Financial Crises and Labor Market Turbulence

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August 17, 2009

Abstract

Financial crises cause a significant reallocation of labor across sectors and occupations. This results in productivity losses, as workers devote time to learning new skills, among other possible transition costs. In other words, crises are periods of high turbulence in the sense of Ljungqvist and Sargent (1998). In this paper, we provide strong evidence that these productivity losses were substantial in the case of Mexico's 1994-95 crisis. Workers who changed occupations or sectors during the crisis lost more than 10% of their hourly earnings, compared to those who did not move. We also show that these losses in productivity can account for over 40% of the drop in conventionally-measured TFP that took place during the crisis.

Keywords: Financial crises; labor market turbulence, total factor productivity; output fluctuations

JEL classification: E32; F41; J24

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1 Introduction

Financial crises cause real output to collapse. They also cause massive changes in relative prices and, therefore, a significant reallocation of resources. Many workers are constrained to change jobs, occupations or sectors, leading to losses in productivity. In this paper, we provide strong evidence that these losses were significant during Mexico's 1994-95 "Tequila" crisis. We also argue that this fact could help account for the well documented observation that output typically falls much more during crises than what standard measures of labor and capital use would lead us to expect.[1]

We show that the frequency of worker movements across occupations and sectors rises during crises, using data from Mexico's *Encuesta Nacional de Empleo Urbano,* a broad urban household survey. Furthermore, the fraction of involuntary (employer-initiated) separations rises significantly during the Tequila crisis. At the same time, we find that workers who changed sectors and/or occupations experienced a significantly larger fall in hourly earnings than observably similar workers who stayed put in this period. This pattern is robust to a host of econometric considerations. In particular, we use a rich longitudinal data set to control for the effects of worker heterogeneity, and employ semi-parametric methods to ensure that our results do not depend on a particular specification of the earnings function.

That worker productivity losses and the associated losses of earnings should be significant during crises makes intuitive sense. As relative prices change and employers adjust, many workers move, often involuntarily as jobs are destroyed, to vastly different occupations and industries.[2] Our empirical results constitute strong evidence that financial crises are periods of turbulence in the sense of Ljungqvist and Sargent (1998), i.e. periods of rapid change in the economic environment causing unusually high losses of skills for displaced workers.[3]

We also argue that these losses in productivity play a quantitatively significant role in the

[1]See Meza and Quintin (2007) for a review.

[2]As Neal (1995) shows, displacement costs are positively related to the distance between the worker's old and new industry. Kambourov and Manovskii (2009) document substantial returns to occupational tenure.

[3]See von Wachter et. al (2007) for empirical evidence of the wage losses due to separations in the 1982 recession.

behavior of key macroeconomic variables during crises. A drop in the average quality of labor causes measured labor to diverge from effective labor, and output to fall. In this context, a standard growth accounting exercise attributes most of the output change to a a fall in measured total factor productivity (TFP). This makes labor market turbulence a promising explanation for the unusual behavior of measured TFP during financial crises.[4]

To formalize this intuition, we describe a model that establishes the theoretical link between losses in worker productivity and the behavior of conventionally-measured TFP. Specifically, we consider an environment where firms combine the labor of heterogenous workers with physical capital to produce a homogeneous good. Workers differ in terms of the human capital they are able to deliver in each period. We show that aggregate output in this environment is a simple function of aggregate capital, aggregate employment, and the average productivity of workers, establishing a tight link between the reallocation of labor and TFP as it is conventionally defined. Numerical simulations suggest that our estimates of productivity losses at the microeconomic level can account for over 40% of the fall in TFP and output during Mexico's Tequila crisis. Labor market turbulence could therefore be a significant determinant of the real impact of financial crises.

Any study that uses occupation and sector information from survey data must confront the issue of measurement error (see Brown and Light, 1994, Mathiowetz, 1992, and Kambourov and Manovskii, 2009), and ours is no exception. However, we do not expect this to undermine our results for several reasons. First, measurement error issues affect the identification of occupation and sector changes both during the crisis period and outside of it. An increase in both movements and earnings losses during the crisis seems unlikely to be due to an increase in measurement error in this particular period. Second, pure measurement error makes finding significant earnings losses associated with occupation or sector switches less likely, and should,

[4]Several studies (see for example Meza and Quintin, 2007, Gertler et al. 2007, Otsu, 2006) have argued that crises create strong incentives for firms to postpone the use of labor and capital services until conditions improve. They find that factor utilization can account for a significant part in the drop of TFP that occurs during crises. Other explanations for the fall in TFP are founded on financial frictions. Pratap and Urrutia (2008) show that with a cash in advance constraint on firms' purchase of intermediate goods, a rise in interest rates leads to an increase in the misallocation of resources and a fall in TFP.

if anything, weaken the relationship between occupation and sector tenure and earnings. It is also reassuring that identifying switches as a change in both occupation and sector (rather than a change in either respect) produces results similar to our baseline estimations.

Another set of issues common to all studies of the consequences of displacement concerns the determinants of the associated losses. First, the individuals who move may be very different from those who do not, and the difference in earnings between the two may reflect these observed and unobserved differences. We condition on a rich set of observed variables and use pre- and post-crisis earnings to partially deal with the role unobserved heterogeneity. More fundamentally, displacement losses are consistent with a number of economic models.[5] Like Ljungqvist and Sargent (1998), our prior is that skill (human capital) losses are a major cause for the rise in displacement losses that characterizes turbulent economic periods. However, job switches could be correlated with other factors that affect worker productivity and the resulting impact of earnings would owe to those factors rather than losses in specific human capital. The most obvious alternative interpretation for displacement losses is that job changes cause productive matches between a worker and a given employer, sector, or occupation to be destroyed.[6] Our goal in this paper is not to settle this important debate on the causes of displacement losses. Rather, we highlight the losses in productivity caused by this displacement, regardless of their source, and provide strong evidence that these losses become particularly large during crises. This suggests that labor markets should be a focal point of the research on the causes of the devastating effects of financial crises.

The next section describes some of the macroeconomic shocks that occurred during Mexico's Tequila crisis, and the acceleration in involuntary labor flows that characterized that

[5] Jovanovic (1979a) describes a model where workers invest in employer-specific capital over time, formalizing ideas contained in Becker (1962), Oi (1962) and Mincer (1974) among others. Worker productivity also rises with job tenure as a result of learning-by-doing, as argued by Jovanovic and Nyarko (1995). In Jovanovic (1979b), workers learn about the quality of their match with their employer over time so that long employment spells tend to be signal good matches. Lazear (1981) argues that in models where productivity depends on unobservable effort, the optimal compensation profile is characterized by lower initial earnings in exchange for actuarially fair payments later in the life of the employment contract.

[6] As Kambourov and Manovskii (2007) argue, the fact that workers often move to pursue better matches is less of a concern since, if anything, it biases the estimated effect of occupation and sector switches downward.

period. Section 3 establishes that workers who changed sectors and/or occupations during the crisis suffered a substantial loss in hourly earnings, compared to similar individuals who do not move. Section 4 presents a model that formalizes the link between worker productivity and aggregate TFP. In the subsequent section we calibrate the model to the Mexican economy and show that a drop in labor quality compatible with the observed wage losses for movers accounts for over 40% of the fall in observed output and TFP. Calibrating the persistence of the productivity loss to match the persistence of earnings in the data, we find that the model can also account for the slow recovery of TFP after the crisis. Section 6 concludes.

2 Financial turmoil and worker movements

This section documents some of the deep shocks that characterized Mexico's Tequila crisis, and the fact that the pace of worker reallocation increased significantly during that period.

2.1 A myriad of shocks

Financial crises bring about a variety of shocks, making some activities more profitable than others. Figure 1 plots some of these shocks in the case of Mexico's Tequila crisis. Vertical bars mark the start of the Tequila Crisis, namely the very end of 1994. The interest rate on dollar-denominated debt soared during the first two quarters of 1995. Meanwhile, the real exchange rate depreciated by over 50%, and the price of domestic traded goods relative to non-traded goods rose by about 8%. The fiscal environment also changed sharply as the government, in an effort to reduce budget deficits, increased the average consumption tax rate in the first quarter of 1995 from about 10% to over 13%.[7]

As the final panel of figure 1 shows, 1995 was also characterized by a collapse of conventionally-measured TFP. To measure aggregate TFP, we follow standard practice and assume that aggregate technological opportunities are well described by:

[7]The regulated price of energy products also increased drastically in this period.

$$\widehat{y}_t = z_t \widehat{k}_t^{\alpha} l_t^{1-\alpha},$$

where $\widehat{y}_t$ and $\widehat{k}_t$ are detrended output and capital divided by the size of the working-age population, l_t denotes hours worked per working-age individual, and z_t is a stationary TFP process. The data appendix explains how we constructed all aggregate variables. We set α, the capital share, to 0.3, a value in the middle of the range of estimates available in Gollin (2002). The magnitude of the TFP collapse during the Tequila crisis is striking. TFP fell by over 8% during the crisis. This phenomenon is not confined to Mexico. As Meza and Quintin (2007) show with data from Indonesia, South Korea, Thailand, and Argentina, most crises trigger falls in TFP of an unusual magnitude.

2.2 Worker reallocation

The multitude of shocks that hit Mexico in 1995 created strong incentives for worker movements across employers, occupations and sectors. To gauge the intensity and the consequences of these movements, we use detailed microeconomic data from a nationally representative quarterly employment and remuneration survey, the *Encuesta Nacional de Empleo Urbano* (ENEU). This is a rotating panel with up to 5 quarters of information for each worker, which includes individual data such as age, gender, education, marital status, and occupation and job characteristics such as benefits received, employer size, and sector of activity. Our sample consists of all individuals between the age of 16 and 65 for the period 1988 to 1999 at a quarterly frequency, for a total of about 3 million observations.

The survey reveals that the composition of the labor force changed significantly in 1995. Most prominently, the country's open unemployment rate increased throughout 1995, from 3.4% in the last quarter of 1994 to 6.5% by the third quarter of 1995. As figure 2 shows, a large fraction of this unemployment was involuntary, i.e. employer initiated.[8] Before the

[8] Appendix A.1 provides a formal definition of involuntary separations, and of other variables we use in our empirical analysis.

crisis, terminations were initiated in roughly equal proportions by employers and employees. In 1995 however, the fraction of employer-initiated terminations increased to more than 70% and did not return to pre-crisis levels until the end of the following year.

Inactivity spells, whether voluntary or involuntary, are only part of the reallocation story. Many workers who remained employed through the crisis reported a change in sector or occupation during this period.[9] To identify meaningful changes at a disaggregated level, we consider changes at the 4-digit level of the sectoral and occupational classification. The 4-digit level of the Mexican classification corresponds roughly to the 3-digit level of the census code classification employed by Kambourov and Manovskii (2009) in most of their analysis of returns to sector and occupation tenure. For example, the 4-digit level of the Mexican classification separates medical professions into doctors, dentists, veterinarians etc., whereas the three-digit level lumps all medical professions together. As Kambourov and Manovskii (2009) argue, this is the level of detail where human capital seems most likely to be category-specific. We will nonetheless discuss estimation results for the coarser 3-digit level by way of sensitivity analysis.

Figure 3 shows the Kolmogorov-Smirnov test statistic for changes in the distribution of workers across sectors and occupations at the 4-digit level from quarter to quarter. The test statistic rises sharply in 1995, reflecting significant changes in the occupational and sectoral composition of the work force.[10]

Changes in the distribution of workers across sectors and occupations reflect net, rather than gross flows. The longitudnal nature of the ENEU data also allows us to provide direct evidence that the gross rate of occupational and sector change accelerated in 1995. Table 1 shows the fraction of workers that change sector and occupation between the last quarter of each year and the preceding year. This fraction increased noticeably between 1994 and

[9] For the sake of brevity, we concentrate on a few indicators, but reallocation took place along a number of different dimensions. For instance, the fraction of workers employed by large firms fell markedly during the crisis, as did the fraction of workers who received the benefits mandated by Mexico's labor laws.

[10] Since the occupational classification changed in the second quarter of 1992, we cannot compute the change in occupational distribution between 1991-1992. We obtained similar results at the three-digit level.

1995, as did the fraction of workers who changed sectors only. Only 34% of workers report no change in either sector or occupation in 1995, down from 41% in the previous year.[11] From 1996 onwards, worker movements came back to pre-crisis levels. This suggests that the movements that had taken place in the previous years were not immediately reversed.

Table 1: Frequency of movements across sectors and occupations

	Sector change only	Occupation change only	Both	No change
1988.4 to 1989.4	0.12	0.23	0.30	0.36
1989.4 to 1990.4	0.13	0.24	0.27	0.36
1990.4 to 1991.4	0.13	0.23	0.27	0.37
1991.4 to 1992.4	NA	NA	NA	NA
1992.4 to 1993.4	0.14	0.21	0.26	0.40
1993.4 to 1994.4	0.13	0.22	0.24	0.41
1994.4 to 1995.4	0.20	0.18	0.28	0.34
1995.4 to 1996.4	0.12	0.22	0.23	0.43
1996.4 to 1997.4	0.12	0.22	0.23	0.43
1997.4 to 1998.4	0.10	0.22	0.24	0.43
1998.4 to 1999.4	0.11	0.23	0.25	0.42

While it is not possible to decompose flows across occupations and sectors between employer and employee-initiated movements (since the survey only inquires about the reason for terminations from currently unemployed workers), we do know whether the individuals who changed sector or occupation during a given 4-quarter period were unemployed at some point in the interim. If unemployed at some point, we also know whether they left of their own accord or not. Table 2 shows the fraction of movers who were unemployed for at least one quarter during each calendar year, and the fraction that were involuntarily unemployed.

The fraction of movers who experienced at least one unemployment spell between the fourth quarter of 1994 and the fourth quarter of 1995 increased markedly to 7% for movers

[11]The drop in the fraction of individuals that changed occupation without changing sectors could reflect a decline in upward mobility in this period. In other words, promotions that involve a change in occupation from worker to manager are probably less frequent in periods of crisis.

Table 2: Fraction of unemployed movers

	4-digit sample		3-digit sample	
	Unemployment	Involuntary	Unemployment	Involuntary
1988.4 to 1989.4	0.0252	0.0129	0.0268	0.0142
1989.4 to 1990.4	0.0356	0.0205	0.0379	0.0207
1990.4 to 1991.4	0.0332	0.0195	0.0347	0.0203
1991.4 to 1992.4	NA	NA	NA	NA
1992.4 to 1993.4	0.0449	0.0311	0.0483	0.0336
1993.4 to 1994.4	0.0502	0.0385	0.0531	0.0408
1994.4 to 1995.4	0.0695	0.0607	0.0750	0.0653
1995.4 to 1996.4	0.0573	0.0461	0.0608	0.0486
1996.4 to 1997.4	0.0414	0.0273	0.0429	0.0289
1997.4 to 1998.4	0.0389	0.0266	0.0406	0.0277
1998.4 to 1999.4	0.0373	0.0244	0.0385	0.0256

Notes: Unemployment figures give the fraction of workers who change sectors and/or occupations between the fourth quarter of two consecutive years, and who report being unemployed in at least one quarter in the interim. The involuntary column reports the fraction of these workers who became involuntarily unemployed.

at the 4-digit level, and 7.5% for movers at the 3-digit level. These numbers are much larger than the corresponding figures during other periods. Over 87% of this unemployment was involuntary, compared to around 50% outside the crisis.

In summary, the Tequila crisis was accompanied by significant movements in labor markets, many of which were employer-initiated. We will now show that these labor market movements were associated with significant wage losses.

3 Labor market reallocation and earnings

Our basic thesis is that the acceleration of labor reallocation that occurs during crises causes losses in worker productivity. Movements that occur during crises are more likely to be involuntary, or employer-initiated. Furthermore, since these are periods of rapid and large relative price changes, many workers have to move to occupations and sectors much different from their prior employment experience. We would thus expect more displaced workers to find themselves in jobs for which their accumulated skills are ill-suited, and where new skills must be acquired, causing at least transitory losses in productivity. This section formally tests this hypothesis by comparing the change in the earnings of individuals who stay in the same sector and occupation with the earnings of individuals who experience a change in either respect. If movers tend to become less productive than workers who stay put, we would expect them to have lower earnings, even after controlling for other individual characteristics. Our hypothesis is that these differences should be particularly high during crisis periods.

3.1 Parametric results

Tables 3 and 4 show the results of estimations of variations on standard Mincer regressions designed to determine the effect of occupational and sectoral changes on real hourly earnings. The variable *Stayers* takes value 1 at time t if the individual stays in the same occupation and the same sector in that quarter as in the previous quarter, and takes value 0 otherwise.[12] The *Crisis Dummy* is set to 1 for all quarters of 1995. Table 3 uses the 4-digit sector and occupation classification to construct the dummy for stayers, while table 4 considers moves at the 3-digit level. In addition to standard controls, dummies for formal employment, large firms and self-employment are included. We consider an individual formally employed if he/she receives health insurance or retirement benefits, as mandated by Mexico's labor laws. All estimations include fixed effects to account for unobserved heterogeneity and the non-random nature of occupation and sector changes. All variables are defined in appendix A.1.

The coefficients on standard variables all have their expected signs. Earnings rise with age, are higher for formal sector workers and self-employed workers. Large firms pay a significant wage premium. The returns associated with staying in the same occupation and sector tend to be quantitatively small and negative in normal times. Accounting for individual heterogeneity, the wages of movers are, on average, about 0.8% higher than the wages of stayers. This changes markedly during the crisis. Although wages for stayers fall by about 10% in this period, the

[12] Since we observe individuals for at most 5 quarters, we cannot construct a variable measuring sectoral or occupational tenure.

Table 3: Parametric results for changes at the 4-digit level

Dependent Variable: Log Real Hourly Earnings			
Constant	1.14801 (0.03398)	1.25998 (0.03419)	1.25495 (0.03421)
Age	0.02711 (0.00184)	0.02437 (0.00184)	0.02444 (0.00184)
Age^2	-0.00053 (0.00003)	-0.00054 (0.00003)	-0.00054 (0.00003)
Education	0.00494 (0.00075)	0.00479 (0.00075)	0.00479 (0.00075)
Formal	0.11003 (0.00112)	0.10964 (0.00112)	0.10970 (0.00112)
Self Employed	0.25256 (0.00138)	0.25214 (0.00138)	0.25202 (0.00138)
Large Firm	0.07075 (0.00116)	0.07092 (0.00116)	0.07093 (0.00116)
Stayers	-0.00850 (0.00073)	-0.00723 (0.00073)	-0.00365 (0.00118)
Crisis Dummy	-0.10919 (0.00293)	-0.11842 (0.00294)	-0.11590 (0.00302)
Crisis × Formal	0.00739 (0.00304)	0.00800 (0.00304)	0.00757 (0.00304)
Crisis × Self Employed	-0.02600 (0.00327)	-0.02378 (0.00327)	-0.02281 (0.00327)
Crisis × Large Firm	-0.00084 (0.00287)	-0.00176 (0.00287)	-0.00198 (0.00287)
Crisis × Stayers	0.06761 (0.00223)	0.05970 (0.00224)	0.05626 (0.00241)
Individual Effects	yes	yes	yes
Year Effects	no	yes	yes
Year × Stayers	no	no	yes

Notes: Standard errors are in parenthesis.

wage gap between movers and stayers reverses its sign and increases substantially. Individuals who change sector and/or occupation during the crisis suffer a penalty of about 6% compared to other workers. This is robust to the inclusion of year dummies, and to allowing for yearly variation in the returns to stayers, as the second and third specifications show.[13]

Table 4 confirms this pattern when sector and occupation changes are defined using the 3-digit rather than the 4-digit level classification. During normal times the returns from moving are quantitatively insignificant and slightly positive on average, ranging from 0.2% to 0.7%. During the crisis however, they become sharply negative, at about -7%. As before, these results continue to hold after including a time-varying coefficient on the stayer dummy.

To highlight the singularity of the crisis period, table 5 shows the premium for stayers

[13]It is worth noticing that the change in the formality premium and the firm size premium during the crisis is negligible. Individuals who moved to self employment saw their wages fall by about 2.5%. However, the magnitude of labor flows to self employment is dwarfed by moves between sectors and occupations.

Table 4: Parametric results for changes at the 3-digit level

Dependent Variable: Log Real Hourly Earnings			
Constant	1.14354 (0.03390)	1.25645 (0.03411)	1.25077 (0.03413)
Age	0.02729 (0.00183)	0.02451 (0.00184)	0.02459 (0.00184)
Age^2	-0.00053 (0.00003)	-0.00054 (0.00003)	-0.00054 (0.00003)
Education	0.00491 (0.00075)	0.00477 (0.00075)	0.00476 (0.00075)
Formal	0.11012 (0.00112)	0.10972 (0.00112)	0.10978 (0.00112)
Self Employed	0.25226 (0.00138)	0.25188 (0.00138)	0.25176 (0.00138)
Large Firm	0.07087 (0.00116)	0.07103 (0.00116)	0.07103 (0.00116)
Stayers	-0.00777 (0.00075)	-0.00654 (0.00075)	-0.00212 (0.00123)
Crisis Dummy	-0.10907 (0.00301)	-0.11841 (0.00302)	-0.11523 (0.00310)
Crisis × Formal	0.00654 (0.00304)	0.00726 (0.00304)	0.00683 (0.00304)
Crisis × Self Employed	-0.02366 (0.00327)	-0.02171 (0.00326)	-0.02076 (0.00327)
Crisis × Large Firm	-0.00216 (0.00287)	-0.00293 (0.00287)	-0.00310 (0.00287)
Crisis × Stayers	0.06489 (0.00233)	0.05731 (0.00233)	0.05316 (0.00251)
Individual Effects	yes	yes	yes
Year Effects	no	yes	yes
Year × Stayers	no	no	yes

Notes: Standard errors are in parenthesis.

each year, relative to 1994. For most years outside the crisis, this premium is negative and small. In sharp contrast, the crisis-period coefficient is large and statistically significant.

3.2 Semiparametric results

To ensure that these results are not driven by changes in a few sectors or occupations, or by the parameterization of the wage equation, we now implement a semiparametric matching estimator of the impact of sectoral and occupational changes on wages. This method also has the advantage of dealing with selection on the basis of observed characteristics more effectively by restricting comparisons to similar workers. We match workers on the basis of initial sector and occupation, as well as propensity scores.[14] The latter are defined as the probability of treatment, where treatment in this context means a change in sector, occupation, or both.

[14]For more details on propensity score matching, see Rosenbaum and Rubin (1983, 1984). Dehejia and Wahba (2002) discuss propensity score matching in a non-experimental context.

Table 5: Returns to stayers

Year × Stayers	4-digit level	3-digit level
1988	-0.01666 (0.00379)	-0.01848 (0.00393)
1989	0.00325 (0.00354)	0.00196 (0.00365)
1990	0.00839 (0.00354)	0.00689 (0.00366)
1991	-0.00604 (0.00352)	-0.00705 (0.00363)
1992	-0.01332 (0.00266)	-0.01534 (0.00275)
1993	-0.00457 (0.00269)	-0.00557 (0.00281)
1995	0.05626 (0.00241)	0.05316 (0.00251)
1996	0.00672 (0.00255)	0.00635 (0.00265)
1997	-0.01499 (0.00248)	-0.01763 (0.00257)
1998	-0.00170 (0.00236)	-0.00260 (0.00245)
1999	-0.00760 (0.00240)	-0.00794 (0.00248)

Notes: The table shows the coefficient on the time and stayer dummy interaction variable for each year based on the final specification in Tables 3 and 4. Standard errors are in parenthesis.

The propensity score for each period is estimated using a probit on individual and firm characteristics such as age, education, gender, self-employment and formality status, and firm size. It is important to emphasize that the resulting scores should not be interpreted in a literal, causal sense, but rather as a convenient method for collapsing multidimensional characteristics into a single-dimensional index for ease of matching. Given our purposes, it is important to verify that estimated scores are an effective proxy for observable worker characteristics. Table 10 in the appendix shows that average characteristics for individuals with similar propensity scores are never statistically different for movers and stayers. By comparing workers with similar propensity scores, we are comparing observably similar workers.

We consider yearly intervals, and compare wages between the fourth quarters of each year. Results are similar for different comparisons, but comparing fourth quarter numbers is convenient because the Tequila crisis began at the end of the fourth quarter of 1994. At a given date the treatment group consists of workers who change sector, occupation or both during the subsequent year. Formally, let N_t be the set of workers who are employed both at date t and at date $t+1$ (four quarters later), and let $N_t^T \subset N_t$ be the subset of workers who remain employed but experience a change in sector and/or occupation between date t and date $t+1$.[15] For a given worker $i \in N_t$, let $o_t(i)$ and $s_t(i)$ denote respectively the worker's occupation and sector, while $p_t(i)$ is his/her propensity score, i.e. the estimated ex-ante probability of experiencing a job change at date t. For each worker i in date t's treatment group N_t^T, we form the following control group:

$$N_t^C(i) = \{j \in N_t - N_t^T : \; o_t(j) = o_t(i), \quad s_t(j) = s_t(i), \text{ and } |p_i - p_j| < \epsilon\},$$

where $\epsilon > 0$ is a specified tolerance level. In other words, the control group comprises of workers in the same sector and occupation as worker i at date t, whose propensity score is close to worker i's, but do not experience a change between date t and date $t+1$. To form a comparison wage, we assign each worker $j \in N_t^C(i)$ a weight that depends on how close their propensity score is to worker i's. Specifically,

$$\eta_{ij} = \frac{\frac{1}{|p_i - p_j|}}{\sum_{m \in N_t^C(i)} \frac{1}{|p_i - p_m|}},$$

so that the weight assigned to a given worker in the control group is proportional to the inverse of the distance between their propensity score and worker i's.

The resulting *Caliper* matching estimator is given by:

$$\delta_{t+1} = \frac{1}{\# N_t^T} \sum_{i \in N_t^T} \left[(w_{i,t+1} - w_{i,t}) - \sum_{m \in N_t^C(i)} \eta_{im} \left(w_{m,t+1} - w_{m,t} \right) \right]$$

where for all $i \in N_t$, $w_{i,t}$ and $w_{i,t+1}$ are worker i's log earnings at date t and $t+1$, respectively. In other words, we compare the change in log wages of individuals who moved from sector s or occupation o between date t and $t+1$ to the change in log wages of a group of similar individuals who stayed put in the same sector and occupation during the same period.

The results of this exercise are summarized in table 6 for $\varepsilon = 10^{-3}$. We present two

[15] It is possible for workers to experience an unemployment spell between these two periods.

Table 6: Semiparametric results

	4 digit		3 digit
	δ^1	δ^2	δ^3
1988.4 to 1989.4	0.0835 (0.0960)	-0.0131 (0.0631)	0.0891 (0.0925)
1989.4 to 1990.4	-0.0815 (0.1604)	-0.0029 (0.0897)	-0.2068 (0.1170)
1990.4 to 1991.4	0.1469 (0.1098)	0.0743 (0.0697)	-0.0712 (0.1087)
1991.4 to 1992.4	NA	NA	NA
1992.4 to 1993.4	0.0432 (0.0715)	0.0295 (0.0437)	-0.0157 (0.0527)
1993.4 to 1994.4	0.0550 (0.0554)	0.0076 (0.0363)	0.0371 (0.0587)
1994.4 to 1995.4	-0.1294 (0.0378)	-0.0878 (0.0156)	-0.1428 (0.0614)
1995.4 to 1996.4	-0.0355 (0.0541)	-0.0584 (0.0329)	-0.0048 (0.0528)
1996.4 to 1997.4	0.0838 (0.0501)	-0.0155 (0.0317)	0.0743 (0.0480)
1997.4 to 1998.4	0.0118 (0.0458)	0.0237 (0.0291)	0.0079 (0.0426)
1998.4 to 1999.4	-0.0154 (0.0406)	0.0032 (0.0257)	-0.0051 (0.0342)

Notes: $\varepsilon = 10^{-3}$. Standard errors are in parenthesis. Individuals are considered movers if they change sectors and/or occupations. δ^1 is the estimated effect of changes when 4 digit movers are matched on propensity scores, initial 4 digit sector and occupation. δ^2 matches 4 digit movers on propensity scores, initial 2 digit sector and occupation. δ^3 matches 3 digit movers on propensity scores, initial 3 digit sector and occupation.

sets of estimates at the 4-digit level.[16] δ^1 refers to the matching estimator where individuals who change sector and/or occupation at the 4-digit level are compared with individuals in the same initial 4-digit sector and occupation in an ε-neighborhood of their propensity score. However, these stringent requirements eliminate a large fraction of our sample. The second estimator, δ^2 still considers moves at a 4-digit level, but matches individuals on initial 2-digit sector and occupation, allowing us to double the size of the sample. The results in both cases are similar and confirm our parametric results. During the crisis, movers experience a loss of 9% to 13% greater than stayers on average. In normal times, this effect disappears and the differences in the change of log wages are small or imprecisely measured. δ^3 in the same table shows that this effect is robust at the 3 digit level. Earnings losses for movers are over 14% higher than for stayers durnig the crisis. Outside the crisis, these relative losses do not show any clear pattern and are rarely statistically significant.

[16]Results for 10^{-4} are very similar.

These semiparametric results confirm that labor movements during the crisis were accompanied by significant losses in hourly earnings.[17] We now turn to their economic significance.

4 Labor market turbulence and TFP

The microeconomic data we have discussed provide strong evidence of large and statistically significant productivity losses among workers who changed occupations and sectors during Mexico's Tequila crisis. This section presents numerical simulations that suggest that beyond their strong statistical significance, the estimates of productivity losses that we document in this paper have important consequences for the behavior of key macroeconomic variables.

In order to formalize and quantify the effects of labor market turbulence on aggregate productivity and output, we describe an open economy, neoclassical model where the map from the worker productivity process to conventionally-measured TFP can be made explicit. We then simulate the effects of a shock to the productivity process consistent with the empirical evidence we presented in the previous section, and compare these effects to the Mexican data. This exercise amounts to standard neoclassical accounting augmented to account for variations in unmeasured movements in the labor supply.

4.1 A model of TFP

Consider a discrete-time environment populated by a measure one of workers, and a representative, stand-in firm. All workers are endowed with a unit of time in each period, and we will assume for simplicity that they do not value leisure, hence devote it to work.

Denote the quantity of labor that worker $i \in [0,1]$ can deliver to the firm at date t by x_t^i. This effective labor supply evolves over time according to a Markov chain with finite support

[17]These results are robust to a host of alternative specifications, including kernel weights or equal weights for the caliper matching, as well as a decomposition of the earnings losses into losses due to sectoral changes and those due to occupational changes. In all cases, results are similar. Relative earnings per hour for movers fall during the crisis while they do not change significantly outside the crisis. These results are available on request from the authors.

X and transition probability function π. We also assume that a law of large number holds so that for all $(x, x') \in X^2$, a fraction $\pi(x, x')$ of workers of labor productivity x at date t see their productivity move to x' at date $t + 1$.

To keep the dimension of the economy's state at date t manageable, we adopt the representative family approach of Ljungqvist and Sargent (2007). Specifically, all workers belong to the same representative household that chooses a consumption plan $\{c_t^i : i \in [0, 1], t \geq 0\}$ to maximize

$$\int_0^1 \left(\sum_{t=0}^{+\infty} \beta^t \frac{(c_t^i)^\sigma}{\sigma} \right) di$$

where i indexes the household's member in $[0, 1]$ and $\sigma < 1$.

The representative household has access to an international capital market where one-period risk-free claims earn exogenous return r_t at date t. In this sense, we model Mexico as a small, open economy. We denote by a_t the household's net holding of this asset at date t. To rule out Ponzi schemes, we assume that asset holdings are bounded below, and that this exogenous bound is large enough in absolute value so as not to bind in equilibrium.

The household can also invest in physical capital, which it sells to the firm at price $1 + r_t^k$ at date t. Letting k_t be the quantity of capital held by households in period t, adjusting capital across periods carries a cost $\frac{\psi}{2} (k_{t+1} - k_t)^2$, where $\psi > 0$.[18]

In each period, the firm purchases capital from the household and hires workers of varying productivity. At date t the firm operates with capital K_t and with a measure N_t of workers with productivity levels distributed according to p_t. It will soon become clear that in any equilibrium in this environment, the firm will always be willing to hire all available workers.

We assume that at any date a worker of productivity level $x \in X$ combined with a quantity k of capital produces quantity $x^{1-\alpha} k^\alpha$ of the consumption good, where $\alpha \in (0, 1)$. We will think of a worker together with some capital as a job.[19] It follows that given input levels

[18] As is well-known, adjustment costs are necessary in open economy models to prevent investment from being counterfactually volatile. Assuming that adjustment costs are borne by households rather than firms is immaterial. An equivalent decentralization would have firms make investment decisions and bear adjustment costs. The specification we use shortens the exposition by keeping the firm's problem static.

[19] Ljungqvist and Sargent (2007) think of the same pair as a firm.

N, K, and the distribution of workers across skill levels p, at a given date, the firm maximizes gross aggregate output by choosing a capital allocation $k : X \mapsto I\!R_+$ to maximize:

$$\sum_{x \in X} Np(x)[x^{1-\alpha} k(x)^\alpha] \text{ subject to } \sum_{x \in X} Np(x)k(x) = K.$$

Clearly, it is optimal for the firm to equate the marginal product of capital across workers. Some algebra then implies that:

Proposition 4.1. *Given aggregate capital $K > 0$, aggregate labor N, and a distribution p of productivity, gross aggregate output is given by*

$$F(K, N, p) = \left(\sum_{x \in X} p(x)x \right)^{1-\alpha} K^\alpha N^{1-\alpha}.$$

Proof. Given our functional forms, equating marginal products across workers requires that $k(x) = xk(1)$ for all $x \in X$. Feasibility then implies that $k(1) = \frac{K}{N \sum_{x \in X} p(x)x}$. Plugging this information into the objective function shows maximized aggregate output to be:

$$\begin{aligned} \sum_{x \in X} Np(x)[x^{1-\alpha} k(x)^\alpha] &= \sum_{x \in X} Np(x)[x^{1-\alpha} (xk(1))^\alpha] \\ &= [N^{1-\alpha} K^\alpha] \times \frac{\sum_{x \in X} p(x)x}{\left(\sum_{x \in X} p(x)x\right)^\alpha} \\ &= \left(\sum_{x \in X} p(x)x \right)^{1-\alpha} K^\alpha N^{1-\alpha}. \end{aligned}$$

□

This aggregation result will enable us to measure the importance of unmeasured movements in the labor supply for the behavior of conventionally-measured TFP during Mexico's Tequila crisis. Indeed, note that:

$$\text{Conventionally-measured TFP } \equiv \frac{F(K, N, p)}{K^\alpha N^{1-\alpha}} = \left(\sum_{x \in X} p(x)x \right)^{1-\alpha}.$$

In particular, a fall in the quality of labor triggered by a spike in involuntary separations causes a drop in conventionally-measured TFP.

With this aggregation result at hand, we can complete the description of the firm's problem. Let w_t be the price of effective labor at date t. Our result above implies that it is only the total effective labor $N \sum_{x\in X} p(x)x$ that matters for the firm, so that a worker's earnings must be proportional to his contribution to this aggregate.[20] Given a rate δ of depreciation of physical capital, it follows that at date t the firm chooses a capital level K_t and a total effective labor level L_t that solves[21]:

$$\max K_t^{\alpha} L_t^{1-\alpha} - K_t(\delta + r_t^k) - L_t w_t.$$

As usual, with constant returns to scale, this problem only pins down the capital-labor ratio at which the firm is willing to operate.

Given these pricing conventions, the household's budget constraint at date t is given by:

$$\int_0^1 c_t^i di + a_{t+1} + k_{t+1} = \int_0^1 w_t x_t^i di + k_t(1 + r_t^k) - \frac{\psi}{2}\left(k_{t+1} - k_t\right)^2 + a_t(1 + r_t).$$

Since we have assumed that the distribution of labor productivity obeys a law of large numbers, and because we assume for the time being that the household foresees all prices perfectly, the household problem involves no uncertainty. Therefore, given (a_0, k_0) and the initial distribution $\{x_0^i : i \in [0,1]\}$ of worker productivity, the household simply chooses among affordable consumption profiles the one that maximizes $\int_0^1 \left(\sum_{t=0}^{+\infty} \beta^t \frac{\left(c_t^i\right)^{\sigma}}{\sigma}\right) di$. Standard arguments show that it is optimal for the household to equate consumption across household members at all dates so that we may write $c_t^i \equiv c_t$ for all t.

Given (a_0, k_0) and the initial distribution $\{x_0^i : i \in [0,1]\}$ of worker productivity, an equilib-

[20] Strictly speaking, this is true under the assumption that the firm does not offer insurance contracts to workers.

[21] Note that $1+r_t^k$ is the *net* price of physical capital. In other words, letting R_t^k denote the gross rental rate at date t, $r_t^k = R_t^k - \delta$. Making depreciation part of the firm's problem simplifies the discussion of endogenous capital utilization which follows later.

rium in this environment is a sequence of prices $\{w_t, r_t^k\}_{t=0}^{+\infty}$, household decisions $\{a_t, k_t, c_t\}_{t=0}^{+\infty}$, and firm decisions $\{L_t, K_t\}_{t=0}^{+\infty}$ such that:

1. Given prices, $\{a_t, k_t, c_t\}_{t=0}^{+\infty}$ solves the household's problem;
2. Given prices, (L_t, K_t) solves the firms's problem at date t for all $t \geq 0$;
3. The market for capital clears at all dates: $k_t = K_t$ for all $t \geq 0$;
4. The market for labor clears at all dates: $L_t = \int x_t^i di$ for all $t \geq 0$.

Simple manipulations of first-order conditions from the household's and the firm's problems show that the evolution of the capital stock and output in equilibrium in this open economy environment is characterized by the following second order difference equation, for all $t \geq 0$:

$$1 + r_{t+1} = \frac{1 + \left(\alpha_k \frac{y_{t+1}}{k_{t+1}} - \delta\right) + \psi\left(k_{t+2} - k_{t+1}\right)}{1 + \psi\left(k_{t+1} - k_t\right)}, \tag{4.1}$$

where k_t is the capital stock and y_t is gross output at date t. Given initial capital and a sequence of interest rates, this equation can be simulated using a shooting algorithm.[22]

In the next section, we model turbulence as a shock to the worker productivity process and calibrate it using data on the rise in worker movements and our estimates of the loss in earnings associated with these movements during the crisis. We consider both the case where this shock is fully anticipated and the case where it comes to agents as a complete surprise, and compute the predictions of the model for capital use, gross output and, most importantly for our purposes, conventionally-measured TFP.

We will also ask by way of sensitivity analysis how making capital utilization endogenous affects the model's quantitative predictions. Financial crises create ideal conditions for large swings in capital utilization since productivity is below trend while interest rates remain above average for several quarters. A sudden drop in the quality of labor, all else equal, causes the

[22]For details, see appendix C.

capital output ratio to fall, hence should cause utilization to fall as well. The endogenous response of utilization should therefore magnify the effect of labor turbulence on TFP.

To make this formal, assume that the firm can alter the rate at which it utilizes the capital it allocates a particular worker. We assume that a worker of productivity $x \geq 0$ who operates with a quantity $k > 0$ of capital at utilization level $u > 0$ produces output $x^{1-\alpha}(uk)^{\alpha}$. Raising utilization thus raises a workers output, but as in Greenwood, Hercovitz and Huffman (1988), we assume that it also raises the quantity of capital lost to depreciation. Specifically, the depreciation rate for an amount of capital used at level $u > 0$ is $\delta(u) = \frac{u^{\phi}}{\phi}$ where $\phi > 1$. These new assumptions lead to a slightly altered version of our aggregation result:

Proposition 4.2. *Assume that capital utilization is endogenous. Given aggregate capital $K > 0$, aggregate labor $N > 0$, and a distribution p of productivity, gross aggregate output is given by*

$$F(K, N, p) = \left(\sum_{x \in X} p(x)x\right)^{1-\alpha} (uK)^{\alpha} N^{1-\alpha},$$

where utilization solves:

$$u \equiv \left(\alpha \frac{F(K, N, p)}{K}\right)^{\frac{1}{\phi}}.$$

The simplicity of this result owes to the fact that it is optimal for the firm to equate capital output ratios and utilization rates across workers of different productivity. It implies that when capital utilization is endogenous,

$$\text{Conventionally-measured TFP} \equiv \frac{F(K, N, p)}{K^{\alpha} N^{1-\alpha}} = u^{\alpha} \left(\sum_{x \in X} p(x)x\right)^{1-\alpha}, \text{ where } u \equiv \left(\alpha \frac{F(K, N, p)}{K}\right)^{\frac{1}{\phi}}.$$

A drop in the quality of labor now affect TFP not only directly but also via its effect on the capital-output ratio, hence on utilization. Simulating the resulting model amounts to simulating the same second-order difference equation as before, except that the ratio of capital to output and depreciation now depend on optimal utilization choices as well.

5 Numerical simulations

We can now simulate the effects of a shock to the worker productivity process consistent the microeconomic evidence we have presented. Our goal is to quantify the potential importance of the losses associated with labor market turbulence for the behavior of output and aggregate productivity during Mexico's Tequila crisis.

5.1 Data and parameterization

We first need to find a data counterpart for the interest rate sequence we take as exogenous in the previous section. We will think of a period as one quarter. We calculate the interest rate r_t during quarter t as

$$r_t = \frac{(1 + Tbill\ rate_t)\,(1 + MX\ Brady\ spread_t)}{1 + US\ inflation_t} - 1, \tag{5.1}$$

where $Tbill\ rate_t$ is the interest rate on US Treasury bills, $MX\ Brady\ spread_t$ is the spread between the return paid by (dollar-denominated) Mexican Brady bonds and the interest rate paid by US Treasury bills, and $US\ inflation_t$ is the relative change in the US GDP deflator. In other words, our proxy for r_t is the real return paid by Mexican Brady bonds. Our sample of Mexican Brady bond data starts in the last quarter of 1990 and ends in the first quarter of 2003, and is shown in the first panel of figure 1.

Next, parameters must be specified. We set α, the capital share, to 0.3, a value consistent with the evidence discussed by Gollin (2002). We make $\delta = 0.02$ which corresponds to yearly rate of depreciation of physical capital of 8%. Preference parameters have no bearing in this version of the model on the behavior of capital, output and TFP. However, the equilibrium we compute assumes no asymptotic growth in any real variable. Such an equilibrium only exists in this environment provided we assume that $\beta \equiv \frac{1}{1+r}$ where r is the long-run value of the interest rate. We choose the adjustment cost parameter to match the standard deviation of the investment to GDP ratio in Mexico prior to 1995. We also choose initial capital to

Table 7: Parameters

Parameter	Description	Value	Target
α	Capital share	0.30	Capital income to GDP ratio (Gollin, 2002)
δ	Depreciation rate	0.02	8% yearly rate of depreciation
ψ	Adjustment cost	0.18	Standard deviation of investment-to-GDP ratio before 1994-Q4
r	Final interest rate	0.9%	Brady bond return in 2003-Q1
β	Discount rate	0.92	$\frac{1}{1+r}$
X	Productivity support	$\{1, 4.5\}$	Standard deviation of residual in earnings regression before 1994-Q4 (table 3)
$P(\sigma = C)$	Job change probability outside the crisis	0.20	Frequency of sector or occupation change before 1994-Q4 (table 1)
$\pi^S(x_H\|1)$	Productivity transition outside the crisis	0.20	Autocorrelation of residual in earnings regression before 1994-Q4 (table 3)
ω	Turbulence shock	0.82	Gap in earnings change between movers and stayers in 1995 (table 6)
$\tilde{P}(\sigma = C)$	Job change probability during crisis	0.23	Frequency of sector or occupation change in 1995 (table 1)

match the capital-output ratio in Mexican data at the beginning of our sample.[23]

There only remains to specify the worker productivity process. We assume that the Markov chain's support is $X = \{1, x_H\}$ where $x_H > 1$. In order to map our empirical findings into the model, it is useful to decompose the specification of the Markov transition matrix that governs the evolution of worker productivity into two orthogonal subprocesses. First, all workers receive a draw from a binary random variable $\sigma \in \{S, C\}$ which is i.i.d across periods. We will interpret $\sigma = S$ as the event that the worker stays in the same sector and occupation, while $\sigma = C$ represents a sector or occupation change. Then, given $\sigma \in \{S, C\}$, worker productivity evolve according to transition matrix π^{σ}.

Since in our data 60% of workers change either sectors or occupation each year outside of the crisis period, we set the <u>quarterly</u> probability that $\sigma = S$ to 0.8. Our data also suggest

[23]The construction of all data counterparts to our model variables is described in detail in appendix A.2.

that the earnings of workers who stay put do not differ systematically from the earnings of workers who move outside of the crisis period. One way to generate this in our model is to assume that $\pi^S = \pi^C$ outside of 1995.

We follow Ljungqvist and Sargent (2007) and assume that the productivity transition matrix is symmetric during tranquil times. We select $x_H = 4.5$ so that at the unique invariant distribution corresponding to this matrix (namely the distribution that puts equal mass on both types of workers, as a result of symmetry), the standard deviation of log worker productivity matches the standard deviation of the residual in quarterly Mincer regressions with fixed effects specified as in the last column of table 3. This standard deviation is roughly 0.74 over the period up to the last quarter of 1994. The cross-terms of the transition matrix are selected to roughly match the autocorrelation of this residual before the crisis, namely 0.65. All told, outside the crisis, we set:

$$\pi^S = \pi^C = \begin{bmatrix} 0.8 & 0.2 \\ 0.2 & 0.8 \end{bmatrix}.$$

We model the change in the worker productivity process that occurs during the crisis as follows. Prior to the first quarter of 1995, the productivity distribution is at its invariant value. During each quarter of the crisis, our empirical results suggest that the yearly frequency of movements across sectors or occupations rises from 0.6 to 0.66. We decrease the likelihood that $\sigma = S$, accordingly, from $P(\sigma = S) = 0.80$ to $\tilde{P}(\sigma = S) = 0.76$.

Based on our estimates, we take average conditional losses associated with those moves to be roughly 10%. This represents the midpoint of our estimates, which range from 6 to 14%. To make our model consistent with this number, we replace π^C by a new transition matrix $\tilde{\pi}^C$ during the crisis, where:

$$\begin{aligned} \tilde{\pi}^C(2,2) &= \omega \pi^C(2,2), \\ \text{while } \tilde{\pi}^C(1,2) &= \omega \pi^C(1,2) \end{aligned}$$

and $\omega \in (0,1)$ is such that the average productivity loss for workers whose $\sigma = C$ at least once during the crisis is 10% lower by the end of 1995 than the average productivity of workers who experience no change. The required correction is $\omega = 0.82$ so that:

$$\tilde{\pi}^C = \begin{bmatrix} 0.836 & 0.164 \\ 0.344 & 0.656 \end{bmatrix}.$$

After 1995, π^C governs the evolution of productivity for changers once again, and we let the distribution return to its invariant value over time at the convergence rate inherent to our specification of the transition matrix.

Finally, we need to be explicit about agents' expectations. We will consider two scenarios. Under perfect foresight, agents know the entire sequence of interest and wage rates. They also expect interest rates to remain constant at their last value in our sample for the indefinite future. This implies that the capital stock series converges in equilibrium to an invariant value and enables us to implement a shooting algorithm. In the second scenario, agents only foresee shocks up to the last quarter of 1994, but wrongly expect that thereafter interest rates will remain at their pre-crisis average and that there will be no change to the productivity process. Once the crisis strikes, agents immediately update their expectations to the true processes. This "perfect surprise" approximates a situation where agents perceive a financial crisis to be low probability event.

5.2 Results

5.2.1 The impact of labor market turbulence

The result of the combined interest rate and worker productivity shocks under perfect foresight is shown in figure 4. We normalize each statistic to be 1 in the last quarter of 1994. The figure compares the behavior of capital intensity, output and TFP to their data counterpart. Because we assume in the model that employment does not vary over time, the more reasonable data counterpart for our model's notion of TFP is $\frac{Y}{K^\alpha}$ where Y is GDP and K is the capital stock, rather than the standard $\frac{Y}{K^{\alpha}N^{1-\alpha}}$. The first statistic drops by almost 10% in the data, while the second falls by 8%, as discussed in section 2.1. Our model would account for a larger share of the behavior of the second statistic, but this is a trivial consequence of the assumption of exogenous employment.

The first panel of the figure depicts the magnitude of the labor shock we feed into the model. Average worker productivity falls by a cumulative 6% during 1995 (the fraction of low productivity workers rises by 9%), and then begins to converge towards its invariant value.

The behavior of the capital-output ratio before the crisis depends on the expectation scenario. Under perfect foresight, the model predicts – counterfactually – that the capital output ratio should have fallen before the crisis, as agents correctly foresee the upcoming period of high interest rates and low productivity. This problematic feature no longer emerges when we simulate a perfect surprise scenario, as the second panel of figure 4 shows. Under that scenario, agents do not expect a crisis to occur and accumulate capital according to those optimistic expectations. The pattern the model generates for both output and the capital output ratio before the crisis now becomes quite consistent with the evidence.

Under both scenarios, the capital-output ratio rises when the crisis strikes because output falls on impact whereas it takes a while for the capital stock to adjust. Once the recovery starts the ratio falls, but eventually begins to rise again as capital nears its long-run value.[24]

The third panel of the figure shows the impact of the productivity shock on output. Output falls by nearly 4.5%, which is close to half (46%) of the overall impact of the crisis on GDP in the data. TFP (measured as $\frac{Y}{K^{\alpha}}$) falls by about 4%, which is roughly 43% of the corresponding fall in the data. Put another way, a worker productivity shock calibrated to the microeconomic evidence we produced in this paper can account for nearly half for the empirical behavior of output and TFP in Mexico during the Tequila crisis.

This first experiment makes the strong assumption that only workers who experience a sector or occupational change see their productivity fall during the crisis. This is inconsistent

[24]This long-run value is quite high because by the end of our sample interest rates have fallen to a quarterly rate of roughly 1 percent.

with the evidence shown in table 3. When the crisis strikes, output falls somewhat less than the aggregate supply of labor which, in our model, implies that the price of labor rises. Since stayers see no change in their average productivity by assumption in this first experiment, their earnings rise slightly during the crisis, under both expectation scenarios.

In order for the earnings of stayers to fall in our model as they do in the data, their productivity must fall too. Assume therefore that when the crisis strikes, the support of the productivity distribution becomes $\{A, Ax_H\}$ where $A < 1$. That is, assume that all workers experience a common shock to their productivity prospects. As in the previous experiment, we continue to assume that the transition matrix of movers changes during the crisis in such a way as to generate a cumulative, average earnings gap of 10% between movers and stayers. We select the size of the common shock (A) so that GDP per worker falls by the same magnitude in our model as it does in the data. We specify the persistence of the shock so that it has a half-life of three and a half quarters (a standard target in business cycle studies.) Specifically:

$$A_{t+1} = 0.90A_t + 0.1.$$

Figure 5 shows the results of this combined set of shocks. The effective supply of labor falls much more than in the first experiment because of the aggregate shock. As a result of our choice of A, the model produces (by assumption) a fall in output that comes close to its data counterpart, and this also holds for conventionally-measured TFP. The model now approximates the shape of the recovery of both series well. What's more, the model now approximates much better the behavior of the capital-output ratio during the crisis, under both expectation scenarios. In the perfect-surprise case, the ratio takes somewhat longer to recover because agents revise their expectations when the crisis strikes which depresses capital accumulation for several quarters.

The common shock generates a reduction of earnings for stayers of about 5%. The output to labor ratio still falls in this experiment which causes wage *rates* (the price of labor) to rise, but stayers now experience a productivity shock of magnitude such that their earnings fall

Table 8: Sensitivity analysis

	GDP (Y)	Capital-to-GDP ratio	TFP ($\frac{Y}{K^{\alpha}}$)
Data (1995-Q4 vs 1994-Q4)	-9.75	+9.67	-9.47
Benchmark parameterization	-4.49	+3.15	-4.06
Capital share			
$\alpha = 0.15$	-5.48	+1.64	-4.91
$\alpha = 0.45$	-3.10	+3.46	-3.21
Three-digit estimates			
$\tilde{P}(\sigma = C) = 0.185$, earnings gap=14%	-5.11	+3.80	-4.68
Correlated job changes			
P(Job change at t | Job change at $t-1$)=0.88, $\omega = 0.91$	-4.54	+3.20	-4.11
Endogenous capital utilization			
$\phi = 1.46$	-5.51	+1.99	-4.46

by the desired amount.

5.2.2 Sensitivity analysis

The foregoing experiments suggest that labor market turbulence accounts for roughly half of the behavior of output and TFP during the crisis. This section discusses the sensitivity of our findings to key aspects of our calibration.

The importance of turbulence for TFP depends on the labor share in production. Making labor more important in production obviously magnifies the importance of worker productivity for output and TFP. As table 8 shows, simulating the same turbulence shock as above can account for over 50% of the fall in TFP when the labor share is 85% rather than 70%. On the other hand, it accounts for only 3% of the fall in TFP when the share is 55%.

We motivated a benchmark value of the earnings gap between stayers and movers of 10% with the empirical results we obtained with sectors and occupation coded at the four-digit level in the Mexican classification. If one uses the coarser 3-digit classification of both variables, the frequency of sector or occupation changes falls, but the wage impact of those changes during the crisis rises. The third panel of table 8 shows the impact of calibrating parameters to 3-digit estimates rather than 4-digit estimates. This has little impact on our findings.

One strong assumption we make in our quantitative analysis is that job change draws are independent over time. It seems clear that workers' past occupational history should help predict future losses. Workers who experienced a job loss recently are probably more likely to change jobs again in the future than other workers. To allow for this possibility, assume that, σ, the job change indicator variable, follows a symmetric Markov process with diagonal term 0.88.[25] This value for the diagonal term makes the frequency of yearly job changes at the invariant distribution 0.66, the target value during the crisis.[26] We then adjust ω so that the gap between stayers and movers does not change. The results of this experiment, shown in the fourth panel of table 8, are virtually the same as in the benchmark case.

The reason for this is simple: the drop in the quantity of effective labor that takes place during 1995 is only a function of the frequency of job losses and of the impact of losses on productivity. As long as the targets for those are unchanged, results for TFP cannot change. Because the recalibration of the productivity process affects the dynamic path of labor during 1995 and after the crisis, GDP and capital-intensity numbers can change somewhat, but the table shows those effects to be minor. By the same logic, using a finer support for the distribution of worker productivity cannot alter our basic findings as long as the same calibration targets are matched.

Finally, we have assumed so far that capital utilization remains constant throughout our sample period. Recent work has shown that factor utilization can significantly magnify the effect of the shocks that occur during financial crises. How much can capital utilization magnify this direct impact of turbulence? The last panel of the table provides an answer by showing the predictions of a model with endogenous utilization under perfect foresight where we assume that the curvature of the depreciation function is $\phi = 1.46$. This value, given our

[25] This is calibrated from the empirical frequency of movers to change jobs in successive periods.

[26] Because we continue to assume $\pi^S = \pi^C$ outside of 1995, assuming a different Markov process outside the crisis to reflect a lower frequency of job changes would make no difference in our simulations.

other parameters yields a steady state depreciation rate of roughly 2%, which is the constant rate we specified in the exogenous case.[27] Because the capital-output ratio goes up when the crisis strikes, utilization now falls. The utilization drop is small however, and output and TFP fall as they did before. Capital utilization does little to change the impact of turbulence.[28]

6 Conclusion

In this paper, we presented evidence that during Mexico's 1995 financial crisis, workers whose sector or occupation changed experienced a much large fall in hourly earnings than workers who stayed put. This finding is robust to a host of econometric considerations, suggesting that the welfare consequences of financial turbulence are unevenly distributed, and are particularly high among workers whose jobs are destroyed.

This is a promising explanation for the collapse of conventionally-measured total factor productivity that occurs during crises. Labor market turbulence is likely to reduce average worker productivity by destroying accumulated experience and skills. We describe a simple model in which the mapping from worker productivity shocks to total factor productivity can be formalized. Numerical simulations show that a shock to the individual worker productivity process calibrated to match the new empirical evidence we provide in this paper accounts for over 40% of the fall in TFP that took place in Mexico during the Tequila crisis. This suggests that the labor market consequences of financial turmoil are large and significant, and could account for a significant part of the real impact of crises.

[27]As tends to be the case with these models (See Meza and Quintin, 2007, for a discussion) the capital output ratio becomes more volatile, so that matching the pre-crisis volatility of investment requires that we raise the value of the adjustment cost significantly.

[28]Adding an aggregate shock as in our second experiment causes a much larger change in the capital output ratio and a much more significant fall in utilization, an effect emphasized by Meza and Quintin (2007).

A Data sources and construction

A.1 Mexico's *Encuesta Nacional de Empleo Urbano* (ENEU)

The microlevel data we use in this study come from the ENEU, which is a nationally representative household survey designed to gather socio-demographic and occupational information about the labor force in Mexico. Information is gathered on individuals over 12 years of age and covers over 60% of all urban areas in Mexico. As mentioned in the text, data are collected every quarter from a rotating panel of households. One fifth of all households are replaced every quarter, and it is therefore possible in principle to follow a given individual for up to 5 quarters. To make sure that individual identifiers are properly recorded, we discarded from the analysis any sequence of individual identifiers where gender characteristics are not constant, or the age sequence displays an inconsistent pattern. The following list defines the variables we use in our analysis:

1. *Employed individuals*: We consider a worker employed if they worked in the previous week, or did not work but were on paid vacation, sick leave or strike. Individuals who did not work but were joining (or re-joining) work within the month are also categorized as employed.

2. *Unemployed individuals*: Respondents who report that they did not work in the previous week and were looking for a job or are waiting for a response from a prospective employer are classified as unemployed.

3. *Involuntarily unemployed*: We consider workers to be involuntarily unemployed if they report to be unemployed because their employer laid them off or went bankrupt, if their contract expired and was not renewed, or if their employer moved.

4. *Formal Sector*: Individuals are considered formally employed if they receive public or private health insurance benefits, or hold retirement accounts.

5. *Self employed*: Individuals who report to be sub-contractors, owners or own-account workers are classified as self-employed.

6. *Large firms*: We define a firms to be large if it employs more than 50 employees.

7. *Hourly Earnings*: The survey collects information on monthly earnings of workers and hours worked per week. To calculate hourly earnings, we multiply hours worked by 4.33 to get monthly hours worked. If individuals report that they earn an *aguinaldo*, i.e. a thirteenth month salary which is a common form of bonus in Mexico, we multiply the ratio of monthly earnings to monthly hours worked by 13/12. Earnings per hour are monthly earnings divided by monthly hours worked and are deflated by Mexico's consumer price index. Hours are recorded up to a maximum of 94 per week, and topcoded above that threshold. Earnings are topcoded at 999,990 pesos. Since topcoded

observations constitute a very small fraction (less than 0.1%) of our sample, we dropped them.

A.2 Macroeconomic data

Measuring aggregate TFP on a quarterly basis in Mexico requires empirical counterparts for $\widehat{y}_t, \widehat{k}_t$ and l_t. We use quarterly data when available, and impute quarterly series from yearly series otherwise. All data are in 1993 prices, and data from original sources are seasonally adjusted using the Census Bureau's X12Q-Arima procedure. Quarterly series are available from Mexico's Instituto Nacional de Estadística, Geografía e Informática (INEGI) and Mexico's Central Bank. Because GDP per hour as we compute it below displays no trend over our period of study (1990 to 2003), we did not detrend the output or capital stock series. Neoclassical accounting over longer time periods (see e.g. section 2 in Meza and Quintin, 2007) would require some detrending of these series.

Using data on private and public gross fixed capital formation, and purchases of durable goods, we construct three capital stock series using the perpetual inventory method. We assume a yearly depreciation rate of 6% for private capital, 5% for government capital and 20% for durable goods.[29] The total stock of capital is the sum of the three resulting series.

We calculate the data counterpart of output in our model by subtracting from GDP indirect business taxes, and adding the imputed returns and depreciation of government capital and durable goods. To calculate gross returns to government capital and the stock of durables we assume a net yearly return of 4% and the same depreciation rates as above.

To measure the size of Mexico's working age population, we use the yearly series for population of age 15 to 64 reported in Bergoeing et al. (2002). We use yearly growth rates of population to infer implicit quarterly rates of population growth. To measure hours worked, we first calculate (seasonally adjusted) average hours worked in the manufacturing sector from Mexico's Manufacturing Sector Survey available from INEGI.[30] To calculate a measure of workers relative to total working age population, we multiply quarterly measures of the ratio of economically active population relative to population of age 12 and higher by the employment rate. Our measure of the labor input is hours per employees times the ratio of employed persons to population, scaled by 1300, an approximation of the total number of hours of discretionary time available in a quarter.

[29] The average yearly depreciation rate implied by these numbers for the total stock of capital is around 8%, the number we use in our benchmark parameterization.

[30] The survey produces monthly series for man-hours and for employment. There are two versions of the survey. The first one has data from 1987.01 to 1995.12. The second one has data starting in 1994.01. We splice the quarterly hours per employee of the two surveys.

Table 9: Probit for propensity scores at 4-digit level

	Constant	Age	Education	Gender	Formal	Civil Status	Firm Size
1988.4 to 1989.4	0.317	-0.007	0.003	0.319	0.154	-0.072	
	0.087	0.002	0.005	0.046	0.040	0.046	
1989.4 to 1990.4	0.109	-0.009	0.009	0.379	0.007	-0.019	0.039
	0.090	0.002	0.005	0.047	0.059	0.048	0.010
1990.4 to 1991.4	0.254	-0.007	-0.003	0.428	0.092	-0.165	0.014
	0.090	0.002	0.005	0.047	0.058	0.048	0.009
1992.4 to 1993.4	-0.056	-0.006	0.010	0.284	-0.015	-0.119	0.059
	0.063	0.001	0.003	0.032	0.041	0.034	0.007
1993.4 to 1994.4	-0.125	-0.004	0.005	0.366	0.037	-0.124	0.047
	0.059	0.001	0.003	0.030	0.038	0.031	0.006
1994.4 to 1995.4	0.050	-0.004	0.004	0.259	0.034	-0.147	0.081
	0.058	0.001	0.003	0.029	0.039	0.031	0.007
1995.4 to 1996.4	0.156	-0.009	-0.002	0.406	-0.011	-0.150	0.036
	0.054	0.001	0.003	0.027	0.035	0.029	0.006
1996.4 to 1997.4	0.124	-0.007	-0.001	0.384	-0.030	-0.190	0.036
	0.052	0.001	0.003	0.026	0.034	0.027	0.006
1997.4 to 1998.4	0.182	-0.009	-0.002	0.383	0.046	-0.142	0.026
	0.051	0.001	0.003	0.025	0.033	0.026	0.006
1998.4 to 1999.4	0.092	-0.008	0.005	0.370	0.053	-0.167	0.036
	0.047	0.001	0.003	0.023	0.030	0.024	0.005

Notes: Standard errors are below estimates. Education is measured in years. The formal, gender and civil status dummies take value 1 for formally employed, male, and married workers, respectively, and value 0 or others. Size is measured by a continuous variable that varies positively with the size of the firm. There is no data on firm size for self employed individuals in 1988.4. Because the occupation classification changed in 1992, probits cannot be computed for the 1991.4 to 1992.4 period.

B Propensity score estimation

Tables 9 shows the probit specification we used to estimate yearly propensity scores for movers at the 4-digit level. Results are similar at the 3-digit level. The categorical variable takes the value 1 if the individual changes sector and/or occupation in a given year, 0 otherwise. While results vary from year to year, some consistent patterns emerge. For instance, unmarried males are more likely to change sectors and occupations. Neither education nor formality seem to be significant.

Since we use propensity scores to match individuals, it is critical to verify that individuals with similar propensity scores have similar observable characteristics. Table 10 shows the t-statistic from a hypothesis test for differences in means for various characteristics of movers and stayers, across different propensity scores intervals. As the table shows, even for coarse propensity score categories, differences in means are not significant, and we cannot reject the hypothesis that individuals with similar propensity scores have similar characteristics.[31]

C Computations

Simple manipulations of first-order conditions for profit and utility maximization show that output can be reduced to a function of capital, so that equation (4.1) is a second order difference equation in capital only. We assume that after the first quarter of 2003 all exogenous variables stay forever at their level in the first quarter of 2003. Given k_0 (the initial level of the capital stock), we look for the unique k_1 such that the economy eventually converges to steady state via a standard shooting algorithm. All endogenous variables can then be calculated as a function of the path of physical capital. In the perfect surprise (PS) experiment, the algorithm is restarted in the first quarter of 1995 using as initial value for capital the value agents would choose under the expectations assumed before 1995.

In the case with capital utilization, the model produces the same second order difference equation for capital as before, except that output and depreciation now depend on utilization. But one easily shows that utilization is a function of the capital-output ratio. Therefore, equation (4.1) can once again be written as a second order difference equation in capital, and the same shooting algorithm can be used.

Since our Brady bonds data start in the last quarter of 1990 and end in the first quarter of 2003, we make the last quarter of 1990 date 0 and set the initial value of the capital stock to its data value at that date. Likewise, we assume that interest rates will remain for ever at their value in the first quarter of 2003. Changing the value of the asymptotic interest rate changes the steady state value of the capital stock hence can alter the shape of the output and capital-output path as the distance between k_0 and this steady state value changes. This has little impact on the behavior of output and TFP during the crisis however, since that behavior is governed mainly by the size of the labor shock, and its persistence.

[31]Since the lowest propensity score in our sample is about 0.25, and the highest is about 0.8, we compress the lowest category and highest category of propensity scores

Table 10: Difference in means of characteristics of stayers and movers

	Propensity Score	Age	Education	Gender	Formal	Civil Status	Firm Size
1988.4 to 1989.4	0.0 to 0.5	0.14	-0.13	0.00	0.28	-0.29	
	0.5 to 0.6	-0.09	-0.05	0.01	-0.12	-0.05	
	0.6 to 0.7	0.02	0.04	0.07	0.07	0.06	
	0.7 to 1.0	-0.20	0.04	0.00	0.05	-0.08	
1989.4 to 1990.4	0.0 to 0.5	0.06	0.23	0.04	-0.02	0.11	0.03
	0.5 to 0.6	0.03	0.09	0.03	0.04	0.03	0.10
	0.6 to 0.7	-0.02	0.02	0.06	-0.02	-0.01	0.00
	0.7 to 1.0	-0.22	-0.12	0.00	0.10	-0.05	-0.03
1990.4 to 1991.4	0.0 to 0.5	-0.07	0.05	0.00	0.07	0.04	0.09
	0.5 to 0.6	-0.01	-0.10	0.08	-0.10	-0.01	-0.07
	0.6 to 0.7	0.01	0.01	0.07	0.09	0.06	0.05
	0.7 to 1.0	0.01	0.17	0.00	0.07	-0.04	0.10
1992.4 to 1993.4	0.0 to 0.5	0.09	-0.07	0.14	0.06	0.04	0.10
	0.5 to 0.6	-0.03	-0.03	-0.03	0.08	0.04	0.14
	0.6 to 0.7	-0.05	0.09	0.03	-0.03	-0.03	-0.02
	0.7 to 1.0	-0.07	0.01	0.00	-0.03	-0.07	-0.17
1993.4 to 1994.4	0.0 to 0.5	0.01	0.02	0.08	0.02	-0.02	0.19
	0.5 to 0.6	-0.07	0.00	-0.02	0.05	-0.07	0.04
	0.6 to 0.7	0.03	0.05	0.08	0.02	0.08	0.01
	0.7 to 1.0	-0.04	0.01	0.00	-0.10	-0.09	0.01
1994.4 to 1995.4	0.0 to 0.5	0.08	-0.10	0.14	-0.03	0.03	-0.03
	0.5 to 0.6	-0.03	0.10	-0.03	0.09	0.03	0.21
	0.6 to 0.7	-0.01	-0.01	0.02	-0.02	-0.02	0.02
	0.7 to 1.0	-0.07	0.00	0.11	0.00	-0.01	0.02
1995.4 to 1996.4	0.0 to 0.5	0.05	0.07	0.11	0.08	0.04	0.09
	0.5 to 0.6	-0.02	0.01	0.01	0.06	-0.01	0.06
	0.6 to 0.7	-0.15	-0.03	-0.02	-0.08	-0.08	-0.06
	0.7 to 1.0	-0.17	-0.05	0.00	-0.08	-0.13	-0.09
1996.4 to 1997.4	0.0 to 0.5	0.07	-0.02	0.10	-0.02	0.04	0.02
	0.5 to 0.6	-0.04	0.05	0.00	0.10	0.00	0.10
	0.6 to 0.7	-0.11	-0.04	-0.04	-0.07	-0.12	-0.09
	0.7 to 1.0	-0.04	0.09	0.00	-0.07	0.00	0.04
1997.4 to 1998.4	0.0 to 0.5	-0.01	0.06	0.13	0.04	0.05	0.06
	0.5 to 0.6	0.00	-0.02	0.03	0.03	0.02	0.05
	0.6 to 0.7	-0.13	0.02	-0.06	0.01	-0.10	-0.02
	0.7 to 1.0	-0.24	0.00	0.00	-0.05	0.00	-0.06
1998.4 to 1999.4	0.0 to 0.5	-0.01	0.09	0.14	0.13	0.09	0.12
	0.5 to 0.6	-0.01	-0.03	0.02	0.04	-0.09	0.04
	0.6 to 0.7	-0.07	0.03	0.03	-0.03	0.01	-0.01
	0.7 to 1.0	-0.15	0.01	0.00	-0.09	-0.10	-0.11

Notes: Statistics are t-statistics from a test of difference of means for stayers and movers. An asterisk denotes 5% significance. There is no data on firm size for self employed individuals in 1988.4.

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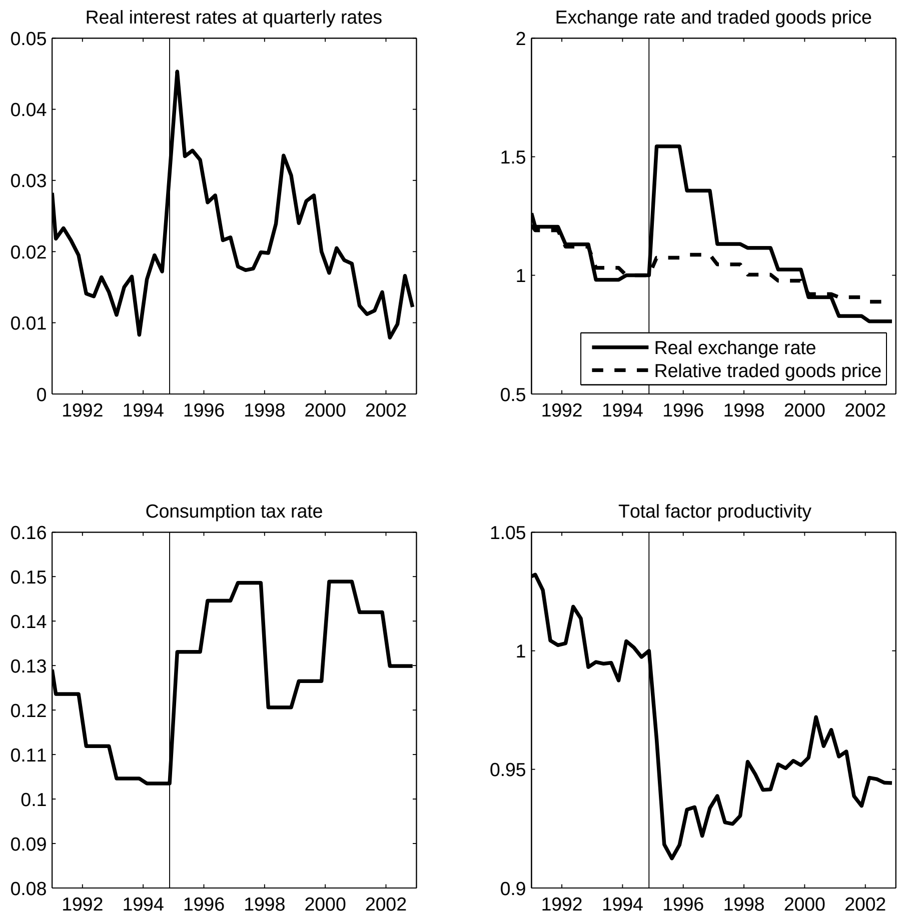
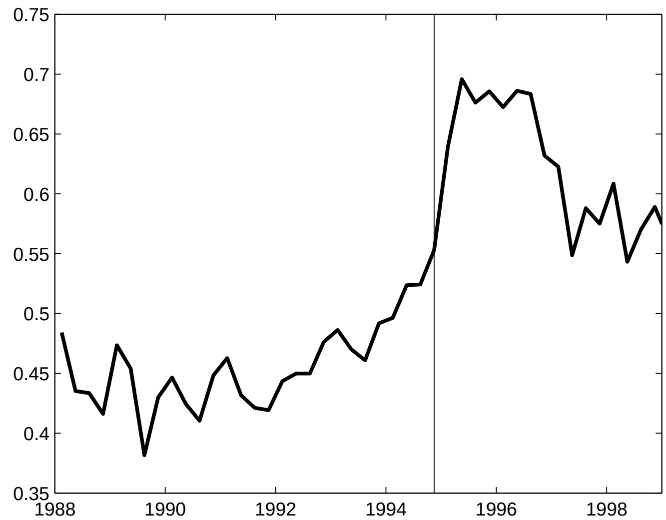
Figure 1: Shocks during Mexico's Tequila crisis



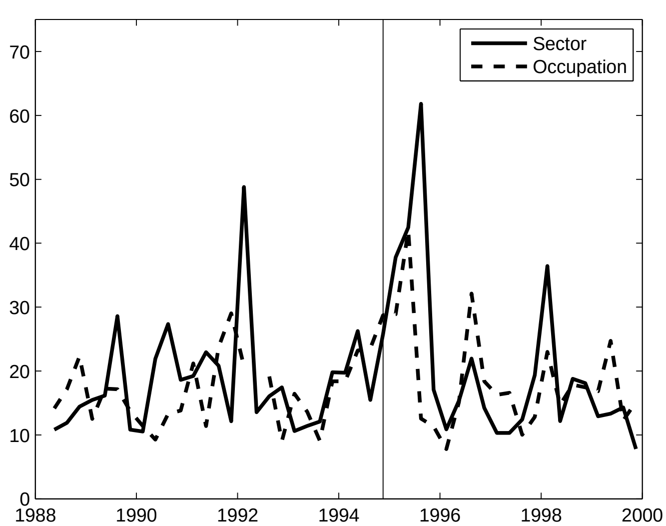
Source: INEGI, Banco de México, and authors' calculations. Real interest rates are quarterly real returns paid by Mexican Brady bonds. The relative price of traded to non-traded goods is calculated as in Pratap and Urrutia (2008). Traded goods include agriculture and manufacturing, and non-traded goods are services. Consumption tax rates are average effective tax rates calculated as in Mendoza et al. (1994).

Figure 2: Fraction of involuntary terminations



Source: ENEU, INEGI.

Figure 3: Kolmogorov-Smirnov test statistic for distributional change



Source: ENEU, INEGI, authors' calculations.

Figure 4: Impact of labor market turbulence alone

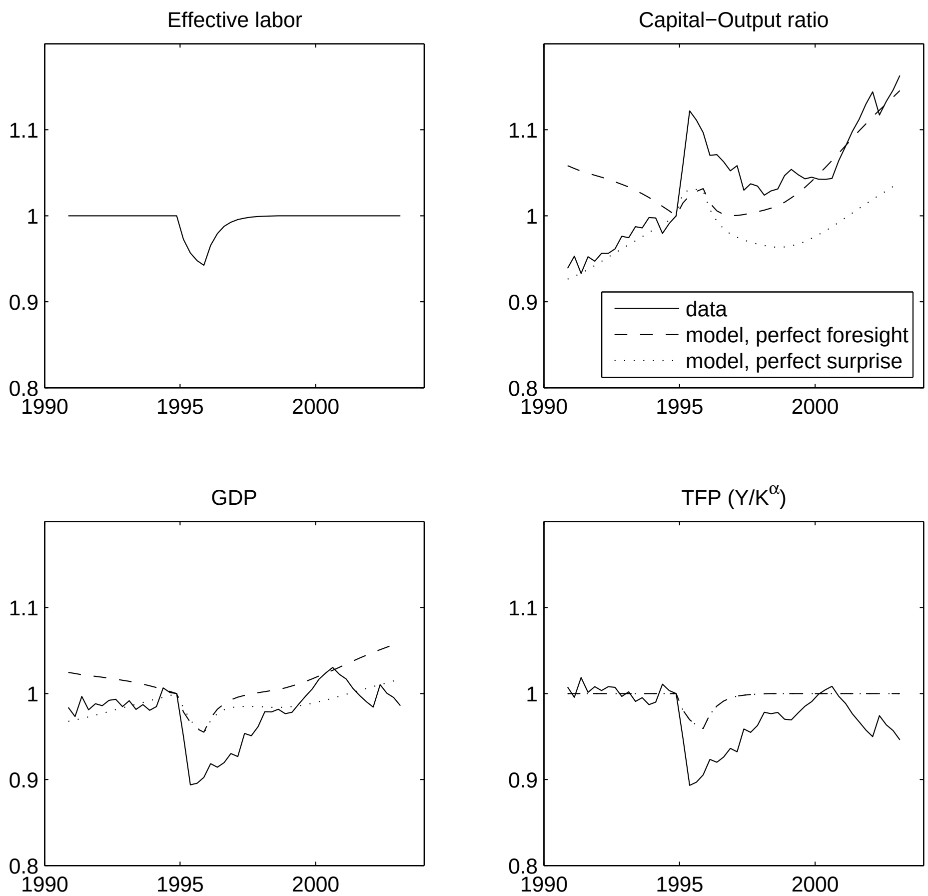


Figure 5: Combined impact of labor market turbulence and an aggregate shock