lee and Carter (1992) are limited to the Gaussian paradigm and restricted to time series. Several recent developments based upon classical estimation procedures are not robust to exceptional periods due to wars and epidemics. This article offers a more informative, robust alternative to forecasting infant mortality in years of severe economic crises.

We adopt a quantile approach to study the effect of economic crisis on infant mortality. Because infant mortality is largely driven by *in utero* conditions and perinatal medical care (Cutler, 2004), economic crises that force pregnant women to cut consumption or restrict their access to health care can be expected to increase the mortality of newborns. While the long-term impact of an

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economic crisis on mortality is confounded by a large number of health shocks over an individual's lifetime (Cutler *et al.*, 2007), health shocks early in life can be expected to have a major impact on an infant's survival. In this article, we quantify how many infant lives are lost when macroeconomic crises strike, defined as periods of prolonged negative economic growth.

Data from the US suggests that improved neonatal medical care for low birth weight babies have been a major driver behind reducing infant mortality since the 1960s, accounting for as much as 19% of total life expectancy increase (Cutler, 2004). Second, historical studies suggest that overall improved nutrition measured as increases in caloric intake are important in extending life expectancy ever more so than medical advances (Fogel, 1997, 2004). Third, it is well established that socioeconomic differences at any given time within countries translate into differences in infant mortality (Lochner *et al.*, 2001; Case *et al.*, 2002; NCHS, 2006). For these three reasons alone, economic crises that cause even short-term consumption cuts, loss of access to health care and relative downward socioeconomic mobility can be expected to increase infant mortality. Yet no study has systematically tested this relationship across countries. The existing evidence is mixed, with earliest results showing long-lasting negative effects of recessions (Barker, 1990), while subsequent studies have successfully challenged those results, showing at best mixed or no effect of economic crises on life expectancy generally (Rasmussen, 2001; Cutler, 2004). A separate line of research using national survey data reports that reductions in smoking, excess weight and work hours improves health (Ruhm, 2000, 2003, 2005). However, no conclusive findings exist on how crises affect infant mortality in particular (Gerdtham and Ruhm, 2006).

This article combines a comprehensive macroeconomic dataset with a new statistical approach based on quantile regressions designed to address issues of robust inference in data with unobserved cross-country heterogeneity. Specifically, we consider a version of the estimator introduced by Koenker (2004) for a dynamic (large-T) panel data model. Our approach is motivated by recent studies that illustrate the usefulness of panel data and quantiles for forecasting (Issler and Lima, 2009; Rossi and Harvey, 2009). We employ multiple time-series macroeconomic indicators collected for all advanced industrialized economies (defined as member of the Organization for Economic Cooperation and Development (OECD)), as well as detailed infant mortality data that is sex-specific.

II. Models and Methods

In this article we depart from a traditional mean regression analysis of the data and instead pursue a quantile regression framework (Koenker and Bassett, 1978; Koenker, 2005). Cross-country studies are often criticized for their lack of robustness to unobserved heterogeneity both across countries and across time. This is an unavoidable fact of studies employing aggregate data since it is not possible to estimate different specifications for each country in each time period. While a fully random coefficient model is not possible, quantile regression provides a convenient and easily interpretable alternative framework which is substantially more robust to this critique than the linear regression model.

This article considers the following model:

$$\log(m_{it}) = \rho \log(m_{it-1}) + \boldsymbol{x}_{it}'\beta + \alpha_i + u_{it}, \quad i = 1, \ldots, N; \; t = 1, \ldots, T \tag{1}$$

$$\alpha_i = g(\boldsymbol{x}_{i1}, \ldots, \boldsymbol{x}_{iT}, m_{i1}, \ldots, m_{iT}, \upsilon_i) \tag{2}$$

The first equation is the classical panel data model where the logarithm of infant mortality m_{it} is the response variable for country i at time t, $\boldsymbol{x}$ is a vector of exogenous independent variables that includes an intercept and u is the error them. Equation 2 considers the case of correlation between the independent variables and the individual effects. The variable υ is assumed to be independent of u.

The model has the following random coefficient representation:

$$\log(m_{it}) = \rho(u_{it}) \log(m_{it-1}) + \boldsymbol{x}_{it}'\beta(u_{it}) + \boldsymbol{z}_{it}'\alpha \quad u_{it}|\boldsymbol{d}_{it}, \boldsymbol{x}_{it}, z_{it} \sim \mathcal{U}(0,1) \tag{3}$$

$$\tau \mapsto \rho(\tau)\log(m_{it-1}) + \boldsymbol{x}_{it}'\beta(\tau) + \boldsymbol{z}_{it}'\alpha \tag{4}$$

where $\boldsymbol{z}_{it}$ is an indicator variable for the individual effect α_i, $\mathcal{U}(\cdot)$ denotes a uniform distribution, and τ is the τ-th quantile of the conditional distribution of y.

It is convenient to write Equation 1 in a more concise matrix notation,

$$\boldsymbol{M} = \rho \boldsymbol{M}_{-1} + \boldsymbol{X}\beta + \boldsymbol{Z}\alpha + \boldsymbol{u} \tag{5}$$

where $\boldsymbol{M}$ is a $NT \times 1$ vector of the logarithm of infant mortality, $\boldsymbol{M}_{-1}$ is a $NT \times 1$ vector that includes the lag dependent variable, $\boldsymbol{X}$ is a $NT \times p$ matrix of independent variables and $\mathrm{Z} = \boldsymbol{I}_N \otimes \boldsymbol{1}_T$, where $\boldsymbol{1}$ is a $T \times 1$ vector of ones.

We estimate Equation 4 considering the following penalized quantile regression estimator:

$$\arg \min_{\rho,\beta,\alpha \in \mathcal{G}\times\mathcal{B}\times\mathcal{A}} \sum_{j=1}^{J} \sum_{t=1}^{T} \sum_{i=1}^{N} \omega_j \rho_{\tau_j}(\log(m_{it}) - \rho \log(m_{it-1}) - \boldsymbol{x}'_{it}\beta - \alpha_i) + \lambda P(\alpha) \tag{6}$$

where $\rho_{\tau_j}(u) = u(\tau_j - I(u \leq 0))$ is the standard quantile loss function (see, e.g. Koenker, 2005), ω_j is a relative weight given to the j-th quantile and λ is the tuning parameter. The function $P(\alpha)$ is a l_1 penalty term that is defined as, $P(\alpha) = \|\alpha\|_1$.

The method proposes to estimate simultaneously J quantiles obtaining $\{\hat{\rho}(\tau_j,\lambda), \hat{\beta}(\tau_j,\lambda), \hat{\alpha}_i(\lambda)\}_{j=1}^{J}$. Notice that the case $\rho = 0$ gives the penalized quantile regression estimator introduced by Koenker (2004) and $\lambda = 0$ gives the estimator considered in Galvao (2009). This article considers a small-N, large-T panel, therefore the potential biases arising from a short-T panel are small as demonstrated in the empirical section.

Tuning parameter selection

As in any regularization problem, the section of the tuning parameter λ is of fundamental interest. Cross Validation (CV) and Generalized Cross Validation (GCV) are commonly used in the least squares literature (see, e.g. Fan and Li, 2001), but they require practical and theoretical investigation in quantile regression for a dynamic panel data model. Because GCV is based on projections and least squares residuals, its use does not appear to be direct for quantile regression (Koenker *et al.*, 1994; He *et al.*, 1998). In this article, we select the tuning parameter following a procedure motivated by the standard Akaike Information Criterion (AIC)-type approach, $\hat{\lambda} = \arg\inf \|\hat{u}(\tau,\lambda)\|_1 + \mathrm{d}f_\lambda/(2NT)$, where $\hat{u}(\tau,\lambda) = \log(m) - \hat{\rho}(\tau,\lambda)\log(m_{-1}) - \boldsymbol{x}'\hat{\beta}(\tau,\lambda) - \boldsymbol{z}'\hat{\alpha}(\lambda)$ and $\mathrm{d}f_\lambda$ is the number of nonzero estimated parameters. The number of nonzero estimated coefficients represent a simple estimate of the degrees of freedom (Zou *et al.*, 2007). Of course, this λ selection device is rather time consuming and needs to be implemented by considering a grid.

Inference

The covariance matrix has the standard sandwich formula representation $\hat{\boldsymbol{J}}(\tau,\lambda)^{-1}\hat{\boldsymbol{S}}(\tau,\lambda)\hat{\boldsymbol{J}}(\tau,\lambda)^{-1}$ and can be easily computed using the bootstrap. In our case, the procedure can be implemented as follows. We draw a country from a sample of countries and we include all T subjects for that country. We continue sampling countries (with replacement) as indicated before until we obtain a sample of N countries. Using this new sample and for a given value of λ, we compute penalized estimate $\{\rho^*(\tau,\lambda), \beta^*(\tau,\lambda), \alpha^*(\lambda)\}$. We reiterate this procedure B times to obtain the SE of the estimator. Finally, we repeat the procedure for different λs. Alternatively, one may estimate the asymptotic covariance matrix considering standard approaches. For instance, in the case of $\lambda \to 0$ and one quantile τ, one could consider,

$$\hat{\boldsymbol{S}}(\tau) = \frac{\tau(1-\tau)}{NT} \sum_{i=1}^{N} \sum_{t=1}^{T} \boldsymbol{\Psi}_{it}\boldsymbol{\Psi}'_{it}$$

$$\hat{\boldsymbol{J}}(\tau) = \frac{1}{2NTh_{NT}} \sum_{i=1}^{N} \sum_{t=1}^{T} I(|\hat{u}_{it}(\tau)| \leq h_{NT})\boldsymbol{\Psi}_{it}\boldsymbol{\Psi}'_{it}$$

with $\boldsymbol{\Psi}_{it} = (\log(m_{it-1}), \boldsymbol{x}'_{it}, z'_{it})'$, $\hat{u}_{it}(\tau) = \log(m_{it}) - \hat{\rho}\log(m_{it-1}) - \boldsymbol{x}'_{it}\hat{\beta}(\tau) - \boldsymbol{z}'_{it}\hat{\alpha}$ and h is a properly chosen bandwidth (see Koenker (2005) and Chernozhukov and Hansen (2008) for additional details including specific choices of h).

III. Economic Crises and Infant Mortality

Infant mortality in the OECD

Advanced industrialized economies differ greatly in their infant mortality rates, with the US currently ranked at the bottom (Schroeder, 2007). In Fig. 1 we plot the trends in infant mortality for OECD countries over the period 1950 to 2000. The sex-specific mortality rate is defined as the total number of deaths in a given year for every 1000 infants of a given gender under the age of 5 in a given country. For all countries this measure has shown a strong downward trend over the past half-century, reflecting improvements in medical technology. For example, the mortality rate of male infants in the US has been reduced from 8/1000 to just under 2/1000 over this period. Notice, however, that while mortality rates have trended downwards for all countries, the rate at which mortality has been reduced has varied substantially across countries. Thus, while the US was situated close to the median of the distribution of cross-country mortality rates in 1950, it has achieved substantially fewer reductions in mortality rates than any of the other industrialized countries and by the year 2000 found itself at the extreme of the distribution with the highest infant mortality rate in the OECD.

Economic crises

It is difficult to accurately measure an economic crisis and no unique definition exists. In this study we

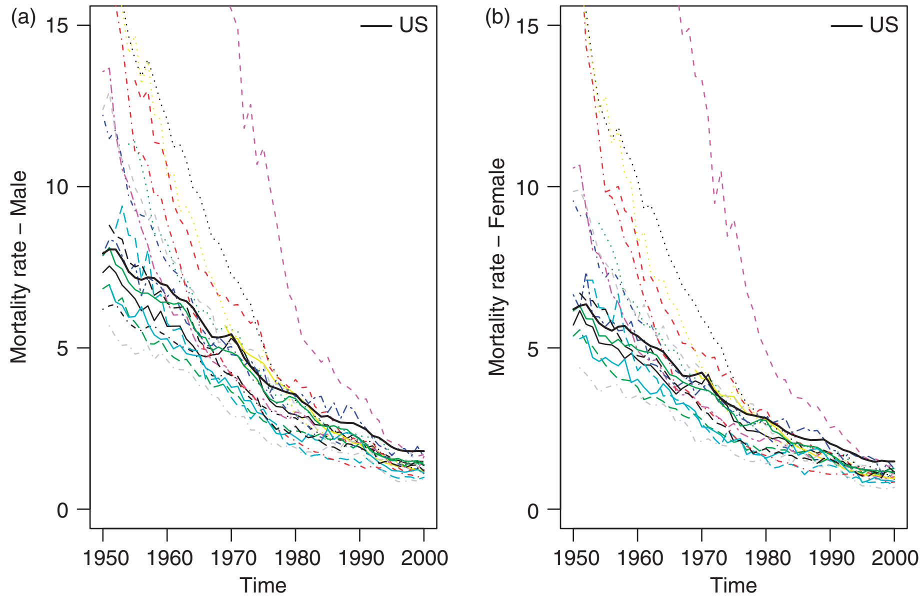

Fig. 1. Trends in infant mortality for OECD countries during 1950–2000. Time series of sex-specific infant mortality for males (left) and females (right) measured as the number of deaths of infants below the age of 5 per 1000 births, obtained from the World Health Organization (WHO). Time series for each member country of the OECD shown separately, illustrating the differential decay rates, with the US infant mortality rate (thick black line) changing from the median of the range in 1950 to the top in 2000 for both sexes

define an economic crisis to be an annual recession, that is we require output to fall as measured in the annual national accounts. This measure is insensitive to short run fluctuations in output which are evened out at yearly frequency. A yearly measure not only focuses our attention on more severe recessions than the standard definition, but it is also more appropriate in studies of mortality for which data is only reported at yearly frequency. As the economy starts to contract, consumers cut spending, including nutritional and health care expenses associated with perinatal care. Employer sponsored health care becomes a binding constraint as unemployed workers are forced to liquidate savings and are ultimately left without access to health care during pregnancy and after birth with dramatic effects on infant health and development.

There is substantial heterogeneity in the timing and severity of economic crises in OECD countries over the period 1960–2000 as shown in Fig. 2. Most economic crises have corresponded to yearly output contractions of less than 3%. Much of the economic history of advanced industrialized countries is immediate in a display of economic growth which shows pronounced clustering of the crises in the mid-1970s, early 1980s and early 1990s. The period immediately after World War II corresponded to a prolonged period of economic expansion that ended with the oil price crisis of 1974. The early 1980s featured a series of economic crises resulting from the Central Banks' attempt to control high inflation. The economic crises in the early 1990s were generated by a complex sequence of events that combined the stock market crash of 1987 with a spike in oil prices resulting from the First Gulf War. Some countries such as Finland, which experienced an extreme recession, were additionally hit by unique factors such as the collapse of trade with the disintegrating Soviet Union. All these crises led to widespread unemployment and affected the lives of individuals worldwide.

IV. Empirical Results

Data

The WHO provides annual reported data on mortality statistics by age, sex, and cause of death as obtained from civil registration systems in countries.

The underlying cause of death is coded by the respective national authority and is meant to capture the disease which ultimately led to death according to the rules specified by the International Classification of Diseases (ICD) system. These

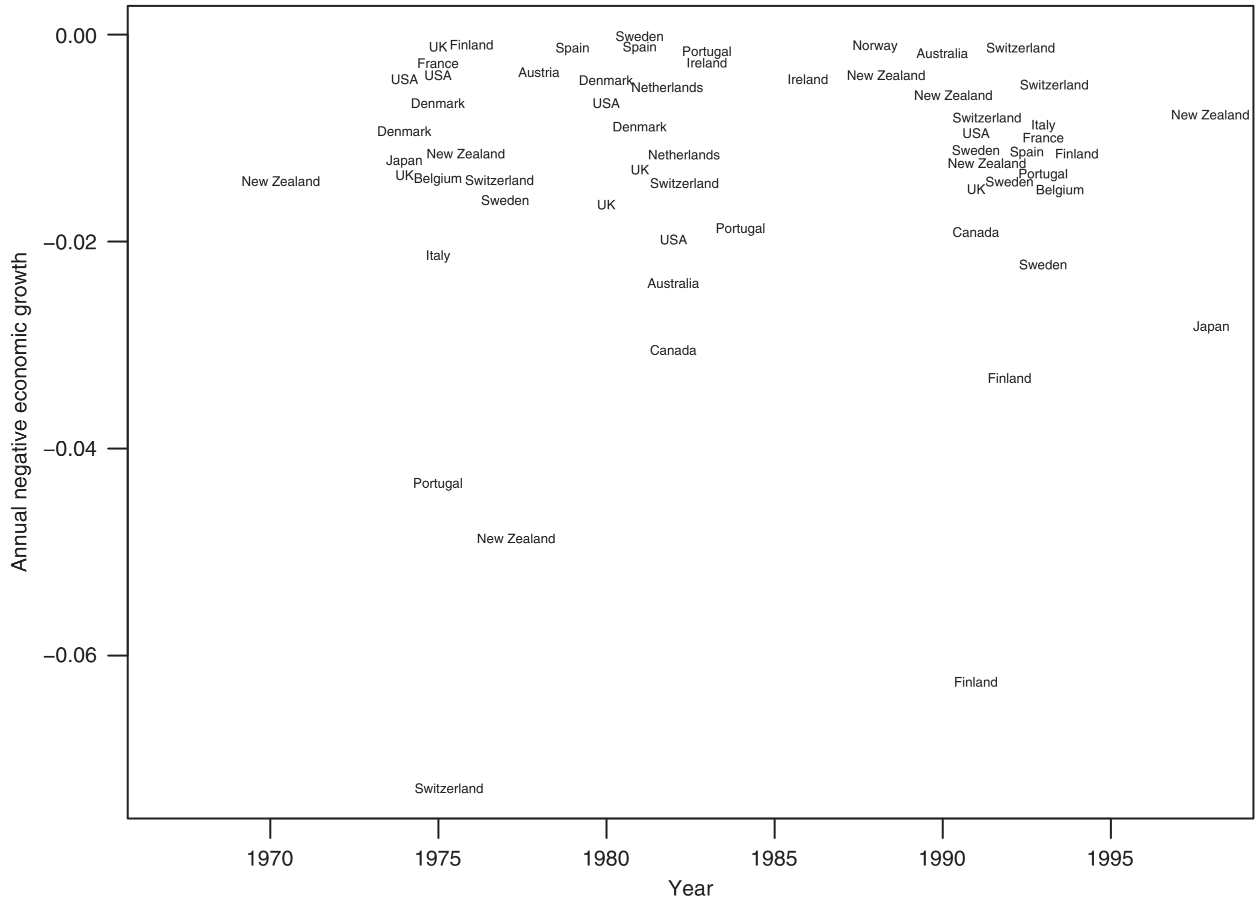

Fig. 2. Economic crises in OECD countries during 1960–2000. The timing, severity and location of economic crises, 1960–2000, according to the national accounts of member states of the OECD. An economic crisis is defined as an annual recession, showing a fall in economic output as measured by the annual national accounts

definitions are revised periodically in light of scientific advances and adopted by all member countries. Thus, subject to the correct implementation at the country level it provides a directly comparable set of figures for mortality in different countries. In spite of the great care which has been taken to collect consistent information across countries, it is difficult to exclude the possibility of systematic bias due to misdiagnosis and under-reporting. By restricting our attention to only the advanced industrialized countries we minimize the impact of biases due to incorrect and incomplete recording of death certificates. In addition, we follow the method of Girosi and King (2008) and focus our attention on the four main causes of infant mortality, broadly defined from the underlying subcategories: cardiovascular, digestive, respiratory (both infectious and chronic) and perinatal (around the time of delivery: fetal deaths at no less than 20 weeks of gestation and neonatal, or early infant deaths (MacDorman and Kirmeyer, 2009)). By restricting our attention to a more limited set of causes, we wish to remove certain channels which we deem to be *a priori* implausible.

To measure economic performance, we use measurements of the main economic indicators, available from the OECD Statistical Database. Our main variable of interest is an indicator of economic crises defined as annual recessions. In order to control for the different magnitudes of recessions, we define the variable as equal to the magnitude of the recession conditional on the country being in a recession. The variable is zero during normal periods of economic growth. We additionally control for a number of country-specific variables such as the level of Gross Domestic Product (GDP) in the previous year, unemployment, government expenditures on health, change in unemployment, inflation, gender and the level of human capital. In order to account for the trending behaviour of mortality as illustrated in Fig. 1, we also control for the logarithm of mortality lagged by one year.

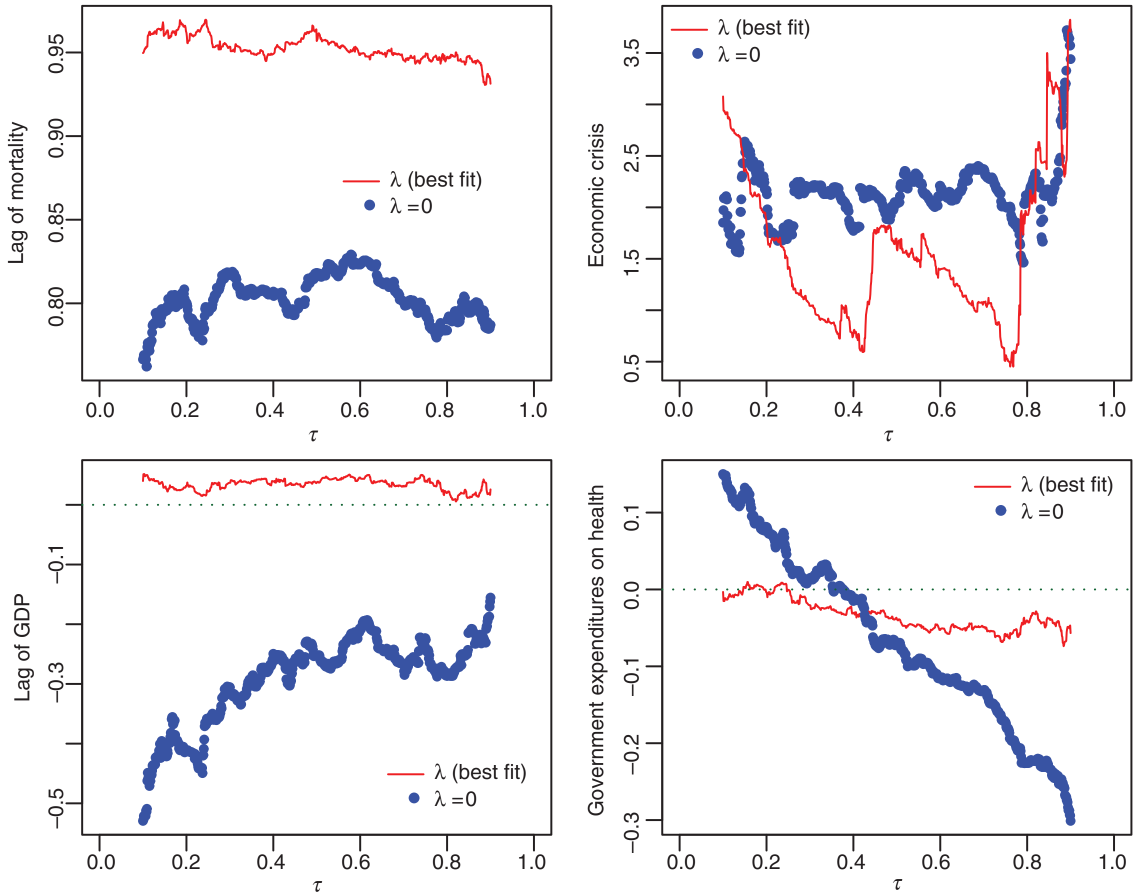

Fig. 3. Covariates effects over quantiles τ of the conditional distribution of the logarithm of infant mortality rate

Results

In order to estimate the impact of economic crises on infant mortality, we first estimate the panel quantile regression model for the log mortality rate, where the mortality rate is computed as the sum of the deaths from the four main causes. Figure 3 presents the estimated effects corresponding to the covariates of interest at different quantiles $\tau \in \mathcal{T}$. This allows us to determine how these effects including economic crises impact mortality at different quantiles of the distribution of mortality.

The impact of an economic crisis seems to be increasing in the quantiles of the mortality distribution. The results indicate that for a country at the median of the distribution of mortality, a crisis corresponding to a 1% annual recession corresponds to 2.04% higher infant mortality ($p = 0.025$), while a country at the 90th percentile of the distribution of mortality experiences a 3.4% higher mortality rate ($p = 0.007$). The effects are statistically significant in the upper tail of the distribution of mortality but insignificant at the 95% confidence level in the lower tail of the distribution corresponding to countries with low mortality. In Fig. 3, we also investigate the effect of government expenditures on health. The effect is statistically insignificant at the low quantiles of the mortality distribution, but becomes negative and statistically significant at the high quantiles of the mortality distribution. At the 90th percentile of the distribution of mortality, a 1% increase in government spending leads to only a 0.3% decrease in infant mortality ($p < 0.001$). This indicates that while the government can use spending on health to mitigate some of the negative effects of an economic crisis, spending alone, keeping everything else equal, is insufficient and the effect of an economic crisis will likely dominate and cost lives. At the median of the distribution, a 1% increase in spending reduces infant mortality by only 0.07% ($p = 0.095$). The fact that government spending appears to be irrelevant at the low levels of mortality may indicate the importance of existing institutional structures independent of the amount of spending.

We should be careful when interpreting the results on the government expenditure on infant mortality. It is possible that this variable is not truly exogenous and subject to reverse causality or affected by some other missing variable which jointly determines both infant mortality and government expenditure. We partly deal with this issue by controlling for the most comprehensive set of main economic indicators, not previously considered in mortality forecasting. It is not immediately clear how to construct an instrumental variable strategy to address concerns that remain; however, we have developed an instrumental variables version of our econometric model that can be easily applied when new empirical strategies are developed (Harding and Lamarche, 2009). While our focus on infant mortality rather than total mortality may limit some of these concerns, we nevertheless urge caution in interpreting these results in a *causal* manner.

The above discussion suggests that unobserved factors may ultimately share a substantial responsibility in determining whether a country has high or low infant mortality. The same factors may also determine to what extent a country is affected by a substantial economic shock or whether government spending can be used to minimize the impact of business cycles on infant mortality. In Fig. 4(a), we plot the estimated quantile individual effects for $\lambda = 0$ for all countries over the distribution of mortality. It is remarkable to see that the individual effect for the US is positive and dominates all the other individual effects. This suggests that unobserved social and institutional features in the US affect infant mortality to a very substantial degree. This captures the often cited puzzle that the US spends vast amounts on health yet performs poorly relative to other countries. Notice that the individual effect for countries with low mortality such as Finland, Norway or Austria is small and in fact negative, thus contributing to lower infant mortality at all quantiles. Figure 4(b) shows the standard lasso-type profile of the penalized estimates as λ changes. It also shows the optimal value of the tuning parameter, $\hat{\lambda}$, indicated by the vertical solid line. In Fig. 4(c), we present the estimated country effects evaluated at the optimal value of the tuning parameter. It is interesting to note that for $\lambda = \hat{\lambda}$, the individual effects at some quantiles for the US and Japan are nonzero. This suggests that the individual effects of those countries represent a distributional shift, while the country effects for the other advanced economies are simply location shifts (Fig. 4(c)).

Additionally, we consider a series of robustness checks (detailed tables are available from the authors). We investigated the possibility that an economic crisis has a more permanent detrimental effect on infant mortality. We expanded our analysis by adding a series of indicators for the 5 years following an economic crisis and estimating the presence of an effect over the 5 years following a crisis. We have not found any statistically significant effects of an economic crisis on infant mortality later on. This may be due to the fact that the negative effect of a crisis is short-lived and the health outlook of infants improves substantially once the economy re-emerges from a deep recession. Since we do not have individual level data the lack of any statistically measurable effect may also reflect the addition of new generations of infants, born after the economic crisis to the same cohort, thus making it impossible to separate in the aggregate figures the infants who were affected by the economic shock and those who were not.

Lastly, we use the approach to produce in-sample forecasts for infant mortality in the US in the most outlying years in terms of negative economic performance: 1974, 1975, 1980, 1982 and 1991. The results are shown in Table 1. The table also reports forecasts from the conditional mean version of the quantile regression model. At first glance, a simple comparison of infant mortality and its predictions reveals that the conditional median approach to forecasting provides a better alternative to the conditional mean. An alternative way to examine the evidence presented in the table is to compute the estimated prediction error at time t as $e_t(\tau, \lambda) = |M_t - \hat{M}_t(\tau, \lambda)|/M_t$ and compare with the estimated prediction error obtained by the mean approach $e_t = |M_t - \hat{M}_t|/M_t$. As insinuated before, we find that the mean forecast error for females $\boldsymbol{e} = (7.0, 1.8, 3.3, 1.6, 2.6)'$ is strictly dominated by the median forecast error $\boldsymbol{e}(\tau, \lambda) = (5.2, 0.9, 2.6, 0.2, 0.4)'$, and the mean forecast error for males $\boldsymbol{e} = (7.4, 3.1, 3.6, 2.1, 1.7)'$ is strictly dominated by the median forecast error $\boldsymbol{e}(\tau, \lambda) = (5.7, 2.0, 3.4, 1.2, 0.0)'$. When we compare the performance for all years, we find similar results if λ is away from the minimum and maximum values of the tuning parameter in the grid (Fig. 5). The figure shows that several λ parameters produce a relative improvement in the predicted forecast error with respect to quantile regression, least squares and least squares fixed effects methods. Remarkably, the robust methods offer an estimated forecast error reduction of more than 1 percentage point, from approximately $(4.03, 3.89)$ percent offered by classical methods to $(2.93, 2.78)$ offered by quantile regression.

Counterfactual analysis

How many lives would have been saved if the economic crises did not happen? In order to answer this question we perform a series of in-sample simulations based on our estimated quantile

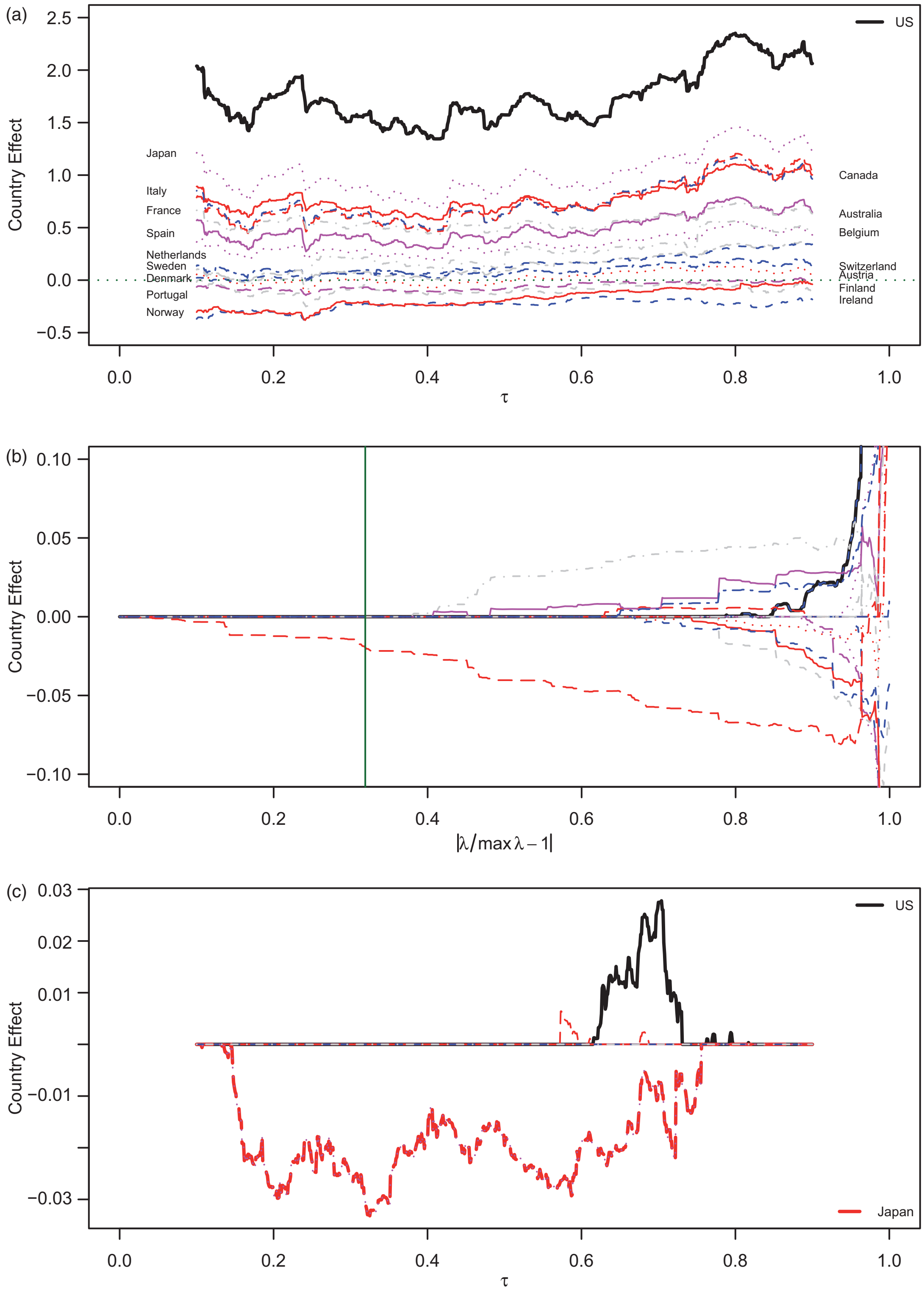

Fig. 4. Country effects over quantiles τ of the conditional distribution of the logarithm of infant mortality rate. The estimated country-specific effect for the US is positive and dominates the individual effects for all other countries. (a) shows results for $\lambda = 0$; (b) presents the profile of the country effects at the median. The vertical solid line indicates $\hat{\lambda}$, the optimal tuning parameter according to the AIC-type formula presented in Section 'Tuning parameter selection'; (c) presents results for $\lambda = \hat{\lambda}$

Table 1. Forecasting infant mortality in periods of severe economic crisis, United States, 1970–2000.

		Female					Male				
Year	Annual recession	Data	Mean prediction	Prediction	Counterfactual	Difference	Data	Mean prediction	Prediction	Counterfactual	Difference
Panel A: 0.5 Quantile											
1974	0.43%	16 349	17 486	17 206	17 055	151	22 515	24 189	23 791	23 583	208
1975	0.39%	15 363	15 646	15 501	15 378	123	20 857	21 495	21 269	21 100	169
1980	0.66%	11 891	11 503	11 581	11 425	156	15 852	15 286	15 315	15 109	206
1982	1.98%	10 750	10 579	10 726	10 302	424	14 405	14 100	14 232	13 669	563
1991	0.95%	8978	8748	8938	8766	172	11 856	11 657	11 856	11 628	228
Panel B: 0.9 Quantile											
1974	0.43%	16 349	17 486	17 905	17 642	263	22 515	24 189	24 656	24 294	362
1975	0.39%	15 363	15 646	15 885	15 673	212	20 857	21 495	21 713	21 423	290
1980	0.66%	11 891	11 503	11 891	11 623	268	15 852	15 286	15 686	15 333	353
1982	1.98%	10 750	10 579	11 188	10 452	736	14 405	14 100	14 807	13 833	974
1991	0.95%	8978	8748	9346	9045	301	11 856	11 657	12 366	11 968	398

Notes: The table also reports a comparison of in-sample predictions with and without economic crisis. The variable economic crisis is an interaction between an indicator for annual economic recessions and negative annual growth. Other included variables are: logarithm of mortality and logarithm of GDP $t-1$, unemployment, changes in unemployment, inflation, gender, human capital, a linear trend and country fixed effects.

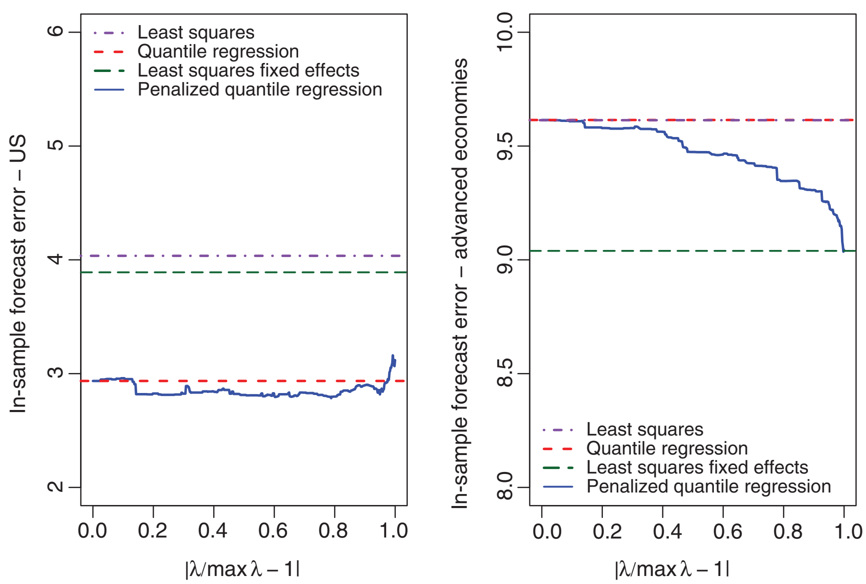

Fig. 5. Profile of the estimated forecast error. We consider the penalized quantile regression estimator for different tuning parameters λs. We compare the forecasted error of classical panel data estimators and quantile regression estimator

specification for the period 1970 to 2000. Quantile regression has several equivariance properties including the so called equivariance to monotone transformations. Logarithmic functions are monotonic, therefore we can write Equation 4 as

$$Q_{\log(M)}(\tau|c, x, \alpha) = \log(Q_M(\tau|c, x, \alpha)) \qquad (7)$$

and then use $\exp(\hat{Q}_{\log(M)}(\tau|c, x, \alpha))$ to obtain quantile-specific in-sample predictions. We perform the analysis for the US. Since it is not possible to determine the position of the US in the conditional distribution of infant mortality exactly, we compute possible scenarios at both the median of the distribution and the 90th percentile. In order to estimate a counterfactual scenario we let the variable identifying economic crises c be zero everywhere and re-compute the model prediction. The difference between the model prediction which includes an economic crisis variable and the hypothetical model prediction without an economic crisis corresponds to our estimate of the cost of an economic crisis in terms of infant mortality.

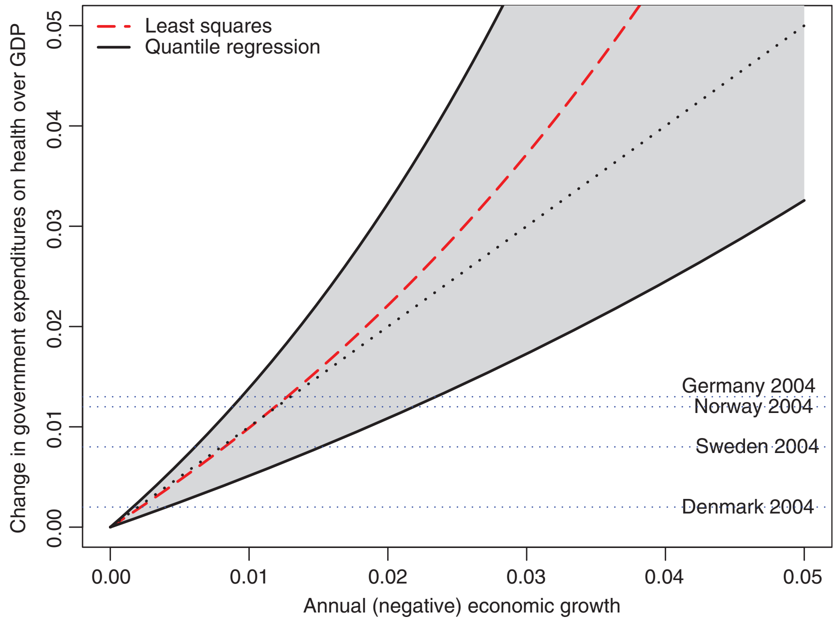

Fig. 6. Extent to which government spending may help mitigate the impact of an economic crisis on infant mortality

We report the results in Table 1. The difference between the two forecasts is substantial and we estimate that each economic crisis costs the lives of several 100 to close to 2000 infants, depending on the severity of the crisis and the strength of the impact of the economic crisis. If we use the conservative forecasts at the median, we find that the 1982 economic crisis was associated with a 4% (temporary increase in infant mortality while the 1991 recession was associated with a 1.9% increase in mortality. These numbers are surprising in that they show that even under conservative estimates the impact of an economic crisis on infant mortality is more than double the size of the economic recession. We also compare our model predictions with the actual number of deaths at each point in time and find that the model discussed above performs remarkably well in matching the number of deaths on the basis of a small number of economic determinants. For most observations the model predictions at the median and the 90th percentile bracket are close to the actual number of deaths. The remaining discrepancies are due to the unexplained component of our model. The overall very good fit, especially in more recent years, appears to suggest that our predictions of the counterfactual effect of a world without economic crisis are reasonably accurate.

While we have to be cautious in interpreting the effect of government spending due to a potential endogeneity problem, the current economic crisis in the US makes it unavoidable to ask the question whether increased government spending will help mitigate the impact of the crisis on infant mortality. In order to answer this question we solve for the amount of government spending required to compensate for each level of a potential criris.

In Fig. 6 we use the median and the 90th percentile forecasts to construct the bounds for the severity of an economic crisis that the US can overcome by increasing its government spending on health in order to avoid an increase in infant mortality. If the US were to increase its level of government spending on health to the level currently in effect in Germany (as a percentage of GDP), it would avoid an increase in infant mortality for an annual recession of magnitude between 1% and 2%. Our counterfactual analysis seems to imply that an increase in government spending on health in the US to the levels seen in Europe would avoid the costly loss of human life which is historically associated with economic crises. Notice, however, how costly economic crises ultimately are. Figure 6 also shows that the amount of government spending on health that can compensate for an economic crisis corresponding to a 4% annual recession is substantially higher than what has been adopted in the past.

V. Discussion

Very little attention has been given to the human costs of economic crises when developing economic policy. The evidence presented in this article suggests that economic crises are extremely costly. While the increase in the number of infants dying during an economic crisis may not seem very large when compared to the population of the US, it is nevertheless very substantial when we remember that infant mortality is a rare event in an advanced industrialized country. A 2% increase in infant mortality during an average economic crisis is not easy to ignore. While we are cautious in interpreting the effect of government spending due to a potential endogeneity problem, the analysis suggests that government spending on health may help to alleviate the human cost of economic crises.

The current analysis focuses on aggregate demographic and economic data and remains silent on the micro-determinants of mortality. This is due to the lack of suitable data. Nevertheless, we hope that the stylized facts identified in this article will stimulate additional research aimed at identifying the exact economic and biological channels through which economic crises affect mortality. It is our view that the effects are driven by a mixture of immediate channels such as poor nutrition but also by the availability of appropriate highly advanced medical care to prevent, detect and treat many of the conditions that drive infant mortality during economic recessions.

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