Financial Crises and Labor Market Turbulence

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Abstract

Financial crises in emerging markets cause a large reallocation of labor as economies confront a variety of shocks and relative prices change drastically. Using household survey data for Mexico, we find that individuals who switched industry or occupation during the 1994-95 crisis lost about 10% of their hourly earnings on average compared to similar workers who did not move. This suggests that many workers became less productive in the process of migrating to different economic activities. We describe a simple map from our earnings estimates to aggregate TFP and show that productivity losses associated with occupation and industry changes can explain about 40% of the observed fall in TFP in Mexico in 1995.

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

JEL classification: E32; F41; J24

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1 Introduction

Financial crises in emerging countries lead to sharp drops in real output. In fact, output typically falls much more than standard measures of capital and labor and, therefore, conventionally-measured TFP collapses during most emerging market crises.[1] Understanding the sources of this decline in TFP is a crucial step towards understanding the economic impact of financial crises.

In this paper, we argue that the distribution of earnings losses during crises provides a key insight into the causes of the collapse of aggregate productivity. Using household survey data from Mexico, we find that individuals who changed industry or occupation during the 1994-95 "Tequila" crisis experienced a much larger fall in their hourly earnings than those who stayed put. Depending on the details of the estimation, we find that, on average, movers saw their wages fall by 6% to 14% more in 1995 than observably similar workers who remained in the same occupation and industry. Importantly, this effect only emerges during the crisis. At other times, the average effect of occupation or industry changes is either insignificant or positive. We also find that the frequency of moves rises during crises, compounding the aggregate size of the earning losses associated with industry changes.

These results are strong evidence that crises are periods of turbulence in the sense of Ljungqvist and Sargent (1998), i.e. periods of rapid change in the economic environment that damage worker productivity. As we document in the next section, Mexico experienced a variety of macroeconomic shocks in 1995. These shocks altered relative prices and increased the pace of reallocation of resources, especially labor. Moreover, we find that the fraction of job losses initiated by employers rather than by employees rose significantly in 1995. A spurt in employer-initiated reallocation of workers across occupations and sectors is likely to lower the productivity of the concerned workers, at least temporarily, as skills specific to previous jobs become less useful and new skills must be acquired. This provides a natural explanation for the negative effect of moves on earnings.[2] During less turbulent times, moves

[1] See e.g. Calvo et. al. (2006), Bergoeing et. al. (2002) and Meza and Quintin (2007) .

[2] Neal (1995) shows that displacement costs are positively related to the distance between the worker's old

are much more likely to be voluntary, and less likely to involve drastic changes in occupations or industries.[3] This intuitive interpretation can explain why moves tend to be associated with large earning losses during Mexico's Tequila crisis, but not during more tranquil periods.

While this interpretation seems plausible, there could be other explanations for our findings. Individuals who move may be very different from those who do not, and the difference in earnings between the two groups may reflect this heterogeneity. We condition on a rich set of observed variables, and use differences between pre- and post-crisis earnings to partially deal with unobserved heterogeneity. Estimates for various subsamples of agents further mitigate the possibility that selection on the basis of unobservable characteristics could account for our findings.

On a theoretical level, displacement losses are consistent with several economic models.[4] Our prior is that skill (specific human capital) losses are a major cause for the earnings losses associated with job changes that characterize turbulent economic periods. An obvious alternative explanation is that job changes cause productive matches between a worker and an employer, industry, or occupation to be destroyed. Our goal in this paper is not to settle this debate on the causes of displacement losses. Rather, we show that these losses become particularly large during crises, regardless of their source. Our findings imply that labor markets should be a focal point of the research on the effects of financial crises.

Any study that uses occupation and industry information from survey data must confront

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and new industry. Kambourov and Manovskii (2009) document substantial returns to occupational tenure. von Wachter et. al. (2007) provide empirical evidence on the wage losses due to separations during the 1982 recession in the US.

[3]Under the cyclical upgrading view of labor markets for instance, workers tend to upgrade to better employment opportunities when economic conditions are favorable. See e.g. Lubick and Krause (2006).

[4]These include models where workers invest in employer-specific capital such as Jovanovic (1979a) which formalizes ideas contained in Becker (1962), Oi (1962) and Mincer (1974) among others. Displacement losses can also occur in models of learning by doing (Jovanovic and Nyarko 1995). If employers and employees learn about the quality of matches over time (Jovanovic 1979b) displacement losses occur when long lasting (and hence more productive) matches are dissolved. Finally models in which effort is unobserved, such as Lazear (1981) predict that the optimal compensation profile consists of low initial earnings in exchange for higher actuarially fair payments later in the life of the contract. This profile could result in displacement losses for workers with longer tenures.

the issue of measurement error[5] and ours is no exception. We do not expect this to undermine our results since measurement error issues exist both during the crisis period and outside of it. A change in labor movements and earnings losses during the crisis seems unlikely to be due to an increase in measurement error in this particular period. If anything, pure measurement error makes finding significant earnings losses associated with occupation or sector switches less probable. Robustness checks such as identifying switches as a change both in occupation and industry (rather than a change in either one), or estimating wage losses associated with moves at broader levels of the occupation or industry classification, produce similar results to our baseline estimation.

To quantify the effect of worker productivity losses during the crisis on aggregate variables we describe a small open economy model with heterogeneous agents where aggregate output can be written as a function of the capital stock, employment and the average productivity of workers. In that economy, a fall in the effective quantity of labor is equivalent to a fall in conventionally-measured TFP. Under the assumption that earnings reflect worker productivity, our estimates for the frequency of moves during the crisis and their effect on earnings enable us to calibrate the size of the fall in effective labor in 1995. We also specify the worker productivity process to match the autocorrelation of residual earnings we estimate in the empirical section, which in turn pins down the persistence of the shock to average worker productivity during the crisis. Under this parameterization, we find that worker productivity losses during the crisis cause a 4% fall in TFP and a 5% drop in output. This corresponds to roughly 40% of the fall in TFP in the data, and 50% of the fall in GDP. Our parameterization also implies a slow recovery pattern, consistent with post-crisis evidence.

Combined, our microeconomic estimates and accounting exercise suggest that labor market turbulence played a significant role in the behavior of macroeconomic variables in Mexico during the 1994-95 crisis. What makes our aggregate calculations unique is that they are founded on detailed microeconomic evidence, and a careful estimation of the losses associated with industry or occupation changes during the crisis. Given the singularity of the crisis in

[5] See Brown and Light (1994), Mathiowetz (1992), and Kambourov and Manovskii (2009).

this respect, it is clear that labor reallocation played a significant role in the unusual behavior of TFP during Mexico's Tequila crisis.[6]

While our estimates are based on Mexican data, we expect that studies of similarly detailed panel data for other emerging markets will reveal that the regularity we document in this paper characterizes most crises and, therefore provides a promising explanation for the consistent behavior of TFP across these episodes. By their sheer magnitude, crises in emerging markets provide ideal conditions to detect robust patterns in labor market movements and earnings losses.[7] Losses in worker productivity associated with labor market movements could also account for part of the procyclicality of TFP in industrialized nations. As first documented by Jacobson et al. (1993), displacement losses tend to rise during recessions. Krebs (2007) argues that taking this empirical regularity into account makes the welfare consequences of business cycles significantly higher than conventional estimates would suggest. The logic we have outlined in this paper suggests that this regularity could also account for a significant part of the drop in TFP that characterizes most recessions.

The rest of the paper is organized as follows: section 2 describes the macroeconomic shocks that occurred during the Mexico's 1994-95 crisis, documents the associated fall in measured TFP, and the fact that the pace of labor reallocation increased in 1995. Section 3 estimates the loss of hourly earnings for workers who changed industry and/or occupation during the crisis relative to those who did not. Section 4 sets out the framework we use to assess the quantitative importance of this mechanism in explaining the fall in TFP. Section 5 concludes.

[6]Benjamin and Meza (2009) also find that labor reallocation accounts for a significant part of the fall in TFP in the case of Korea's 1997-98 crisis, but they focus on a different mechanism, namely the fact that the labor share of less productive sectors rose during the crisis. Kehoe and Ruhl (2009), on the other hand, find that labor reallocation towards the traded sector cannot account for the behavior of TFP during Mexico's Tequila crisis. While their calculations include costs to adjusting labor, they do not take into account the productivity losses we discuss in this paper. Hsieh and Klenow (2009) also study the link between allocation of resources and TFP from a different perspective. They measure the effect of a permanent misallocation of capital and labor in China and India compared to the United States.

[7]Using data from 39 middle income countries, Tornell and Westermann (2002) find that in the aftermath of credit crises, the composition of output changes noticeably in favor of the traded sector. We suspect that a look at more disaggregated panel evidence – where available – will reveal that the patterns we document in this paper characterize most of these episodes as well.

2 Financial turmoil and worker movements

In this section we document some of the macroeconomic shocks that characterized Mexico's 1994-95 crisis and describe the behavior of TFP. We also describe labor flows across industrial sectors and occupations during that period.

2.1 Macroeconomic volatility

Figure 1 displays several statistics that illustrate the extent of macroeconomic instability in Mexico in 1995. Vertical bars mark the start of the crisis, namely the 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 landscape also shifted 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%.[8]

The fourth panel of the figure shows that GDP per worker (the ratio of GDP to the size of the working-age population, see appendix A.2 for details) collapses by over 10% in 1995. The ratio of aggregate hours worked to the working population also falls, but by a much lower fraction. In other words, output per hour falls drastically during the crisis.

Since the capital stock changes little, 1995 is 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:

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

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. We set α, the capital share, to 0.3, a value in the middle of the range of estimates

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

available in Gollin (2002).

The magnitude of the TFP collapse during the Tequila crisis (over 8%) is striking. As is now well-documented, this phenomenon is not confined to Mexico. Calvo et. al. (2006) present data for 22 different financial crises[9] and find that on average, TFP declined by 8.4% in these episodes. Meza and Quintin (2007) find similar results for recent crises in Indonesia, South Korea, Thailand, and Argentina.

The final panel of figure 1 displays another typical consequence of crises in emerging markets:[10] a trade balance reversal. Mexico was running trade and current account deficits as foreign capital flowed into the country in the early 1990s. These capital inflows dried up when the crisis struck and the trade balance reversed to a surplus. Only by 1998 does the trade balance return to negative territory.

2.2 Worker reallocation

The multitude of shocks that hit Mexico in 1995 created strong incentives for worker movements across employers, occupations and industries. 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). The ENEU is a rotating panel with up to 5 quarters of information for each worker. It includes individual data such as age, gender, education, marital status, and occupation and job characteristics such as benefits received, employer size, and industrial 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, with a total of about 3 million observations.

Figure 2 shows the quarterly unemployment rate computed from the ENEU. In the third quarter of 1995, it peaked at 7.4% from a yearly average of 3.7% in 1994. This increase in unemployment was short lived, however, and the average unemployment rate in 1995 was

[9]These include the Latin American debt crises of the 1980s, the "Tequila" crises of the first half of the 1990s, and the East Asian and the Russian crises of the late 1990s.

[10]See Chari et. al (2005) for a discussion.

only 2.5% higher than that of 1994. Nor was there a substantial increase in the duration of unemployment spells. The fraction of individuals with unemployment spells of one quarter or less barely declined from 84 to 82% while the fraction of individuals with spells between 1 and 2 quarters increased by only 2%. The incidence of longer durations remained virtually unchanged.[11]

Figure 2 also shows that a large fraction of transitions into unemployment in 1995 were involuntary, i.e. employer initiated.[12] Before the 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.

Unemployment spells, whether voluntary or involuntary, are only part of the reallocation story. Many workers who remained employed through the crisis reported a change in industry or occupation during this period.[13] To identify meaningful changes at a disaggregated level, we consider changes at the 4-digit level of the industrial and occupational classification, which corresponds roughly to the 3-digit level of the US census code classification used by Kambourov and Manovskii (2009) to analyze 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 aggregates all medical professions. As Kambourov and Manovskii (2009) argue, this is the level of detail where human capital seems most likely to be category-specific. As a robustness check, we will also discuss estimation results for the coarser 3-digit level.

In Table 1 we use the longitudinal aspect of the ENEU to compute the gross rates of

[11]Using our data, we can follow individuals and therefore calculate unemployment durations for up to 5 quarters. These results are available upon request.

[12]Involuntary separations include terminations caused by bankruptcy or business relocation, or the expiration of a fixed-term contract. Appendix A.1 provides a formal definition of involuntary separations, and other variables we use in our empirical analysis.

[13]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. The details are documented in Pratap and Quintin (2008).

industry and occupation changes. The fraction of individuals who change industry but keep the same occupation increases from 13 to 20% during the crisis while the fraction of individuals who change both industry and occupation rises from 24 to 28%. All told, the fraction of individuals who change either occupation or industry rises from 59% to 66% in 1995. Interestingly, the fraction of changes in occupation but not industry falls during the crisis. In other words, most of the increase in flows in 1995 involves industry changes either alone or in combination with a change in occupation.[14] In the next section, we will show however that earnings losses associated with changes in occupation during the crisis are significant even if they do not involve a change in industry.

Table 1: Frequency of movements across industries and occupations

	Industry 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

Table 2 further decomposes labor flows across 2-digit industries. The top panel shows the 10 fastest growing industries in term of employment during the crisis, while the bottom panel shows the industries that suffered the largest contractions during the same period. The industry that expanded the most was electricity, a sector controlled by the federal government,

[14]Net flows between industries and occupation follow a similar pattern as measured using the index defined by Kambourov (2009). Net flows between industries spike in 1995, while there is a smaller increase in net flows across occupations.

followed by transport and then leasing. The largest net exit took place in construction, a notoriously cyclical sector. Contrasting rankings in 1995 to those for 1994 and 1996 shows that the crisis affected some industries much more than others. For example, while the construction sector shrank by 1.2 percent during the crisis, it experienced the largest net increase the following year.[15] Similarly, wood and cork products, which showed the largest expansion in the year prior to the crisis, suffered the third largest contraction during the crisis. Electricity, the fastest growing industry in 1995, ranks much lower in 1994 or 1996. Finally, entry and exit rates tend to be highly correlated during the crisis, a pattern that holds outside of the crisis as well.

While it is not possible to decompose flows across occupations and industries between employer and employee-initiated movements,[16] we do know whether the individuals who changed industry or occupation during a given 4-quarter period were unemployed at some point in the interim. If unemployed, we also know whether they left of their own accord or not. Table 3 shows the fraction of movers who were unemployed for at least one quarter during each calendar year and the fraction of these workers that were involuntarily unemployed, i.e. lost their job because their employer laid them off or stopped operating. The fraction of movers who experienced at least one unemployment spell between the fourth quarter of 1994 and the fourth quarter of 1995 jumps up to 7% for movers 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 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

[15]The effect of the crisis on employment in several industries also proved quite persistent, as measured by the change in the average growth rate in employment between 1991 and 1994 and between 1995 an 1998. Industries that show the biggest gains in those 3-year growth rates include several textile sub-sectors, government-controlled sectors such as electricity and public administration, and commerce. Industries that show the biggest losses include hotels and restaurants and traditional manufacturing sectors such as wood and cork products and metallic products.

[16]The survey only inquires about terminations causes for currently unemployed workers.

associated with significant wage losses.

3 Labor market reallocation and earnings

Our basic thesis is that the labor reallocation that occurs during crises causes losses in worker productivity. As the results above indicate, movements that occur during crises are more likely to be involuntary, or employer-initiated. Furthermore, during periods of rapid relative price shifts, many workers have to move to occupations and industries very different from their prior employment experience. We would thus expect more displaced workers to find themselves in jobs ill-suited to their accumulated skills, and where new skills must be acquired, causing at least transitory losses in productivity and earnings. During normal times however, the fraction of involuntary moves is smaller, and transitions across vastly different industries and occupations less likely to take place. For these reasons, transitions are less likely to be associated with earnings losses outside crises.

This section formally tests this hypothesis by comparing the change in the hourly earnings of individuals who stay in the same industry and occupation with those 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 relative losses should be particularly high during crisis periods.

3.1 Parametric results

Tables 4 and 5 show the results of estimations of variations on standard Mincer regressions designed to determine the effect of occupational and industry 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 industry in that quarter as in the previous quarter, and takes value 0 otherwise.[17]

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

The *Crisis Dummy* is set to 1 for all quarters of 1995. Table 4 uses the 4-digit industry and occupation classification to construct the dummy for stayers, while table 5 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. Estimations include fixed effects to account for unobserved heterogeneity and the non-random nature of occupation and industry changes. Variables are defined in appendix A.1.

The coefficients on standard variables all have their expected signs. Earnings rise with age and tend to be higher for formally employed workers and self-employed workers. Large firms pay a significant wage premium. The returns associated with staying in the same occupation and industry 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. The wage gap between movers and stayers reverses its sign and becomes substantially larger. Individuals who change industry and/or occupation during the crisis suffer a penalty of about 6.5% compared to other workers. This pattern 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.[18]

Table 5 confirms this pattern when industry 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 -6%. As before, these results continue to hold after including a time-varying coefficient on the stayer dummy.

To highlight the uniqueness of the crisis period, table 6 shows the premium for stayers each year, relative to 1994. For most years outside the crisis, this premium is negative and small. In contrast, the coefficient in the crisis period is large and statistically significant.

[18] 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 industries and occupations.

Finally, table 7 considers the returns to sector and occupation separately. The dummy variables *I-Stayer* and *O-Stayer* take value 1 for individuals who stay in the same industry and occupation respectively, 0 otherwise. The column shows results at the 4-digit level while the second column shows results at the 3-digit level. Earnings losses associated with industry changes are comparable to those associated with occupation changes during the crisis, at about 4.5 % each. As before, movers are not penalized outside the crisis period.

3.2 Semiparametric results

To ensure that these results are not driven by changes in a few industries or occupations, or by the parameterization of the wage equation, we now implement a semiparametric matching estimator of the impact of industry 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.

The effect of moves on wages losses can be written as follows:

$$\delta = E(\Delta w^m | X, M = 1) - E(\Delta w^s | X, M = 1)$$

where the expectation is over the sample of movers in a given period, Δw^m denote the change in log wages for a given mover, and Δw^s is the log wage change this mover would have experienced had they not changed industry and/or occupation. We use the indicator variable M to distinguish movers from stayers, while X is a list of earning-relevant individual and employer characteristics.

Since $E(\Delta w^s | X, M = 1)$ is unobservable, we need to proxy for it with $E(\Delta w^s | X, M = 0)$, the wage change of a sample of observably similar workers who stayed put. If the conditional independence assumption (CIA) holds, i.e.

$$\Delta w^m, \Delta w^s \perp M | X,$$

then,

$$\delta = E(\Delta w^m | X, M = 1) - E(\Delta w^s | X, M = 0).$$

The CIA requires that to the extent that selection into moves occurs, it can only affect wage changes on the basis of characteristics spanned by X. Note that differencing wages addresses potential issues associated with selection on unobservable but fixed characteristics.[19]

For ease of matching, we follow standard practice and proxy for multidimensional characteristics X with a propensity score $p(x)$, which measures the probability that a worker with a set of characteristics x will experience a change in industry and/or occupation in a given period.[20] We estimate propensity scores using a probit on individual and job related characteristics such as age, gender, self employment and formality status and firm size. The results of this estimation are shown in table 10. Table 11 shows that individuals with similar propensity scores also have similar observable characteristics. The table compares the mean characteristics of stayers and movers in similar propensity score intervals. Even using coarse intervals renders these mean differences insignificant. This indicates that by matching movers and stayers on the basis of propensity scores, we are in fact matching similar workers.

We consider yearly intervals, and compare wages between the fourth quarters of each year.[21] At a given date the treatment group consists of workers who change industry, 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 industry and/or occupa-

[19]On the other hand time-varying, unobservable characteristics could affect the interpretation of our results. For instance, if employers first dismiss workers who for some reason are paid above their marginal product, this could account for some of the impact of moves. One could instead argue that "underpaid" workers are more likely to move or, more generally, that workers tend to move because they find a better match, biasing the effect of moves in the other direction. In general, the importance of time-varying unobserved effects for our results is hard to gauge, and could bias them in either direction. We discuss selection issues further in section 3.3.

[20]Rosenbaum and Rubin (1983,1984) show that if the CIA holds and if $0 < p(x) < 1$ almost surely, conditioning on the propensity score is equivalent to conditioning on the characteristics themselves.

[21]Results are similar for third quarter comparisons, but comparing fourth quarter numbers is convenient because the crisis began at the end of the fourth quarter of 1994.

tion between date t and date $t+1$.[22] For a given worker $i \in N_t$, let $o_t(i)$ and $s_t(i)$ denote respectively the worker's occupation and industry, 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. The control group comprises of workers in the same industry and occupation as worker i at date t, whose propensity score is close to worker i's, but do not move industry or occupation between dates t and $t+1$. 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. That is, we compare the change in log wages of individuals who moved from industry 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 during the same period.

The results of this exercise are summarized in table 8 for $\varepsilon = 10^{-3}$. We present two sets of

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

estimates at the 4-digit level.[23] The first estimator, δ^1, is based on matches of workers in the same industry and/or occupation at the 4-digit level, and in the same ε-neighborhood in terms of propensity scores. However, these stringent matching requirements constrain us to discard almost half of our sample. The second estimator, δ^2, still considers moves at the 4-digit level, but matches individuals on initial 2-digit industry 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. The table also provides a matching estimator for moves at the 3-digit level (δ^3). Earnings losses for movers at this level are over 14% higher than for stayers during the crisis. Outside the crisis, these relative losses do not show any clear pattern and are rarely statistically significant.

The last two columns show the results for individuals who change industry only, and those who change occupation only. These movers (at the 4-digit level) are matched with people who remained in the same initial industry and occupation as them. The impact of either change taken separately is very similar to the impact of a changes in either occupation or sector. Our results are also robust to a host of alternative specifications, including kernel weights or equal weights for the caliper matching. In all cases, relative earnings per hour a significantly lower for movers than for stayers during and only during the crisis.

3.3 Alternative interpretations

A natural explanation for our findings is that job changes during crises involve losses in industry or occupation-specific human capital, or the destruction of good matches, resulting in worker productivity losses. In this section, we discuss other possible interpretations.

First, if wages are rigid on the downside, individuals who keep their jobs may experience smaller earning losses during adverse times than individuals who take new jobs. Beaudry and

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

DiNardo (1991) show that wages are correlated with the unemployment rate that prevails at the start of the employment spell, which is typically interpreted as evidence of downward wage rigidity.[24] In the specific case of Mexico's crisis, it seems unlikely that downward wage rigidity could account for the earning patterns we document in this paper. Castellanos (2003) and Bell (1997) find no empirical evidence of downward wage rigidity in Mexico. Castellanos, Garcia-Verdu and Kaplan (2004) find some evidence of downward nominal wage rigidity in Mexico using matched employer-employee data but, at the same time, find that this nominal rigidity does not translate into stickiness in real wages, especially during times of high inflation, such as 1995.[25] Wage rigidity, therefore, is not a likely explanation the real wage penalty we find for movers in 1995 in Mexico.

A related concern is that the wage drop for movers reflects a disproportionate fall in their bargaining power. Standard search models (see, e.g. Pissarides, 2000) predict that wages reflect match productivity, labor market tightness, the utility of non-market activities, and the bargaining power of workers. Labor market conditions affect both movers and stayers but a fall in the bargaining power of movers that exceeds that of stayers could partially account for their greater fall in earnings in 1995.

Another potential explanation for our findings is that workers who change sectors or occupations in Mexico are systematically different from other workers along dimensions for which we do not have data, inducing a selection bias. For instance, workers who experience a change during the crisis may tend to be drawn from the set of less productive workers in their job of origin. Our matching estimators compare changes in earnings for workers with similar observed characteristics who begin in the same occupation and industry, which limits the risk that our results are driven by only a few categories of workers. We account for unobserved

[24] See for example Thomas and Worrall (2007,1988) and Harris and Holmstrom (1988). However, there are other possible interpretations. As Hagedorn and Manovskii (2009) show, in a model with no downward wage rigidity where wages depend on match-specific productivity, past labor market conditions also affect current wages through the quality of the match.

[25] Unlike the previous studies, the study by Castellanos et. al (2004) is based on Social Security Administration records and does not include informal sector workers. Unsurprisingly, they find nominal wage rigidity clustered around the minimum wage.

time-invariant characteristics by looking at first differences in wages rather than levels.

A further concern could be that some of these unobserved characteristics could be time varying. The lower wages of movers during crises could reflect liquidity constraints that prevent individuals from waiting for better paying jobs. On the other hand of course, individuals who accept jobs quickly may also do so because they have better general skills than those who wait. For either reason, workers who return to work quickly following a termination could experience different earning losses from other movers. To investigate this issue, we consider the subsample of movers who do not report any unemployment spells between moves in 1995 and estimate the changes in their wages (at the 3 and 4-digit level). These movers experience very similar wage losses compared to the full sample, which includes workers with at least one unemployment spell.

Another dimension of time-varying heterogeneity could be that movers are more likely to be coming from contracting industries during crises than during other time periods. Workers who leave shrinking industries are more likely do so by necessity than by choice, which could affect their average earnings losses.[26] To study this possibility, we re-estimated our matching estimators comparing movers and stayers from the subsample of the top 100 contracting industries each period. We find that the wage losses for movers out of contracting industries are much larger and statistically significant during the crisis, unlike in other times.

Overall, the most probable explanation for our findings appears to be that workers who change occupations or industries during the crisis become less productive, at least temporarily. We now turn to quantifying the consequences of these productivity losses for aggregate variables.

[26]We note that this would be perfectly consistent with our prior that human capital losses play a key role in our findings.

4 Macroeconomic effects of labor market turbulence

The microeconomic data this paper studies provide strong evidence of large and statistically significant productivity losses among workers who changed occupation and/or industry during Mexico's 1995 crisis. This section measures the importance of these losses for the behavior of key macroeconomic variables during and after the crisis.

To formalize the mapping from worker productivity losses to aggregate quantities, 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 which they supply to the firm.[27] 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 X and transition probability function π. Assume further 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 $t+1$.

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 μ_t.

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 $\alpha \in (0,1)$.[28] Given input levels (N, K) and the distribution μ of workers across skill levels, the firm chooses a capital allocation

[27]In other words, workers do not value leisure and, what's more, do not experience any unemployment in our model. As section 2 explains, the typical duration of unemployment spells is very short in Mexico (almost 85% of all spells last 1 quarter or less) and barely rises during the crisis. Most workers who lose their jobs return to work almost immediately, most probably because unemployment benefits are negligible. This preference specification also implies that employment is constant during and outside the crisis, which means that this model is trivially consistent with the fact that aggregate hours worked fell much less than output in 1995 in Mexico. Accounting more fundamentally for this behavior of hours is left for future work.

[28]One can think of a worker together with some capital as a job. Ljungqvist and Sargent (2007) think of the same pair as a firm.

$k : X \mapsto I\!R_+$ to maximize gross output $F(K, N, \mu)$. That is,

$$F(K, N, \mu) \equiv \max \sum_{x \in X} N\mu(x)[x^{1-\alpha}k(x)^\alpha]$$

subject to:

$$\sum_{x \in X} N\mu(x)k(x) = K.$$

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

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

Under the assumption that workers are paid the value of their marginal product, this aggregation property implies a simple mapping from the distribution of earnings to the distribution of productivity. Indeed, the marginal contribution of a worker to output depends only on her contribution to total effective labor $N \sum_{x \in X} \mu(x)x$. It follows that earnings are linear in productivity. In particular, earning changes at the worker level between two periods are proportional to productivity changes. Therefore, this paper's estimates of earnings losses during the crisis can be mapped directly into a shock to the productivity process in 1995.[29]

Specifically, the estimates discussed in the previous section suggest that 60% of workers changed occupation or industry during the crisis (at the 4-digit level) and that, on average, these workers lost around 10% more in earnings than workers who experienced no change. In and of itself and maintaining the assumption that earnings are linear in productivity, this relative productivity loss implies a decline in the average quality of labor $\left(\sum_{x \in X} \mu(x)x\right)$ of $1 - 0.6 \times 0.9 \approx 6\%$. Assuming a capital share of 30% this translates to a drop in aggregate TFP of $1 - 0.94^{0.7} \approx 4\%$.

[29] The linear relationship between earnings and productivity is due to the fact that the firm equates the marginal product of capital across workers, which implies that the capital to worker productivity ratio is constant across workers.

Since the aggregation approach and the model we lay out below both assume that employment does not vary over time, the more reasonable data counterpart for this predicted aggregate productivity fall 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. The model would account for a larger share of the behavior of the second statistic, but it is trivial consequence of the assumption of exogenous employment. All told then, a conservative estimate is that the worker productivity losses documented in this paper can explain about 40% of the observed fall in TFP in Mexico in 1995.

Clearly, the importance of worker productivity shocks for TFP depends critically on the labor share. Making labor more important in production obviously magnifies the importance of worker productivity for output and TFP. The same 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 30% of the fall in TFP when the share is 55%.

Measuring the consequences of this shock on output requires more structure since the behavior of output depends on the response of endogenous variables such as aggregate capital use. Assume as in Ljungqvist and Sargent (2007) that all workers belong to the same representative household. For the purpose of studying the behavior of aggregate variables, this environment is equivalent to an economy with a single representative agent who can supply quantity $x_t \equiv \sum_{x \in X} \mu_t(x)x$ of labor to the firm where μ_t is the distribution of worker productivity at date t.

The representative household chooses a consumption plan $\{c_t : t \geq 0\}$ to maximize $\sum_{t=0}^{+\infty} \beta^t \frac{c_t^{1-\sigma}}{1-\sigma}$ where $\sigma > 0$. The household has access to an international capital market where one-period risk-free claims earn an exogenous return r_t at date t. Making this assumption amounts to modeling Mexico as a small, open economy. Denote by a_t the household's net holding of this asset at date t and assume that asset holdings are bounded below at a level that does not bind in equilibrium. The household can also invest in physical capital, which it sells to the representative firm at price $1 + r_t^k$ at date t. Letting k_t be the quantity of capital held by the household in period t, adjusting capital across periods carries a cost $\frac{\psi}{2}\left(k_{t+1}-k_t\right)^2$, where $\psi>0$.

Letting w_t be the price of effective labor at date t and given a rate δ of depreciation of physical capital, the firm chooses a capital level K_t and a total effective labor level L_t to solve:

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

In turn, given the price of labor, the household's budget constraint is:

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

Given (a_0, k_0) and the initial level $x_0>0$ of worker productivity, an equilibrium 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 household and firm decisions are optimal given prices and the markets for labor and capital both clear. 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.

In order to simulate the effect of worker productivity losses during the crisis, parameters must first be calibrated. Table 9 summarizes our parameterization. Given those parameters, sequences of interest rates and productivity levels imply paths for all endogenous variables. As is standard practice in this context, set the interest rate series to:

$$r_t = \frac{(1 + Tbill\ rate_t)\,(1 + MX\ \ Brady\ spread_t)}{1 + US\ inflation_t} - 1, \tag{4.2}$$

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. The first panel of figure 1 shows the resulting series at a quarterly frequency.

As for the productivity process, recall that the goal in this section is to isolate the impact of the worker productivity losses the previous section documents. Since there is no evidence of significant losses associated with moves prior to the crisis, normalize x_t to 1 prior to 1995Q1. During the crisis, x_t falls by $\frac{6\%}{4}$ each quarter so that the average quality of labor has fallen by 6% by the fourth quarter of 1995.

The difficulty lies in specifying the persistence of that shock. The most natural way to estimate this persistence would be to track the workers who changed occupations or industries in 1995 for several years but workers only remain in the ENEU data set for up to 5 quarters. One alternative is to calibrate the individual worker productivity process to match estimates of the quarterly autocorrelation of earnings in ENEU data and infer the persistence of the worker shock in 1995 from this process. A second alternative is to simply assume that the worker productivity shock in 1995 has a similar persistence as the overall TFP shock ($\frac{Y}{K^{\alpha}}$, that is) in the data. Since both methods produce similar results, we will adopt the second, simpler approach.[30]

By the second quarter of 1997, roughly half of the 10% collapse in TFP in 1995 is erased. Setting

$$x_{t+1} = 0.88x_t + 0.12$$

for $t \geq$ 1995Q1 gives the worker productivity shock a similar half-life as overall productivity.

We consider two scenarios for the household's expectations regarding interest rates and productivity shocks. Under perfect foresight, agents know the entire sequence of both shocks. 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

[30]The working paper version of this paper pursues the first approach in complete details.

invariant value and enables us to implement a shooting algorithm.[31] In the second scenario, the household only foresees shocks up to the last quarter of 1994, but wrongly expects that thereafter interest rates will remain at their steady state level $\left(\frac{1}{\beta}-1\right)$ and that there will be no shock to the productivity process. Once the crisis strikes, the household immediately updates its expectations to the true processes. This "perfect surprise" approximates a situation where agents perceive a financial crisis to be low probability event.

Figure 3 shows the result of the combined interest rate and worker productivity shocks where each statistic is normalized to be 1 in the last quarter of 1994. The first panel of the figure depicts the magnitude and persistence of the productivity shock calibrated above. The second panel of the figure shows the response of the capital-output ratio. Under perfect foresight, the model predicts – counterfactually – that the capital output ratio should have fallen before the crisis, as the household foresees the upcoming period of high interest rates and low productivity. This problematic feature no longer emerges under a perfect surprise scenario. Under that scenario, agents do not expect a crisis to occur and accumulate capital according to those optimistic expectations.

GDP mirrors this pre-crisis pattern and, in fact, the model generates paths for both output and the capital output ratio before the crisis that are 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.[32] All told and under both expectation scenarios, output falls by nearly 4.5% during the crisis, which is close to half of the overall impact of the crisis on GDP in the data.

The perfect foresight scenario fails to predict the trade balance reversal depicted in the last panel of figure 1.[33] Under perfect foresight, consumption growth depends only on the

[31]For details, see appendix C.

[32]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.

[33]Computing the trade balance path requires specifying the level of assets at the start of the simulation period. We choose a_0 so that the debt-to-GDP ratio in 1994 is roughly 35%, as it is in the data. Computational details are available upon request.

path of interest rates and the consumption path is smooth. When output collapses in 1995, the trade balance deteriorates. In complete contrast, the perfect surprise scenario correctly predicts that the trade balance should go from negative (roughly -5% in 1994, much like in the data) to significantly positive in 1995. When agents suddenly revise their expectations in the first quarter of 1995 and realize that the present value of their future income is much lower than expected, aggregate consumption falls drastically, much more than output. The trade balance, as a result, rises. If anything in fact, it rises too much, to over 15% of GDP.

This excess volatility of the trade balance is primarily the result of the size of the interest rate shock during the crisis. To see this, consider a counterfactual scenario under which interest rates remain at their long-term value $\left(\frac{1}{\beta} - 1\right)$ during and after the crisis instead of spiking up while the economy continues to experience a productivity shock.[34] As figure 4 shows, the two expectation scenarios now make similar predictions with the important exception of the trade balance. The perfect foresight scenario continues to miss the trade balance reversal while the perfect surprise scenario predicts a pattern that meshes remarkably well with the evidence. Note in addition that the fall in output becomes somewhat smaller because the more benign interest rate scenario implies a higher capital intensity in 1995.

In summary, the worker productivity shocks this paper has documented can account for 40% of the fall in aggregate TFP and output in Mexico in 1995.[35] In other words, not only are worker productivity losses large and significant at microeconomic level in 1995, they can also account for an important part of the aggregate impact of the crisis.

5 Conclusion

We presented evidence that during Mexico's 1995 crisis, workers who changed industry or occupation experienced a much larger fall in hourly earnings than workers who stayed put.

[34] One can also assume that interest rates are at their steady state value throughout the simulation period. Results are similar. The experiment described above amounts to shutting down the crisis' impact on interest rates and seems easier to interpret.

[35] The working paper version of discusses the sensitivity of this fraction to various aspects of our calibration and to the possibility that labor and capital utilization may also fall during the crisis.

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 who change occupations or industries during the crisis.

These findings suggest a promising explanation for the collapse of conventionally-measured total factor productivity that typically occurs during emerging market crises. Labor market turbulence is likely to reduce average worker productivity by eroding the value of accumulated experience and skills. We calculate that this could account for over 40% of the fall in TFP that took place in Mexico during the Tequila crisis. Put another way, the labor market consequences of financial turmoil are large and significant and could account for a significant part of the real impact of crises.

What implications do our estimates have for the current financial crisis? At least in the United States, the current crisis is following a very different pattern from the typical emerging market crisis. Employment has fallen faster than output and aggregate productivity has risen dramatically. On the face of it, this suggests that emerging market crises have little insight to offer into the sources of the current difficulties experienced by industrialized nations. However, the current crisis has brought its share of displacements, and the logic we have outlined in this paper implies that this will eventually have a significant impact on productivity. In a country like Mexico, where unemployment benefits are negligible, displaced workers have little choice but to quickly return to work, making the effects of displacements on productivity nearly immediate. The vast majority of workers who become unemployed in Mexico return to work in one quarter or less, even during the crisis. In the United States, more significant unemployment insurance make unemployment spells longer, which may mute the effect of displacement spurts on productivity in the short run. Our findings suggest that the consequences of recent displacements could hurt productivity growth as employment recovers.

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 employee*: 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 (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.[36] 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 industry from Mexico's Manufacturing industry Survey available from INEGI.[37] 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.

B Propensity score estimation

Tables 10 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 industry and/or occupation in a given year, 0 otherwise. While results vary from year to year, some consistent patterns emerge. For instance,

[36] 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.

[37] 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.

unmarried males are more likely to change industries 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 11 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.[38]

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 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.

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.

[38]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

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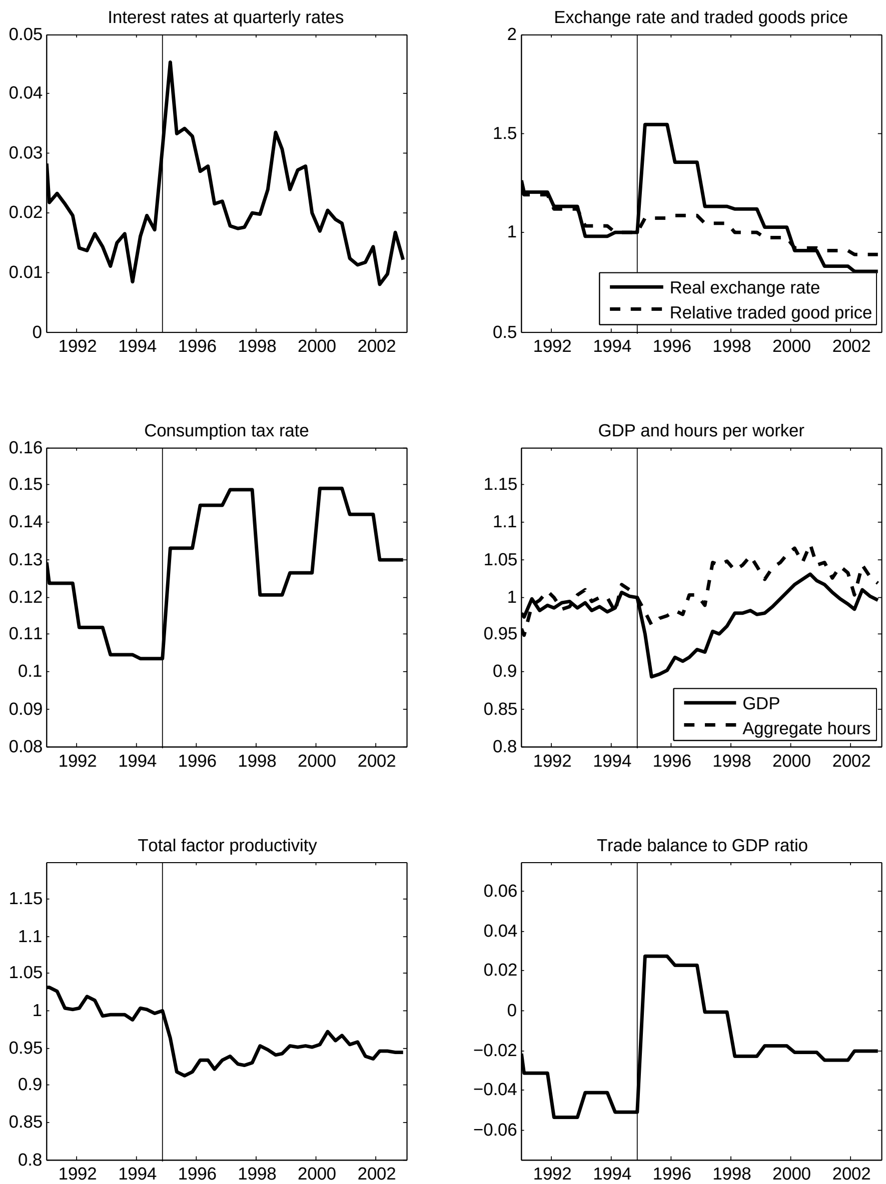
Figure 1: Macroeconomic volatility during Mexico's Tequila crisis



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: Unemployment rate and employer-initiated separations

Source: ENEU, INEGI, and authors' calculations.

Figure 3: Impact of worker productivity and interest shocks

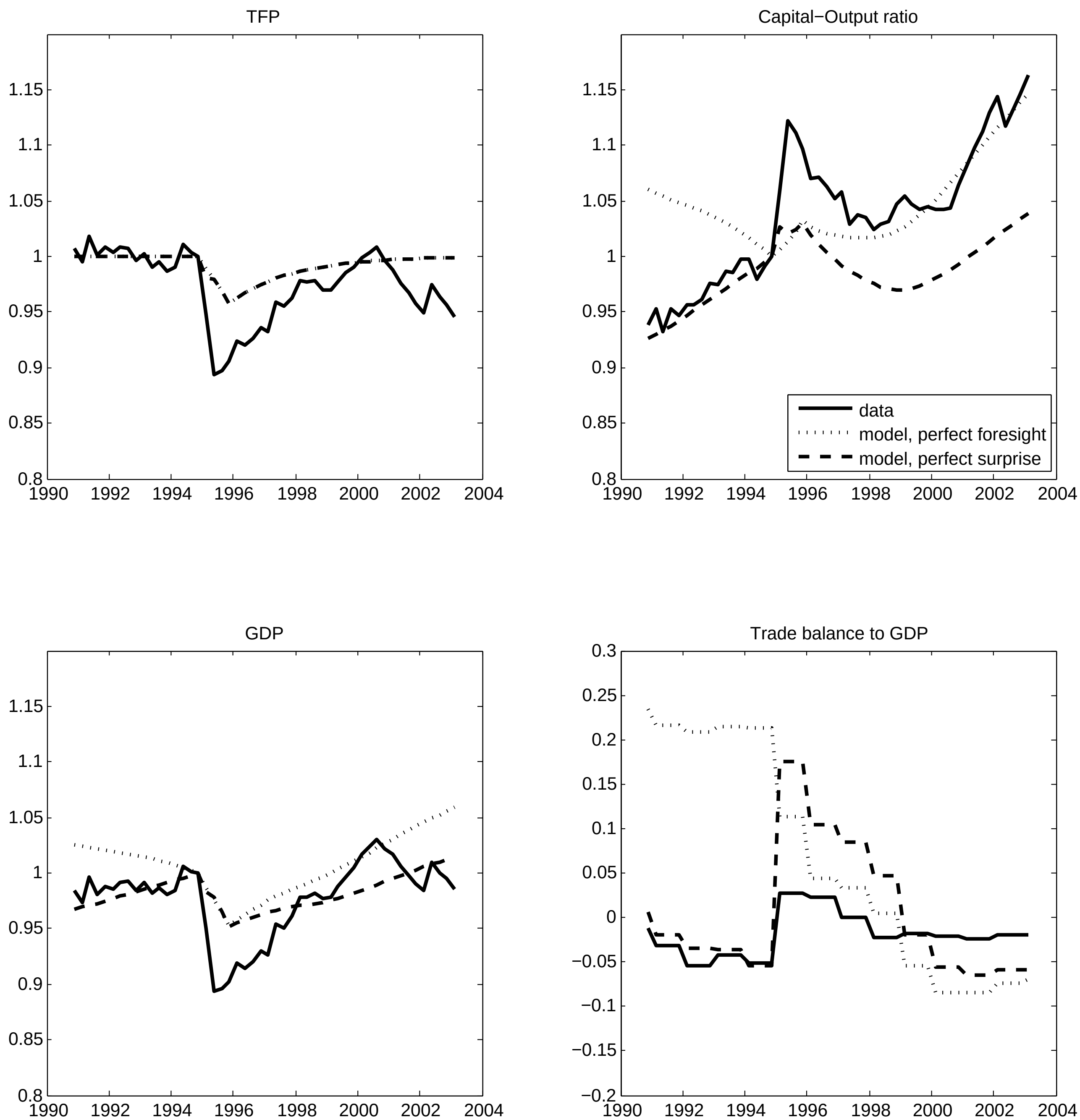


Figure 4: Impact of worker productivity shock alone

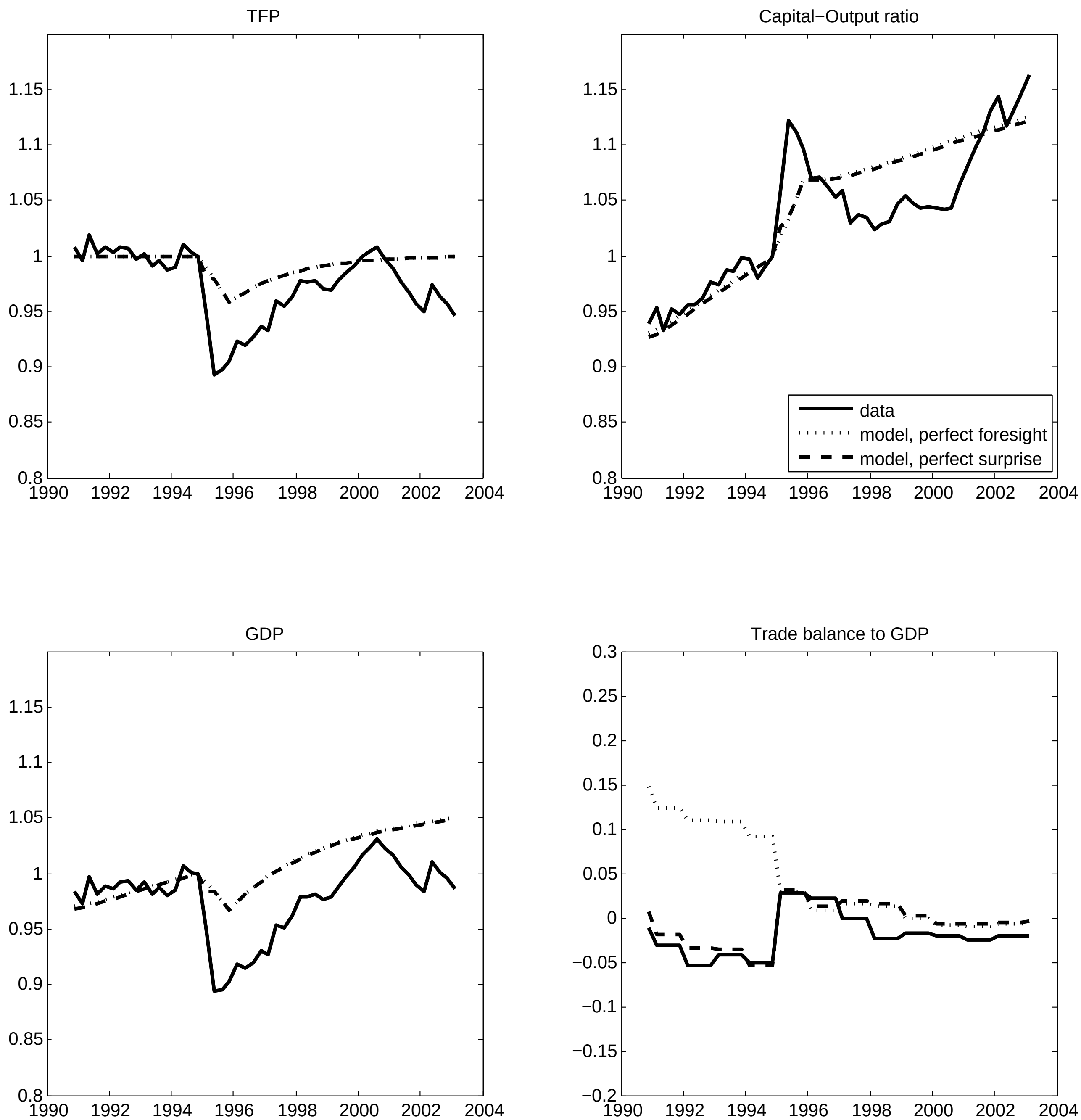


Table 2: Labor flows across industries 1994.4 to 1995.4

SIC	Largest Expansion Industry	Net Change (Percent)	Rank Last Year	Rank Next Year	Entry (Percent)	Exit (Percent)
61	Electricity	0.48	20	16	0.51	0.04
64	Transport	0.23	5	12	1.31	1.08
72	Leasing and Repair	0.21	6	31	3.82	3.60
27	Clothing	0.19	7	3	0.48	0.28
73	Public Admin	0.19	18	8	1.61	1.42
42	Plastic	0.14	15	13	0.42	0.27
54	Electronic Eqpt	0.12	3	20	0.35	0.22
47	Non Ferrous Metals	0.12	12	4	0.15	0.04
51	Non-electric machinery, eqpt.	0.11	23	25	0.26	0.15
62	Commerce	0.09	26	30	3.99	3.90
68	Professional and Technical Services	0.10	3	18	1.44	1.35
18	Animal Food	0.09	14	12	0.10	0.01
SIC	Largest Contraction Industry	Net Change (Percent)	Rank Last Year	Rank Next Year	Entry (Percent)	Exit (Percent)
34	Basic Petrochemicals	-0.04	8	23	0.04	0.07
39	Soaps, Detergents, Cosmetics	-0.04	17	7	0.08	0.12
40	Other Chemical Products	-0.04	5	10	0.05	0.09
22	Carbonated Drinks	-0.04	13	22	0.19	0.23
35	Other Basic Chemicals	-0.04	19	24	0.10	0.14
38	Pharamaceutical Products	-0.04	10	18	0.05	0.10
65	Post, Telegraph, Communications	-0.04	14	18	0.12	0.17
66	Financial Services	-0.04	22	12	0.27	0.31
70	Medical Services	-0.05	2	16	0.66	0.71
48	Metallic Furniture, Machinery, Eqpt	-0.06	12	18	0.07	0.13
50	Other Metallic Products	-0.06	18	9	0.35	0.41
59	Other Manufacturing Industries	-0.07	14	3	0.18	0.25
9	Sand, Gravel and Clay Quarrying	-0.09	11	16	0.01	0.10
56	Automobiles	-0.09	9	6	0.06	0.15
63	Restaurants and Hotels	-0.09	12	10	1.19	1.27
32	Books, magazines, other publishing	-0.11	11	29	0.19	0.29
28	Shoes and Other Leather Articles	-0.12	21	6	0.23	0.35
30	Other Wood and Cork Products	-0.13	1	27	0.33	0.46
55	Batteries and Lightbulbs	-0.20	15	4	0.19	0.39
60	Construction and Installation	-1.23	17	1	2.02	3.25

Note: Net changes, entry and exit are percentage changes calculated using all employed individuals who are present in the last quarters of successive years. The last year column refers to the change between 1993.4 and 1994.4 and the next year column refers to the change between 1995.4 and 1996.4.

Table 3: 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 industries 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.

Table 4: 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.

Table 5: 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.

Table 6: 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 4 and 5. Standard errors are in parenthesis.

Table 7: Parametric results for industry and occupation

Dependent Variable: Log Real Hourly Earnings		
	4-digit	3-digit
Age	0.02724 (0.00184)	0.02743 (0.00183)
Age^2	- 0.00053 (0.00003)	-0.00053 (0.00003)
Education	0.00492 (0.00075)	0.00489 (0.00075)
Formal	0.11022 (0.00112)	0.11030 (0.00112)
Self Employed	0.25241 (0.00138)	0.25215 (0.00138)
Large Firm	0.07085 (0.00116)	0.07095 (0.00116)
I-Stayers	- 0.00546 (0.00096)	-0.00563 (0.00102)
O-Stayers	- 0.00546 (0.00083)	-0.00461 (0.00086)
Crisis Dummy	- 0.13206 (0.00350)	-0.13339 (0.00371)
Crisis $\times$ Formal	0.00548 (0.00304)	0.00487 (0.00303)
Crisis $\times$ Self Employed	-0.02504 (0.00327)	-0.02307 (0.00327)
Crisis $\times$ Large Firm	-0.00193 (0.00287)	-0.00309 (0.00287)
Crisis $\times$ I-Stayers	0.04456 (0.00277)	0.04436 (0.00305)
Crisis $\times$ O-Stayers	0.04477 (0.00259)	0.04413 (0.00269)

Notes: Standard Errors in parenthesis. All specifications include individual and time effects and stayer effects interacted with year.

Table 8: Semiparametric results

	4 digit δ^1	δ^2	3 digit δ^3	Industry only	Occupation only
1988.4 to 1989.4	0.0835 (0.0960)	-0.0131 (0.0631)	0.0891 (0.0925)	0.1363 (0.0769)	0.0139 (0.0598)
1989.4 to 1990.4	-0.0815 (0.1604)	-0.0029 (0.0897)	-0.2068 (0.1170)	-0.0975 (0.1363)	0.1723 (0.1519)
1990.4 to 1991.4	0.1469 (0.1098)	0.0743 (0.0697)	-0.0712 (0.1087)	0.1221 (0.0856)	0.0121 (0.1430)
1991.4 to 1992.4	NA	NA	NA	NA	NA
1992.4 to 1993.4	0.0432 (0.0715)	0.0295 (0.0437)	-0.0157 (0.0527)	0.0985 (0.0567)	0.0954 (0.0703)
1993.4 to 1994.4	0.0550 (0.0554)	0.0076 (0.0363)	0.0371 (0.0587)	-0.0451 (0.0466)	0.0256 (0.0664)
1994.4 to 1995.4	-0.1294 (0.0378)	-0.0878 (0.0156)	-0.1428 (0.0614)	-0.1336 (0.0644)	-0.1231 (0.0525)
1995.4 to 1996.4	-0.0355 (0.0541)	-0.0584 (0.0329)	-0.0048 (0.0528)	-0.0626 (0.0271)	-0.0881 (0.0398)
1996.4 to 1997.4	0.0838 (0.0501)	-0.0155 (0.0317)	0.0743 (0.0480)	-0.0151 (0.0105)	0.0041 (0.0208)
1997.4 to 1998.4	0.0118 (0.0458)	0.0237 (0.0291)	0.0079 (0.0426)	-0.0651 (0.0216)	0.0210 (0.0104)
1998.4 to 1999.4	-0.0154 (0.0406)	0.0032 (0.0257)	-0.0051 (0.0342)	0.0524 (0.0315)	-0.0344 (0.0298)

Notes: $\varepsilon = 10^{-3}$. *Standard errors are in parenthesis. Individuals are considered movers if they change industries and/or occupations.* δ^1 *is the estimated effect of changes when 4-digit movers are matched on propensity scores, initial 4-digit industry and occupation.* δ^2 *matches 4-digit movers on propensity scores, initial 2-digit industry and occupation.* δ^3 *matches 3-digit movers on propensity scores, initial 3-digit industry and occupation. The industry only column matches movers who changed industry but remained in the same occupation with stayers from their initial industry and occupation. The occupation only column matches movers who changed occupation but not industry with stayers from their initial occupation and industry.*

Table 9: 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	$\frac{1}{1+r}$
σ	Intertemporal elasticity	2	Mendoza (1991)

Table 10: 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.

Table 11: 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.