Corruption, Organizational Failure, and Industrial Regeneration*

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Abstract

Corruption is known to have serious, negative economic consequences and, in particular, suppress entrepreneurial effort. Here we look into how corruption affects the process of "industrial regeneration," where failures of organizations at one point in time lead to the creation of new organizations in the next. We develop a model of industrial regeneration, and theorize that this model will reveal regeneration only where corruption is well controlled. The coefficient of regeneration is estimated using data over much of Europe for a number of years, and estimates are shown to be robust over a variety of specifications. Corruption is found to decrease industrial regeneration, and at high levels corruption entirely extinguishes the effect.

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Does corruption retard industrial regeneration? The economic costs of corruption are extensive, going far beyond the volume of bribes paid. Endemic corruption distorts the allocation of resources in an economy from more productive to less productive uses (Baumol, 1990; Murphy et al., 1993; Svensson, 2005). Broad studies of macroeconomic change tell us that development depends on whether institutions generally, and corruption in particular, inhibit productive activity (Acemoglu et al., 2005; Hafner et al., 2016; Klapper et al., 2010 Rose-Ackerman and Palifka, 2016). Meanwhile, research on economic and organizational evolution shows that organizational failure fuels the regeneration of industries. Research on the business cycle follows Schumpeter (1934), who problematizes the "resorption" of resources that are released during economic downturns. At the level of firms and industries, various traditions allow for the importance of organizational failure to economic progress -- de-selecting less efficient organizations (Nelson and Winter, 1982) and so improving the performance of industries and surviving firms over time (Klepper, 1996; Knott and Posen, 2005). But how is this process of industrial regeneration affected by the institutional environment, in particular by corruption?

Our aim is to answer this question by developing a model of industrial regeneration, which we then estimate using data from contexts with different levels of corruption. Specifically, we model industrial regeneration as the process where organizational failures at one point in time fuel the ensuing creation of new organizations at the next point in time. By obtaining estimates of our model using data across multiple countries, we find that regeneration appears to be quite strong in some contexts, while in others it is entirely extinguished by corruption.

Industrial Regeneration

Industrial regeneration occurs when organizational failure fuels the creation of new organizations. At the organizational level, regeneration takes place when an organization replaces resources with new resources from the environment (McNeil and Thompson, 1971). But when an organization fails, this process is truncated and the resources of the organization are released into the environment – including people, material resources, capital, relationships, and market positions. Some of these resources will remain dormant. Some will be absorbed by surviving organizations that grow (Nelson and Winter, 1982). And some will become available to entrepreneurs who may recombine them as part of forming new organizations, an essential step in industrial regeneration. Industrial renewal is key to the "circular flow" of the economy, where organizations are created, replacing others that fail (Schumpeter, 1934). When this happens, failure spawns new combinations of productive inputs. Consequently, the positive effect of failures on new organizational founding has been called a "renewal process" (Delacroix and Carroll, 1983). Macrosociologically, the economic and social changes brought about through failures and foundings could be thought of as "ecological succession" (McKensie, 1968). But the process of regeneration occurs at the level of particular industries, visible whenever organizational failures stimulate the creation of new firms in the same industry.

At first glance, it might seem that industrial regeneration is already built in to ecological models of organizations through the operation of "carrying capacity." Resources released by failure become available to support the creation of new organizations, essentially increasing the carrying capacity for organizations in a given context. As it stands, ecological models of organizational founding typically build in the environment's carrying capacity. The availability of resources is part of the business cycle, and such economic effects are normally modeled as part of the carrying capacity's effect on the founding rate. Similarly, the elimination of competition with the failure of firms would be built into a so-called "density dependent" founding model, where large numbers of rivals would be expected to decrease founding rates. If the effects of organizational failure operate through an increase in the environment's carrying capacity, there is no need for a model that specifies a distinct regeneration effect.

Yet some ecological models of organizational founding do include a measure of (lagged) organizational failures, and often find a positive effect (see Carroll and Hannan, 2000, for a review). This result implies that there is a distinct effect of resources that have recently become available. With the failure of an organization, resources that were previously controlled become newly at risk of redeployment into the creation of new organizations. Over time the disposition of these resources changes: Either they become less likely to be redeployed over time, or there is a mix of redeployable and non-redeployable resources and the former become utilized so that over time only the latter remain. Either way, this reasoning implies an immediate but transitory positive effect of organizational failure on an industry's organizational founding rate, as in the model:

$$\lambda_{i,j,t} = \lambda^*_{i,j,t}\exp(\theta f_{i,j,t-1})$$

where $\lambda_{i,j,t}$ is the organizational founding rate in industry i within country j at time t, $\lambda^*_{i,j,t}$ is a baseline rate for a given industry-country-year modeled stochastically as a function of observables, and $f_{i,j,t-1}$ is the (lagged) realized probability of organizational failure in industry i within country j.[1] Economic, institutional, and cultural effects on the founding rate, as well as indicators to capture unobserved heterogeneity, can be included in the specification of the baseline rate $\lambda^*_{i,j,t}$. With these effects controlled, evidence of industrial regeneration is found if $\theta > 0$, such that lagged failures positively affect ensuing rates of organizational founding. In this way, θ can be thought of as a *coefficient of regeneration*.

Regenerative Value

The coefficient of regeneration likely varies worldwide due to the very different institutional contexts that exist. Economic growth rates are known to vary considerably across countries, reflecting a broad range of institutional differences (Acemoglu et al. 2005, Kornai et al., 2009; Spence, 2011). Sociological studies of innovation and change similarly note the importance of institutional differences, with some structures more "vulnerable to innovation" than others (Padgett and Powell, 2012: 26). And studies of worldwide business observe that such institutional differences persist, despite the globalization of the world economy (Guillen, 2001). Consequently, an estimate of the coefficient of regeneration obtained in any particular context at any given point in history may be very different than estimates obtained from other places or at other times. The possibility that regeneration is context-dependent brings about the potential to use cross-national data to test theoretical propositions about what accelerates, or

[1] Models of population dynamics within organizational ecology routinely include lagged numbers of organizational foundings and failures in models of organizational founding and failure rates (see Carroll and Hannan, 2000). By and large, these are studies of single industries. In this study, we look at all industries over many countries, and so confront the problem of very different counts of numbers of failures from context to context. Consequently, we model failure in terms of the realized probability of failure in order to adjust for these differences.

retards, regeneration. In short, it may be possible to describe institutions according to their "regenerative value."[2]

In particular, with increasing attention on globalization, developmental economists have focused on the importance of corruption to economic growth, and usefully define corruption as "the extent to which public power is exercised for private gain" (Kaufmann et al., 2010). So defined, corruption and tolerance of corruption are seen to be part of an institutional pattern that reduces the productive capacity of economies (see, e.g., World Bank Commission on Growth and Development, 2008). Corruption helps to account for the so-called "resource curse," where economic growth is negatively related to the natural resource endowments of a country (Stiglitz, 2006). But the effects of corruption go beyond the public sector, in that government corruption generates distortions throughout the economy (Schleifer and Vishny, 1993; Svensson, 2005). Furthermore, corrupt behavior becomes normative among those who routinely operate in corrupt contexts (Fisman and Miguel, 2007). And more generally, corruption has been found to reduce the effectiveness of institutions in supporting economic development in terms of resource allocation, access to education, and income distribution, among other factors (Rose-Ackerman and Palifka, 2016; Spence, 2011).

Various researchers have applied this thinking specifically to entrepreneurship. Entrepreneurial effort is suppressed when entry and growth are taxed via Kafkaesque rules and regulations that serve as opportunities for officials to seek bribes (de Soto, 1989; Bertrand et al., 2007; Kaufmann and Wei, 1999; Klapper et al., 2010; Rose-Ackerman and Palifka, 2016). Gilinskiy (2005) describes a never-ending series of bribes required to become an entrepreneur in

[2] This idea is analogous to the biological construct of "reproductive value." See Fisher, 1930.

Russia: “One has to bribe when registering a business, when renting premises from state bodies, when acquiring licenses for their utilization from state bodies, when obtaining low-interest bank credit, when reporting to tax inspectors, and when completing customs formalities.” In Peru in the 1980s, de Soto (1989) reports that attempting to set up a garment factory by wholly legitimate means required navigating a 10-month bureaucratic maze. Investigators were asked for a bribe on ten separate occasions -- and agreed to pay twice for fear there was no other way to continue. This red-tape and bureaucratic graft pushes entrepreneurs into the informal sector. Following these arguments, differences in corruption levels across countries should be included in the baseline rate of organizational founding where one would expect corruption to reduce the founding rate.

In particular, we are interested in the impact of corruption on the regeneration process. That is, corruption not only suppresses entrepreneurial effort generally, but specifically impedes the ability for entrepreneurs to utilize the resources released from prior failures to start new businesses. Some of the same arguments for why corruption suppresses the founding rate also apply to regenerative capacity. If starting a business is time consuming and costly, entrepreneurs will be less able to be responsive to market opportunities driven by recent failures. Resources that would otherwise be available to new entrepreneurs will instead by absorbed by established firms or decay as they lay dormant.

We highlight three additional mechanisms that also explain why corruption potentially impedes regeneration. First, corruption can sap failing firms of resources that would otherwise be made available for recombination by new firms. Second, the revelation of endemic corruption on the occasion of a failure can increase the perceived risk of entrepreneurship. Third, corrupt officials can bias the redistribution of resources by delaying or intervening in bankruptcy and liquidation proceedings.

Businesses fearful that success will be expropriated by the government will underinvest in developing new capabilities and over-invest in rent-seeking and positional advantages (Baumol, 1990; Fisman and Svensson, 2007). Further, entrepreneurs in corrupt countries will be biased towards short-term investment and against capital projects that are immobile. Thus, when these firms fail, the resources they release will be less valuable for future entrepreneurs. For example, Hirschman (1967) observes the reluctance of farmers in Southern Italy to transition from traditional cereals to higher value fruits and vegetables in the aftermath of a major irrigation project. The farmers feared coming under the dominion of the Camorra, a politically powerful criminal organization that controls fruit and vegetable trade around Naples. In a cross-sectional study of Ugandan firms, Svensson (2003) finds that firms with higher sunk costs are targets for demands from corrupt officials. Rose-Ackerman and Palifka (2016) highlight how the growing popularity of floating power stations in the developing world is part of a transparent effort by electric producers to make exit relatively inexpensive.

Further, firms in corrupt environments are apt to seek out state support when they are struggling, becoming "zombie firms" that provide little economic value and strip resources from more innovative competitors (Caballero et al., 2008; Khwaja and Mian, 2005; McGowan et al., 2017; Nelson, 1981). When these firms finally do fail, there is little of value for new entrepreneurs to salvage. Corruption can also leak into the bankruptcy process, because local judges and government officials can use the discretion involved with bankruptcy proceedings to allocate liquidated assets to preferred sources or permit failing firms to reorganize inefficiently

(Lambert-Mogiliansky et al., 2007; Mogiliansky et al., 2003; Weiss and Wruck, 1998). Rather than freeing up resources, organizational failures plagued by corruption feature resources diverted according to whom has de-facto control. These distributive inefficiencies in the bankruptcy process obstruct the circular flow of resources from failed firms to new entrants (Lee et al., 2011).

Moments of failure also tend to reveal latent corruption in countries and industries. In his essay on how con men deal with their victims, Goffman (1952) notes the importance of the instant when the con is revealed. He pays special attention to that delicate moment when the reality of the situation becomes clear to all. More generally, the spirit of Goffman's approach can be applied to the broad range of contexts involving corruption. Corruption may be ongoing in many places at many times, but we typically find out about these practices when a reckoning takes place – and the day of reckoning for organizations occurs when they fail. In many cases, this reckoning brings with it shock and disappointment as the extent and price of corrupt practices come into the light of day – as seen in the many tales still told in the wake of the global financial crisis of 2008. For example, the failures of Fannie Mae and Freddie Mac brought to light the portfolio of influence tactics the two government-sponsored mortgage giants used to circumvent government oversight and enrich their executives (Morgenson and Rosner, 2011). In one New York Times interview, published over a decade before the financial crisis, House Banking Committee Chairman Jim Leach observed: "no institution in America has as sophisticated tentacles into the legislature and the executive branch as Fannie Mae," but few listened (Stevenson, 1997). Ten years later, the imminent failure of the two firms driven by gross mismanagement of housing related risks precipitated a \$187.5 billion taxpayer bailout, prompting an explosion of articles and books highlighting their misdeeds.

In terms of the model, this hypothesis can be tested by allowing the regenerative effect θ to vary from country to country and over time according to the extent to which corruption is under control, denoted $C_{j,t}$: $\theta_{j,t} = \theta + \theta_c C_{j,t}$. Support for our argument is found if $\theta_c > 0$. Corruption has not only a "main effect" on entrepreneurship, but also carries a negative regenerative value, reducing the rate at which industries convert failures into new businesses.

Data and Models

Estimating θ requires data on a number of discrete organizational populations, and estimating θ as a function of institutional characteristics requires that these data span multiple institutional environments. Comprehensive data of this sort, without systematic size or survivor bias, can be difficult to obtain. An exception is the ORBIS database from Bureau van Dijk. These data have been collected over several years and for parts of Europe appear to be quite comprehensive in recent years, including firms both living and failed, public and private, and of all sizes (Kalemli-Ozcan et al., 2015). While the ORBIS database also includes accounting data on size, those data are missing in many cases. But the data do include industry, country, and dates of entry and exit (or merger and acquisition) for the vast majority of firms. For this analysis, data release 114 (2013) was used, which contains data covering all industries in Austria, Belgium, Denmark, Finland, France, Germany, Ireland, Italy, the Netherlands, Norway, Portugal, Spain, Sweden, Switzerland and the United Kingdom for the period 2003 through 2010. Since the model requires that independent variables be lagged a year, this means the window covered by this analysis spans 2004 through 2010, although data for some countries begins later due to clear evidence of survivorship bias.

A number of steps were taken to clean the ORBIS data for analysis. The data included information on firms across all industries, but some firms were removed from the data before analysis. European Classification of Economic Activities (NACE) Rev. 2 4-digit classes 6202, 7022, 7490, and 8299 were "consultants" of various sorts, and appeared to include large numbers of individuals who self-identified in this way for tax purposes in many countries. Firms classified in classes 6420, 6430, 6810, 6820, and 7010 were also excluded to remove holding companies, activities of head offices (distinct from their firms), trusts and funds, and sales and rentals of one's own real estate. And in many places, the apparent coming and going of firms due to data inconsistencies over time was resolved by comparing records historically. The end result was a dataset capturing the life histories of approximately 21 million firms.

From the firm life histories, an industry-country-year-level data set was constructed, where the industry is defined by the NACE Rev. 2 3-digit group. Firms are classified into NACE groups depending on the "character of goods and services produced," "the uses to which the goods and services are put," and "the inputs, the process, and the technology of production" (Statistical Office of the European Communities, 2008). We include all industry-country-years for which there is at least one firm that is in business at the beginning of the focal year. For each industry-country-year, we then calculate the following:

- Firm count: The count of firms in business at the beginning of the year.
- Entry count: The count of new entrants, defined by the date of incorporation, when available.

- Entry rate: The count of new entrants divided by the firm count (multiplied by 100)
- Failure count: The count of firms that fail, defined as firms that are dissolved, enter bankruptcy, begin insolvency proceedings, become dormant, or become inactive. Firms that exit the data due to mergers, take-overs, or demergers are not included in the failure count.
- Failure rate: The failure count divided by the sum of the firm count and entry count (x 100).

In our empirical analysis, our dependent variable is the entry count. In order to capture industrial regeneration, we estimate coefficients on the lagged failure rate. We use the rate rather than the count in order to account for the wide variation in industry sizes across and within countries. We also control for competitive effects by including lagged firm density and its square in our model of the baseline entry rate (Carroll and Hannan, 2000).

Our measure of the level of corruption is the World Bank's Control of Corruption Index, which is published as a part of the World Bank's ongoing Worldwide Governance Indicators project (Kaufmann et al., 2010). The index varies by country and year. Importantly, the the index does not solely capture rates of bribery and illegal graft by government officials. Instead, it seeks to capture a wide variety of indicators associated with corruption, including perceptions of the attractiveness of the country as a place to do business, nepotism in the civil service, strength of anti-corruption laws and protections for whistleblowers, public trust in politicians, ethics rules and legal remedies for senior government officials, open-bidding for public contracts, and opportunities for corruption caused by excessive or burdensome government regulations. The World Bank's index is the output of an unobserved components model that aggregates twenty-three indicators of national corruption perceptions and anti-corruption policies from commercial business information providers (e.g., Economist Intelligence Unit), non-governmental organizations (e.g., Transparency International), and public sector sources (e.g., European Bank for Reconstruction and Development) (Kaufmann et al., 2010). The index is scaled so that each the scores for each year have a mean of zero and standard deviation of one. The countries in our sample tend to have above-average control of corruption (or, below average corruption). The country with the lowest average control of corruption score is Italy (0.3), the median average score is Great Britain (1.78), and the highest average score is Denmark (2.47). The World Bank's index correlates extremely highly with other commonly used indices of the intensity of corruption, including the International Country Risk Guide's corruption indicator and the Corruption Perception Index produced by Transparency International (Svensson, 2005).

Our baseline models estimating the coefficient of regeneration take the following form:

$$\lambda_{i,j,t} = \lambda^*_{i,j,t} \exp(\theta f_{i,j,t-1} + \theta_c C_{j,t-1} f_{i,j,t-1})$$

$$\lambda^*_{i,j,t} = \exp(\alpha_j + \gamma_t + \xi_s + \beta X_{i,j,t-1})$$

where i indexes industries, j indexes countries, t indexes years, λ is the count of new entries, f is the failure rate, C is the control of corruption index, α_j is a country fixed-effect, γ_t is a year fixed-effect, ξ_s is a section fixed-effect (the section is the first level of the NACE Rev. 2 classification system), and X is a vector of covariates that vary by industry, country, and/or year. In the empirical models, X includes the lagged values of firm density (linear and quadratic), GDP growth, unemployment rate, and rate of firm entry.

In our model of the baseline entry rate, country-level fixed effects control for stable characteristics of countries, such as the political system, legal regime, and national culture. Year fixed effects control for any macro-level shocks that impact all countries in the data. Section fixed effects capture stable differences between types of firms, including the propensity for certain industry groups to face greater “latitude” for corruption (Hirschman, 1967). Examples of NACE sections include ‘agriculture, forestry and fishing’, ‘manufacturing’, and ‘financial and insurance activities.’ The inclusion of the lagged entry rate as a covariate controls for within country-industry autocorrelation. We also control for GDP growth and the unemployment rate in order to capture local economic conditions. In additional included as robustness checks, we also include country-year fixed effects, and/or country-industry fixed effects in our models of λ^*. Summary statistics for the variables in our model are reported in Table 1.

[TABLE 1 GOES ABOUT HERE]

We estimate negative binomial regression models, which is common for modeling count outcomes, such as firm entry, in the presence of overdispersion. We cluster our standard errors on the level of the country-year, because our measure of corruption varies at this level. Our models are estimated in Stata/IC 14.2.

Results

We report the results of our regression analysis in Table 2. The first model reports coefficients on key covariates in the model of the baseline entry rate. We find that better economic conditions generate more entry and corruption depresses entry, which is consistent with the prior literature. We also find that the main effect of firm density is positive, but the quadratic effect is negative, which conforms to prior studies as well (Carroll and Hannan, 2000).

The second model includes an estimate of the coefficient of regeneration. We find that a one percentage point increase in the failure rate produces approximately a two percent increase in the number of entries in the subsequent year. In the third model, we allow the coefficient of regeneration to covary with the extent of corruption. We find support for our hypothesis. Low corruption countries display evidence of a regeneration effect, whereas in high corruption countries failures tend to suppress new entries in the subsequent period. Further, the approximately 25 percent decline in the coefficient on the control of corruption between the second and third models indicates the importance of the regeneration process in mediating the relationship between corruption and entrepreneurship.

[TABLE 2 GOES ABOUT HERE]

In any cross-country panel regression analysis, there are potential alternative causal pathways that could arguably be the source of a spurious significant relationship. As our base models already include country and year fixed effects, our models control for sources of unobserved heterogeneity that are stable within country (e.g., geography, political system, cultural traits) and within year (e.g., worldwide macroeconomic and geopolitical trends). Nevertheless, we report a series of additional models in order to demonstrate the robustness of the observed effects to parameterization choices.

One concern is that our result is being driven by structural zeroes in the data. There may be some industries that are barren, for all intents and purposes, and highly unlikely sources of new entry. In our data, approximately twelve percent of industry-country-years have no entries. Thus, we re-estimate our models using zero-inflated negative binomial regression models. In the zero-inflated model, we simultaneously estimate a logistic regression which predicts whether or not there is entry in an industry-country-year and a negative binomial model that reports regression coefficients conditional on the likelihood of firm entry. In our model predicting zero entries, we include the lagged entry count and a linear and quadratic effect of the lagged firm count.

The zero-inflated model, reported in Table 3, suppresses the main effect of regeneration in the negative binomial model considerably. Although the coefficient remains positive, it is now statistically indistinguishable from zero. However, the regeneration effect continues to significantly vary with the level of corruption. Higher corruption countries continue to not observe a regeneration effect, whereas lower corruption countries experience a positive relationship between failures and future entry.

[TABLE 3 GOES ABOUT HERE]

Other concerns in the empirical analysis are driven by the potential for omitted variables. One possibility is that there are characteristics that are unique to specific industries within countries that are driving the regeneration effect. In order to control for the potential that unobserved cross-industry heterogeneity is driving our results, we re-estimate models using industry-country fixed effects. However, the inclusion of both the lagged entry rate and country-industry fixed effects in a regression model predicting $\lambda_{i,j,t}$ creates the potential for dynamic panel bias (Baltagi, 2013). Although dynamic panel estimators do exist for count data, these models are generally estimated in the context of the linear regression model (Flannery and Hankins, 2013), which is how we proceed here.

Specifically, we first estimate log-linear models of the following form:

$$\ln(\lambda_{i,j,t} + 1) = \ln(\lambda^*_{i,j,t}) + \theta f_{i,j,t-1} + \theta_c C_{j,t-1} f_{i,j,t-1} + \varepsilon_{i,j,t}$$

The log-linear models estimate the conditional mean of the log of the entry count, with one added to the observed count to allow inclusion of country-industry-years with no observed entries. Unlike the previously estimated count models in which the independent variables are modeled as having a multiplicative effect on entry, taking the log of the right hand side of the equation implies that the independent variables have an additive effect. This allows us to estimate a linear regression models.

Table 4 reports the results of log-linear regression models with the same controls as in the original negative binomial regression models reported in Table 2. Coefficient estimates from the log-linear regressions are very similar to the negative binomial models. The failure rate continues to have a positive impact on the entry count and the interaction of the failure rate and the the control of corruption is positive at the 0.01 significance level.

[TABLE 4 GOES ABOUT HERE]

Table 5 reports same models with industry-country fixed effects included. We use the Blundell-Bond dynamic panel estimator (Baltagi, 2013; Roodman, 2009). Each of the models reported here fails to reject the null of no second-order autocorrelation at the 5 percent significance level in an Arrellano-Bond test and fails to reject the null of invalid over-identifying restrictions at the 5 percent significance level in a Sargan-Hansen test. As with the prior models, we observe a positive main effect of regeneration in the second model and a positive coefficient on interaction of the failure rate and control of corruption. However, in the fixed effects models, the main effect of corruption on firm entry and the coefficient on the lagged entry rate are no longer significantly different from zero at the 0.05 significance level.

[TABLE 5 GOES ABOUT HERE]

We next estimate linear models with country-year fixed effects. The inclusion of country-year fixed effects restricts the variation identifying the model to differences in the failure rates across industries within countries and years. In addition to controlling for any unobserved country-year level covariates, these models also allow us to take into account the potential that our results are biased due to measurement error. While there may be differences in the quality of the data within country over time, we find it harder to believe that there are systematic differences in data quality across industries *within* country-years. As a result of the inclusion of the fixed effect, we can no longer identify parameters associated with the level of corruption or the macroeconomic controls.

Table 6 reports the coefficient estimates from the country-year fixed effects models. The results of the coefficients of interest continue to follow the hypothesized pattern: the main effect of failure on the log of the entry count in the second model is positive and significant, as is the interaction of the failure rate and control of corruption in the third model.

[TABLE 6 GOES ABOUT HERE]

Finally, we address the possibility that there is an omitted variable that varies on the industry-country-year level that biases our coefficient estimates. For example, certain country-industries could experience sustained booms (recessions) driven by idiosyncratic factors that would negatively (positively) correlate with the lagged failure rate and positively (negatively) correlate with the number of entries. In order to address this potential source of endogeneity, we derive an instrument for the failure rate.

We construct our instrument in the following manner. First, we disaggregate our data into classes (the fourth level of the NACE classification). Classes are nested inside of our "industries," which we have defined by the third level of the the NACE classification. We assume that the observed failure rate for class cl in industry i and is the sum of an EU-wide failure rate for the class and local idiosyncratic component. Let $f_{cl,j,t}$ indicate the observed failure rate for a class-country-year, $f^*_{cl,t}$ equal the EU-wide failure rate for the class-year and $\eta_{cl,j,t}$ represent the part of the failure rate driven by local factors:

$$f_{cl,j,t} = f^*_{cl,t} + \eta_{cl,j,t}$$

We can decompose the failure rate in each industry into the weighted sum of the failure rates of in each class, in which the weights are the proportion of the number of firms each industry that classified in a given class. Let $n_{cl,j,t}$ indicate the number of firms in a class-country-year.

$$f_{i,j,t} = \sum_{cl \in i} \frac{n_{cl,j,t}}{\sum_{cl \in i} n_{cl,j,t}} \left[f^*_{cl,t} + \eta_{cl,j,t} \right]$$

We use the observed mean failure rate in all countries other than the focal country, denoted $\overline{f_{cl,-j,t}}$, as an estimator of $f^*_{cl,t}$ (for a discussion of similar instruments, see Goldsmith-Pinkham et al., 2018). We then calculate the expected failure rate for each industry-country-year, $\widehat{f_{i,j,t}}$:

$$\widehat{f_{i,j,t}} = \sum_{cl \in i} \frac{n_{cl,j,t}}{\sum_{cl \in i} n_{cl,j,t}} \overline{f_{cl,-j,t}}$$

Finally, in order to purge potential sources of contemporaneous endogeneity due to possible across-country, within-year correlations of $\eta_{cl,j,t}$, we lag the expected failure rate by one period, $\widehat{f_{i,j,t-1}}$, and use this is our instrument for the observed failure rate, $f_{i,j,t}$. Similarly, we use the lagged interaction of the expected failure rate and the control of corruption index, $C_{j,t-1}\widehat{f_{i,j,t-1}}$, as our instrument for the interaction of the failure rate and the level of corruption, $C_{j,t}f_{i,j,t}$. The exclusion restriction required for the validity of the instrumental variables regression is that $\widehat{f_{i,j,t-1}}$ is conditionally uncorrelated with potential omitted endogenous variables. As our instrument for the failure rate is derived solely from failure rates in other countries in prior years, we believe that this assumption holds.

The results of the instrumental variables regression analysis are reported in Table 7. Models 1 and 2 report the instrumental variables estimates of the coefficient of regeneration with and without an interaction with the control of corruption. As in many of the prior models, we observe a robust regeneration effect. However, that effect is conditional on observing a low level of corruption. Note that in these models, the main effect of control of corruption on the entry rate shrinks by over 60 percent between the two models. Model 3 reports the coefficients from the first-stage regression for Model 1. The highly significant coefficient on $\widehat{f_{i,j,t-2}}$ gives confidence to its validity as an instrument. Models 4 and 5 report coefficients for first-stage regressions for Model 2. The significant coefficients on $\widehat{f_{i,j,t-2}}$ in Model 4 and $\widehat{f_{i,j,t-2}}C_{j,t-2}$ support the claim that the instrumental variables regression in Model 2 is well-identified.

[TABLE 7 GOES ABOUT HERE]

Discussion and Conclusion

We began by asking whether corruption retards industrial regeneration, defined as the process where organizational failures lead to the generation of new organizations. Our model estimates point to powerful institutional effects on industrial regeneration. Whether regeneration occurs depends on whether corruption is widespread. Only where corruption is well controlled do we see the process of industrial regeneration take place. Where corruption is rife, organizational failure does not increase founding rates; in fact, founding rates are markedly lower in the wake of failures when corruption is high.

This pattern supports the theoretical arguments made here. The resources released by failing firms in corrupt countries fail to be repurposed by new entrepreneurs. Our study cannot differentiate between the multiple plausible mechanisms we offer. It is possible that the resources themselves are less valuable of strategic choices made by the failing firms. It is possible that resources are diverted away from new entrepreneurs due to corrupt bankruptcy and liquidation processes. It is also possible that organizational failure is the moment when past patterns of ongoing corruption come to be revealed. Such moments are not times for reinvestment in new entrepreneurial ventures, as the results here show.

Perhaps the most surprising finding in this study is that the regenerative consequences of corruption are more robust to specification error than is the main effect of corruption on levels of new firm founding. By and large, studies argue for and demonstrate a negative effect of corruption on economic growth. And studies of the entrepreneurial process typically point to corruption as a problem that inhibits the process of legally sanctioning a new firm. But our findings raise the question of whether prior work relating corruption to levels of entrepreneurship may, in fact, be picking up corruption's effect on the process of industrial regeneration.

To conclude, this research has obvious implications for policy and for understanding the process of regeneration as we see it worldwide. There are also implications for organizational ecology. For decades, organizational ecologists have routinely studied particular industries to test their theories, sometimes for convenience and sometimes due to theoretical argument. Yet if the process of regeneration varies more by country than by industry, we may need to question whether our findings are generally applicable or whether we must stipulate the institutional conditions under which findings hold.

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Table 1: Summary statistics

Variable	Mean	Std. Dev.	Min.	Max.	N
Control of Corruption ($C_{j,t}$)	1.638	0.572	0.127	2.446	24,420
Entry Count$_{i,j,t}$ ($\lambda_{i,j,t}$)	188.117	639.324	0	12136	24,420
Entry Rate$_{i,j,t}$	8.337	11.279	0	366.667	24,420
Failure Rate$_{i,j,t}$ ($f_{i,j,t}$)	2.741	4.241	0	100	24,420
Firm Count$_{i,j,t}$	20.502	56.176	0.01	900.45	24,420
Real GDP Growth Rate$_{i,j,t}$	1.175	2.942	-8.269	6.334	24,420
Unemployment Rate$_{i,j,t}$	6.819	2.892	2.529	19.945	24,420

Table 2: Founding Rate Models

EQUATION	VARIABLES	(1) $\lambda_{i,j,t}$	(2) $\lambda_{i,j,t}$	(3) $\lambda_{i,j,t}$
$\lambda_{i,j,t}$	Entry Rate$_{i,j,t-1}$	0.0459***	0.0458***	0.0451***
		(0.00817)	(0.00806)	(0.00793)
	$C_{j,t-1}$	0.892***	0.932***	0.696**
		(0.296)	(0.294)	(0.284)
	GDP Growth$_{j,t-1}$	0.0327	0.0328	0.0357
		(0.0343)	(0.0342)	(0.0340)
	Unemployment Rate$_{j,t-1}$	-0.0851**	-0.0860**	-0.0820**
		(0.0415)	(0.0415)	(0.0408)
	Firm Density$_{i,j,t-1}/10^2$	0.0391***	0.0389***	0.0389***
		(0.00190)	(0.00193)	(0.00195)
	Firm Density$^2_{i,j,t-1}/10^6$	-0.00421***	-0.00419***	-0.00418***
		(0.000205)	(0.000208)	(0.000209)
	$f_{i,j,t-1}$		0.0213**	-0.0833***
			(0.00987)	(0.0238)
	$C_{j,t-1}f_{i,j,t-1}$			0.0596***
				(0.0140)
$ln(\alpha)$	Constant	0.409***	0.407***	0.405***
		(0.0323)	(0.0320)	(0.0317)
	Observations	24,365	24,365	24,365

Robust standard errors in parentheses

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 3: Zero-Inflated Founding Rate Models

EQUATION	VARIABLES	(1) $\lambda_{i,j,t}$	(2) $\lambda_{i,j,t}$	(3) $\lambda_{i,j,t}$
$\lambda_{i,j,t}$	Entry $\text{Rate}_{i,j,t-1}$	0.0421***	0.0421***	0.0416***
		(0.00763)	(0.00762)	(0.00757)
	$C_{j,t-1}$	0.859***	0.865***	0.706**
		(0.299)	(0.298)	(0.288)
	GDP $\text{Growth}_{j,t-1}$	0.0344	0.0344	0.0362
		(0.0364)	(0.0364)	(0.0363)
	Unemployment $\text{Rate}_{j,t-1}$	-0.0861**	-0.0863**	-0.0839**
		(0.0428)	(0.0427)	(0.0420)
	Firm $\text{Density}_{i,j,t-1}/10^2$	0.0349***	0.0348***	0.0348***
		(0.00156)	(0.00157)	(0.00158)
	Firm $\text{Density}^2_{i,j,t-1}/10^6$	-0.00374***	-0.00374***	-0.00373***
		(0.000172)	(0.000173)	(0.000173)
	$f_{i,j,t-1}$		0.00327	-0.0653**
			(0.00714)	(0.0271)
	$C_{j,t-1}f_{i,j,t-1}$			0.0386***
				(0.0144)
$Pr(\lambda_{i,j,t} = 0)$	$\lambda_{i,j,t-1}$	-0.759***	-0.759***	-0.757***
		(0.0746)	(0.0741)	(0.0741)
	Firm $\text{Density}_{i,j,t-1}/10^2$	-2.888***	-2.889***	-2.913***
		(0.606)	(0.605)	(0.607)
	Firm $\text{Density}^2_{i,j,t-1}/10^6$	0.506***	0.506***	0.509***
		(0.0825)	(0.0824)	(0.0828)
	Constant	1.072***	1.072***	1.072***
		(0.0717)	(0.0718)	(0.0718)
$ln(\alpha)$	Constant	0.0848***	0.0848***	0.0841***
		(0.0302)	(0.0302)	(0.0300)
	Observations	24,365	24,365	24,365

Robust standard errors in parentheses

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 4: Log-linear Founding Models

VARIABLES	(1) $ln(\lambda_{i,j,t}+1)$	(2) $ln(\lambda_{i,j,t}+1)$	(3) $ln(\lambda_{i,j,t}+1)$
Entry $\text{Rate}_{i,j,t-1}$	0.0109***	0.0112***	0.0109***
	(0.00266)	(0.00267)	(0.00261)
$C_{j,t-1}$	0.890***	0.934***	0.754**
	(0.294)	(0.295)	(0.288)
GDP $\text{Growth}_{j,t-1}$	0.0298	0.0296	0.0320
	(0.0328)	(0.0327)	(0.0322)
Unemployment $\text{Rate}_{j,t-1}$	-0.0842**	-0.0857**	-0.0815**
	(0.0368)	(0.0374)	(0.0364)
Firm $\text{Density}_{i,j,t-1}/10^2$	0.0354***	0.0352***	0.0352***
	(0.00115)	(0.00113)	(0.00113)
Firm $\text{Density}^2_{i,j,t-1}/10^6$	-0.00464***	-0.00463***	-0.00462***
	(0.000273)	(0.000269)	(0.000267)
$f_{i,j,t-1}$		0.0202**	-0.0545***
		(0.00795)	(0.0155)
$C_{j,t-1}f_{i,j,t-1}$			0.0426***
			(0.0103)
Observations	24,365	24,365	24,365
R-squared	0.651	0.652	0.654

Robust standard errors in parentheses
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 5: Industry-Country Fixed Effects Founding Rate Models

VARIABLES	(1) $ln(\lambda_{i,j,t}+1)$	(2) $ln(\lambda_{i,j,t}+1)$	(3) $ln(\lambda_{i,j,t}+1)$
Entry Rate$_{i,j,t-1}$	0.00223	0.00274	0.00235
	(0.00245)	(0.00241)	(0.00237)
$C_{j,t-1}$	-0.285*	-0.290*	-0.281*
	(0.145)	(0.154)	(0.148)
GDP Growth$_{j,t-1}$	-0.00255	-0.00117	0.0128
	(0.0416)	(0.0407)	(0.0413)
Unemployment Rate$_{j,t-1}$	-0.148**	-0.149**	-0.107
	(0.0594)	(0.0644)	(0.0719)
Firm Density$_{i,j,t-1}/10^2$	0.0450***	0.0450***	0.0448***
	(0.00137)	(0.00139)	(0.00139)
Firm Density$^2_{i,j,t-1}/10^6$	-0.00583***	-0.00582***	-0.00580***
	(0.000305)	(0.000304)	(0.000304)
$f_{i,j,t-1}$		0.00703	-0.0348**
		(0.00720)	(0.0164)
$C_{j,t-1}f_{i,j,t-1}$			0.0255**
			(0.0113)
Observations	24,365	24,365	24,365
Number of Country-Industry Groups	4,153	4,153	4,153

Robust standard errors in parentheses

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 6: Country-Year Fixed Effects Founding Rate Models

VARIABLES	(1) $ln(\lambda_{i,j,t}+1)$	(2) $ln(\lambda_{i,j,t}+1)$	(3) $ln(\lambda_{i,j,t}+1)$
Entry Rate$_{i,j,t-1}$	0.0176***	0.0179***	0.0176***
	(0.00306)	(0.00307)	(0.00302)
Firm Density$_{i,j,t-1}/10^2$	0.0426***	0.0424***	0.0424***
	(0.00135)	(0.00134)	(0.00133)
Firm Density$^2_{i,j,t-1}/10^6$	-0.00564***	-0.00562***	-0.00561***
	(0.000325)	(0.000322)	(0.000320)
$f_{i,j,t-1}$		0.0196**	-0.0474***
		(0.00826)	(0.0175)
$C_{j,t-1}f_{i,j,t-1}$			0.0382***
			(0.0111)
Observations	24,365	24,365	24,365
R-squared	0.489	0.490	0.491

Robust standard errors in parentheses

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 7: Instrumental Variables Founding Rate Models

VARIABLES	(1) $ln(\lambda_{i,j,t}+1)$	(2) $ln(\lambda_{i,j,t}+1)$	(3) $f_{i,j,t-1}$	(4) $f_{i,j,t-1}$	(5) $C_{j,t-1}f_{i,j,t-1}$
$f_{i,j,t-1}$	0.143***	-0.108			
	(0.0397)	(0.120)			
$C_{j,t-1}f_{i,j,t-1}$		0.154**			
		(0.0713)			
Entry Rate$_{i,j,t-1}$	0.0210***	0.0201***	-0.0153***	-0.0154***	-0.0199***
	(0.00369)	(0.00355)	(0.00322)	(0.00320)	(0.00628)
$C_{j,t-1}$	1.170***	0.548	-1.878***	-1.956***	0.363
	(0.351)	(0.382)	(0.458)	(0.463)	(0.900)
GDP Growth$_{j,t-1}$	0.0366	0.0436	0.0338	0.0350	-0.00289
	(0.0363)	(0.0353)	(0.0384)	(0.0386)	(0.0690)
Unemployment Rate$_{j,t-1}$	-0.0989**	-0.0833**	0.0821*		
	(0.0409)	(0.0373)	(0.0446)		
Firm Density$_{i,j,t-1}/10^2$	0.0405***	0.0402***	0.00691***	0.00692***	0.0134***
	(0.00132)	(0.00131)	(0.00170)	(0.00171)	(0.00355)
Firm Density$^2_{i,j,t-1}/10^6$	-0.00527***	-0.00523***	-0.000734***	-0.000735***	-0.00152***
	(0.000298)	(0.000290)	(0.000267)	(0.000268)	(0.000561)
$\widehat{f_{i,j,t-2}}$			0.116***	0.0780**	-0.0981*
			(0.0183)	(0.0340)	(0.0513)
$\widehat{f_{i,j,t-2}}C_{j,t-2}$				0.0245	0.184***
				(0.0256)	(0.0478)
Observations	20,209	20,209	20,209	20,209	20,209
R-squared	0.438	0.410			

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1