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Essays on Migration and Monetary Policy

A Dissertation submitted in partial satisfaction of the
Requirements for the degree Doctor of Philosophy

in

Economics

by

Scott Charles Borger

Committee in charge:

Professor Valerie A. Ramey, Chair
Professor Wayne Cornelius
Professor James D. Hamilton
Professor Gordon Hanson
Professor Garey Ramey

2009

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Chair

University of California, San Diego

2009

DEDICATION

Dedicated to Sarah.

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Chapter 3, in full, is joint work with James Hamilton and Seth Pruitt. The dissertation author was a primary author of this paper.

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ABSTRACT OF THE DISSERTATION
Essays on Migration and Monetary Policy

by

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Doctor of Philosophy

University of California, San Diego

2009

Professor Valerie A. Ramey, Chair

The dissertation is comprised of three chapters, each a free-standing paper.

The first chapter estimates the inflow of undocumented migrants to the United States. I find that the estimates are consistent with the previous estimates in the literature and the methodology provides a longer time series of undocumented migrants inflows than currently exists in the literature. The inflows of undocumented migrants are correlated with the business cycle in both the United States and Mexico.

The second chapter models the decision to migrate over different costs structures and finds that both the lower- and upper-income shifted inward as a result of the increased smuggling fees over the previous 15 years. The model is estimated in low-cost and high-cost periods of migration to determine whether the decision to migrant has changed for different income groups.

The third chapter estimates the market-perceived monetary policy rule by using macroeconomic announcements to forecast changes in market expectations. We find evidence that between 1994 and 2007 the market-perceived Federal Reserve policy rule changed: the inflation response became more hawkish, and the output response vanished.

Chapter 1: Estimates of the Cyclical Inflow of Undocumented Migrants to the United States

Abstract

This paper constructs estimates for the inflow of undocumented migrants to the United States using survey-based micro estimates of the probability of apprehension per attempt and aggregate apprehensions data reported by U.S. Customs and Border Protection. The robustness of the constructed data is considered by comparing the implied stock from the constructed series with previous estimates of undocumented migrants in the United States. The estimates are within the unenumerated-correction margin of error of the post-2000 Census estimates in the literature. Moreover, the estimated inflow implies a strong correlation with the business cycle in the United States and Mexico with larger influxes associated with economic conditions in Mexico.

JEL: E32, F22, E24, J61, E63.

Key Words: International Migration, Unemployment, Geographic Labor Mobility.

1.1 Introduction

Undocumented migrants who crossed the border without proper documentation or who remained in the United States past the time allowed by their visas constitute a sizable share of the foreign-born population. However, the lack of a long time-series on the inflows of undocumented migrants in the United States since the 1980s limits our understanding of the correlation between immigration and aggregate economic indicators in the United States. This paper proposes a new methodology to construct an annual inflow of unauthorized migrants across the US-Mexico border that is consistent with (i) previous estimates of the stock of undocumented migrants from Mexico, (ii) indirect estimates of the inflows and (iii) the distribution of migrant trips in micro-surveys. The constructed inflow series is also consistent with the finding in Hanson and Spilimbergo (1999) in that undocumented migrant inflows respond to economic conditions in the United States and Mexico with significant inflows during years where the economy in Mexico is in recession.

Current estimates of the flow of undocumented migrants can be characterized into two subcategories. First, the ‘residual’ methodology uses Census, Current Population Survey or American Community Survey data to estimate the stock of the foreign-born population residing in the United States. By estimating the under sampled populations from post-enumeration surveys, the number of foreign-born residents without legal documentation is calculated as the residual of the total foreign-born population after removing known legal migrants. The projected population of undocumented migrants are subject to under-enumeration or an undercount in the

U.S. Census and the Current Population Surveys and therefore researchers have used different assumptions about the undercount rate.

The residual methodology provides valuable information on the stock of undocumented migrants, but historically provides infrequent estimates before the mid-1990s of the net flow of migrants when the change in the stock of migrants is averaged over the estimated frequency. Hence, the infrequent and abbreviated data makes the methodology ineffectual in accounting for any possible relationship of immigration to the business cycle. For example, Costanzo et al. (2003) estimates an approximate 6 million increase in the stock of undocumented migrants in the United States between 1990 and 2000 at the 20 percent undercount rate. This translates to an average net in-migration of 600,000 per year over the decade. Yet, the data cannot answer the question of whether the number of arrivals per year decreased during the recession in 1991, increased during the economic boom of the late 1990s, or responded to the increased border enforcement that commenced in the mid-1990s. In order to assess the responsiveness of migration to the business cycle, we must augment the existing stock data with new direct measures of the flow of undocumented migrants.

The second methodology for estimating the flow of undocumented migrants is the apprehension-implied 'indirect estimation' in Hanson and Spilimbergo (1999) where the likelihood of apprehension is estimated from border patrol intensity, wages in Mexico and the United States and political economy factors. The intensity of the border control efforts is characterized by linewatch hours – the number of hours that U.S. Border Patrol agents devote to actually patrolling the border, as opposed to administrative and investigative duties. However, the indirect estimation approach

provides only relative rather than level estimates of the inflow fluctuations.

This paper remedies the deficiency of data on the flow of undocumented migrants by constructing the time-series from the aggregate apprehensions data combined with micro-estimates of the probability of border patrol apprehension per attempt to cross the border. The probability-implied inflow of undocumented migrants will provide more information on the timing of migrant inflows during the previous three decades. Moreover, I will construct a measure the implied stock of undocumented migrants from the newly constructed inflow data and compare it with the previous estimates of the stock of undocumented migrants.^{1.1}

One disadvantage of this approach is that it does not calculate an estimate of the inflow of overstayers – foreign-born residents in the United States who entered the United States with valid student or travel visas, then overstayed the time permitted by their visa. According to estimates by the Pew Hispanic Center, between 40-45 percent of the stock of unauthorized migrants in the United States consists of visa overstayers. (Passel, 2006) The inflow data reported in this paper will not include any estimate of this subset of undocumented migrants. References hereafter to the inflow of undocumented migrants will be referring to clandestine entrants across the Southwest border rather than visa overstayers. However, this subset of the unauthorized immigrant population is of considerable economic interest given the proximity of Mexico to the United States and the keen responsiveness of clandestine migrants to economic conditions make my estimated flows more relevant for business cycle and

^{1.1}Hanson (2006) provides a good overview of the literature on the estimates of undocumented migrants.

policy analysis.^{1,2}

The paper is organized as follows. Section 2 articulates the methodology for the construction of the time-series data and provides a description of the micro-surveys used to construct the estimates. Section 3 conducts a series of robustness checks by using the newly constructed inflow data to (i) compare estimates of the inflow-implied stock of undocumented migrants residing in the United States with the residual methodology estimates, (ii) compare the magnitude of the inflows with the distribution of migrant trips in a large survey of migrant histories, and (iii) compare the variation in the inflows with the apprehension-implied indirect estimates. Section 4 estimates the responsiveness of migrant inflows to economic conditions in the United States and Mexico. Section 5 concludes.

1.2 Estimated Inflows of Undocumented Migrants

There are two components to the estimate for the inflow of undocumented migrants. First, aggregate apprehensions by the border patrol provides the scale of the movement of migrants. Second, micro-estimates of the probability of apprehension per attempt to cross the border (the ‘probability of apprehension’) is required to percentage of migrants that elude detection. The estimate for the probability of apprehension is estimated with a new and unique dataset that provides information about individual migrations across the border – the Mexican Migration Field Research Project (‘MMFRP’) dataset. The estimates from the MMFRP dataset will

^{1,2}Cornelius, Fitzgerald and Borger (2009) find that migrants are able to traverse the border in less than 3 weeks after a relative in the United States reports there is a job available for them when the migrant arrives.

provide the series that is consistent with literature, but with larger confidence intervals. In addition, the inflows are estimated with the large sample but limited scope dataset that provides migrant histories of the household head – the Mexican Migration Project(‘MMP’) dataset. The MMP-estimated inflows will provide more precision around the estimates, but the inflows are inconsistent with literature.

1.2.1 Probability of Apprehension and Aggregate Migrations

The number of apprehensions in a given period can be deconstructed as the number of people who attempted to cross the border clandestinely and the probability of being apprehended as follows:

$$A = n(1)p(1) + n(2)p(2) + \dots \quad (1.1)$$

where A is the number of aggregate apprehensions reported in a given year, $n(i)$ is the number of migrants making at least i attempts to cross the border, and $p(i)$ is the probability of being apprehended by the Border Patrol on their i th attempt. The number of apprehensions can also be characterized as follows:

$$A = np + (np\delta)p + (np^2\delta^2)p + \dots \quad (1.2)$$

where n is the number of migrants attempting to cross the border at least once, p is the constant probability of apprehension in a given period and δ is the fraction of migrant attempting to cross the border after being apprehended by the border patrol. In order to characterize equation (1) with equation (2), two assumptions are required. First, the constant probability of apprehension in a given period on different attempts.

This assumes that the migrant would not adjust their behavior or methodology after failing to cross the border. Although this is a strong assumption, there is evidence in Cornelius, Fitzgerald and Borger (2009) that similar crossing methodologies are employed by migrants and smugglers until the migrant is able to successfully cross the border. Second, the assumption that the discouragement factor, δ is constant across trips also assumes the migrant will be discouraged from crossing at the same rate on their second trip as on their fifth trip. This is not a strong assumption according to the data. The incredibly low discouragement rate in the data, 1.2 percent in the MMFRP data and 1 percent in the MMP data, indicates that an unsuccessful attempt to cross the border that would not be followed by another attempt is rare and independent of the number of attempts previously made by the migrant.

Apprehensions then can be simplified as follows:

$$A = np \sum_{s=1}^S p^{s-1} \delta^{s-1} \quad (1.3)$$

where s is an index of the number of attempts and S is the maximum number of attempts that a migrant could make in trying to cross the border in a given period. The total number of migrants who successfully crossed the border can be solved by first calculating the number of migrants who attempted to cross as a function of the aggregate apprehensions data and the micro-estimates on the probability of being apprehended and the rate of discouragement.

$$n = \frac{A}{p\Omega(S)} \quad (1.4)$$

where $\Omega(S) = \sum_{s=1}^S p^{s-1} \delta^{s-1}$ and is the migrant flow factor. The total number of successful migrations can then be characterized by the following:

$$M = n(1)(1 - p(1)) + n(2)(1 - p(2)) + \dots \quad (1.5)$$

where M is the number of inflow of migrants to the United States. Using the same assumption above, the number of migrations can be simplified:

$$M = n(1 - p) + np\delta(1 - p) + np^2\delta^2(1 - p) \quad (1.6)$$

$$M = n(1 - p) \sum_{s=1}^S p^{s-1} \delta^{s-1} \quad (1.7)$$

$$M = n(1 - p)\Omega(S) \quad (1.8)$$

The number of migrations can be characterized as a function of aggregate apprehensions and the probability of being apprehended without requiring an estimate of the discouragement rate.^{1.3}

$$M = A \frac{(1 - p)}{p} \quad (1.9)$$

where an estimate of p is calculated as $p_t = \sum A_t / \sum \Lambda_t$ where Λ_t is the number of attempts observed in the sample in the given year t.^{1.4}

It should be noted that while undocumented migrants who cross the southwestern border of the United States are predominately of Mexican origin, the estimates in this paper are dependent upon the probability of Mexican-born migrants having the

^{1.3}An alternative methodology was used in a previous draft of the paper that estimated the ratio of successful migrations per apprehension. The methodology produced almost identical results as the results reported in this paper, but the probability approach made it more clear to the reader the assumptions required to estimate the inflow of migrants.

^{1.4}Attempts are assumed to occur during the same year. This is a reasonable assumption given that attempts are usually made on consecutive days and nights. *Fuentes* and *García* (2009) provides a good description of the *coyote* industry on the US-Mexico border including information on the technique used by *coyotes*.

same propensity as non-Mexican migrants of being apprehended. It is possible that more extensive family networks, language, or access to ‘coyotes’ (human smugglers) with better knowledge of the border-crossing obstacles give Mexican nationals an advantage in evading the Border Patrol. However, with CBP reporting that more than 90 percent of annual apprehensions are of Mexican citizens, the distortions from this assumption should be minimal on the overall estimates.

1.2.2 MMFRP Estimated Inflows of Undocumented Migrants

The set of data that provides individual observations of migrations is from the Mexican Migration Field Research Project,^{1,5} which conducts highly detailed survey studies of the populations of high-emigration communities in rural Mexico and in U.S. receiving cities for migrants from these localities. Five surveys have been conducted to date, among migrants and potential migrants in *Tlacuitapa, Jalisco* (2005, 2007), *Tunkás, Yucatán* (2006, 2009), and *San Miguel Tlacotepec, Oaxaca* (2007). The present analysis makes use of a panel dataset of migrant histories from the MMFRP’s three most recent surveys. The surveys record the migrant histories on both sides of the border providing basic demographic information and specific information about their migrations including documentation status of the migrant, the number of apprehensions by the border patrol, usage of ‘coyotes’ (human smugglers) and whether the migrant succeeded or failed in crossing the border.

The MMFRP surveys were conducted in three regionally distinct migrant-sending communities with different trajectories of migration to the United States.

^{1,5}MMFRP is an ongoing research project of the University of California-San Diego’s Center for Comparative Immigration Studies

Tunkás, Yucatán, surveyed in January 2009, is a town still in its first generation of international migration. However, the town has had significant earlier migrations to destinations within Mexico, notably Cancun and Mexico City. *Tlacuitapa, Jalisco*, studied in January 2007, is in its fourth generation of U.S.-bound migration, with little tradition of internal migration. *San Miguel Tlacotepec, Oaxaca*, surveyed in December 2007, is in its second generation of migration to the United States. Interviews with U.S.-based migrants from these towns were conducted within a month of the Mexico-based fieldwork, using contacts established in the sending community. Migrants from *Tunkás* and *San Miguel Tlacotepec* were interviewed primarily in Southern California, while *Tlacuitapa's* US-based migrants were interviewed in Oklahoma City and the San Francisco Bay Area. Additional interviews were conducted across the United States over the telephone.

Table 1.1: SUMMARY STATISTICS OF UNDOCUMENTED MIGRANTS IN SURVEY COMMUNITIES

Variable	<i>Tunkás,</i> <i>Yucatán</i>	<i>Tlacuitapa,</i> <i>Jalisco</i>	<i>Tlacotepec,</i> <i>Oaxaca</i>	Total
Male Migrants	63.8%	75.7%	67.5%	67.8%
Males In US	71.8%	65.9%	52.4%	64.5%
Coyote Use	81.3%	81.7%	74.5%	79.4%
Percent Apprehended	27.8%	31.5%	46.4%	34.3%
Age	37.1	39.0	35.6	37.2
Age at First Migration	21.8	20.9	21.0	21.3
Married	74.0%	80.1%	75.5%	76.1%
Number of Children	2.3	2.7	2.4	2.4
Employment (Most Recent US Trip)				
Construction	9.3%	53.1%	18.3%	23.7%
Agriculture	0.5%	6.3%	37.6%	13.1%
Service	64.3%	31.8%	35.6%	47.1%
N	360	222	246	828

Note: Mexican Migration Field Research Program Data.

Table 1 provides a summary of the characteristics of the MMFRP's surveyed communities. First, there are slight differences between the surveyed communities in the percent of undocumented males in the United States. However, the percent of males in the U.S. undocumented population is 58 percent according to Passel (2006), which is slightly lower than the 65 percent found in the MMFRP sample. Second, the type of U.S. employment acquired by migrants from each of the sending communities during their most recent sojourn in the United States differs significantly, with *Tunkás'* migrants primarily in the service sector, *Tlacuitapa's* primarily in the construction sector, and *Tlacotepec's* in both the agricultural and service sectors.^{1.6}

Figure 1.1 exhibits the annual data of each of the series required for the construction of the MMFRP-estimated inflows of undocumented migrants. Figure 1.1a displays the estimated probability of apprehension per attempt (p_t) and the bootstrapped confidence intervals at the 5th and 95th percentile for the probability. Figure 1.1b reports the annual apprehensions (A_t). Figure 1.1c is the estimated inflow of undocumented migrants to the United States over the previous three decades with confidence intervals. The estimated inflows are more clearly exhibited in Figure 1.2 with years in which there was a US and/or Mexico recession shaded accordingly. The years before the Immigration Control and Reform Act of 1986 (IRCA) saw large inflows of undocumented migrants with an estimated 4 million migrants entering the

^{1.6}Estimates from Passel (2005) on aggregate employment data for undocumented migrants in the United States would suggest 49 percent are in the service sector, 17 percent in construction and 3 percent in agriculture. This would suggest that the sampled communities are overly representative of migrants from the construction and agricultural sectors which could have cyclical or seasonal components to their migration patterns. It should be noted that the sectoral estimates are for both overstayers and clandestine entrants and therefore might not be overly representative of the sectoral divisions in unauthorized migrant employment.

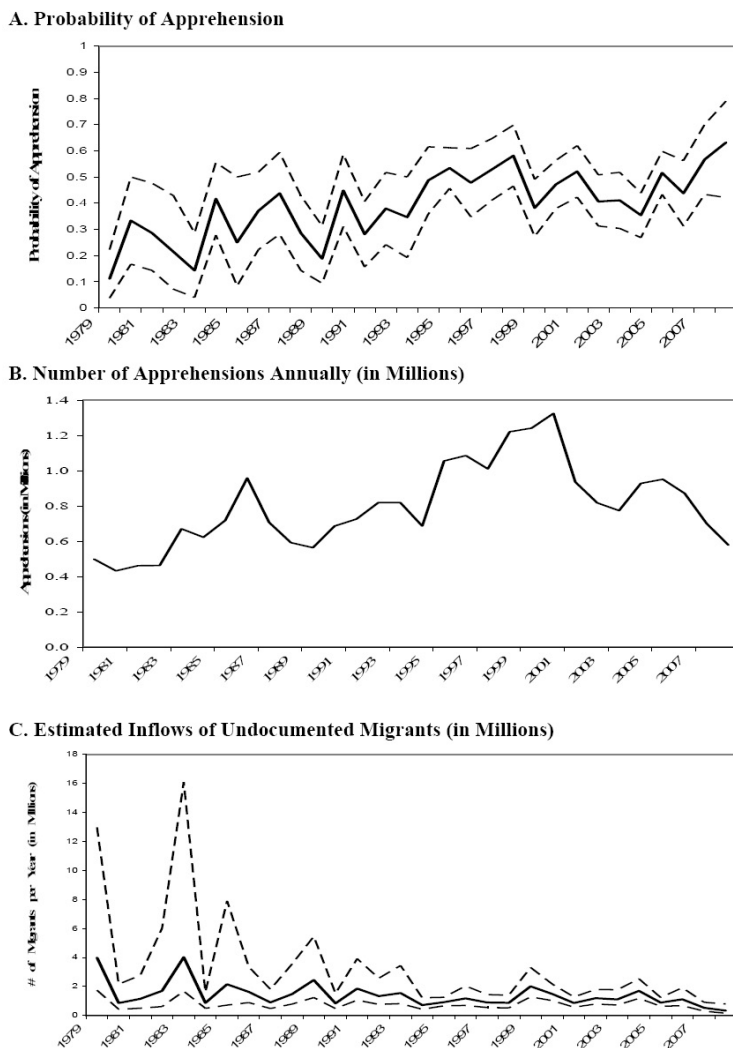


Figure 1.1: CONSTRUCTION OF INFLOWS FROM OBSERVED MMFRP PROBABILITY

Note: **Panel A:** Probability of apprehension observed in the MMFRP data set with the bootstrap-estimated upper and lower confidence bounds at the 5th and 95th percentiles. Estimates for the period 1979 to 2008 reported. **Panel B:** Annual apprehensions reported by the U.S. Customs and Border Protection. **Panel C:** Estimate of the inflow of undocumented migrants from equation 1.9 using the probability of apprehension reported in Panel A and the aggregate apprehensions from Panel B. The confidence intervals are determined from the upper and lower confidence bounds of the apprehensions probability.

United States during these periods. These years also correspond to periods where Mexico was in an economic contraction while the United States was not. There is also an acceleration in the number of migrants at the end of the economic cycles of the

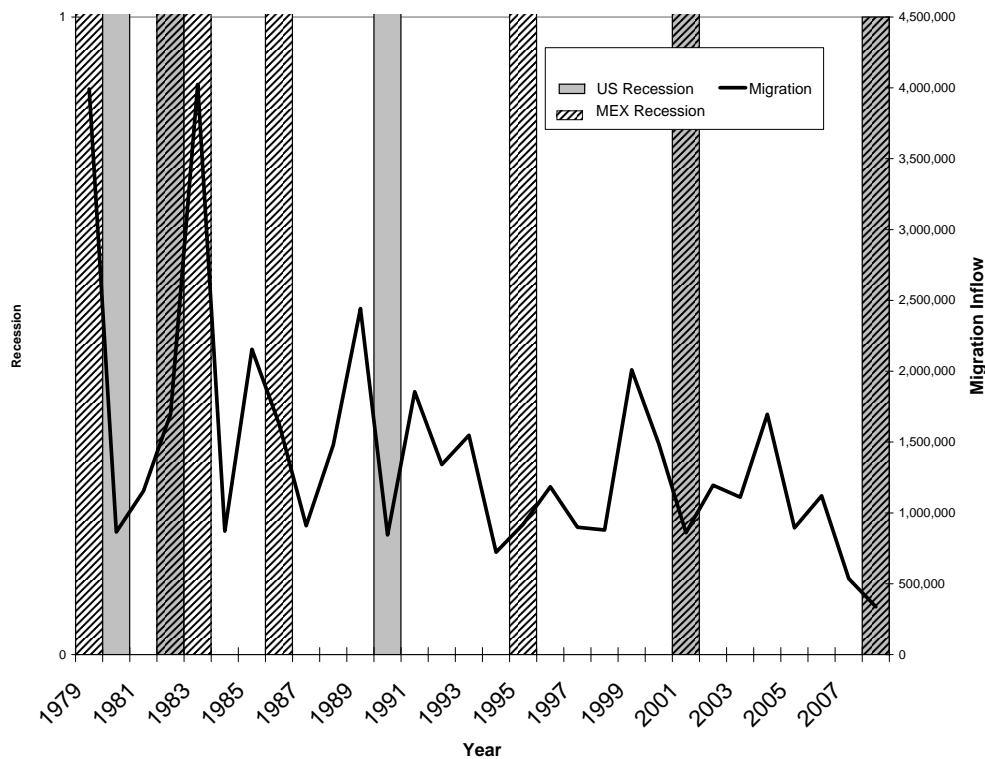


Figure 1.2: MMFRP ESTIMATED INFLOWS OF UNDOCUMENTED MIGRANTS TO THE UNITED STATES

Note: Mexico recession dates (cross-hatched) signifies negative real GDP growth during a given year. US recessions (shaded) are the NBER recession dates.

late-1980s and the late-1990s and a contraction in the inflows during the recessions of both 1991 and 2001. Moreover, the decline in inflows since the contraction in the construction sector in 2007 is evidenced with an estimated 338,000 undocumented migrants crossing the border during 2008. This is more than a 90% contraction since its peak in the early 1980s.

1.2.3 MMFRP Contiguous Years Estimate

I consider a second approach to estimating the probability of apprehension because of the small sample properties of the MMFRP data and the possibility of recollection bias associated with migrant history surveys. Since the expected appre-

hension rates for years surrounding a given year's migration would probably be similar with similar border enforcement policies, I construct a pooled distribution of migrations with observations from the previous year, the current year and the subsequent year to estimate the current year's probability. This approach could be described as a centered 3-year moving average of the probability of apprehension observed in the MMFRP data ('MMFRP-3'). The calculation of the MMFRP-3 probability uses the median observation from the bootstrap drawing with replacement from the distribution of observations in periods t , $t-1$ and $t+1$. Then the probability is calculated:

$$p_t^b = \frac{\sum_{t-1}^{t+1} \sum_1^{n(t)} A_t}{\sum_{t-1}^{t+1} \sum_1^{n(t)} \Lambda_t} \quad (1.10)$$

where $n(t)$ is the number of migrant trips observed in period t , Λ_t is the number of attempted crossings, and p_t^b is the probability calculated from one draw of the distribution. This process is replicated 10,000 times and the median observation is recorded as the estimated MMFRP-3 probability of apprehension. Figure 1.3a shows the estimated MMFRP-3 probability with confidence intervals. As expected, the smoothed ratio over three years provides much tighter confidence intervals.

Figure 1.3c is the estimated annual inflows with peaks of around 1.6 million undocumented migrants per year and troughs of around 700,000 migrants. The current period in this model does not look that much different from the inflows in 1995. Note that estimates for 2008 are not possible with this estimation approach and therefore the current level of inflows is not yet observed. Figure 1.4 places the MMFRP-3 inflows in the context of the business cycles. The smoothing out of the

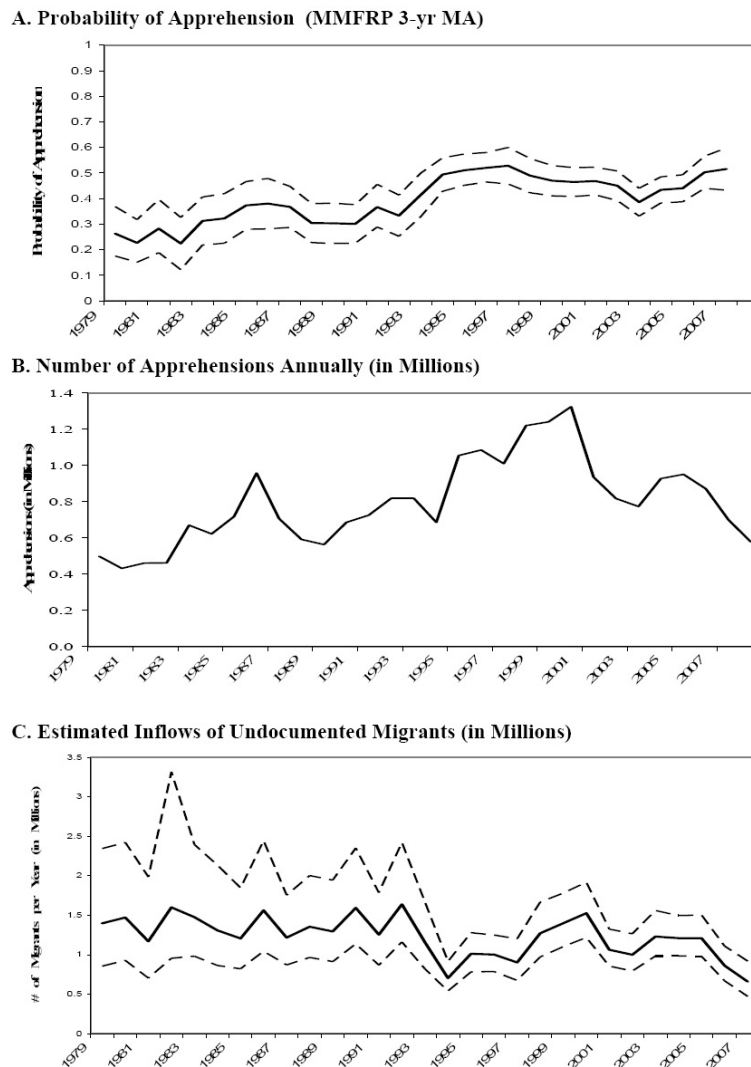


Figure 1.3: CONSTRUCTION OF INFLOWS FROM MMFRP-MA(3)

Note: Panel A: Probability of apprehension estimated from MMFRP data set with the draws from the previous year, current year and subsequent year. Estimates for the period 1977 to 2007 reported. **Panel B:** Annual apprehensions reported by the U.S. Customs and Border Protection. **Panel C:** Estimate of the inflow of undocumented migrants from equation 1.9 using the probability of apprehension reported in Panel A and the aggregate apprehensions from Panel B. The confidence intervals are determined from the upper and lower confidence bounds of the apprehensions probability.

probability of apprehensions also smooths out some of the business cycle properties.

Nevertheless we see constant inflows during the 1980s with inflows between 1.2 and 1.6 million undocumented migrants per year. It should be noted that this was a period of significant circular migration, where the migrant would return to Mexico

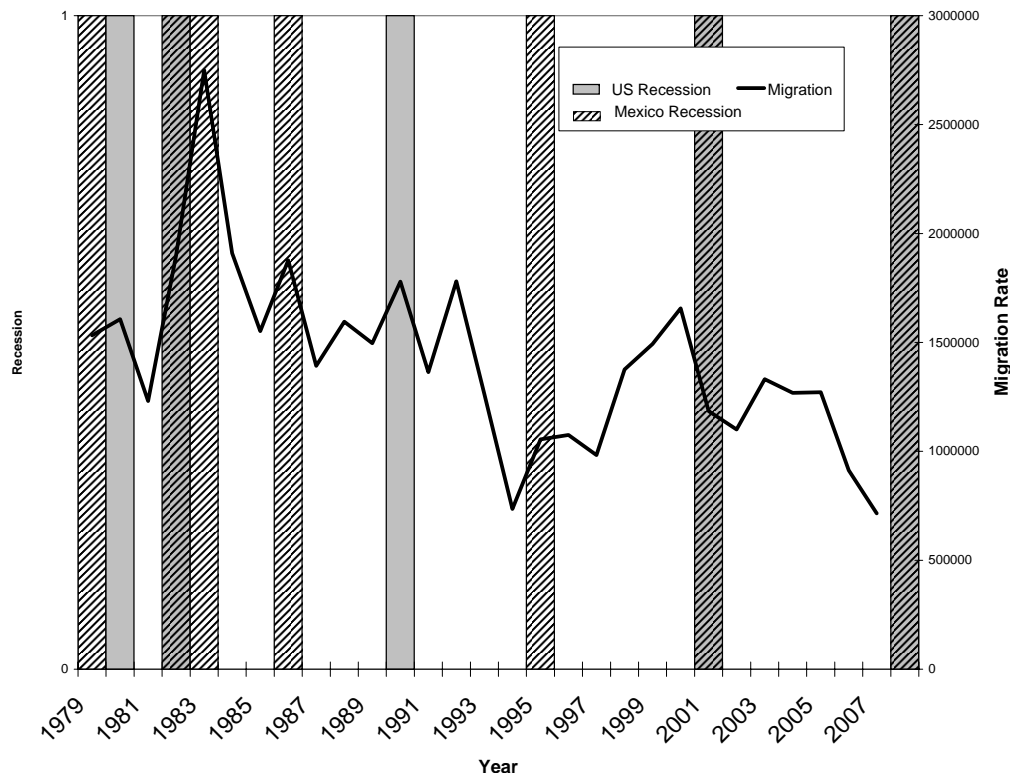


Figure 1.4: MMFRP 3-YR ESTIMATED INFLOWS OF UNDOCUMENTED MIGRANTS TO THE UNITED STATES

Note: Mexico recession dates (cross-hatched) signifies negative real GDP growth during a given year. US recessions (shaded) are the NBER recession dates.

during the winter months. Therefore many of these inflows could represent the same migrants. The decline in the inflows in 1994 corresponds to the period of increased border enforcement. This deterrent however was short-lived, with inflows reaching their 1980s peaks by the end of the economic expansion of the late-1990s.

1.2.4 MMP Estimated Inflows of Undocumented Migrants

The third approach to constructing an estimate for the inflows of undocumented migrants calculates the probability of apprehension using data from the Mexican Migration Program (MMP), a long-term research project now based at Princeton

University that has surveyed a larger and a more geographically diverse set of migrant-sending communities in Mexico.^{1.7} The number of observations in the MMP dataset is large and provides much tighter estimates of the probability of apprehension. The estimated MMP ratio was lower on average with a 28% probability of apprehension per attempt compared with an average of 38% and 39% probability in the observed and smoothed MMFRP estimates, respectively. (See Table 1.2) The estimated MMP ratio in figure 5a exhibits a constant trend in the probability of apprehension which is in contrast to the trends observed in the MMFRP data. The disadvantages of the MMP-inflow estimates are their inconsistencies with previous estimates of undocumented migrants in the literature and with the distribution of migrant trips reported by respondents to the MMP survey.

Table 1.2: PROBABILITY OF APPREHENSION ESTIMATES WITH MMFRP AND MMP SURVEY

Variable	MMFRP	MMFRP-3	MMP
Probability of Apprehension (1979-2005)			
Mean	0.376	0.387	0.284
Standard Deviation	0.125	0.091	0.052
Median	0.382	0.279	0.380
Correlation of Probability and Linewatch Hours (1979-2004)			
Correlation	0.507	0.617	0.270
Unconditional Elasticity - Prob. and Hours (1979-2004)			
E	0.025	0.026	0.018
(s.e.)	(0.001)	(0.001)	(0.001)
N	828	828	5641

Note: MMFRP is the probability estimated with the Mexican Migration Field Research Program dataset. MMFRP-3 is a constructed probability drawing from the distribution with replacement of migratory trips across the border from the previous year, the current year and the subsequent year to estimate the current year probability. MMP is the probability estimated in the Mexican Migration Project. Linewatch hours or Hours are the number of hours the border patrol spend patrolling the southwest border.

^{1.7}Other surveys such as the Mexican government's *Encuesta sobre Migración en la Frontera Norte de México* (EMIF), 1993-2004, were considered to estimate the apprehensions-to-migrant ratio, but these surveys either lacked information on apprehensions or the year of the migration.

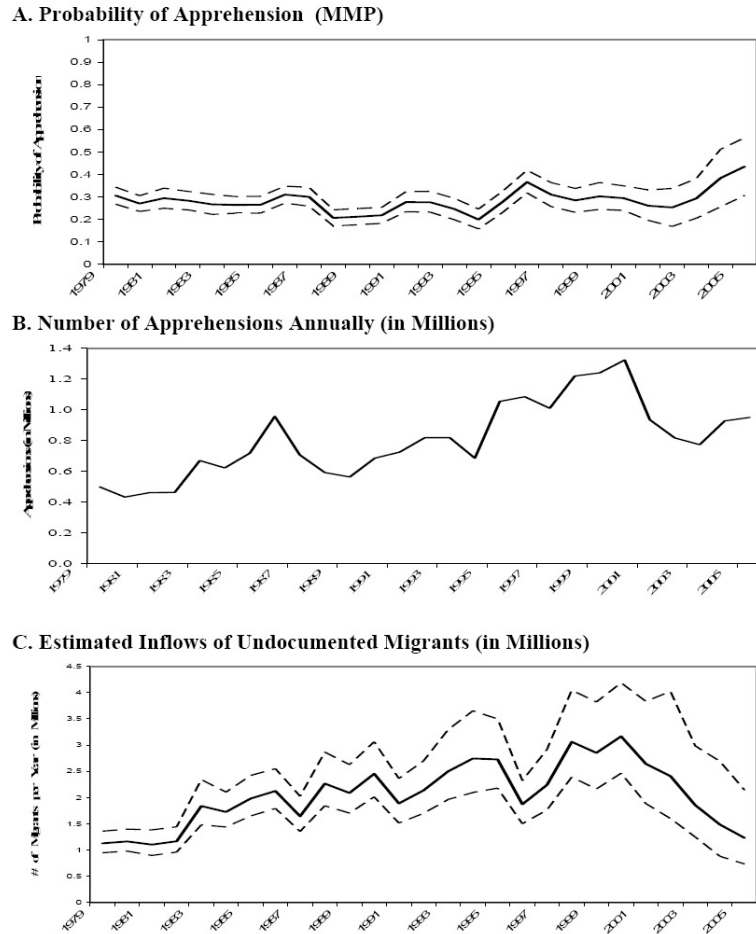


Figure 1.5: CONSTRUCTION OF INFLOWS FROM MMP PROBABILITY

Note: Panel A: Probability of apprehension estimated from the MMP data set with the bootstrap-estimated upper and lower confidence bounds at the 5th and 95th percentiles. Estimates for the period 1977 to 2005 reported. **Panel B:** Annual apprehensions reported by the U.S. Customs and Border Protection. **Panel C:** Estimate of the inflow of undocumented migrants from equation 1.9 using the probability of apprehension reported in Panel A and the aggregate apprehensions from Panel B. The confidence intervals are determined from the upper and lower confidence bounds of the apprehensions probability.

The probability of apprehension estimate would indicate little effect of the increase in border enforcement intensity in the mid-1990s and the exponential increase in linewatch hours of border patrol during the most recent decade. This is evidenced in table 1.2 with the correlation between the MMFRP probability estimates and linewatch hours is 0.51, whereas the correlation between the MMP probability esti-

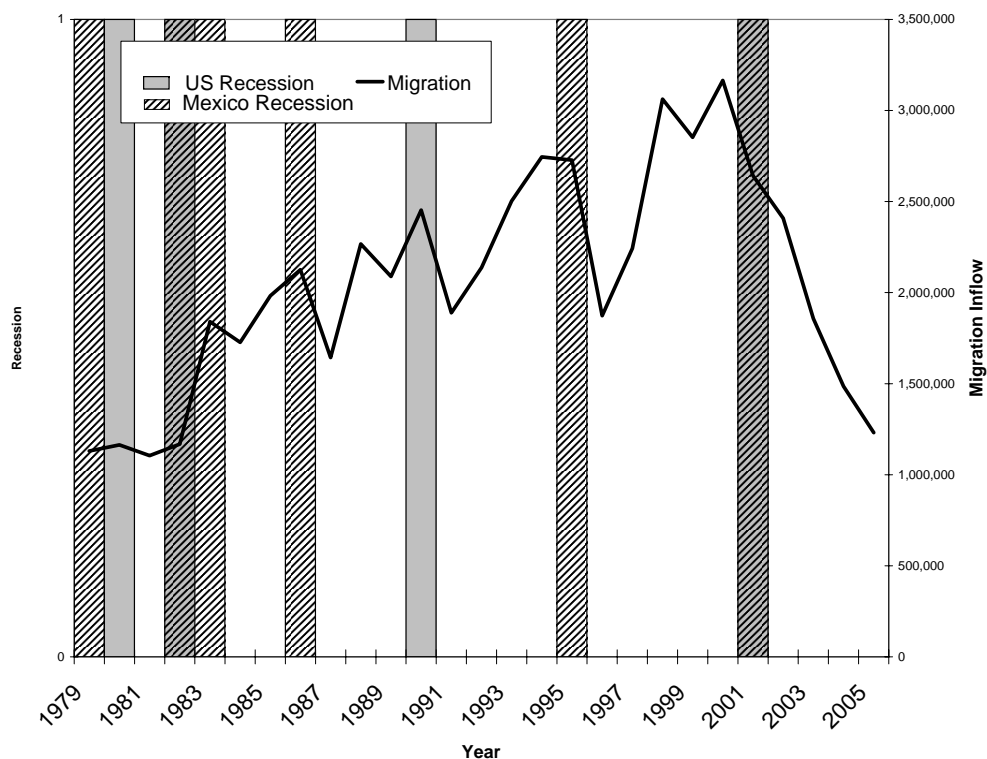


Figure 1.6: MMP ESTIMATED INFLOWS OF UNDOCUMENTED MIGRANTS TO THE UNITED STATES

Note: Mexico recession dates (cross-hatched) signifies negative real GDP growth during a given year. US recessions (shaded) are the NBER recession dates.

mates and linewatch hours is 0.27. Moreover, the differences between the MMFRP and MMP data have different implications for the probability of apprehension with increased linewatch hours. The unconditional elasticity of linewatch hours on apprehensions was estimated with a percent increase in the linewatch hours having more than twice the percentage point increase in the MMFRP data as the MMP data. In the context of testing the robustness of the inflow estimates in the next section, the differences between the two estimates will be considered.

Figure 1.5c exhibits the MMP-estimated inflows which has a distinct upward trend through the early 2000s, in contrast with the MMFRP data and Hanson (2006)

that has inflows decreasing over this period. Figure 1.6 graphs the MMP-inflows at the business cycle frequency in the United States and Mexico. The response of the inflows to economic conditions in Mexico is consistent with previous findings that push factors contribute to migrations to the United States. However, the trough of the flows during the recession in the 1980s misses the acceleration of migrations associated with the legislative process around the Immigration and Control Act of 1986(IRCA).

1.3 Consistency of the Inflow Estimates

The significant efforts previously made in the literature to estimate the stock of undocumented migrants provides a means to verify the reasonableness of the estimation technique and the underlying data. Hereinafter, I will demonstrate that the MMFRP-inflow estimate is consistent with the post-2000 stock of undocumented migrants from Mexico, the distribution of trips in the MMP migrant history surveys, and the indirect estimates of the inflow of undocumented migrants. However, the MMP-inflow estimate is inconsistent with these measures.

1.3.1 The Stock of Undocumented Migrants

To estimate the consistency of the inflow estimates, I calculate the implied stock of undocumented migrants from the inflow data and compare the implied stock of undocumented migrants with previous estimates of the stock of undocumented migrants from Mexico to test whether the inflow data series provides a magnitude of migrants that is consistent with previous estimates in the literature.

The stock of undocumented migrants has often been calculated by a residual methodology that subtracts the number of legal resident aliens from the enumerated foreign-born population as estimated by the U.S. Census, the Current Population Survey or the American Community Survey. The differentiation between the enumerated and unenumerated population is an important distinction since estimates rely on the cooperation of undocumented migrants with government-based surveyors. Estimates in the 1980s used the Alien Registration Program to determine the number of documented immigrants. The discontinuation of the Alien Registration Program in 1981 required a projection each subsequent year of new immigrations.

Costanzo et al. (2001), Bean et al. (2001), INS (2001), Passel (2005), and Hoefer et al. (2006, 2007) estimate the stock of undocumented migrants residing in the United States by using a residual methodology that subtracts the number of foreign-born persons who are known to reside in the United States through visa entries and exits from the total number of foreign-born respondents to government household surveys and estimated mortality rates. Then taking into account some undercount in the responses of undocumented migrants, the difference between the survey's estimate of the foreign-born and the known foreign-born population is the estimate of the undocumented population living in the United States.

In addition to the information on the inflows, I also estimate the probability that a documented migrant would return back to Mexico from the MMP data. Unlike the assumption made in the MMFRP data – that idiosyncracies between migrant communities would be insignificantly different in apprehension rates since all migrants would make every effort to elude the border patrol and cross the border undetected

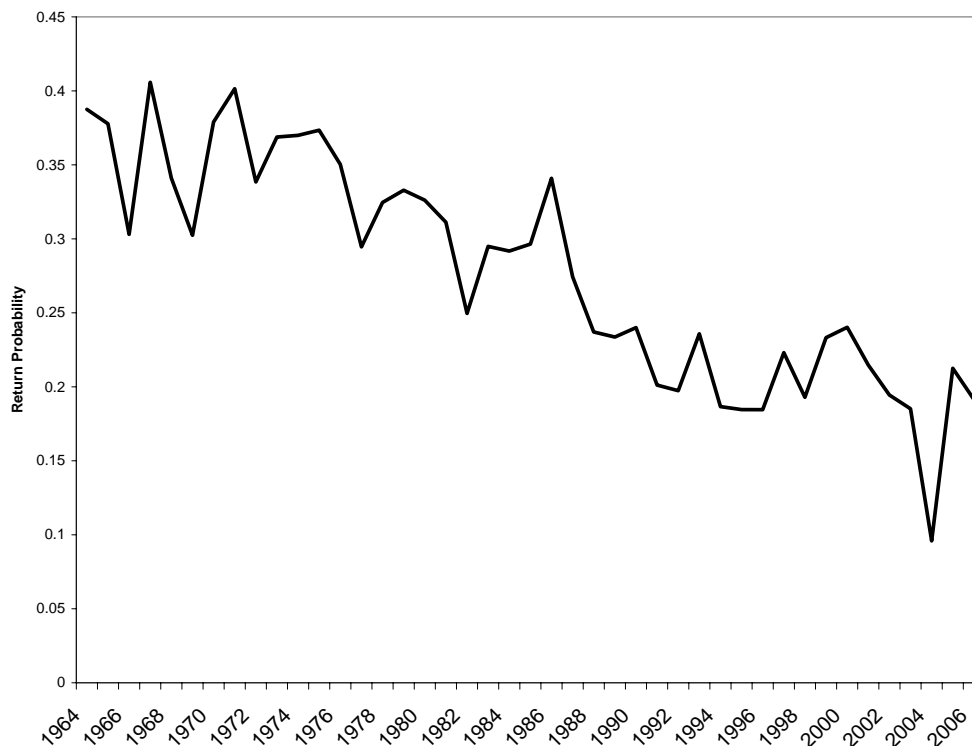


Figure 1.7: PROBABILITY OF RETURNING TO MEXICO

Note: Return probabilities are calculated from the MMP migrant histories of undocumented migrants. Using the reported year of the migrant trip and the amount of time they spent in the United States on a given trip, the number of undocumented migrants who reported returning to Mexico in the sample in a given year was divided by the number of migrants recorded as being in the United States in that year.

– different community customs and migrant trajectories could provide different estimates for the probability of return. Therefore, all return probabilities are estimated over the larger MMP sample with 118 different surveyed communities. Figure 1.7 exhibits the downward trend in returning back to Mexico. In the 1960s and 1970s, many of the undocumented migrants in the United States were agricultural workers who remained in the United States only for the agricultural season returning back to Mexico during the winter. In the late 1980s and early 1990s the return probability dropped to 20% as families were reunified in the United States and border

enforcement intensity increased.

Using the return data, I estimate the stock of undocumented migrants by subtracting off the returned migrants from the stock of migrants in the previous period and then adding the new inflow for the current year. In addition, the IRCA legislation in the 1980s provided a process for legalization for which I need to account. One method would be to use the fact that anyone residing the United States before 1980 received amnesty and therefore start the stock of undocumented migrant from that date. Instead, since receipt of permanent resident status was over a period of time, I use estimates from the Office of Immigration Statistics to subtract transitions from undocumented to permanent resident status of Mexican nationals. There are two stylized facts the stock of undocumented migrants should be able to replicate. First, the number of undocumented migrants receiving permanent resident status from either the January 1, 1980 threshold or the agricultural workers that worked for 90 days between May 1, 1985 and May 1, 1986 totaled approximately 3 million. Therefore any estimate of the stock of undocumented migrant in the early 1980s should have at least 3 million undocumented migrants. Second, the under-count in the 2000 U.S. Census was much less significant among Hispanics than in previous surveys and therefore would expect the surveys using the current census weights to provide a better estimation of the undocumented population. Therefore, any estimate should also approximate the recent stock estimates in the literature.

Figures 1.8-1.10 report the estimated stock of undocumented migrants who reside in the United States after crossing the Southwest border for each of the constructed series. In addition, the previous estimates of the stock of undocumented

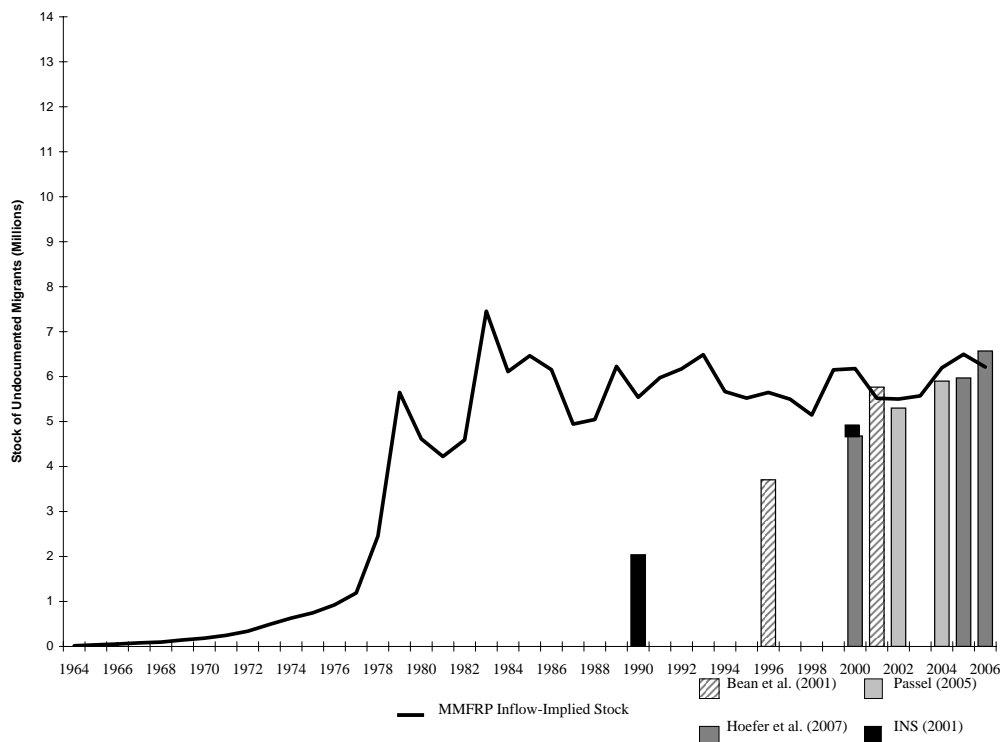


Figure 1.8: MMFRP ESTIMATE OF THE STOCK OF UNDOCUMENTED MIGRANTS VS. ESTIMATES IN LITERATURE

Note: The stock of undocumented migrants is calculated by using the inflow estimates and multiplying the current stock of migrants by the return probability estimated in the MMP dataset. The stock is reduced by the number of unauthorized migrants receiving permanent resident status in a given year, estimated by the Office of Immigration Statistics.

migrants from Mexico are provided to demonstrate that the MMFRP constructed data is consistent with both the trend and the magnitude of the post-2000 period. The restriction to Mexican national migrants does underestimate the stock of undocumented migrants who would traverse the border through clandestine entry since migrants of Mexican origin constitute about 90 percent of undocumented migrants from Central America.^{1.8} However, the stock estimate for Mexico provides a constant measure to compare the implied stock estimates and the previous estimates.

^{1.8}In contrast to the inflow estimate, the share of nationalities other than Mexico in the stock of undocumented migrants is more due to lower return rates. About 15 percent of the stock of undocumented migrants from Central America are from El Salvador, Nicaragua, and Honduras.

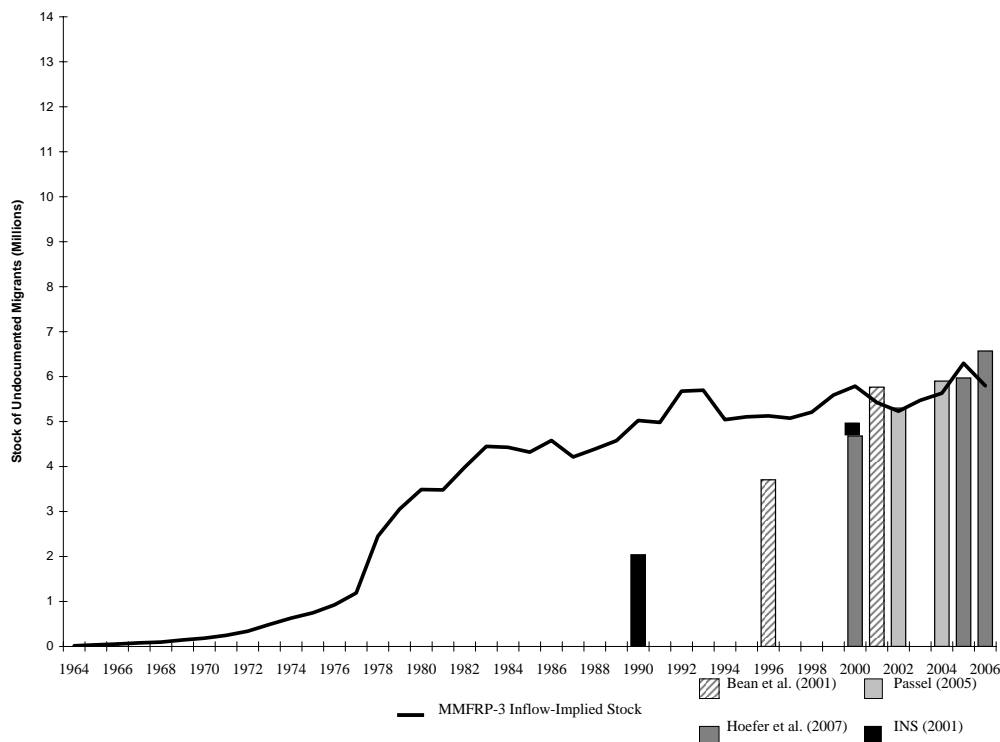


Figure 1.9: MMFRP 3-YEAR ESTIMATE OF THE STOCK OF UNDOCUMENTED MIGRANTS VS. ESTIMATES IN LITERATURE

Note: The stock of undocumented migrants is calculated by using the inflow estimates and multiplying the current stock of migrants by the return probability estimated in the MMP dataset. The stock is reduced by the number of unauthorized migrants receiving permanent resident status in a given year, estimated by the Office of Immigration Statistics.

The differences in the magnitude could be accounted for by the different assumptions that each of the authors made about the unenumerated population in the sample. The INS (2001), Passel (2005) and Hoefer et al. (2006, 2007) use an undercount rate of 10 percent whereas the numbers reported for Bean et al. (2001) was an undercount rate of 25 percent. Other factors that might contribute to the magnitude of the MMFRP-implied stock being higher than previous estimates is that 10 percent of those who traverse the border are not Mexican citizens and therefore are not counted in the estimates reported in figures 1.8-1.10. This fact combined

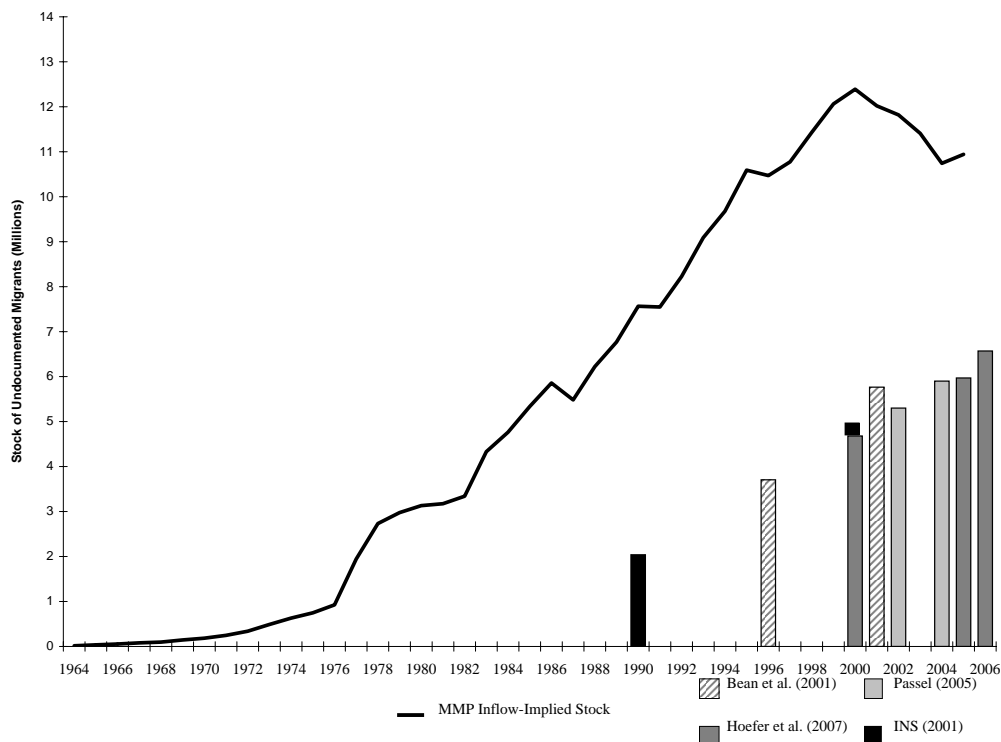


Figure 1.10: MMP ESTIMATE OF THE STOCK OF UNDOCUMENTED MIGRANTS VS. ESTIMATES IN LITERATURE

Note: The stock of undocumented migrants is calculated by using the inflow estimates and multiplying the current stock of migrants by the return probability estimated in the MMP dataset. The stock is reduced by the number of unauthorized migrants receiving permanent resident status in a given year. The differences between the stock estimates and the MMP-implied stock estimates is attributable to the lower probability of apprehension which could be a function of the MMP question asking about *deportaciones* rather than *agarrado*.

with the different assumptions about the undercount rate would indicate that both the magnitude and trend of the estimated stock implied by the MMFRP constructed series are reasonable.

1.3.2 MMFRP and MMP Differences

The reported stock of undocumented migrants in figure 1.10 from the MMP estimated inflows would seem to indicate that the MMP ratio provides too low of a

probability of apprehension for what we should have observed in the sample.^{1.9} Since the MMP data is a larger data, it is important to note why the MMP data reports more migrants are successfully crossing the border per apprehension made by the border patrol.

The difference between the two surveys that would account for the differences in the inflow estimates is the construction of the survey question. The MMFRP survey asks how many times the person was *agarrado* which implies caught or stopped by the border patrol. This is in contrast with the MMP survey which asks the respondent on a given trip the number of times the person was *deportaciones* which could imply caught but could also imply the legal proceeding that is much more formal than the self-deportation policies of the last two decades. The distribution of apprehensions in the later period in the MMP data is much more centered around zero and one than what one would expect from micro-evidence on border crossings since the early 1990s.

In addition, other differences were considered that could account for the differences in reported apprehensions. First, demographic assessments were made between the two surveys with age being significant predictor of the number of times a migrant was apprehended. The older a person attempting to clandestinely cross the border, the more likely they would be apprehended by the border patrol. However, the mean and variance of age in the two samples were almost exactly the same.

Second, gender differences between the two surveys could compose the difference if women were more likely to be apprehended on the border since the MMP

^{1.9}The low probability of apprehension implies a high stock of migrants since more migrants are crossing the border undetected and therefore the aggregate apprehensions are capturing fewer of migrants that would have crossed given the low apprehension probability.

data is primarily composed of male heads-of-households with women only representing 2 percent of the respondents to the migration histories. However, in both surveys, women were less likely rather than more likely to be apprehended.^{1.10}

Third, aggregation error could account for the differences in the inflow of undocumented migrants since apprehension differences could be the result of policy differences in different sectors along the border. For example, the initial intensification of border enforcement were in the San Diego and El Paso sectors and could have skewed the aggregate inflows. However, when the data was disaggregated to sectoral apprehension rates and sectoral apprehensions, the difference between the disaggregated estimates and the aggregated estimates were small, with approximately a 5 percent upward bias in inflows. This would not account for the difference between the two surveys.

1.3.3 Distribution of Migrant Trips

However, the MMP data provides an information on the distribution of migrant trips of the survey participants over the past half century with surveys that span the last two decades. A characterization of the distribution will provide an additional consistency check on the magnitude and variability in the inflows of undocumented migrants. Trips where the respondent indicated crossing the border without documentation were divided into the year the survey was conducted and the year that the respondent reported crossing their first time and their most recent time. Then randomly drawing 20 times from each of the survey years to prevent over-sampling

^{1.10}See Cornelius et al. (2009) for discussion on gender differences in crossing the border.



Figure 1.11: DISTRIBUTION OF MIGRATION TRIPS IN THE MMP SAMPLE

Note: The distribution of migrant trips is calculated over the larger and more diverse sample of migrant trips in the MMP data sampled over the previous two decades. Both equal and weighted samples were randomly drawn from each survey year and replicated 10,000 times to determine the likelihood of observing a migrant trip in a given year. Migrant trips from 1960 to 2006 were estimated. The graph exhibits 1979 to 2006 for purposes of comparison with inflow estimates.

of the years where the survey was conducted more intensely, I recorded the number of times a migrant trip year was observed. I then replicated this process 10,000 times and averaged the migrant trip years observed.

Figure 1.11 exhibits the distribution of migrant trips in the MMP data. The trips reported by the migrants are similar to the estimates calculated from the MM-FRP data rather than the estimates from the MMP data. The greatest inflows were in the early- and mid-1980s with a significant contraction in the rate of inflows since 2000. Figure 1.11 also presents a weighted distribution of trips which takes into ac-

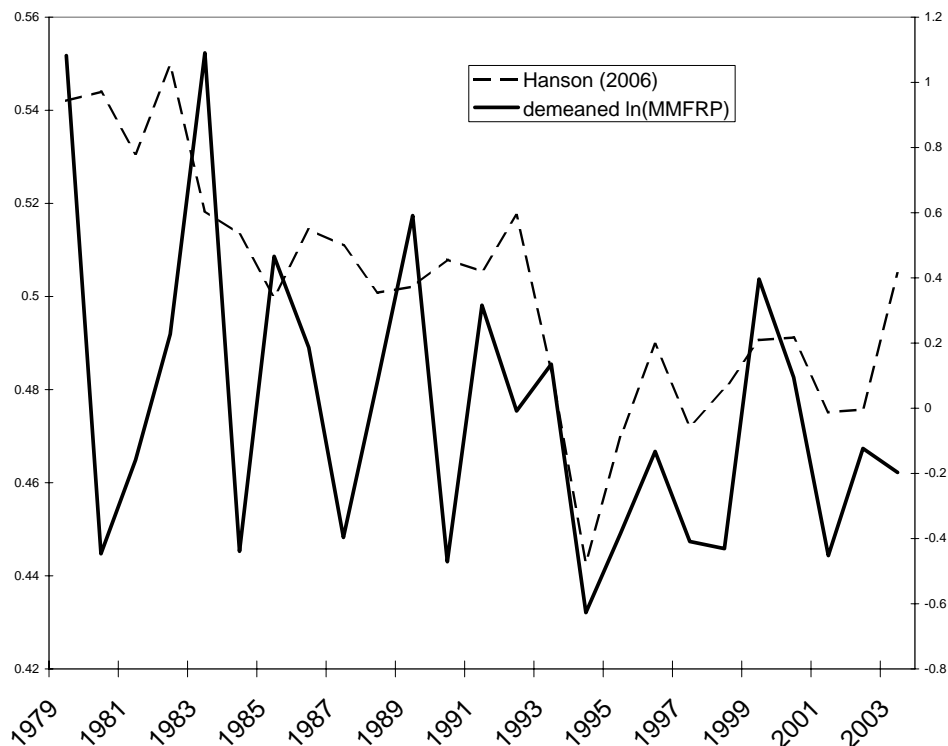


Figure 1.12: MMFRP AND INDIRECT ESTIMATES OF INFLOWS

Note:The indirect estimate is the annual inflow variation calculated in Hanson (2006) which is a reduced form of Hanson and Spilimbergo (1999). The MMFRP estimated inflow is transformed by taking the natural logarithm and demeaned to provide a comparison with estimates in Hanson (2006).

count the fact that we would observe later years less frequently by the construction of the drawn distributions. Rather than randomly drawing 20 times from each of the survey years, each additional survey year would receive an additional observation such that migrant trips in survey year 2006 would be drawn 40 times whereas 1987 would be drawn 20 times. Although more migrant trips were observed, the shape of the distribution remains remarkably the same.

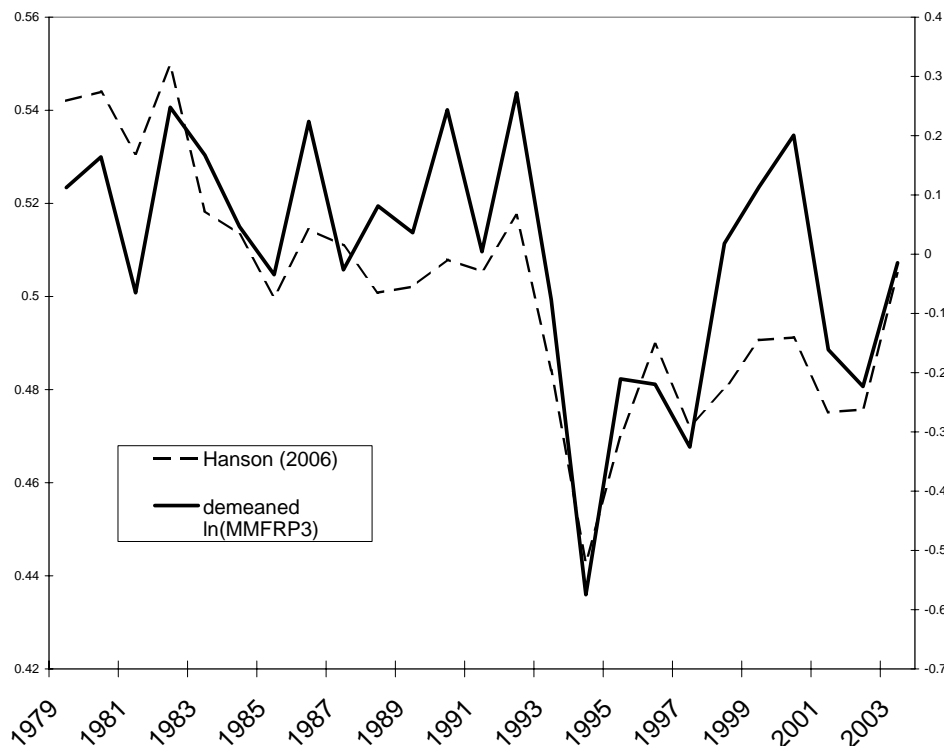


Figure 1.13: MMFRP-3 AND INDIRECT ESTIMATES OF INFLOWS

Note:The indirect estimate is the annual inflow variation calculated in Hanson (2006) which is a reduced form of Hanson and Spilimbergo (1999). The MMFRP-3 estimated inflow is transformed by taking the natural logarithm and demeaned to provide a comparison with estimates in Hanson (2006).

1.3.4 Indirect Estimates of the Inflow of Undocumented Migrants

Hanson and Spilimbergo (1999) model the flow of undocumented migrants indirectly through the use of government data on border apprehensions and the factors that contributed to the probability of being apprehended such as linewatch hours, US wages, Mexico wages, and other factors. In addition, Hanson and Spilimbergo argued that there exists a political economy rationale for different border enforcement policies both over time and during the year and used instruments to capture these

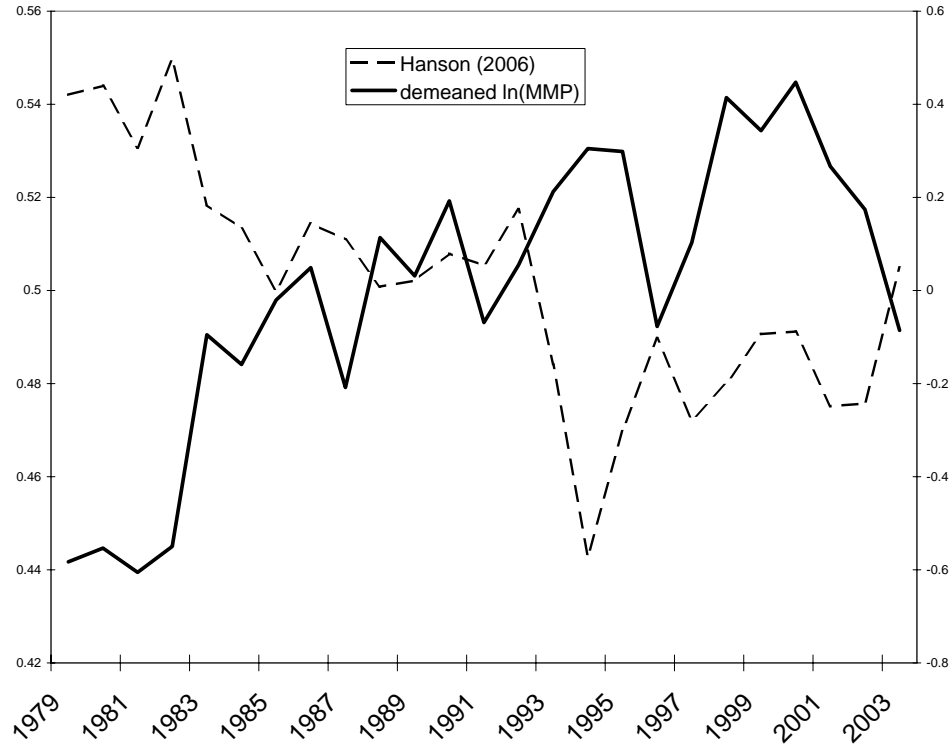


Figure 1.14: MMP AND INDIRECT ESTIMATES OF INFLOWS

Note:The indirect estimate is the annual inflow variation calculated in Hanson (2006) which is a reduced form of Hanson and Spilimbergo (1999). The MMP estimated inflow is transformed by taking the natural logarithm and demeaned to provide a comparison with estimates in Hanson (2006).

effects. Apprehensions at the border are then described by the following equation:

$$A_t = P(H_t, M_t) * M(W_t^{mx}, W_t^{us}, P_t, \Omega_t, \Gamma_t)$$

where A_t is the apprehensions, $P(H_t, M_t)$ is the probability of being apprehended and is a function of border enforcement levels (H_t) and the number of migrants. $M(\cdot)$ is the number of migrants who cross the border, which is a function of wages in Mexico (W_t^{mx}), wages in the United States (W_t^{us}), the probability of being apprehended (P_t), information on the projections of these factors (Ω_t), and individual characteristics (Γ_t). Hanson (2006) estimates a reduced form of the apprehensions

equation:

$$\alpha_0 + (1 - \alpha_2)\ln M_t = \ln A_t - \alpha_1 \ln H_t$$

where the relative change in the number of migrants (M_t) are estimated from the number of apprehensions (A_t) and the linewatch hours by the Border Patrol (H_t) using the estimates of α_1 from estimates in Hanson and Spilimbergo (1999).

Figure 1.12 through figure 1.14 contrasts the demeaned logarithm of the constructed inflow series to provide comparable results with the reduced form estimate of inflow fluctuations in Hanson (2006). The fluctuations in the demeaned natural log of the MMFRP inflow estimate are much more volatile than the indirect estimates. However, since the indirect estimates are the reduced form, the significant fluctuations that might be associated with the business cycle might be muted. However, the demeaned natural log of smoothed MMFRP-3 inflow estimates are similar in variation and timing of the fluctuations. In contrast, the MMP inflow estimates are almost exactly inversely related to the indirect estimates with a correlation between the series of -0.83. (See table 1.3)

1.3.5 Consistency of MMFRP-Inflow

Despite its small sample size, the MMFRP inflow more closely matched the stock estimates, exhibited similar magnitudes over the time period in the constructed distribution of migrant trips, and corresponded to the variability in the apprehensions-implied indirect estimates and therefore provides a reasonable estimate of the previous three decades' inflows of undocumented migrants to the United States.

1.4 Business Cycle Analysis

The responsiveness of migrants to economic conditions in the receiving country context was first documented in Jerome's (1926) seminal work *Migration and the Business Cycle*. He argued that cyclical labor costs moderated the business cycle and this moderation impeded by the movements of immigrants into the labor force. Conversely, Kuznets and Rubin (1954) noted the possibility that foreign labor supply in the United States acts as a stabilizing reservoir over the business cycle assuming unconstrained labor movements by moderating the growth rate of the population. However, the lack of high-frequency data to measure the movements of undocumented migrants left questions about the impact of the recent and significant migrant influx on the business cycle. The newly constructed data series can provide some insight into this nearly century-long debate.

The cyclical movements in the magnitude of the inflow of unauthorized migrants to the United States is commonly assumed, but the identification of these shifts in immigration due to business cycle conditions has been limited by the data on the inflow. Hanson and Spilimbergo (1999), using the indirect approach, find that apprehensions of migrants, controlling for political economy factors, are responsive to the real wage in the United States. Likewise, I find that each of the estimated inflow estimates possess a strong correlation with the real wage. (See table 1.3)

Table 1.3 also characterizes the inflows of each estimated series during four distinct economic periods. The MMFRP estimated inflows increase significant in periods where Mexico is in recession or both the United States and Mexico are in

Table 1.3: BUSINESS CYCLE CHARACTERISTICS OF ESTIMATED UNDOCUMENTED MIGRANT INFLOWS

Variable	MMFRP	MMFRP-3	MMP
Average Deviation from Previous Year Inflow			
Mexico Recession	968,888	-25,543	170,990
US Recession	-771,457	-308,160	-265,099
Both in Recession	850,034	-293,694	74,452
Neither in Recession	-6,199	-26,601	-62,496
Correlation with Aggregate Economic Variables			
US Real Wage	0.305	0.202	0.213
US Unemployment	0.036	-0.013	0.231
US GDP	-0.036	-0.089	0.195
MEX Real Wage	-0.154	-0.478	-0.059
MEX GDP	-0.352	-0.170	-0.041
US/MEX Growth Difference	0.312	0.105	0.141
US/MEX Wage Ratio	0.125	0.347	0.053

Note: MMFRP is the probability observed in the Mexican Migration Field Research Program dataset. MMFRP-3 is a constructed probability drawing from the distribution with replacement of migratory trips across the border from the previous year, the current year and the subsequent year to estimate the current year probability. MMP is the probability observed in the Mexican Migration Project.

recession. However, when only the United States is in recession, we see that the inflows of undocumented migrants decreases significantly. This indicates strong push factors for migration from Mexico with limited pull factors. The periods of economic expansion for both countries resulted in a very small decrease in the average inflow. The MMP estimated inflows also can be characterized in the same way with smaller, but positive inflows occur during Mexican-only or dual recessions and decrease during US-only recessions.

In addition, in table 1.3 I display the correlations between the natural log difference of the inflows and the aggregate economic indicators. Since most unauthorized migrants' primary reason for emigration is economic opportunities, one should expect the inflow of undocumented migrants to correspond to periods in the United States when jobs were more plentiful. However, the correlation between unemployment and

the real gross domestic product (GDP) in the United States and the MMFRP inflow estimates are very low. Yet, a decrease in the real wage or GDP in Mexico is correlated with a increase in the inflow of undocumented migrant to the United States. The growth differential between the two countries provides a metric for economic opportunities that might be available to a flexible labor participant. The correlation between the MMFRP inflow estimate and the growth differential between the United States and Mexico is strongly positively correlated at 0.31. The wage ratio between the two countries was more correlated with the smoothed out MMFRP-3 inflow estimate.

The cyclical response of migrants contrasts the previous finding in the literature using net flow measurements from the residual methodology. Passel (2005) found only a slight decrease in response of migrants to economic conditions in the United States, whereas gross flows would indicate that migrants are responding to economic conditions. Davis and Haltiwanger (1992) demonstrated that gross flows rather than net flows, which had been previously done in the labor literature, are necessary to look at the cyclical behavior of the labor market. Apparently, the same is true of unauthorized migrants – a subset of the labor force that migrates across international borders in search of economic opportunities.

1.5 Conclusion

The construction of a new data set on the inflow of undocumented migrants to the United States with a more frequent time-series is an important step in understanding how changing economic conditions in the United States and Mexico influence

migrant inflows. The MMFRP estimated inflows were consistent with the estimated stock of undocumented migrants in the post-2000 period, the previous indirect estimate of the inflows of undocumented migrants, and the business cycle conditions to which micro-research on migrant behavior would predict them to respond. The MMP estimated inflows implied too high a stock of undocumented migrants throughout the sample period, indicating a lower probability of apprehension relative to what would be consistent with the current stock estimates.

The approach presented in this paper provides an estimate for the inflows of undocumented migrants at a much higher frequency than previous estimates. However, future research that involves migrant histories could provide significant improvements to the precision of the probability of apprehension and therefore precision to the estimate of the inflows. It should be noted that if there exists a legalization process in the future for undocumented migrants, a one page survey in connection with the legalization process that inquired about migrants' trips across the border could provide a much larger sample and a much more precise estimate of the gross flows of undocumented migrants.

The information from constructing inflows of undocumented migrants provide researchers and policymakers a more informative understanding of how the stock of unauthorized migrants residing in the United States evolved. The initial analysis on these inflows would suggest that the United States saw increases in undocumented migrants during periods of US economic expansions and Mexican economic contractions. Moreover, the decrease in recent inflows provides topics for future research on whether the reduction is the results of border enforcement policy or the significant

contraction of the economy in the United States. Nevertheless, the movement of the gross inflow of migrants provides valuable insight into the factors that contributed to such inflows. Finally, the level of inflows of unauthorized migrants provide knowledge to policymakers on the ability of labor markets to absorbed additional workers and inform any decisions on the scale of possible future guest worker programs.

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A Appendix

A.1 Data

Data for the apprehensions ratio used the Mexican Migration Field Research Project (MMFRP) survey data conducted by the Center for Comparative Immigration Studies at the University of California, San Diego. To calculate the stock of undocumented migrants residing in the United States, the return probability was calculated using the Mexican Migration Project survey data, a long-term research project now based at Princeton University that has surveyed 118 migrant-sending communities. The observations for migrant histories is 6430. The return probability was calculated by including only migrants who reported being undocumented on their last migration to the United States. The year of the trip and the duration of the trip were recorded and therefore the year of the return trip could be estimated. Then taking the sample of migrants residing in the United States in a given year, the percent of those migrants who returned to Mexico was calculated.

In addition, the number of undocumented migrants from Mexico gaining permanent resident status was subtracted from the inflow-derived stock of migrants to arrive at the estimated stock. The estimates are provided by the Office of Immigration Statistics in the Department of Homeland Security and they estimate the number of migrants residing in the United States without documentation before receiving their permanent resident status at 48 percent. It should be noted that using only Mexican citizens who gained permanent resident status both overestimates the number

of undocumented migrant who resided in the United States in the year before and underestimated the number of undocumented migrants receiving permanent status from other countries.

Data for the number of apprehensions and the linewatch hours were compiled originally by the U.S. Immigration and Naturalization Service and now are made available through the U.S. Customs and Border Protection. The data from 1963:7 to 2004:9 are available on Gordon Hanson's webpage, <http://irpshome.ucsd.edu/faculty/gohanson/data.htm>. There are significant seasonal fluctuations of apprehensions at the border with political economy and labor market demand rationales.

Estimates of the MMFRP-implied stock of the undocumented migrants at the business cycle frequency is found in figure A1.

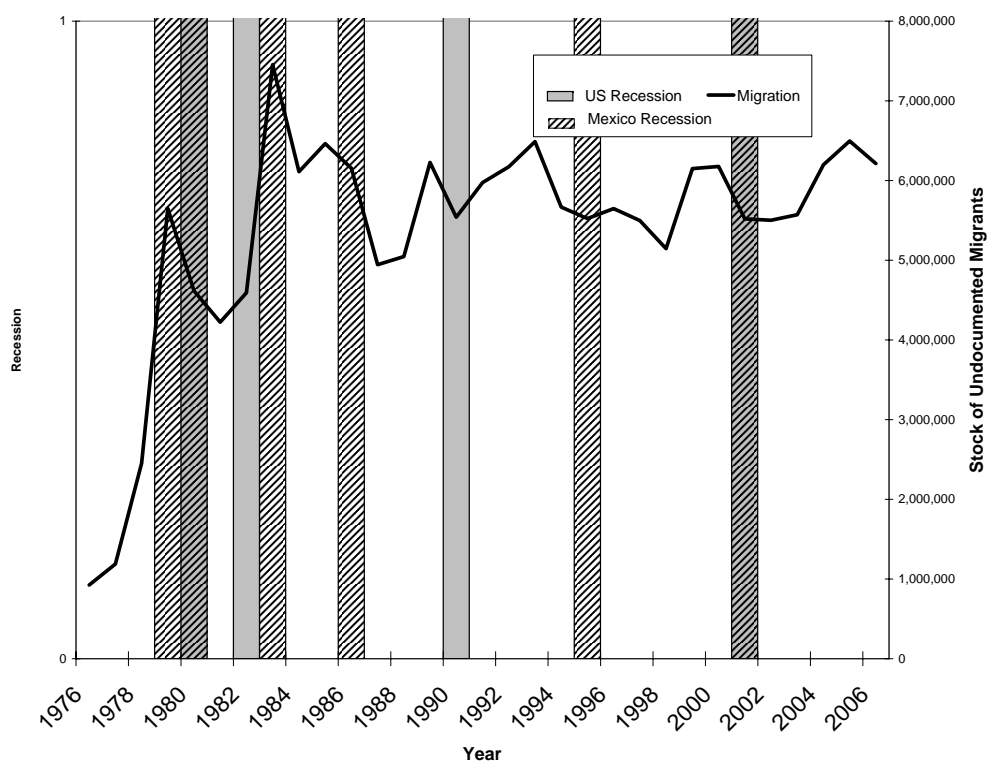


Figure A1: MMFRP STOCK ESTIMATES AT BUSINESS CYCLE FREQUENCY

Note: The MMFRP stock estimates vary at the business cycle frequency with declines during US recessions and increases during Mexico recessions.

Chapter 2: The Dynamics of Border Enforcement and Inequality in Mexican Migrant-Sending Communities

Abstract

The significant increase in smuggling ('coyote') fees for clandestine entry into the United States across the Southwest border has potentially changed migration patterns across income classes. This paper models the decision to migrate over different cost structures and finds that both the lower- and upper-income thresholds for migration are shifted inward as a result of the increase in fees during the previous 15 years. Moreover, the escalation of coyote fees hollows out the middle-class, increasing inequality in sending communities. The model is tested by estimating migration behavior in low-cost and high-cost migration periods, controlling for the reduction in migration costs that results from more dense social networks contacts in the United States. Communities without dense social networks observed a reduction in migration among low-income potential migrants in the high-cost period.

2.1 Introduction

The costs of unauthorized migration fall into two categories. The explicit costs of such migration consist of the fee required by the *coyotes* (people-smugglers) who assist the migrant in crossing the international border and secondarily of the cost of transportation to the border. The implicit costs of migration include the psychological burden of being away from home and the difficulties associated with finding employment once the person arrives in the receiving country. While the implicit costs have been reduced by the formation of social networks in the United States, the explicit costs have significantly increased in real terms during the last 15 years, coinciding with the intensification of border enforcement.

The goal of this paper is to assess the effect of higher costs on (i) the propensity to migrate for a distribution of ability types and (ii) inequality in the sending villages. In a model that includes a capital threshold to pay coyote fees, the wage ratio between the United States and Mexico, I consider the decision of the household with variable migration costs. The model is tested by estimating the migration behavior in low-cost and high-cost migration periods controlling for the reduction in migration costs that results from more dense social network ties to the United States.

Mckenzie and Rapoport (2007) examined the non-linear relationship of income and migration and how this relationship varied with different levels of historical migration rates. They showed that expanding social networks reduced the cost of migration. This paper will consider how the cost reduction of the expanding social networks is counterbalanced by the increase in coyote fees, which requires access to

significant levels of capital to be able to migrate. By considering the explicit cost of smuggling fees, I find the increase in required outlays (i) reduces migration among low-income potential migrants, (ii) reduces migration among higher-income potential migrants by decreasing their net US earnings, and (iii) increases inequality in historically low-migration communities with the hollowing out of the middle class.

Bouillon, Legovini and Lustig (2003) argue that the increase in inequality in rural Mexico is the result of both the difference in returns for higher levels and lower levels of education and the fact that household endowments in southern Mexico growing at a slower pace than other regions in Mexico. I propose an additional reason: Increased inequality in rural Mexico is also the result of an inability in recent years of low-income potential migrants without extensive transnational social networks to raise the capital required for migration.

The increased cost of migration has allowed only those individuals with significant financial resources to migrate. Yet, the highest-income earners in Mexico are more reluctant to migrate because of better opportunities where they reside. This leaves only the middle-class of a rural community to migrate to the United States. Moreover, the significant cost of re-entry into the United States discourages undocumented migrants now living in the United States from participating in circular migration – the frequent, temporary movements between localities in Mexico and the United States that for several generations was the dominant pattern in Mexico-to-U.S. migration. Without circular migration, the middle-class migrates and does not return.

It should be noted that there are two reasons why this shift in the economic

profile of Mexican migrants might be of benefit to U.S. labor markets. First, the liquidity constraints arising from the coyote fees would induce a positive self-selection of migrants with more direct or indirect financial resources. Second, the increased cost would require migrants with higher levels of skills and education to be able to recoup their investment with higher wages in the United States.

The structure of the paper is as follows: Section 2 will discuss the changes in border enforcement policy, *coyote* fees, and in the characteristics of migrants from rural Mexico that can be found in the data collected by the Mexican Migration Field Research and Training Program (MMFRP). Section 3 will model the household's decision to migrate, establish the lower- and upper-bound thresholds for migration and analyze the impact of cost and the wage ratio on these thresholds. Section 4 will show the increasing inequality in the model, realistically calibrated to the US/Mexico data. Section 5 tests the implications of the model by determining whether inequality has risen in communities with both low and high social network densities in the United States. Section 6 summarizes the findings.

2.2 Border Enforcement Intensity and Inequality

Border Enforcement Intensity The intensification of border enforcement in the United States commenced in 1993 with the implementation of Operation Hold-the-Line (El Paso sector) and continued with Operation Gatekeeper (San Diego sector) in late 1994. This shift in policy was followed by a significant expansion of the Border Patrol and an exponential increase in the number of hours agents patrolling the border ('linewatch hours'). Figure 2.1 exhibits the increase in linewatch hours

over the previous four decades.

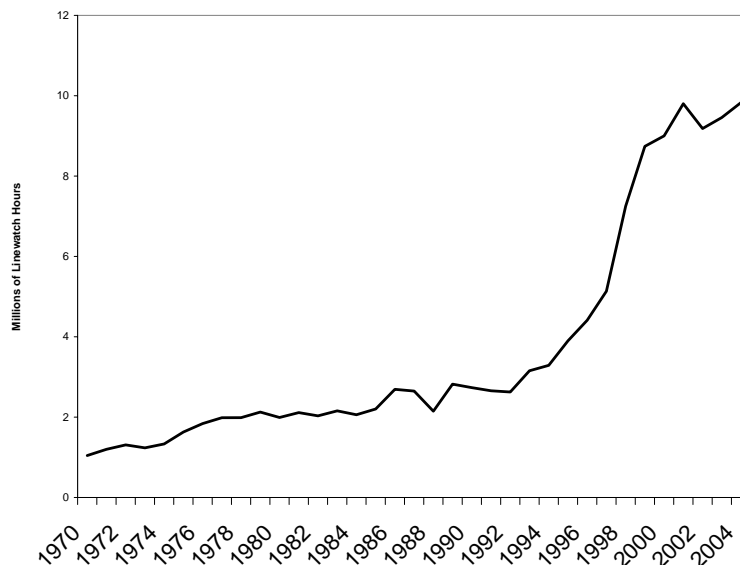


Figure 2.1: LINEWATCH HOURS (1970-2004)

Note: Linewatch hours from 1970 to 2004 are the number of hours agents patrolled the border.

The increase in border enforcement intensity in the United States has raised the costs of migration through higher coyote fees. Gathmann (2008) finds the higher coyote fees are the result of both the enforcement effect, which increased the probability that the coyote himself might be apprehended, and the diversion effect, which forced migrants to use more remote crossing locations. The later effect increases coyote fees to compensate the longer time to 'cross' their clients and the greater physical risk to the coyote himself.

The additional costs change the characteristics and nature of migration. The increase in costs contributed to a decrease in circular migration by male migrants, an increase in the number of permanent rather than temporary migrants, and an increase in the number of family reunifications in the United States. Male migrants

are staying longer in the United States and bringing their wives to settle more there.

In addition to increased costs associated with apprehension effects and diversion effects, there is also a gender composition effect. Women are much more likely to use ‘unconventional’ methods for clandestine entry than their male counterparts, such as crossing through a legal port of entry with false or borrowed documents. Such modes of entry increase the fee charged by coyotes. [See Cornelius, Fitzgerald, and Borger (2009)] As the gender composition of unauthorized migration to the U.S. changed, so did the average coyote fee. However, restricting the analysis to only male migrants to control for any gender composition effect, the significant increase in coyote fees is still apparent.

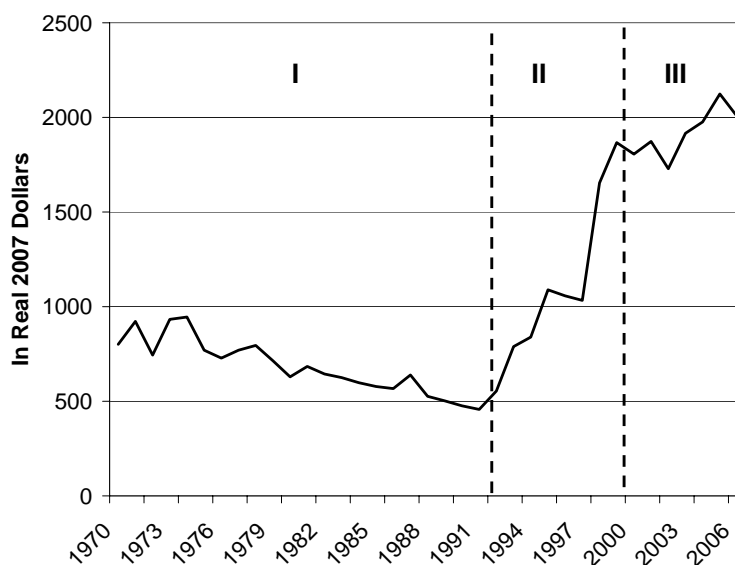


Figure 2.2: COYOTE FEES (1970-2006)

Note: The ‘coyote’ or smuggling fees are calculated from the Mexican Migration Project dataset (MMP118) and are average amounts paid in a given year by migrants entering clandestinely into the United States in 2007 dollars. Adjustments of the fees in real terms uses CPI inflation rates in the United States because coyotes are almost always paid in U.S. dollars and would raise rates to maintain their purchasing power in the United States.

Figure 2.2 uses the Mexican Migration Project (MMP) dataset to calculate the median real coyote fee reported by first-time undocumented male migrants over time. The change in coyote fees and therefore the change in the cost of migration is dramatic over the entire sample from 1970-2006. Period I represents a low-cost migration period from 1970-1992 with a median fee adjusted for inflation of US\$629 (2007\$) . Period II represents the growth period in migration costs between 1993-1998. Period III represents the high-cost migration period, with a median fee of US\$1867 in 2007\$. This paper will use these two contrasting migration-cost regimes (I and III) to test the impact of the intensification of border enforcement on inequality in both the theoretical and empirical models.

Inequality and Border Enforcement in MMFRP Communities The change in capital requirements associated with coyote fees has affected the characteristics of the people who are able to migrant in later periods. In earlier periods of migration, people with less education and less income traversed the US/Mexico border, while migrants during later periods came from average-income and average-educated households. One explanation for this change in the socio-economic characteristics of migrants is the change in the cost of migration. This section will describe the changes in the relative educational levels of migrants and the median length of time per stay by undocumented migrants.

I examined the migration histories of the entire migrant-age population of sending communities in Jalisco, Oaxaca and Yucatan and their networks in the United States. This enabled me to assess the impact of increased capital requirements on the

population of international migrants and the population in the village that remain.

A new data set from the Mexican Migration Field Research Project (MMFRP),^{2.1} provides highly detailed migration histories from residents of communities in Mexico and their counterparts that have migrated to the United States. The MMFRP project has conducted five detailed surveys of migrants and potential migrants in *Tlacuitapa, Jalisco* (2005, 2007), *Tunkás, Yucatán* (2006, 2009), and *San Miguel Tlacotepec, Oaxaca* (2008). The surveys encompass nearly the entire migrant-age (15-65) population in each locality. The present analysis uses data from the *Tlacuitapa* (2007) and *San Miguel Tlacotepec* (2008). Since the dataset records migrant histories in the United States and Mexico, a time-series can be constructed on occupations and educational attainment of migrants and non-migrants.

The dataset has limitations. The lack of panel data on individual income and wealth makes it difficult to determine the effect of migration on inequality. However, the education profiles of nearly all of the migrating population of a community provides information on the educational attainment of migrants over time.

The annual changes in educational attainment of migrants who reside in the United States in a given year and their age cohort counterparts provide information on how a community has transitioned over time. Using similar age cohorts in each community as the measure of comparison is important because (i) the differences in attitudes about education over time can change, (ii) the returns to education can evolve, and (iii) policy and infrastructure changes such as the construction of schools

^{2.1}MMFRP is an ongoing research project of the University of California-San Diego's Center for Comparative Immigration Studies

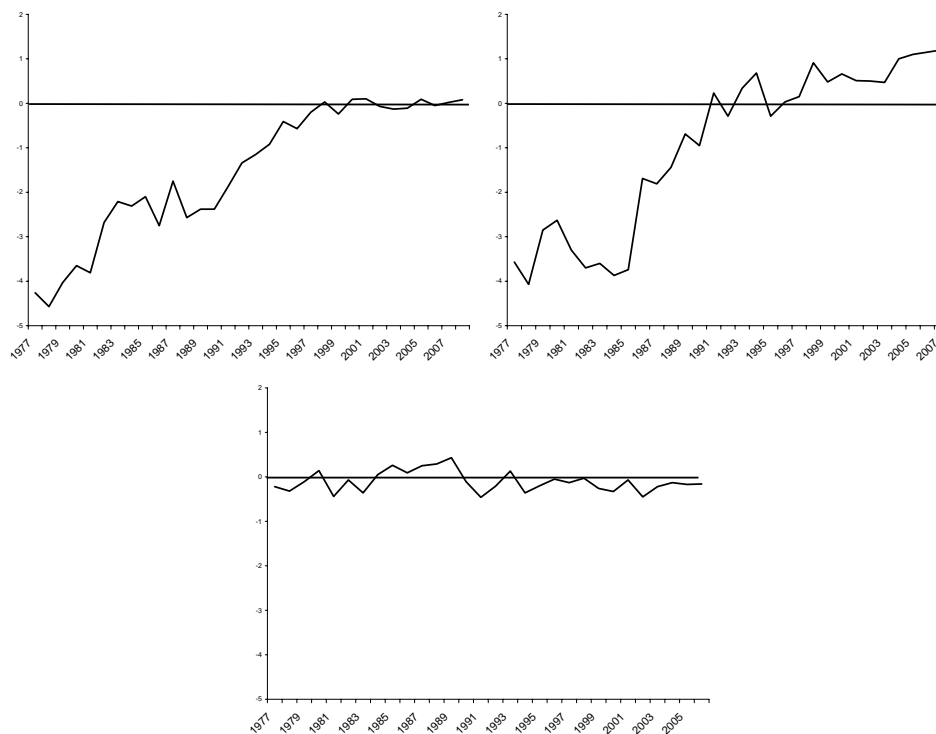


Figure 2.3: DIFFERENCE OF EDUCATION LEVEL OF MALE MIGRANTS FROM COHORTS

Note: All panels: Difference in the educational levels of undocumented migrants in the United States from their age cohorts in the community, 1977-2007. **Top-Left panel:** Difference in education of Tunkas male migrants. Tunkas is a relatively new migrant-sending community. **Top-Right panel:** Difference in education of San Miguel Tlacotopec male migrants. San Miguel Tlacotopec is a relatively new migrant-sending community. **Bottom panel:** Difference in education of Tlacuitapa male migrants. Tlacuitapa is a long-time migrant-sending community.

can impact the level of schooling in a local area. Using male-only cohorts to capture the historical primary pool of potential migrants, the difference in education of those who are in the United States in a given year from their age cohort in the community is estimated.

The educational attainment of migrants relative to their age and gender cohorts in the community is demonstrated in figure 2.2. The educational cohort comparison is estimated as the deviation of a particular person's educational attainment level relative to the average educational attainment of their cohort in their commu-

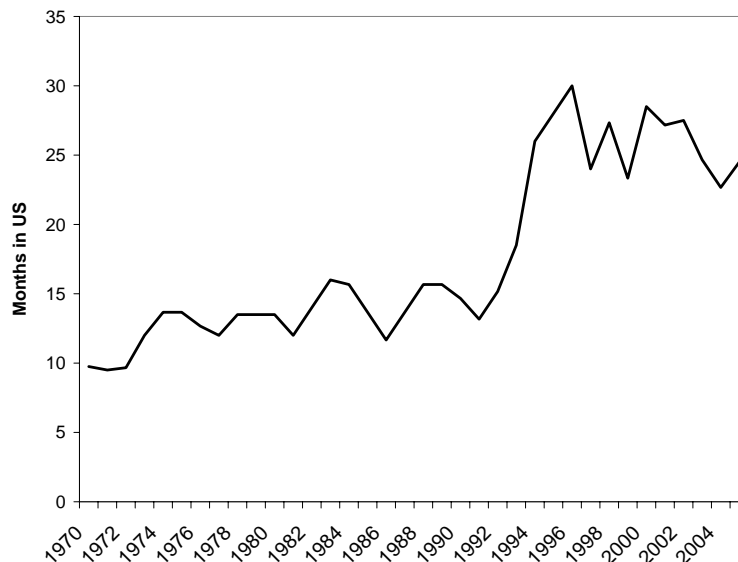


Figure 2.4: MEDIAN TIME IN US PER STAY (1970-2005)

Note: The median time in the United States for undocumented migrants on a given stay in the United States calculated from the Mexican Migration Field Research Project (MMFRP). The data is estimated as a MA(3) to smooth out yearly fluctuations.

nity. The population estimates are for male persons in five-year increment cohorts. Figure 2.2 reports the average deviation of respondent's educational attainment relative to their cohort for each of the respondent in the United States in a given year. In the communities of Tunkas (Top-Left panel) and San Miguel Tlacotepec (Top-Right panel), there has been a steady increase in educational attainment levels of male migrants in the United States relative to their home community. However, Tlacuitapa (Bottom panel) has remained constant throughout this period. One potential explanation for the difference between these communities is the migration trajectories. Tlacuitapa is a long-time migrant sending community with dense social networks in the United States whereas Tunkas and San Miguel Tlacotepec are relatively recent migrant-sending communities. Figure 2.2 provides additional strong evidence in support of the hollowing out of the middle-class that will be more explicitly modeled and

tested hereafter.

There is direct evidence that the patterns of migration have been altered by the increase in coyote fees. Figure 2.4 estimates the median length of time per stay reported by undocumented migrants in the MMFRP surveys from 1970 to 2005 with a 3-yr moving average to smooth fluctuations between years. During the 1970s and 1980s, the median length of stay was between 10 and 15 months. There is a spike in the data in 1994 when border enforcement intensified and the cost of coyotes increased. From 1994 to 2005, the average length of trip is between 25 and 30 months. There is some censorship of the data in the later part of the data since some migrants remain in the United States. However, by reporting the data only until 2005 for trips that have continued into 2009 and reporting the median values, the impact of the censorship is diminished.

The educational differences are distinct, but inconclusive of whether the impact can be attributable to the change in migration costs. The length of time per stay is certainly impacted by border enforcement intensity, but it fails to provide clarification on whether longer trips have an impact on inequality in migrant-sending communities. Therefore, the next section will consider a model of the behavior of migration and simulate the impact of increased costs on inequality on a migrant-sending community.

2.3 Theoretical Model

2.3.1 Basic Setup

In a discrete-time two period framework, I propose a model that considers the dynamics of migration from Mexico to the United States explicitly modeling the

impact of increased costs on migration.^{2.2}

There are three stylized facts of US/Mexico migration that should be incorporated into any model characterizing household behavior with respect to migration. First, the wage gap between the United States and Mexico should impact the decision to migrate. Hansen and Spilimbergo (1999) and Borger (2009) find that the inflows of migrants respond to the wage ratio. Second, there exists a range of income for households that are able to migrate. Since migration from Mexico to the United States frequently does not include the lowest and highest income earners, this should be incorporated into any model on the dynamics of migration. Third, the costs of migration have varied as border enforcement in the United States has increased. As illustrated previously, the costs of migration have tripled in real terms in the last 15 years dramatically increasing the cost of migration and impacting the behavior of migrants.

The model consists of two countries, the United States and Mexico, divided by an international border, and two periods. Migration costs are exogenously determined by the government with its choice of border enforcement intensity. The household draws an ability level in the first period and decides the level of consumption, the saving of assets and whether they will migrate to the United States in the next period or not. If the household chooses to migrate, a share of the cost of migration is paid in the first period, where the share of the cost paid is a function of the size of the household's social network in the United States. The assets of the household must

^{2.2}Carrington, Detragiache and Vishwanath (1996) proposed a model with migration costs with a focus on the behavior of African-American migration from the South to the North.

remain strictly non-negative. This restricts the ability of the household to borrow the costs of migration and therefore their decision is subject to a liquidity constraint. However, the inability to borrow (the 'liquidity constraint') is relaxed if the household has social networks in the United States that allows them to pay only part of the cost in the first period. The incentive to migrate in the second period is determined by whether their consumption in the second period would be greater given that migration occurs. I assume that all agents are able to find employment in either location and the second period's wages are known with certainty.

2.3.2 Household Decision

The household maximizes their consumption, savings, and decide whether they migrate to the United States or not. The household faces the following two period well-behaved utility function with non-satiation and diminishing returns to consumption:

$$U(C_t) + \beta U(C_{t+1}) \tag{2.1}$$

where C_t is consumption in period t and β is the discount rate. The budget constraint for the household in period 1:

$$C_t + a_{t+1} + \Phi(1 - \eta)\Psi_t = \alpha W_t^{mex} \tag{2.2}$$

where a_t is the assets saved in period t, Φ_t is an indicator variable whether the person chooses to migrate or not with the variable equal to 1 if the person migrates from Mexico to the United States and equal to 0 if the person does not migrate. The

parameter η is the fraction of the fee that can be borrowed and is assumed to be related to the size of the person's social network in the United States. Ψ_t is the cost of crossing the international border in the next period. W_t^{mex} is the wage earned in Mexico and α is the ability measure drawn by the household. During the second period, the budget constraint for the household:

$$C_{t+1} + \Phi\eta\Psi_t = (1+r)a_{t+1} + (1-\Phi)\alpha W_{t+1}^{mex} + \Phi\Gamma^u(\alpha)W_{t+1}^{us} \quad (2.3)$$

where r is the return on assets, W_{t+1}^{us} is the wage earned in the United States, and $\Gamma^u(\cdot)$ is transferability of ability levels to productivity of employment in the United States.

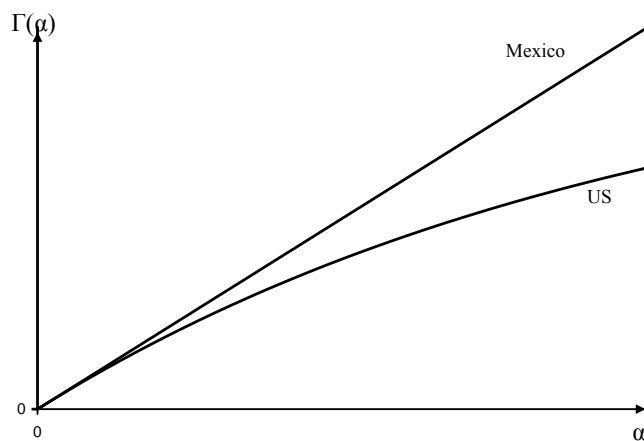


Figure 2.5: PRODUCTIVITY AS A FUNCTION OF ABILITY

Note: This graph characterizes the transferability of endowed ability into productivity in the workforce in the United States and Mexico. Ability draws for households in Mexico translate one-for-one to a productivity measure in Mexico whereas ability translates less than one-for-one into the United States' labor market.

The function $\Gamma^u(\cdot)$ translates native ability levels into productivity in the

United States' labor markets. The function is assumed to be continuous, everywhere differentiable, and an increasing function of ability-type with less than a one-for-one transfer from Mexico to the United States and with diminishing returns:

$$\Gamma_1^u(\cdot) \leq 1 \quad \Gamma_{11}^u(\cdot) < 0 \quad \Gamma^u(0) = 0 \quad \Gamma_1^u(0) = 1 \quad (2.4)$$

The reason for the functional form assumed in equation 2.4 is there might exist language barriers or certification requirements that would prevent native ability levels from being transferred one-for-one to productivity into a foreign workforce. For example, migrants in the agricultural or construction sectors with relatively low ability levels could transfer their skills more readily to the United States than migrants with relatively high ability levels in the medical or legal sectors. Occupations in these sectors would require more education or re-accreditation to use their skills in the US labor market.

The household maximizes utility in equation 2.4.1 with respect to the level of consumption in each period, the level of savings in the first period, whether or not to migrant and subject to the constraint in equation 2.2, equation 2.3, and the liquidity constraint $a_t \geq 0$.

The constrained optimization problem can be solved with a Lagrangian:

$$\begin{aligned}
L = & U(C_t) + \beta U(C_{t+1}) \\
& + \lambda_t \left(\alpha W_t^{mex} - C_t - a_{t+1} - \Phi(1 - \eta)\Psi_t \right) \\
& + \lambda_{t+1} \left((1 + r)a_{t+1} + (1 - \Phi)\alpha W_{t+1}^{mex} + \Phi\Gamma^u(\alpha)W_{t+1}^{us} \right. \\
& \left. - C_{t+1} - \Phi\eta\Psi_t \right) + \mu_{t+1}a_{t+1}
\end{aligned} \tag{2.5}$$

The Kuhn-Tucker necessary conditions for an optimum are the following:

$$U'(C_t) - \lambda_t = 0 \tag{2.6}$$

$$\beta U'(C_{t+1}) - \lambda_{t+1} = 0 \tag{2.7}$$

$$\lambda_t - \lambda_{t+1}(1 + r) = \mu_{t+1} \tag{2.8}$$

The complementary slackness conditions are:

$$\lambda_t \geq 0, \quad \lambda_{t+1} \geq 0,$$

$$\mu_{t+1} \geq 0, \quad a_{t+1}\mu_{t+1} = 0$$

Assets are completely consumed in the second period, so $a_{t+2} = 0$. If a person migrates, their consumption in the second period will be greater than their consumption in the first period and therefore μ_{t+1} will be positive and a_{t+1} will equal zero to sat-

isfy the complementary slackness condition. $\lambda_t \geq \lambda_{t+1}(1+r)$ such that when μ_{t+1} is positive it is strictly greater than and when μ_{t+1} is zero it is equal.

An additional condition must be satisfied if they choose to migrate:

$$\lambda_{t+1} \left[\Gamma^u(\alpha)W_{t+1}^{us} - \alpha W_{t+1}^{mex} - \eta\Psi_t \right] \geq \lambda_t(1-\eta)\Psi_t \quad (2.9)$$

Combining equations 2.6, 2.7 and 2.9, a household's decision to migrate is a function of their net earnings in the United States and the cost of migration.

$$\frac{U'(C_{t+1})}{U'(C_t)} \left[\Gamma^u(\alpha)W_{t+1}^{us} - \alpha W_{t+1}^{mex} - \eta\Psi_t \right] \geq (1-\eta)\Psi_t \quad (2.10)$$

The net US earnings is defined as the wage earned in the United States less the wages the person would have otherwise earned in Mexico and any part of the fee that the person borrowed from their social networks in the first period to be able to migrate.

2.3.3 Implications of the Model

The following analysis will look at the decision of the household without considering the impact that migration has on wages in the United States. The model has five implications of migration.

2.3.3.1 Incentive to Migrate

First, there exists an incentive to migrate to the United States given that for some level of ability, α^* , in equation 2.10, the discounted wages in the United States in the next period less the discounted foregone wages in Mexico and the remainder

of the cost to be paid in the second period is equal to the cost required to be paid in the first period of crossing the border. For any $\alpha_i \geq \alpha^*$, the benefit of migrating will exceed the cost. This is the condition required for migration in the model and corresponds to the basic decision made by economic migrants.

2.3.3.2 Thresholds for Migration

Second, there is a lower-bound and an upper-bound threshold for migration. An individual in Mexico with a low ability draw would have an incentive to migrate to earn higher wages in the United States and would satisfy the condition previous described in section 3.2. However, there exists a lower-bound threshold for migration for ability levels less than or equal to $\underline{\alpha}$, where the earnings in Mexico are less than the cost of crossing the border.

$$\Gamma^m(\alpha)w_t^{mex} < (1 - \eta)\Psi_t \quad (2.11)$$

There also exists an upper-bound threshold for migration, such that the ability level in Mexico is high and corresponds to a relatively low productivity level in the United States. This would result in the earnings of the potential migrant in Mexico exceeding earnings in the United States less migration costs.

$$\left(\frac{w_{t+1}^{us}}{w_{t+1}^{mex}}\right)\Gamma^u(\alpha) - \frac{\alpha}{w_{t+1}^{mex}} - \frac{\eta\Psi_t}{w_{t+1}^{mex}} \geq \frac{(1 - \eta)\Psi_t}{w_{t+1}^{mex}} \frac{U'(C_t)}{U'(C_{t+1})} \quad (2.12)$$

Figure 2.6 depicts the upper-bound threshold using equation 2.13. Equation 2.13 transforms equation 2.12 by normalizing the wage in Mexico to unity and setting the wage ratio between the United States and Mexico at some constant B. For the

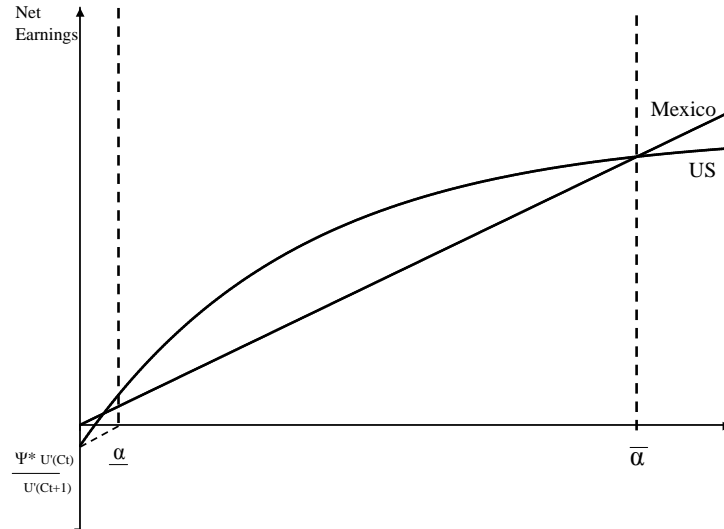


Figure 2.6: UPPER- AND LOWER-BOUND THRESHOLDS

Note: This graph depicts the upper-bound threshold for migration, where the earnings in Mexico exceed the net earnings in the United States.

purposes of describing the thresholds, social networks are assumed to be zero so the individual is required to pay the entire cost in the first period. The upper-bound threshold is $\alpha = \bar{\alpha}$ such that the following equation is satisfied.

$$B * \Gamma^u(\bar{\alpha}) - \frac{\bar{\alpha}}{w_{t+1}^{mex}} = \frac{\Psi_t}{w_{t+1}^{mex}} \frac{U'(C_t)}{U'(C_{t+1})} \quad (2.13)$$

For any α such that $\alpha \geq \bar{\alpha}$, equation 2.12 would be satisfied and the person would choose to stay in Mexico.

2.3.3.3 Wage Ratio and Migration

Third, an increase in the wage ratio between the United States and Mexico increases the number of households that migrate. Figure 2.7 demonstrates the effect of increasing the wage ratio from B to B' through an increase in the wage in the United States holding wages in Mexico constant. The incentive for migration increases and

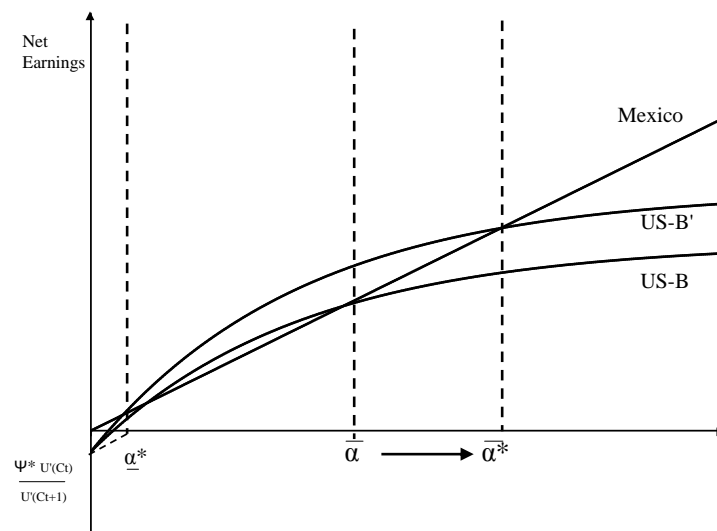


Figure 2.7: IMPACT OF INCREASED US WAGE ON MIGRATION

Note: This graph illustrates the effect on the upper-bound threshold of an increase in wage ratio, from B to B', increasing $\bar{\alpha}$ to $\bar{\alpha}^*$

therefore the upper-bound constraint increases such that $\bar{\alpha}^* > \bar{\alpha}$. However, the constraint on the lower bound threshold still binds since the cost of migration did not change. An increase in the wage ratio from B to B' has no impact on $\underline{\alpha}$. The implication of the model, using the log utility assumption, that an increase in wage ratio corresponds to an increase in migration is an important aspect of migration from Mexico to the United States. A migration population that is responsive to the wage ratio has been empirically demonstrated in the literature and would need to be a component of any theoretical model that characterizes the dynamics of economic migration.

2.3.3.4 Cost and Migration

The fourth implication of the model is that an increase in the cost of migration decreases the number of households that choose to migrate at the lower- and upper-

bound thresholds. For a given wage ratio and ability level in equation 2.12, an increase in the cost of migration decreases migration for ability types around both the lower- and upper-bound thresholds.

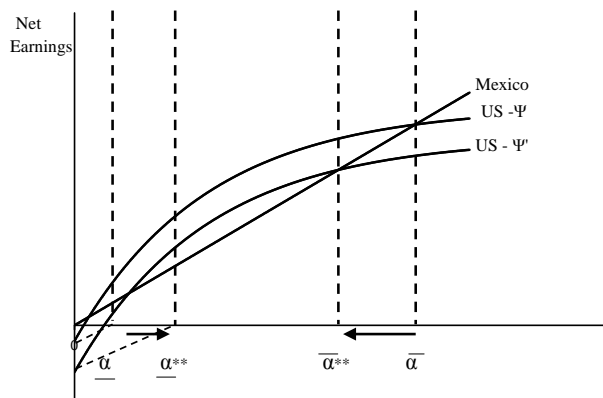


Figure 2.8: IMPACT OF INCREASED COST ON MIGRATION

Note: The increase in the cost of migration constrains more low wage earners and reduces the incentive to migrate for more high wage earners. The increase in migration costs concentrates migration among middle wage earners.

The increase in cost increases the lower-bound threshold in equation 2.11, such that $\underline{\alpha}' > \underline{\alpha}$. Migration in a higher cost environment requires a higher ability type to have the earnings to pay the cost in the first period. Figure 2.8 exhibits the increase in the lower-bound threshold from an increase in cost. Note that lower-bound is not where the US net hourly earnings cross the Mexico hourly earnings. Rather, since the earnings to pay the cost of migration must be made in the first period, the cost is paid by Mexico earnings and therefore a parallel line from the negative cost is drawn. The interest rate is set at zero for the purposes of depicting the lower-bound.

The increase in cost decreases the upper-bound threshold in equation 2.12. For

a given earnings level of a migrant, the increase in cost of migration reduces the net earnings from migration. Therefore, there exists an $\bar{\alpha}^{**} < \bar{\alpha}$ such that the condition in equation 2.12 is satisfied. Figure 2.8 illustrates the decreased upper-bound ability-type threshold from increased costs of migration.

2.3.3.5 Social Networks and Migration

The final implication of the model is that an increase in social networks decreases the lower-bound. Although there are other benefits of social networks for the migrant, the fact that this model captures the ability of social networks to partially relax the liquidity constraint faced by potential migrants is an important dynamic in migration to the United States. In the model, greater social networks implies that it is less likely that equation 2.11 will bind for lower ability-types. Figure 2.9 illustrates the effect on the lower-bound.

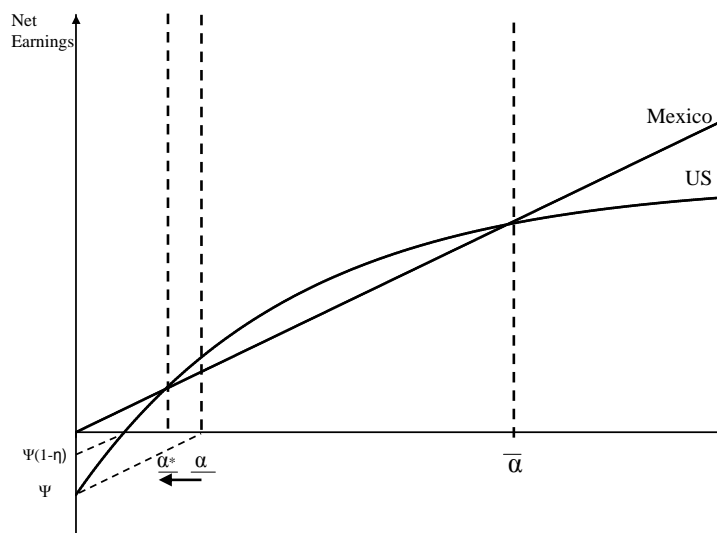


Figure 2.9: IMPACT OF INCREASED SOCIAL NETWORKS ON MIGRATION

Note: This graph illustrates the effect on the lower-bound of an increase in social networks that allows the migrant to pay for part of the cost in the second period, decreasing α to α^* . There is slight effect (not shown) on the upper-bound due to the benefit of paying part of the cost in the second period.

The figure abstracts from the benefit of paying part of the fee in the second period. The difference between the net earnings with an increase in social networks if the benefit of paying the fee in the second period is

$$\frac{\Psi_t}{w_t^{mex}} \left[1 - \frac{U'(C_t)}{U'(C_{t+1})} \right] (\eta - \eta') \quad (2.14)$$

As the discount rate of future earnings (the second term in the brackets) approaches unity, the impact of paying the second period is zero. If family members were assumed to charge an interest rate equal to the discount rate of the household, the net benefit would be the same for different levels of social networks.

2.4 Numerical Analysis

The last section showed qualitatively the impact of increased costs and social networks on the thresholds for migration. Now, I will show that in the model realistically calibrated to the US/Mexico data that higher coyote fees increase inequality in migrant-sending communities without strong social networks in the United States.

2.4.1 Estimation of Model with US/Mexico Data

The utility function is assumed to be log-utility with the household maximizing the follow problem:

$$\ln(C_t) + \beta \ln(C_{t+1})$$

subject to

$$C_t + a_{t+1} + \Phi(1 - \eta)\Psi_t = \alpha W_t^{mex}$$

$$C_{t+1} + \Phi\eta\Psi_t = (1+r)a_t + (1-\Phi)\alpha W_{t+1}^{mex} + \Phi\Gamma^u(\alpha)W_{t+1}^{us}$$

$$a_{t+1} \geq 0$$

The functional forms for the ability transformation function for the United States is

$$\Gamma^u(\alpha) = 1 - e^{-\alpha}$$

which satisfies the conditions of the functional form of $\Gamma^u(\cdot)$ in equation 2.4.

The first order conditions for the household:

$$\frac{1}{C_t} = \lambda_t \tag{2.15}$$

$$\frac{1}{C_{t+1}} = \lambda_{t+1} \tag{2.16}$$

$$1 - \frac{C_t}{C_{t+1}}(1+r) = \mu_{t+1}C_t \tag{2.17}$$

Conditions if choosing to migrate:

$$\begin{aligned} & (\alpha W_t^{mex} - (1-\eta)\Psi_t) \left[(1 - e^{-\alpha})W^{us} - \alpha W^{mex} - \eta\Psi_t \right] \geq \\ & (1-\eta)\Psi_t \left[(1 - e^{-\alpha})W^{us} - \eta\Psi_t \right] \end{aligned}$$

For different levels of social networks:

$$\eta = \mathbf{0}$$

$$\begin{aligned} (\alpha W_t^{mex} - \Psi_t) \left[(1 - e^{-\alpha}) W^{us} - \alpha W^{mex} \right] &\geq \\ \Psi_t \left[(1 - e^{-\alpha}) W^{us} \right] & \end{aligned}$$

$$\eta = \mathbf{1}$$

$$(1 - e^{-\alpha}) W^{us} - \alpha W^{mex} \geq \Psi_t$$

2.4.1.1 Impact of Increased Cost on Migration

The impact of the increased cost of migration from the tripling of the coyote fees over the last 15 years is evident in figure 2.10. This estimation uses the median coyote fee in real terms reported by migrants in the Mexican Migration Project survey. The wage ratio between the United States and Mexico is held constant at 2.32, which is the average estimate for urban males age 35 with educational achievement levels between ninth and twelfth grade in Clemens, Montenegro and Pritchett (2008). The increased cost reduces the upper-bound threshold and increases the lower bound threshold, such that at its tightest in 1999, the lower bound threshold was at the 40th percentile of ability levels and the upper-bound threshold was at the 48th percentile of ability levels.

2.4.2 Impact of Inequality on Migrant-Sending Communities

The change in thresholds for potential migrants from the increased cost of migration affects the characteristics of migrants in the US labor force and alters the composition of the migrant-sending community. With migration reserved exclusively

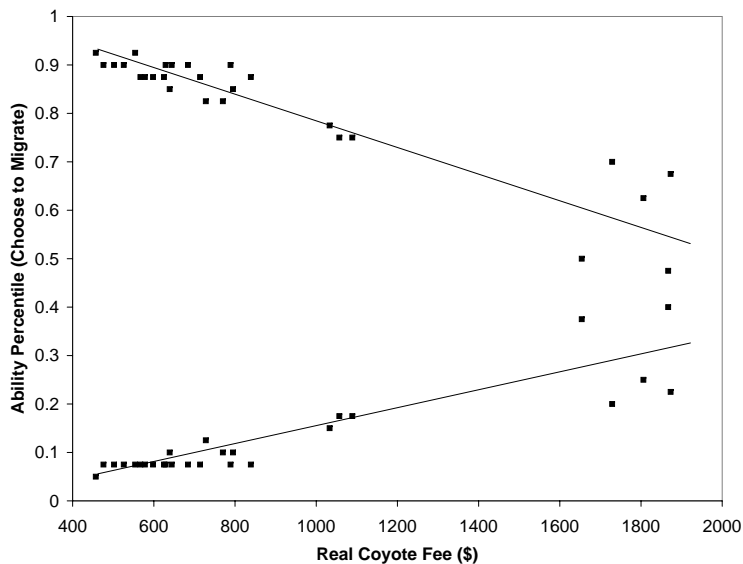


Figure 2.10: IMPACT OF INCREASED COST ON THRESHOLDS

Note: The increase in the cost of migration constrains more low wage earners and reduces the incentive to migrate for more high wage earners. With a constant wage ratio between the United States and Mexico, the increase in migration costs in the data reduces the upper-bound and lower-bound for migration.

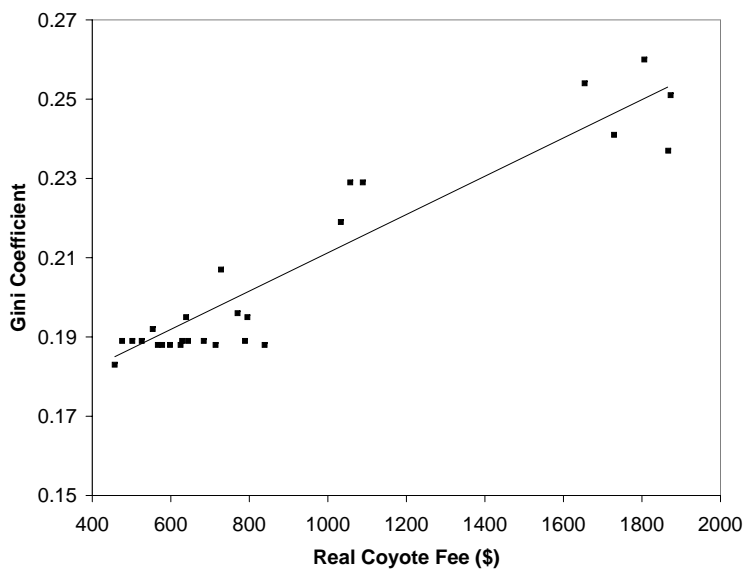


Figure 2.11: IMPACT OF INCREASED COST ON INEQUALITY

Note: Using the thresholds previously calculated, the benefit of migration augments the earnings of the households that are able to migrate. The estimates use the distribution of ability types in the MMFRP data and the gini coefficient as the measure of inequality.

to households with ability types in the mid-range in the high cost environment, the inequality in the migrant-sending community increases. The benefits of migration is assumed to augment the earnings of the households that are able to migrant. To calculate the inequality, I use the distribution of ability types in the MMFRP communities. The ability type is the difference in educational attainment of a respondent relative to their cohorts in the community and previously described in section 2. Earnings of the household are still considered to be one-for-one with ability type but those household who migrant augment their earnings through remittances.

Figure 2.11 demonstrates that an increase in the coyote fees and the narrowing of the ability-type thresholds in the community that are able to migrate increases inequality in the sending community. If migration is an option, a household can earn significantly more than their ability-type would permit if migration was not an option. The increase in coyote fees though has reduced that option for a range of ability-types. In the following section, I am going to test my model empirically to determine whether these thresholds exist and whether the thresholds are consistent across different type communities.

2.5 Empirical Analysis

The intensity of border enforcement has been a policy choice of the United States government with different implications for the type of migrants that come, how long they stay, and the persons in the sending communities that remain. This paper has modeled the impact of cost dynamics on migration rates. The following section will estimate empirically whether different periods of migration costs change

the estimates of who is able to migrate in order to confirm the model's implication on the economic profile of the migrant.

The estimate uses the probability that the household head migrates to the United States in the current year or in the previous two periods. Although the income measures, as described hereafter, are estimated for the current period, the inclusion of the previous two years was required to capture return migrants who would otherwise not be reported in the primarily Mexico-based surveys. This probability over a two year period is in contrast to the one year estimated in McKenzie and Rapoport (2007). The reason is the amount of time migrants report staying in the United States on a given trips. As previously reported in figure 2.4, the median length of trip has increased from 12 months during earlier periods to about 24 months currently. By extending the analysis to two years increases the likelihood that the survey will capture more return migrants in the later period.

The probability of migrating to the United States is a function of a person's income with higher income earners being more able to pay the coyote fees to enter the United States clandestinely while the highest income earners wanting to remain in Mexico. This implies a inverse U-shaped impact of income on the probability to migrate. An additional factor in the probability of migrating is the density of social network in the United States that reduces some of the implicit and explicit costs of migration. For example, some of the coyote fees could be paid or loaned by relatives living in the United States earning higher incomes. These factors that contribute to migration could differ between periods where coyote fees were relatively low and when the fees were significantly higher. The probability is estimated for the two subperiods

by the following equation:

$$Prob_i = \alpha_i + \gamma_{1,i} \ln(I) + \gamma_{2,i} \ln(I)^2 + \gamma_{3,i} \delta + \gamma_{4,i} (\ln(I) * \delta) \quad (2.18)$$

where I proxy for the $\ln(I)$ with the methodology in McKenzie (2005) using reported durable ownership described hereafter, δ is the instrumented density of social networks available to the migrant in the United States, and $i = 1, 2$ based on whether the estimates are in the low-cost or high-cost period of migration. In order to calculate $\ln(I)$, I factorize the reported ownership of durable goods to characterize the consumption of non-durable goods in a period. McKenzie (2005) uses household surveys to demonstrate that this methodology provides a relatively good proximate of income distribution. For the purposes of this paper, the absolute levels of income are not as important as the relative distribution of income over a given group of communities. The MMP survey reports whether the household owns certain durable items. This data is factorized to weight the index and then the weight multiplies the indicator variable for whether the household owns a particular durable item to estimate $\ln(I)$. The density of social networks is instrumented using historical rates of migration of states in Mexico during the period 1954-1959 and 1924. This provides information on networks without the endogeneity of current networks in the United States. The data is divided into the two periods, 1982-1992, that represents low-cost period and 1998-2007, that represents the high-cost migration period. In addition, the sample is restricted to persons without the legal documentation to reside in the United States. Clustered standard errors are used for each community.

Mckenzie and Rapoport (2007) found an inverse U-shaped relationship between income and migration with an increase in social networks in the United States reducing the costs of migration. Using the expanded set of MMP data currently available, this paper finds the inverse U-shaped relationship between income and migration has shifted to higher levels of income with the effect of social networks becoming statistically significant since the increased border enforcement intensity. Moreover, inequality in the migrant-sending communities has increased with a significant increase at the beginning of the growth phase of coyote fees.

The estimate for the impact of border enforcement on the probability of migration is in table 2.1. The results between the different migration lag variables does not affect the general findings. Social networks were statistically insignificant during the 1982-1992 period, whereas social networks were important in the later period. This would imply that income has an inverse-U relationship on the rate of migration, but the shape of the rate of migration changes for different densities of social networks in the United States.

Figure 2.12 illustrates the probability of migration for different levels of income at different densities of social networks. The earlier period between 1982 and 1992, migration rates were similar for the different levels of income and the different densities of historical migration networks (30th, 50th and 70th percentiles reported). However, the period 1998-2007 was a period of higher cost of migration with the coyote fees at three times the previous period. Networks were much more critical to the rate of migration in the later period with higher density of networks increasing the probability of migration for low income potential migrants. The opportunities for migration

for communities with high rates of historical migration varied only slightly between periods.

2.6 Conclusion

This paper demonstrates that the rapid increase in coyote fees is a critical component of the dynamics of Mexico-to-U.S. migration. The increase in coyote fees has constrained migration to the middle class of rural Mexico and has increased

Table 2.1: PROBABILITY OF MIGRATION, NETWORKS, AND BORDER ENFORCEMENT INTENSITY

Probability of head of household migrating in previous two years of survey year				
	(1a)	(1b)	(2a)	(2b)
	1982 – 1992	1998 – 2007	1982 – 1992	1998 – 2007
<i>ln Income Index</i>	0.036*** (0.010)	0.033*** (0.009)	0.033** (0.019)	0.024*** (0.009)
<i>ln Income Index</i> ²	-0.002*** (0.0008)	-0.002*** (0.0006)	-0.003*** (0.0008)	-0.002*** (0.0006)
<i>Network Density</i>	-0.025 (1.998)	2.611** (1.214)	0.716 (0.611)	0.816*** (0.309)
<i>ln(Income) * Network</i>	-0.088 (0.218)	-0.240* (0.137)	-0.091 (0.074)	-0.087** (0.035)
<i>Constant</i>	-0.049 (0.050)	-0.096*** (0.032)	-0.153 (0.103)	-0.095** (0.031)
Migration Lag Variable	A	A	B	B
Observations	5752	9029	5752	9029
Number of Communities	29	60	29	60
Probability of Migrating				
Low Network (30 th Pctl)				
Low-Income	5.4%	1.6%	6.2%	3.4%
Middle-Income	7.9%	3.8%	8.9%	4.9%
High-Income	4.2%	0.5%	4.4%	1.5%
High Network (70 th Pctl)				
Low-Income	4.5%	5.6%	5.1%	7.6%
Middle-Income	6.3%	6.0%	7.5%	7.1%
High-Income	1.8%	0.5%	2.6%	1.1%

Note: Clustered standard errors in parentheses at the community level. *** significant at the 1% level; ** significant at the 5% level; * significant at the 10% level. The total number of communities in the MMP data is 118. Migration lag variable A is the migration rate between 1955-1959 for the state in which the community resides and predicts the future rate of migration to the United States. Migration lag variable B is the migration rate in 1924 for the state in which the community resides.

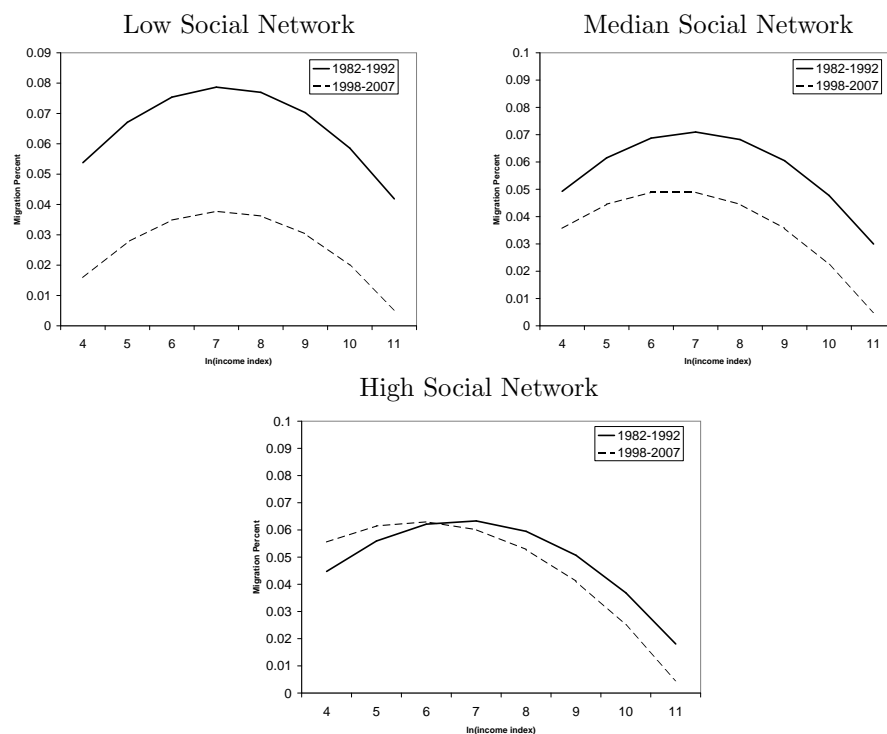


Figure 2.12: PROBABILITY OF MIGRATION IN DIFFERING PERIODS OF BORDER ENFORCEMENT INTENSITY (1982-1992, 1998-2007)

Note: All panels: Estimated probability of migration during different periods of border enforcement intensity. Reported in the figures are the network densities at the 30th, 50th and 70th percentiles, as measured by the percent of migrants who went to the United States from their region in Mexico between 1951-1955. Solid line is the period 1982-1992 and the dashed line is the period 1998-2007.

inequality in migrant-sending communities. The model provides a framework for the household decision that captures many of the important features of the dynamics to migrate. The rising cost of “professionally assisted” clandestine entry narrows the range of ability-types that are able to migrate. This has increased inequality in migrant-sending communities, as the middle-class was hollowed out. In addition, the model demonstrates that the constraint to pay the coyote fee is alleviated by having stronger social networks in the United States.

The empirical test finds that in the high-cost period migration of low-income and high-income potential migrants in low-density social network communities is di-

minished, confirming the increase in inequality predicted in the theoretical model. Yet the increase in coyote costs has had little impact on low-income potential migrants in communities with high-density social networks in the United States.

Social networks play an important role in reducing the cost of migration, as demonstrated. However, in addition to the assistance provided by family in the United States to pay the costs of migration, Espinosa and Massey (1997) have argued that networks reduce the cost of migration by providing assistance in finding employment. Although the primary mechanism through which this paper considers the dynamics of costs is the coyote fee and the liquidity constraint faced by the household with this cost, I leave to future research a secondary mechanism. The secondary mechanism would explicitly model differences in the probability of finding US employment based on the migrant's network density.

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A Appendix

A.1 Data

Data for the undocumented migrant time in the United States and education differences used the Mexican Migration Field Research Project (MMFRP) survey data conducted by the Center for Comparative Immigration Studies at the University of California, San Diego. The coyote fees and the empirical analysis used the Mexican Migration Project survey data to provide a larger and more diverse distribution of migrant trips.

Data for linewatch hours were compiled originally by the U.S. Immigration and Naturalization Service and now are made available through the U.S. Customs and Border Protection. The data from 1963:7 to 2004:9 are available at <http://irpshome.ucsd.edu/faculty/gohanson/data.htm> on Gordon Hanson's webpage.

Data for wages in Mexico was the mean value equal to earnings in the manufacturing sector as reported by the US Bureau of Labor Statistics Hourly Compensation of Production Workers in U.S. Dollars.

Chapter 3:

The Market-Perceived Monetary Policy Rule

Abstract

We introduce a novel method for estimating a monetary policy rule using macroeconomic news. Market forecasts of both economic conditions and monetary policy are affected by news, and our estimation links the two effects. This enables us to estimate directly the policy rule agents use to form their expectations. We find evidence that between 1994 and 2007 the market-perceived Federal Reserve policy rule changed: the output response vanished, and the inflation response path became more gradual but larger in long-run magnitude. In a standard model we show that output smoothing caused by a larger inflation response magnitude is offset by the more measured pace of response. Our response coefficient estimates are robust to measurement and theoretical issues with both potential output and the inflation target.

Keywords: monetary policy rule, market perceptions, nonlinear gmm, fed funds futures

JEL codes: E43, E52, E58

3.1 Introduction

A large literature estimates monetary policy rules of the form proposed by Taylor (1993) that relate the realized fed funds rate to past or expected future indicators of output and inflation. Examples include Evans (1998), Clarida, Gali, and Gertler (2000), Rudebusch (2002), Owyang and Ramey (2004), Primiceri (2005), Boivin (2006), and Kim and Nelson (2006). That kind of estimation is well suited to describe what policy rule the Fed has actually followed.

However, there is also considerable interest in what market participants *expect* the Fed to do. Expectations of future monetary policy are a key part of the monetary transmission mechanism in virtually any macroeconomic model. The Federal Reserve's expected future policy rate influences current interest rates immediately upon the market learning about the Federal Reserve's intentions to stimulate or curtail economic behavior Hamilton (2008). Moreover, Federal Open Market Committee (FOMC) statements provide guidance for the direction of future policy rates and are responded to instantaneously by the market upon their public release (Kohn and Sack (2004)).

The Fed's actual behavior could differ from the market's expectation if the public has questions about the Fed's credibility or the Fed decides to follow a different rule than it has in the recent past. In such circumstances, while policy makers may know the actual policy they intend to follow, they are also keenly interested in how the market expects them to react to new information.

This paper proposes a novel method that enables us to uncover the market's

perceived monetary policy rule. Like many previous researchers (e.g., Gurkaynak, Sack, and Swanson (2005), Faust, Rogers, Wang, and Wright (2007), and Bartolini, Goldberg, and Sacarny (2008)), we identify news by the difference between a macroeconomic data release value and the value expected beforehand by the market. On this news day, we measure the news' effects on economic fundamentals' forecasts and monetary policy forecasts, the latter coming from the change in market prices for fed funds futures contracts. Our contribution is to use a Taylor-Rule structure to link the fundamentals forecast updates with the policy forecast updates in order to estimate the market-perceived parameters for a Taylor Rule.

Our methodology also opens up to researchers the use of daily data, which offers three additional advantages. First, our approach is robust to estimation problems engendered by potential output and the inflation target. Potential output is tricky to define and measure in real time (Orphanides and van Norden (2002), and Orphanides (2001) argues that this can confound policy rule estimation. On the other hand, the Fed's inflation target is unobservable, and moreover a growing literature, including Ireland (2007) and Cogley and Sbordone (2008) among others, has postulated an important historical role for low-frequency variation in the Fed's inflation target. The latency of potential output and the inflation target poses a problem for standard policy rule estimation methods because their values are necessary for measuring the explanatory variables. Our method uses daily data to difference out these slowly moving latent variables from the estimation equations.

Second, our approach offers a cleaner answer for how to handle real-time versus

revised data sets, by focusing on market expectations formed on the basis of the information as it had actually been publicly released as of a particular calendar date.

Third, by looking at the response of fed funds futures prices for contracts of different horizons to a new data release, we are able to measure how long the market believes it will take the Fed to adjust interest rates in response to changing fundamentals. We can thereby obtain new measures of the nature of monetary policy inertia, something that is difficult for traditional methods to estimate.^{3.1} We document a change in the market's perception of the Fed's policy rule in terms of both the magnitude of the ultimate response and in the degree of inertia. Since 2000, the market-perceived monetary policy rule involves an eventual response to inflation that is bigger than that associated with perceived pre-2000 behavior. On the other hand, the market also believes that the Fed is more sluggish in making its intended adjustments. We show in simulations with a simple new-Keynesian model that the first feature would tend to stabilize output, whereas the second feature would be destabilizing. These simulations suggest that the "measured pace" of monetary tightening during 2004-2006 may have been counterproductive.

The remainder of the paper is structured as follows: Section 3.2 introduces our framework and its testable implications. Section 3.3 discusses the empirical strategy based on these implications and describes the data. Section 3.4 presents our baseline full sample results, and then shows evidence of time variation in perceived policy response and estimates parameters on subsamples. Section 3.5 generalizes the approach to estimation of a Taylor Rule with lagged adjustment dynamics and discusses the

^{3.1}See Rudebusch (2002) and Rudebusch (2006) for alternative approaches.

economic significance of those dynamics. We investigate the sensitivity of our conclusions to various assumptions and variable decisions in Section 3.6. Section 3.7 concludes.

3.2 Framework

We begin with a standard Taylor Rule that is assumed by the market to characterize Federal Reserve decisions. Let t represent a particular month and r_t the average daily effective fed funds rate for that month. The market assumes that the Fed sets the funds rate in response to the Taylor Rule variables $\pi_t - \pi_t^*$, the deviation from target of cumulative inflation between $t - 12$ and t , and $y_t - y_t^*$, a measure of the real output gap in t :

$$r_t = r + \beta(\pi_t - \pi_t^*) + \delta(y_t - y_t^*) + u_t \quad (3.1)$$

where y_t is real output growth and y_t^* is potential real output growth.

We will be keeping careful track in this analysis of exactly when data of different sorts arrives. Let $\Omega_{i,t}$ denote the information set that is actually available to market participants as of the i th day of month t ; let $\tilde{\Omega}_{i,t}$ denote the Fed's information set at that time. The formulation (3.1) assumes that the Fed knows the values of $\pi_t - \pi_t^*$ and $y_t - y_t^*$ at the time it sets r_t , even though π_t and y_t would not be known to market participants until some later time. The framework is readily generalizable to a case where the Fed instead sets r_t on the basis of information available as of some day j within month t :

$$r_t = r + \beta\mathbb{E}\left(\pi_t|\tilde{\Omega}_{j,t}\right) - \beta\mathbb{E}\left(\pi_t^*|\tilde{\Omega}_{j,t}\right) + \delta\mathbb{E}\left(y_t|\tilde{\Omega}_{j,t}\right) - \delta\mathbb{E}\left(y_t^*|\tilde{\Omega}_{j,t}\right) + u_t. \quad (3.2)$$

Consider the expectation of (3.1) conditional on information available to the market as of the i th day of month $\tau = t - h$:

$$\mathbb{E}(r_t | \Omega_{i,\tau}) = r + \beta \mathbb{E}(\pi_t | \Omega_{i,\tau}) - \beta \mathbb{E}(\pi_t^* | \Omega_{i,\tau}) + \delta \mathbb{E}(y_t | \Omega_{i,\tau}) - \delta \mathbb{E}(y_t^* | \Omega_{i,\tau}) + \mathbb{E}(u_t | \Omega_{i,\tau}). \quad (3.3)$$

Alternatively, if we take expectations of (3.2) conditional on the information set $\Omega_{i,\tau}$, the identical equation (3.3) follows due to the Law of Iterated Expectations.^{3.2} In either case, we obtain the following expression for the change in expectations between the i th day and the previous day ($i - 1$) of month τ :

$$\begin{aligned} & \mathbb{E}(r_t | \Omega_{i,\tau}) - \mathbb{E}(r_t | \Omega_{i-1,\tau}) \\ = & \beta [\mathbb{E}(\pi_t | \Omega_{i,\tau}) - \mathbb{E}(\pi_t | \Omega_{i-1,\tau})] + \delta [\mathbb{E}(y_t | \Omega_{i,\tau}) - \mathbb{E}(y_t | \Omega_{i-1,\tau})] \\ & - \beta [\mathbb{E}(\pi_t^* | \Omega_{i,\tau}) - \mathbb{E}(\pi_t^* | \Omega_{i-1,\tau})] - \delta [\mathbb{E}(y_t^* | \Omega_{i,\tau}) - \mathbb{E}(y_t^* | \Omega_{i-1,\tau})] \\ & + [\mathbb{E}(u_t | \Omega_{i,\tau}) - \mathbb{E}(u_t | \Omega_{i-1,\tau})]. \end{aligned} \quad (3.4)$$

Equation (3.4) is the key to what follows, stating that updates to the market forecast of future policy are linked to updates to the market forecast of future economic conditions via the market-perceived monetary policy rule.

We will consider a set of $k = 1, 2, \dots, K$ different days within month τ on which particular information becomes available. Consider first $k = 1$, which we associate with the release of, say, the CPI. Let $i(1, \tau)$ denote the day in month τ on which a new inflation number (namely, the value of $\pi_{\tau-1}$) is released. For example, for $\tau =$ December 2008, the CPI data reported on December 16 ($i(1, \tau) = 16$) was the value for November 2008 (so that $\pi_{\tau-1}$ became known on $i(1, \tau)$). Consider then the initial

^{3.2}We assume that $\Omega_{i,\tau} \subseteq \tilde{\Omega}_{j,t}$.

report of the value of $\pi_{\tau-1}$ on day $i(1, \tau)$. We will proxy the news content of this report by comparing the actual value $\pi_{\tau-1}$ with the value expected by the market, which we denote $\tilde{\pi}_{\tau-1}$:

$$\mathbb{E}(\pi_{\tau-1} | \Omega_{i(1, \tau), \tau}) - \mathbb{E}(\pi_{\tau-1} | \Omega_{i(1, \tau)-1, \tau}) = \pi_{\tau-1} - \tilde{\pi}_{\tau-1}.$$

The CPI announcement of $\pi_{\tau-1}$ (arriving on $i(1, \tau)$) has an implication for what market participants would have expected π_t to turn out to be. We propose to model this implication by a linear equation forecasting π_t on the basis of $\pi_{\tau-1}$, $\tilde{\pi}_{\tau-1}$, and $\mathbf{x}_{1, \tau}$, where $\mathbf{x}_{1, \tau}$ denotes a vector of other variables that would have been known to market participants prior to the day $i(1, \tau)$ of month τ :

$$\pi_t = \gamma_{\pi, 1} \pi_{\tau-1} + \xi_{\pi, 1} \tilde{\pi}_{\tau-1} + \zeta'_{\pi, 1} \mathbf{x}_{1, \tau} + v_{\pi, 1, t}. \quad (3.5)$$

The first subscript (π) on the coefficients indicates that this is a coefficient used to forecast subsequent inflation, and the second subscript (1) indicates that the forecast is formed on the day on which the first information variable (the CPI) is released. Note that the coefficients in equation (3.5) are defined as linear projection coefficients, so that $v_{\pi, 1, t}$ is uncorrelated with $\pi_{\tau-1}$, $\tilde{\pi}_{\tau-1}$, and $\mathbf{x}_{1, \tau}$ by the definition of $\gamma_{\pi, 1}$, $\xi_{\pi, 1}$, and $\zeta'_{\pi, 1}$. The consequences of the month τ , day $i(1, \tau)$ news release about $\pi_{\tau-1}$ for market expectations of π_t are then given by

$$\mathbb{E}(\pi_t | \Omega_{i(1, \tau)}) - \mathbb{E}(\pi_t | \Omega_{i(1, \tau)-1, \tau}) = \gamma_{\pi, 1} (\pi_{\tau-1} - \tilde{\pi}_{\tau-1}) \quad (3.6)$$

where we will subsume the dependence of $i(1, \tau)$ on τ when it is clear from the context.

The announcement of $\pi_{\tau-1}$ may also hold implications for market expectations

about real output y_t , which we proxy analogously as

$$y_t = \gamma_{y,1}\pi_{\tau-1} + \xi_{y,1}\tilde{\pi}_{\tau-1} + \zeta'_{y,1}\mathbf{x}_{1,\tau} + v_{y,1,t}$$

$$\mathbb{E}(y_t|\Omega_{i(1),\tau}) - \mathbb{E}(y_t|\Omega_{i(1)-1,\tau}) = \gamma_{y,1}(\pi_{\tau-1} - \tilde{\pi}_{\tau-1}). \quad (3.7)$$

Note that certain elements of $\zeta'_{\pi,1}$ and $\zeta'_{y,1}$ may be set to zero, depending on what elements of $\mathbf{x}_{1,\tau}$ forecast π_t or y_t .

Let $f_{j\tau}^{(h)}$ denote the futures interest rate on day j of month τ for a fed funds futures contract based on r_t , the effective fed funds rate h months ahead. We propose that these fed funds futures offer us a direct observation on how the market expectation of r_t changed on day $i(1)$:

$$f_{i(1),\tau}^{(h)} - f_{i(1)-1,\tau}^{(h)} = \mathbb{E}(r_t|\Omega_{i(1),\tau}) - \mathbb{E}(r_t|\Omega_{i(1)-1,\tau}) + \eta_{r,1} + q_{r,1,\tau}. \quad (3.8)$$

Here $\eta_{r,1}$ captures the average change in the risk premium on fed funds futures contracts and $q_{r,1,\tau}$ any change in the risk premium relative to that average. In the absence of risk aversion in the fed funds futures markets, the terms $\eta_{r,1}$ and $q_{r,1,\tau}$ would be identically zero. There is certainly good evidence for supposing the contribution of risk aversion to daily changes in fed funds prices to be small; see ? and ?.^{3.3} In the estimation strategy adopted here, any changes in the risk premium, along with changes in the market's expectation of the residual in the Taylor Rule, changes in the market's expectation of the inflation target, and changes in the market's expectation

^{3.3}Our method works if either the risk premium is constant, as implied by the common “expectations hypothesis” or under the implication of consumption-based asset pricing models that the risk premium would change little on a daily basis. ? results indicate that “[these] risk premia seem to change primarily at business-cycle frequencies.”

of potential output growth, are incorporated into a specification error $v_{r,1,\tau}$,

$$\begin{aligned} v_{r,1,\tau} = & -\delta [\mathbb{E}(y_t^* | \Omega_{i(1),\tau}) - \mathbb{E}(y_t^* | \Omega_{i(1)-1,\tau})] - \beta [\mathbb{E}(\pi_t^* | \Omega_{i(1),\tau}) - \mathbb{E}(\pi_t^* | \Omega_{i(1)-1,\tau})] \\ & + [\mathbb{E}(u_t | \Omega_{i(1),\tau}) - \mathbb{E}(u_t | \Omega_{i(1)-1,\tau})] + q_{r,1,\tau}. \end{aligned}$$

Substituting (3.6), (3.7), (3.8), and (3.9) into (3.4), we have

$$f_{i(1),\tau}^{(h)} - f_{i(1)-1,\tau}^{(h)} = \eta_{r,1} + (\beta\gamma_{\pi,1} + \delta\gamma_{y,1})(\pi_{\tau-1} - \tilde{\pi}_{\tau-1}) + v_{r,1,\tau}.$$

Consider next a second news release in month τ , namely the real activity indicator $y_{\tau-1}$ released on day $i(2)$. For these days we employ the auxiliary forecasting equations

$$\pi_t = \gamma_{\pi,2}y_{\tau-1} + \xi_{\pi,2}\tilde{y}_{\tau-1} + \zeta'_{\pi,2}\mathbf{x}_{2,\tau} + v_{\pi,2,t}$$

$$y_t = \gamma_{y,2}y_{\tau-1} + \xi_{y,2}\tilde{y}_{\tau-1} + \zeta'_{y,2}\mathbf{x}_{2,\tau} + v_{y,2,t}$$

where $\mathbf{x}_{2,\tau}$ is known prior to day $i(2, \tau)$. From these we derive

$$f_{i(2),\tau}^{(h)} - f_{i(2)-1,\tau}^{(h)} = \eta_{r,2} + (\beta\gamma_{\pi,2} + \delta\gamma_{y,2})(y_{\tau-1} - \tilde{y}_{\tau-1}) + v_{r,2,\tau}.$$

In general, if some indicator $w_{k,\tau-1}$ is released on day $i(k, \tau)$, we have the following three equations:

$$\pi_t = \gamma_{\pi,k}w_{k,\tau-1} + \xi_{\pi,k}\tilde{w}_{k,\tau-1} + \zeta'_{\pi,k}\mathbf{x}_{k,\tau} + v_{\pi,k,t} \quad (3.10)$$

$$y_t = \gamma_{y,k}w_{k,\tau-1} + \xi_{y,k}\tilde{w}_{k,\tau-1} + \zeta'_{y,k}\mathbf{x}_{k,\tau} + v_{y,k,t} \quad (3.11)$$

$$f_{i(k),\tau}^{(h)} - f_{i(k)-1,\tau}^{(h)} = \eta_{r,k} + (\beta\gamma_{\pi,k} + \delta\gamma_{y,k})(w_{k,\tau-1} - \tilde{w}_{k,\tau-1}) + v_{r,k,\tau}. \quad (3.12)$$

Let $\mathbf{z}_{1,\tau} = (1, \pi_{\tau-1}, \tilde{\pi}_{\tau-1}, \mathbf{x}'_{1,\tau})'$ denote the vector including the day $i(1)$ release of $\pi_{\tau-1}$ and the information available as of the day before, where we assume

that $\mathbf{z}_{1,\tau}$ is uncorrelated with $v_{\pi,1,t}$, $v_{y,1,t}$, and $v_{r,1,\tau}$. Similarly, we take $\mathbf{z}_{k,\tau} = (1, w_{k,\tau-1}, \tilde{w}_{k,\tau-1}, \mathbf{x}'_{k,\tau})'$ to be uncorrelated with $v_{\pi,k,t}$, $v_{y,k,t}$, and $v_{r,k,\tau}$, for $k = 1, 2, \dots, K$.

Thus our identifying assumption is that the following vector has expectation zero:

$$\begin{bmatrix} (\pi_t - \gamma_{\pi,1}w_{1,\tau-1} - \xi_{\pi,1}\tilde{w}_{1,\tau-1} - \zeta'_{\pi,1}\mathbf{x}_{1,\tau}) \mathbf{z}_{1,\tau} \\ (y_t - \gamma_{y,1}w_{1,\tau-1} - \xi_{y,1}\tilde{w}_{1,\tau-1} - \zeta'_{y,1}\mathbf{x}_{1,\tau}) \mathbf{z}_{1,\tau} \\ \left[f_{i(1),\tau}^{(h)} - f_{i(1)-1,\tau}^{(h)} - \eta_{r,1} - (\beta\gamma_{\pi,1} + \delta\gamma_{y,1})(w_{1,\tau-1} - \tilde{w}_{1,\tau-1}) \right] \mathbf{z}_{1,\tau} \\ \vdots \\ (\pi_t - \gamma_{\pi,K}w_{K,\tau-1} - \xi_{\pi,K}\tilde{w}_{K,\tau-1} - \zeta'_{\pi,K}\mathbf{x}_{K,\tau}) \mathbf{z}_{K,\tau} \\ (y_t - \gamma_{y,K}w_{K,\tau-1} - \xi_{y,K}\tilde{w}_{K,\tau-1} - \zeta'_{y,K}\mathbf{x}_{K,\tau}) \mathbf{z}_{K,\tau} \\ \left[f_{i(K),\tau}^{(h)} - f_{i(K)-1,\tau}^{(h)} - \eta_{r,k} - (\beta\gamma_{\pi,K} + \delta\gamma_{y,K})(w_{K,\tau-1} - \tilde{w}_{K,\tau-1}) \right] \mathbf{z}_{K,\tau} \end{bmatrix}. \quad (3.13)$$

Note that the ability to distinguish β from δ results from using at least $K \geq 2$ different news releases during month τ . A single release such as the inflation number could in principle have implications both for future inflation (as captured by $\gamma_{\pi,1}$) and future output (as captured by $\gamma_{y,1}$). Hence any response of the fed funds futures prices to that news could come from either the policy rule inflation coefficient (β) or output coefficient (δ). However, $\gamma_{\pi,1}$ and $\gamma_{y,1}$ are each separately observable (from the differing responses of π_t and y_t to $\pi_{\tau-1}$), so the change in the futures price on $i(1)$ tells us one linear combination (namely $\beta\gamma_{\pi,1} + \delta\gamma_{y,1}$) of the policy rule parameters β and δ . But the separate response to the output release on day $i(2)$ gives us a second linear combination ($\beta\gamma_{\pi,2} + \delta\gamma_{y,2}$). Thus, the $3K$ equations above are sufficient to identify β and δ separately.

For each month τ there are K days of interest, for K the number of economic indicators under consideration. Identification of this system is achieved so long as it is not the case that any one indicator always arrives on the same day as another indicator.^{3.4} Of course, it is all right for any two indicators occasionally to arrive on

^{3.4}We make sure this is the case with the indicators we choose below.

the same day.

3.3 Estimation

We begin this section by describing the formal estimation strategy, which is ? generalized method of moments. Then we describe the data used.

3.3.1 Method

Recall that $\tau + h = t$. Denoting

$$\zeta_t^{(h)} = \left(1, \pi_t, y_t, f_{i(1),\tau}^{(h)}, w_{1,\tau-1}, \tilde{w}_{1,\tau-1}, \mathbf{x}'_{1,\tau}, \mathbf{z}'_{1,\tau}, \dots, f_{i(K),\tau}^{(h)}, w_{K,\tau-1}, \tilde{w}_{K,\tau-1}, \mathbf{x}'_{K,\tau}, \mathbf{z}'_{K,\tau} \right)',$$

we rephrase (3.13) as the following population orthogonality condition for each $\theta^{(h)}$, $h = 1, 2, \dots$,

$$\mathbb{E} \left[\mathbf{g} \left(\theta^{(h)}, \zeta_t^{(h)} \right) \right] = 0, \quad (3.14)$$

where θ collects the auxiliary forecasting parameters $(\gamma', \xi', \zeta')'$ along with the main parameters of interest, the policy rule coefficients $(\beta, \delta, \eta_r)'$. Let $\mathcal{Y}_T^{(h)} \equiv \left(\zeta_T^{(h)'} , \zeta_{T-1}^{(h)'} , \dots , \zeta_1^{(h)'} \right)'$ be the vector of all observations for each choice of horizon h . Then we have the sample average

$$\bar{\mathbf{g}} \left(\theta^{(h)}; \mathcal{Y}_T^{(h)} \right) \equiv T^{-1} \sum_{t=1}^T \mathbf{g} \left(\theta^{(h)}, \zeta_t^{(h)} \right)$$

and the GMM estimator (?) for each horizon h minimizes

$$Q \left(\theta^{(h)}, \mathcal{Y}_T^{(h)} \right) = \bar{\mathbf{g}} \left(\theta^{(h)}; \mathcal{Y}_T^{(h)} \right)' \mathbf{W}_T^{(h)} \bar{\mathbf{g}} \left(\theta^{(h)}; \mathcal{Y}_T^{(h)} \right). \quad (3.15)$$

As usual, the optimal weighting matrix $\mathbf{W}_T^{(h)}$ is given by the inverse of the asymptotic variance of the sample mean of $\mathbf{g} \left(\theta^{(h)}, \zeta_t^{(h)} \right)$. In turn, we calculate a heteroskedasticity

and autocorrelation robust estimate $\hat{\mathbf{S}}_T^{(h)}$ of this asymptotic variance, and the efficient GMM estimator uses the inverse of this HAC estimate as the weighting matrix, with the following asymptotic approximations:

$$\hat{\theta}^{(h)} \approx \mathcal{N}\left(\theta^{(h)}, T^{-1}\hat{\mathbf{V}}_T^{(h)}\right) \quad , \quad \hat{\mathbf{V}}_T^{(h)} = \left([\hat{\mathbf{D}}_T^{(h)}][\hat{\mathbf{S}}_T^{(h)}]^{-1}[\hat{\mathbf{D}}_T^{(h)}]'\right)^{-1}$$

$$\text{and } [\hat{\mathbf{D}}_T^{(h)}]' = \left. \frac{\partial \bar{\mathbf{g}}\left(\theta; \mathcal{Y}_T^{(h)}\right)}{\partial \theta'} \right|_{\theta=\hat{\theta}^{(h)}}.$$

Since $\mathbf{g}(\cdot)$ is nonlinear in $\theta^{(h)}$, the minimization of (3.15) is achieved numerically. Our results are calculated by two-step GMM starting from an initial guess provided by a simple two-stage OLS procedure and with other initial conditions considered to obtain some assurance that the global optimum has been found.^{3.5} The inconsistent two-stage OLS procedure would instead first estimate the auxiliary forecasting equations independently, then use these forecast parameter estimates to generate regressors for the Taylor Rule regression.^{3.6} Joint estimation by (nonlinear) two-step GMM is consistent and efficient – see ?.^{3.7} We estimate each horizon h independently from the others so that nothing other than the original data links these estimates to one another.

As mentioned, identification is achieved by considering at least two indicators w , in which case the system (3.15) in general is just-identified. When we use more than two indicators, the system naturally delivers overidentifying restrictions. Additionally, we can impose cross-equation restrictions that create overidentification. Our

^{3.5}We have tried Continually-Updated GMM, but have found this makes little difference to our baseline results.

^{3.6}Since our framework introduces a generated-regressor, the two-stage OLS procedure is inconsistent – see ?.

^{3.7}Our HAC estimator is that of ? with 13 lags.

baseline specification is overidentified for both reasons.

3.3.2 Data

Our data set consists of K particular days for each month over the period 1994:M1 through 2007:M6. Data on fed funds futures contracts come from the Chicago Board of Trade. Fed funds futures are accurate predictors of the effective fed funds rate, as documented in numerous studies including Evans (1998), Gurkaynak, Sack, and Swanson (2007), Piazzesi and Swanson (2008) and Hamilton (2009). We restrict our attention to fed funds futures traded after 1994. One reason, as noted by Gurkaynak, Sack, and Swanson (2007), is that the Federal Open Market Committee began announcing the fed funds target in 1994, and this change in procedure could cause changes in the forecasting relations. In addition, the trading volumes pick up noticeably during this year.^{3.8} At the other end of the sample period, we end our data at 2007:M7 in order to avoid the period of major financial disruptions that started in the late summer of 2007 following the fund freezes by BNP Paribas in early August.

We measure inflation by the year-over-year growth rate of the Core-PCE price index from the BEA. This has been the Federal Reserve's key inflation indicator over the sample we consider. We measure output growth by the year-over-year growth rate of industrial production from the Federal Reserve Board. To use as much data as possible we stay at the monthly frequency and therefore require a monthly output growth series. Industrial production growth has been used by previous studies to proxy of overall output growth (e.g. Stock and Watson (2002)) and is a natural

^{3.8}See Figure A1 for a plot of these data.

candidate for our baseline. As a robustness check we will consider another measure for output growth, Macroeconomic Advisers' monthly GDP.

The economic indicators we consider are data releases from various government agencies that are followed by the Money Market Survey (MMS). Following Gurkaynak, Sack, and Swanson (2005), the median forecast provides a proxy for each variable's market expectation. MMS provides market expectations for several candidate economic indicators. Our choice is guided by asking which economic variables might be most helpful for forecasting output growth and core PCE inflation. It is natural for this purpose to use core CPI inflation (CPIXFE) and industrial production (INDPRD) themselves.^{3.9} In addition, the macroeconomic announcement literature has noted that market participants scrutinize and respond to nonfarm payroll employment (Gurkaynak, Sack, and Swanson (2005), Bartolini, Goldberg, and Sacarny (2008)), and so we will consider that indicator (NFPAY) as well. It is worth noting that NFPAY and the unemployment rate are released on the same day each month, in the BLS Employment Situation report. As mentioned above, this implies that either one of these, but not both, can be used in estimation. Given the importance of NFPAY found by prior studies, this steers us away from the unemployment rate as an indicator. This in turn makes the unemployment rate less attractive a proxy for output growth, since we would naturally then use it as an indicator.

^{3.9}MMS does not survey forecasts for Core-PCE inflation, hence our reliance on Core-CPI inflation. Fortunately, Core-CPI forecasts Core-PCE inflation well – further details are available from the authors upon request.

In terms of the variables entering the auxiliary forecasting equations, we set

$$\mathbf{x}_{k,\tau} = \left(\pi_{\tau-2}, y_{\tau-2}, f_{i(k)-1,\tau}^{(h)}, 1 \right)'.$$

The lagged values of inflation and output growth are included to control for their autoregressive nature. For parsimony, we set to zero the first element of $\zeta_{y,k}$, the coefficient on $\pi_{\tau-2}$ in indicator k 's auxiliary forecasting equation for y_t ; likewise, we zero out the second element of $\zeta_{\pi,k}$, the coefficient on $y_{\tau-2}$ in indicator k 's auxiliary forecasting equation for π_t . The fed funds futures prediction for the day before $i(k)$ is included to control for the predictive content (vis-a-vis each Taylor Rule variable) of the futures price that has already been priced into the contract.

3.4 Results

First we present our baseline full-sample results using three indicators. We then show that statistical tests of our overidentifying restrictions fail to reject our baseline model, along with other specifications considered for robustness. Motivated by related literature, we run tests for breaks in the policy rule parameters and find evidence of their variation over time. Placing the break around the beginning of the year 2000, we present subsample estimates suggesting the market-perceived monetary policy rule has changed over time, and repeat the overidentification tests on the separate subsamples.

3.4.1 Baseline

Our baseline results use three indicators – CPIXFE, INDPRD, and NFPAY – and impose the cross-equation restriction that the average risk premium change is

identical across indicators:

$$\eta_{r,k} = \eta_r, k = 1, 2, \dots, K. \quad (3.16)$$

This cross-equation restriction embodies the assumption that the different economic indicators systematically affect the forecasted policy rate only through changes to forecasted inflation and output, and it adds statistical precision to our estimates; we further discuss and test this restriction in Section 3.6. The policy rule response coefficient estimates are presented in Table 3.1, and we note a few features deserving mention.^{3.10}

Table 3.1: MARKET-PERCEIVED MONETARY POLICY RULE ESTIMATES, BASELINE

	h					
	1	2	3	4	5	6
β	0.3423 <i>0.2046</i>	0.8723** <i>0.1496</i>	1.3487 <i>0.7757</i>	1.1114** <i>0.4305</i>	1.1068* <i>0.5118</i>	1.3733 <i>0.7252</i>
δ	0.0510** <i>0.0092</i>	0.0279 <i>0.0204</i>	0.1603** <i>0.0361</i>	0.1258** <i>0.0306</i>	0.1429** <i>0.0438</i>	0.1938** <i>0.0702</i>

Notes: The policy rule coefficient on inflation is β and on the output gap is δ . HAC standard errors in *italics*. The markers * and ** denote significance at 5% and 1% levels, respectively. There are 160 observations for $h = 1$, 159 for $h = 2$, etc. The indicators are CPIXFE, INDPRD, and NFPAY. Point estimates and standard errors from two-step nonlinear GMM. Data run over 1994:M1-2007:M7.

First, we obtain reasonably precise estimates of the market-perceived policy response to inflation. Horizons two, four, and five all exhibit inflation response coefficients that are significant at the 5% level, and coefficients for the remaining horizons are significant at the 10% level. The output response coefficient is statistically significant and positive at the 1% level for all horizons except the second. These results

^{3.10}Estimates of the constant are reported in Table A1 of Appendix A.1.

suggest that our empirical methodology effectively extracts information from market forecast updates that occur in response to macroeconomic news.

Second, the market does not expect the Fed to implement changes immediately. The response coefficients at longer horizons tend to be larger than the response coefficients at shorter horizons, and 95% confidence intervals for β or δ often exclude the point estimates obtained for different h . Recall that the units of the inflation response coefficients are identical across horizons, as are the coefficients on output. These parameters answer the question: looking h months ahead, what is the response of the forecasted policy rate to a one unit increase in the forecasted rate of inflation or output growth? This feature of the results strongly suggests that the market believes the Fed gradually adjusts policy in response to economic fundamentals, a point we explore further in Section 3.5.

3.4.2 Overidentification and Break Tests

We next evaluate the appropriateness of the assumptions behind these estimates. We first investigate J -tests of overidentifying restrictions given by

$$TQ\left(\hat{\theta}^{(h)}, \mathcal{Y}_T^{(h)}\right) \approx \chi^2(m) \quad (3.17)$$

for m the number of overidentifying restrictions. The p -values for this test are presented in Table 3.2. Recall that our baseline specification overidentifies the model both by using three indicators and by imposing that the policy rule specification error means are identical for these indicators (equation (3.16)). Row 1 displays the p -values associated with the J -statistics for the baseline specification. We fail to re-

Table 3.2: OVERIDENTIFICATION TESTS, BASELINE

	h					
	1	2	3	4	5	6
(1) BASELINE	0.1176	0.1172	0.1099	0.1006	0.1222	0.1044
(2) BASELINE, PRE	0.3657	0.4600	0.3881	0.3827	0.4038	0.4068
(3) BASELINE, POST	0.2790	0.2879	0.2756	0.2963	0.3018	0.3045

Notes: p -values from J -test of overidentifying restrictions, for the baseline specifications. BASELINE is the baseline specification estimated over the full sample. BASELINE, PRE and BASELINE, POST are the baseline specifications estimated over the pre-2000 and post-2000 subsamples, respectively.

ject at the 5% level the overidentifying restrictions for every horizon h , offering some confirmation that our basic framework is consistent with the data.

Papers including Clarida, Gali, and Gertler (2000), Primiceri (2005), and Boivin (2006) have argued that U.S. monetary policy has changed over time. Unfortunately, our data are not available for the period over which those papers find the most dramatic policy changes. Nonetheless, if monetary policy changed once, then it could change again – and market participants are aware of this possibility. We therefore ask whether market participants’ perception of the monetary policy rule have changed over time.

To answer this question, we test for a break in the parameters of interest. Using Andrews’ (1993) break test, we test the null hypothesis that all parameters are constant against the alternative that the policy rule coefficients β , δ , and η_r experienced a break.^{3.11} Letting the policy rule coefficient vector be $\mathbf{b} = (\beta, \delta, \eta_r)'$,

^{3.11}The vector of parameters taken to be constant under both the null and the alternative is the vector of auxiliary forecasting parameters $(\gamma', \xi', \zeta)'$.

we test:

$$H_0 : \mathbf{b}_t = \mathbf{b}_0 \quad \forall t \geq 1 \text{ for some } \mathbf{b}_0 \in \mathbb{R}^3$$

$$H_1(\varpi) : \mathbf{b}_t = \left\{ \begin{array}{ll} \mathbf{b}_1(\varpi) & \text{for } t = 1, \dots, T\varpi \\ \mathbf{b}_2(\varpi) & \text{for } t = T\varpi + 1, \dots, T \end{array} \right\} \text{ for some constants } \mathbf{b}_1(\varpi), \mathbf{b}_2(\varpi)$$

for values of ϖ in (0.25,0.75). We use the sup-Wald statistic and tabulated critical values in ?.

For each horizon considered, there is strong evidence of a break in the policy rule coefficients \mathbf{b} . In particular, for our application the 1% critical value is 16.6: the sup-Wald statistic is estimated to be 204.3, 190.2, 170.6, 168.4, 142.0, and 123.1 for horizons 1 through 6, respectively. Moreover, these maximal statistics occur at nearly the same time for every horizon, at the beginning of the year 2000. In light of this evidence, we re-estimate our baseline model on the pre-2000 and post-2000 subsamples.

Returning to the overidentification test results of Table 3.2, rows 2 and 3 display the p -values for the model estimated across horizons on each subsample. We now find that the model is readily accepted for each subsample. Evidently, the break in the policy parameters was a factor in the lower full sample p -values in row 1. Once the parameters are allowed to differ by sub-period, we find no evidence against our framework.

3.4.3 Time Variation

Table 3.3 displays the estimation results for the two subsamples. We now discuss the output and inflation response coefficients estimated in each subsample

Table 3.3: MARKET-PERCEIVED MONETARY POLICY RULE ESTIMATES, BASELINE PRE-2000 AND POST-2000

		<i>h</i>					
		1	2	3	4	5	6
PRE-2000	β	0.3611 <i>0.2173</i>	0.8309* <i>0.3717</i>	1.2049* <i>0.4708</i>	1.2125 <i>0.7954</i>	1.1116* <i>0.4630</i>	1.3821 <i>0.7610</i>
	δ	0.1550** <i>0.0349</i>	0.1284** <i>0.0314</i>	0.2641** <i>0.0670</i>	0.3968** <i>0.1142</i>	0.3844** <i>0.1364</i>	0.5744** <i>0.1436</i>
POST-2000	β	0.1465** <i>0.0537</i>	0.3797** <i>0.0673</i>	0.4292* <i>0.2110</i>	0.5913** <i>0.1318</i>	0.8237** <i>0.1694</i>	2.2240* <i>0.9529</i>
	δ	0.0366** <i>0.0127</i>	0.0034 <i>0.0071</i>	-0.0474 <i>0.0248</i>	-0.0544* <i>0.0277</i>	0.0401 <i>0.0297</i>	-0.0777 <i>0.0834</i>

Notes: The policy rule coefficient on inflation is β and on the output gap is δ . HAC standard errors in *italics*. The markers * and ** denote significance at 5% and 1% levels, respectively. pre-2000, there are 69 observations for $h = 1$, 68 for $h = 2$, etc.; post-2000, there are 88 observations for $h = 1$, etc. The indicators are CPIXFE, INDPRD, and NFPAY. Point estimates and standard errors from two-step nonlinear GMM. Data run over 1994:M1-2007:M7

and how they differ from one another.

Looking at the output response coefficients, the output response during the 1990s is moderate but tightly estimated. At all horizons the point estimates are positive and significant at the 1% level. The response is around 0.15 in the first month, rising to 0.57 by the sixth month, and hence the policy response exhibits gradual adjustment. However, during the 2000s the response to output changes dramatically. For half of the horizons the output response is insignificant. At the one-month horizon the response to output is slightly positive and significant; for the three- and four-month horizon the response is significant but slightly negative. All three of these horizons' response magnitude are much smaller the smallest response magnitude estimated pre-2000. Taken together, this evidence suggests that during the 1990s the

market perceived a moderate output gap response that essentially vanished during the 2000s.

Looking now at the inflation responses, we see two noteworthy differences across the subsamples. First, the pre-2000 estimates are not as precisely estimated as the post-2000 estimates. Prior to the year 2000 none are significant at 1% level. On the other hand, post-2000 all horizons are statistically significant at the 5% level, with four horizons significant at the 1% level. This suggests that the more recent period has seen greater signal, relative to noise, in the market forecast updates to policy and fundamentals.

Second, the post-2000 inflation response is lower at short horizons and higher at the long horizon. For the first four months after an inflation forecast increase, the forecasted policy response during the 2000s is half what it was during the 1990s. For these early horizons we can reject at the 1% level that the post-2000 inflation responses are equal to their pre-2000 estimated values. At the long horizon, the post-2000 six-month horizon response (2.22) is about 50% greater than the pre-2000 six-month horizon response (1.38). During the 1990s, policy followed the Taylor Principle (a more-than one-for-one response of nominal rates to inflation) by the *third* month after a shock to forecasted inflation; during the 2000s, policy has met this principle only by the *sixth* month.

Together, these observations suggest that the market-perceived policy response to inflation changed over time in two distinct ways: during the 1990s the response adjusted at a quicker pace with a moderate long-run magnitude, while during the

2000s the response adjusted at a slower pace with a larger long-run magnitude.

3.5 Dynamic Analysis of the Policy Response

Up to this point in the paper we have been investigating a static Taylor Rule of the form of equation (3.1). We found that the implied market expectations of how the Fed would respond to news turned out to be a function of the time horizon h , meaning that the Fed is implicitly assumed by the market to implement the policy changes warranted by the news only gradually. We next formulate a more detailed specification of the nature of that lagged response that is consistent with the observed market behavior, developing and calibrating a dynamic Taylor rule. Section 3.5.3 then explores the implications of these changed dynamics using a simple new-Keynesian model.

3.5.1 Dynamic Forecasting Equations

We first modify the earlier notation to make the dependence on the horizon h explicit, rewriting the h -period-ahead forecasting equations (3.11) and (3.10) as

$$y_t = \gamma_{y,k}^{(h)} w_{k,t-h} + \xi_{y,k}^{(h)} \tilde{w}_{k,t-h} + \zeta_{y,k}^{(h)'} \mathbf{x}_{k,t-h+1} + v_{y,k,t}^{(h)} \quad (3.18)$$

$$\pi_t = \gamma_{\pi,k}^{(h)} w_{k,t-h} + \xi_{\pi,k}^{(h)} \tilde{w}_{k,t-h} + \zeta_{\pi,k}^{(h)'} \mathbf{x}_{k,t-h+1} + v_{\pi,k,t}^{(h)}. \quad (3.19)$$

We will also now need a version of equations (3.18) and (3.19) for the case $h = 0$, in order to keep track of the implication of the release of one indicator for the values of other indicators to be released later that month. Suppose that the first indicator released in month $t + 1$ is **NFPAY**, denoted here as $w_{1,t}$. That release could

cause us to update our expectation of the values for INDPD ($y_t = w_{2,t}$) and CPIFFE ($\pi_t = w_{3,t}$) that will be reported later that same month $t + 1$ according to

$$y_t = \gamma_{y,1}^{(0)} w_{1,t} + \xi_{y,1}^{(0)} \tilde{w}_{1,t} + \zeta_{y,1}^{(0)'} \mathbf{x}_{1,t+1} + v_{y,1,t}^{(0)} \quad (3.20)$$

$$\pi_t = \gamma_{\pi,1}^{(0)} w_{1,t} + \xi_{\pi,1}^{(0)} \tilde{w}_{1,t} + \zeta_{\pi,1}^{(0)'} \mathbf{x}_{1,t+1} + v_{\pi,1,t}^{(0)}. \quad (3.21)$$

Thus for example estimates of $\gamma_{y,1}^{(0)}$ and $\gamma_{\pi,1}^{(0)}$ could be obtained by OLS estimation of (3.20) and (3.21). Later in month $t + 1$ when the output indicator $w_{2,t}$ is released, that allows us to know the value of y_t with certainty, which to preserve the general notation we would represent by $\gamma_{y,2}^{(0)} = 1$, and would also induce an update to the forecast for $w_{3,t}$,

$$\pi_t = \gamma_{\pi,2}^{(0)} w_{2,t} + \xi_{\pi,2}^{(0)} \tilde{w}_{2,t} + \zeta_{\pi,2}^{(0)'} \mathbf{x}_{2,t+1} + v_{\pi,2,t}^{(0)} \quad (3.22)$$

When $w_{3,t}$ is finally released, it has no implications for $w_{2,t}$ which is already known ($\gamma_{y,3}^{(0)} = 0$) and changes our forecast of inflation one-for-one ($\gamma_{\pi,3}^{(0)} = 1$).

3.5.2 A Dynamic Taylor Rule

Consider now the following dynamic generalization of (3.1):

$$r_t = r + \beta_1(\pi_{t-1} - \pi_{t-1}^*) + \beta_2(\pi_{t-2} - \pi_{t-2}^*) + \cdots + \delta_1(y_{t-1} - y_{t-1}^*) + \delta_2(y_{t-2} - y_{t-2}^*) + \cdots + u_t. \quad (3.23)$$

Unlike our earlier expression (3.2), equation (3.23) is strictly a backward-looking formulation, presuming that the Fed responds dynamically to the history of available information; note that π_{t-1} and y_{t-1} are the most recent values available as of the end of month t .

Recall that the value of $w_{k,t-h-1}$ is released on day $i(k, t-h)$, and let $f_{i(k),t-h}^{(h)}$ denote the interest rate implied by a futures contract for settlement based on the value of r_t , and quoted as of the end of trading on day $i(k, t-h)$. For example, $f_{i(k),t}^{(0)}$ would reflect an expectation of the current month's fed funds rate on the day that the indicator $w_{k,t-1}$ is released. Take the expectation of (3.23) conditional on market information available on day $i(k, t-h)$ and subtract from it the expectation formed the day before:

$$\begin{aligned} f_{i(k),t-h}^{(h)} - f_{i(k)-1,t-h}^{(h)} &= \eta_{r,k}^{(h)} + \\ &\left[\beta_1 \gamma_{\pi,k}^{(h)} + \delta_1 \gamma_{y,k}^{(h)} + \beta_2 \gamma_{\pi,k}^{(h-1)} + \delta_2 \gamma_{y,k}^{(h-1)} + \cdots + \beta_{h+1} \gamma_{\pi,k}^{(0)} + \delta_{h+1} \gamma_{y,k}^{(0)} \right] \\ &(w_{k,t-h-1} - \tilde{w}_{k,t-h-1}) + v_{r,k,t-h}^{(h)}. \end{aligned} \quad (3.24)$$

For comparison, recalling that $\tau = t-h$, we can rewrite equation (3.12) as

$$f_{i(k),t-h}^{(h)} - f_{i(k)-1,t-h}^{(h)} = \eta_{r,k}^{(h)} + (\beta^{(h)} \gamma_{\pi,k}^{(h)} + \delta^{(h)} \gamma_{y,k}^{(h)})(w_{k,t-h-1} - \tilde{w}_{k,t-h-1}) + v_{r,k,t-h}^{(h)} \quad (3.25)$$

where $\beta^{(h)}$ and $\delta^{(h)}$ denote the original parameters whose estimates we reported in column h of Tables 3.1 or 3.3. Comparing equations (3.24) and (3.25), the values of the dynamic parameters $\{\beta_j, \delta_j\}$ in (3.23) are related to our baseline estimates $\{\beta^{(h)}, \delta^{(h)}\}$ according to

$$\beta_1 \gamma_{\pi,k}^{(h)} + \delta_1 \gamma_{y,k}^{(h)} + \beta_2 \gamma_{\pi,k}^{(h-1)} + \delta_2 \gamma_{y,k}^{(h-1)} + \cdots + \beta_{h+1} \gamma_{\pi,k}^{(0)} + \delta_{h+1} \gamma_{y,k}^{(0)} = \beta^{(h)} \gamma_{\pi,k}^{(h)} + \delta^{(h)} \gamma_{y,k}^{(h)}. \quad (3.26)$$

To arrive at estimates of the dynamic parameters, we chose $\{\beta_j, \delta_j\}_{j=1}^6$ so as to minimize the equally-weighted sum of squared differences between the LHS and RHS of (3.26) across indicators $k = 1, 2, 3$ and horizons $h = 0, 1, 2, \dots, 6$. On the RHS, the

Table 3.4: DYNAMIC TAYLOR RULE PARAMETERS

		j							
		1	2	3	4	5	6	7	<i>sum</i>
PRE-2000	β_j	0.3629	-0.0009	0.8859	-0.0994	0.2395	-0.0542	-0.0464	1.2874
	δ_j	0.1760	-0.0102	-0.0147	0.0399	0.1692	-0.0674	-0.0343	0.2585
POST-2000	β_j	0.0848	0.0830	0.3642	0.2760	0.4918	-0.1552	0.4330	1.5780
	δ_j	0.0060	0.0140	-0.0040	-0.0414	0.0442	0.0302	0.0102	0.0592

Notes: from minimum-distance method described in text, using subsample parameter estimates across all horizons.

values for $\{\beta^{(h)}, \delta^{(h)}, \gamma_{\pi,k}^{(h)}, \gamma_{y,k}^{(h)}\}$ for $h = 1, \dots, 6$ were taken from the earlier split-sample GMM estimation reported in Table 3.3, while values for $h = 0$ were obtained from GMM estimation of $\beta^{(0)}, \delta^{(0)}, \gamma_{y,1}^{(0)}, \gamma_{\pi,1}^{(0)}$, and $\gamma_{\pi,2}^{(0)}$ based on the moment conditions

$$\begin{bmatrix} \left(y_t - \gamma_{y,1}^{(0)} w_{1,t} - \xi_{y,1}^{(0)} \tilde{w}_{1,t} - \zeta_{y,1}^{(0)'} \mathbf{x}_{1,t+1} \right) \mathbf{z}_{1,t+1} \\ \left(\pi_t - \gamma_{\pi,1}^{(0)} w_{1,t} - \xi_{\pi,1}^{(0)} \tilde{w}_{1,t} - \zeta_{\pi,1}^{(0)'} \mathbf{x}_{1,t+1} \right) \mathbf{z}_{1,t+1} \\ \left[f_{i(1),t+1}^{(0)} - f_{i(1)-1,t+1}^{(0)} - \eta^{(0)} - (\beta^{(0)} \gamma_{\pi,1}^{(0)} + \delta^{(0)} \gamma_{y,1}^{(0)}) (w_{1,t} - \tilde{w}_{1,t}) \right] \mathbf{z}_{1,t+1} \\ \left(\pi_t - \gamma_{\pi,2}^{(0)} w_{2,t} - \xi_{\pi,2}^{(0)} \tilde{w}_{2,t} - \zeta_{\pi,2}^{(0)'} \mathbf{x}_{2,t+1} \right) \mathbf{z}_{2,t+1} \\ \left[f_{i(2),t+1}^{(0)} - f_{i(2)-1,t+1}^{(0)} - \eta^{(0)} - (\beta^{(0)} \gamma_{\pi,2}^{(0)} + \delta^{(0)} \gamma_{y,2}^{(0)}) (w_{2,t} - \tilde{w}_{2,t}) \right] \mathbf{z}_{2,t+1} \\ \left[f_{i(3),t+1}^{(0)} - f_{i(3)-1,t+1}^{(0)} - \eta^{(0)} - (\beta^{(0)} \gamma_{\pi,3}^{(0)} + \delta^{(0)} \gamma_{y,3}^{(0)}) (w_{3,t} - \tilde{w}_{3,t}) \right] \mathbf{z}_{3,t+1} \end{bmatrix} \quad (3.27)$$

where as before $\mathbf{z}_{k,t+1}$ denotes information available the day prior to release of $w_{k,t}$.

This last GMM estimation resulted in the estimates $\hat{\beta}^{(0)} = 0.3629, \hat{\delta}^{(0)} = 0.1745$ for the pre-2000 subsample, and $\hat{\beta}^{(0)} = .0424, \hat{\delta}^{(0)} = 0.0031$ after 2000. For all the above calculations, the values $\gamma_{y,2}^{(0)} = 1, \gamma_{y,3}^{(0)} = 0$, and $\gamma_{\pi,3}^{(0)} = 1$ were imposed throughout.

The resulting values of β_j and δ_j are reported in Table 3.4. In the last column is the sum of the parameter values across all j , which gives the long-run response to the inflation or output pressure.

Recall from Section 3.3.1 that the parameter vector $\theta^{(h)}$ for horizon h was

estimated completely independently from any other horizon. This approach of leaving the dynamics implied by $\{\theta^{(h)}\}_{h=0}^6$ completely unrestricted offers at least two benefits. First, nothing in our procedure requires that the long-horizon responses should be bigger than the short-horizon responses. The fact that we nonetheless find them to be increasing in h is strong evidence that the market perceives policy to respond only gradually to changing conditions. Second, our procedure allows the adjustment to inflationary pressures to differ from the adjustment to real activity, similar to the policy rules of Christiano, Eichenbaum, and Evans (1996, 2005). Table 3.4 implies different paths in the response of policy to inflation and output. For example, the pre-2000 response to inflation jumps up at the three-month lag ($j = 3$) while the response to output stays relatively steady until the 5-month lag ($j = 5$). This flexibility in the rule's process is greater than that permitted by including only lags of the policy rate itself, and our estimates suggest this greater flexibility is warranted by the data.

3.5.3 Implications of changes in the dynamics

We now explore the implications of the estimated changes in the Taylor Rule for the consequences of monetary policy. Following Clarida, Gali, and Gertler (2000), we use a standard sticky-price, rational expectations model whose equilibrium conditions, log-linearized around a zero inflation steady state, are

$$\pi_t = \lambda_1 \mathbb{E}_t(\pi_{t+1}) + \lambda_2 (y_t - z_t) \quad (3.28)$$

$$y_t = \mathbb{E}_t(y_{t+1}) - \lambda_3^{-1} (r_t - \mathbb{E}_t(\pi_{t+1})) + g_t \quad (3.29)$$

$$r_t = \beta(L)\pi_t + \delta(L)(y_t - z_t) \quad (3.30)$$

The first equation (3.28) says that inflation today is a function of the output gap and the expectation of next period's inflation, which in turn can be derived from an underlying Calvo pricing structure. With relative risk aversion measured by λ_3 , equation (3.29) is an IS schedule where today's output depends on the ex ante real rate and the expectation of next period's output gap. Equation (3.30) is a dynamic Taylor Rule that closes the model. The model is driven by autocorrelated demand shocks g_t and supply shocks z_t with the same unconditional variance. We take parameter values from Clarida, Gali, and Gertler (2000) and set $\lambda_1 = 0.9967$, $\lambda_2 = 0.3$, $\lambda_3 = 1$, and the shocks' autocorrelation to 0.9655 in our monthly model.

Our goal is to characterize what difference the inflation-response parameters $\beta(L)$ might make for the volatility of macro variables according to this model. To do so, we fix $\delta(L)$ at the pre-2000 values, and calculate the difference in volatilities using pre-2000 and post-2000 values for $\beta(L)$. We find that the post-2000 dynamics imply a 41.2% reduction in the variance of inflation, a 0.2% reduction in the variance of output, and a 33.5% reduction in the variance of the fed funds rate. Alternatively, we fixed the output dynamics $\delta(L)$ at the post-2000 values, and calculated how much difference the change in inflation dynamics $\beta(L)$ made for that specification, with very similar results. These comparisons are reported in the last column of Table 3.5.

We next wanted to see what it was about the post-2000 inflation response that helped stabilize inflation. Was it the overall magnitude of the inflation response, as reflected in the sum of the β_j coefficients, or was it the more gradual post-2000 response, as reflected in the shape of the dynamic response? To find out, we explored

Table 3.5: EFFECTS OF CHANGING INFLATION POLICY RESPONSE

Variable	Output Coeff	Inflation Coefficients			
		PRE PATH, PRE LR	POST PATH, PRE LR	PRE PATH, POST LR	POST PATH, POST LR
<i>Percentage Change in Volatility from Benchmark</i>					
π	PRE	0	-8.7	-39.3	-41.2
	POST	0	-7.9	-40.6	-41.4
y	PRE	0	+24.2	-17.4	-0.2
	POST	0	+30.9	-21.0	+0.7
r	PRE	0	-14.0	-26.3	-33.5
	POST	0	-15.7	-27.6	-35.6

Notes: volatilities of endogenous variables of the sticky-price model described in text. Dynamic Taylor Rule coefficients in Table 3.4. PRE PATH, PRE LR is benchmark using the dynamic Taylor Rule derived from pre-2000 estimates. POST PATH, PRE LR uses the dynamic Taylor Rule derived from post-2000 estimates, with inflation coefficients multiplied by the ratio of the pre-2000 long-run inflation response to the post-2000 long-run inflation response. PRE PATH, POST LR uses the dynamic Taylor Rule derived from pre-2000 estimates, with inflation coefficients multiplied by the ratio of the post-2000 long-run inflation response to the pre-2000 long-run inflation response. POST PATH, POST LR uses the dynamic Taylor Rule derived from the post-2000 estimates. These inflation coefficient modifications are considered holding constant the output coefficients at the pre-2000 values in rows marked PRE, and at the post-2000 values in rows marked POST.

the consequences of changing just one of these two elements at a time. Let β_j^{PRE} denote the pre-2000 inflation responses and β_j^{POST} the post-2000 responses. We calculated what would happen if the inflation responses were given by

$$\beta_j = \beta_j^{\text{POST}} \frac{[\beta_0^{\text{PRE}} + \beta_1^{\text{PRE}} + \dots + \beta_6^{\text{PRE}}]}{[\beta_0^{\text{POST}} + \beta_1^{\text{POST}} + \dots + \beta_6^{\text{POST}}]}$$

so that the sum of the coefficients β_j was restricted to be the same as for the pre-2000 estimates, while the shape of $\beta(L)$ was that for the post-2000 estimates. These results are reported in the column labeled “post-path, pre-LR” in Table 3.5. Such a change would have only modestly improved the variance of inflation, and would have resulted in a significant deterioration in the variability of output.

On the other hand, if we change just the long-run response, but leave the

dynamics the same as for the pre-2000 rule,

$$\beta_j = \beta_j^{\text{PRE}} \frac{[\beta_0^{\text{POST}} + \beta_1^{\text{POST}} + \dots + \beta_6^{\text{POST}}]}{[\beta_0^{\text{PRE}} + \beta_1^{\text{PRE}} + \dots + \beta_6^{\text{PRE}}]},$$

as reported in the “pre-path, post-LR” column of Table 3.5, we would have achieved the full benefits of inflation stabilization as well as additional benefits of output stabilization.

Thus the key improvement in perceived monetary policy was a stronger long-run response to inflation. The fact that the market also perceives these responses to come more slowly in the post-2000 data has in fact been counterproductive.

A lesson from this basic New Keynesian analysis is the following. Increasing the long-run magnitude of inflation response, as the market perceives the Fed to have done, had a stabilizing effect both on inflation and output. Implementing the response more slowly, as the market also perceives the Fed to have done, counteracted what otherwise would have been a benefit for output volatility of the stronger eventual inflation response. The “measured pace” of monetary tightening during 2004-2006 could thus have been a factor contributing to unnecessary volatility of output – doing the same thing more quickly might have produced a better result.

3.6 Sensitivity Analysis

We next investigate the sensitivity of our results to using alternative economic indicators, test the cross-equation restrictions imposed, and look for corroboration of the identifying assumptions from other data sources.

Table 3.6: SPECIFICATION TESTS

	h					
	1	2	3	4	5	6
(4) K=2, PRE	0.0939	0.1061	0.1113	0.0975	0.0957	0.0956
(5) K=2, POST	0.0781	0.0707	0.0721	0.0649	0.0650	0.0705
(6) MGDP, PRE	0.3422	0.3681	0.3723	0.3725	0.3765	0.3974
(7) MGDP, POST	0.3015	0.2816	0.2719	0.2850	0.2857	0.2859
(8) CROSS, PRE	0.9878	0.9668	0.9185	0.9961	0.9829	0.9985
(9) CROSS, POST	0.9999	0.9869	0.9488	0.9999	0.9999	0.9999

Notes: p -values from J -test of overidentifying restrictions, for various alternate specifications. K=2, PRE and K=2, POST use only two indicators (CPIXFE and INDPRD). MGDP, PRE, and MGDP, POST use monthly GDP instead of Industrial Production as the output variable. CROSS, PRE and CROSS, POST tests the cross-equation restriction that the average risk premium change is identical across indicators.

3.6.1 Results for Alternative Economic Indicators

Here we analyze the sensitivity of our baseline results to the data used. First, we report results using only two indicators. Second, we report results using monthly GDP, as calculated by Macroeconomic Advisers, instead of industrial production to measure monthly output. Given the strong evidence of a parameter break, we consider these alternate specifications estimated separately over the two subsamples. Table 3.6 displays the overidentification test results while Table 3.7 presents the response coefficient estimates.

Specifications (4) and (5) of Table 3.7 suggest that the nonfarm payrolls indicator provides useful variation to the estimation. In its absence, the parameter estimates are less precisely estimated at several horizons. We still estimate a pre-2000 steeply adjusting inflation response, nearly identical to the baseline pre-2000 estimates. And again the pre-2000 output response, when statistically significant,

Table 3.7: MARKET-PERCEIVED MONETARY POLICY RULE ESTIMATES, ALTERNATE SPECIFICATIONS

		h					
		1	2	3	4	5	6
(4) K=2, PRE	β	0.3655* <i>0.1451</i>	0.8756** <i>0.2245</i>	1.1693** <i>0.3877</i>	1.1302* <i>0.4897</i>	1.0811 <i>3.6476</i>	1.3718 <i>1.9668</i>
	δ	0.0628** <i>0.0136</i>	0.0487** <i>0.0166</i>	0.1386 <i>0.0762</i>	0.1338 <i>0.1227</i>	0.1875 <i>0.6804</i>	0.1984 <i>0.3485</i>
(5) K=2, POST	β	-0.0737** <i>0.0255</i>	4.7939 <i>60.3866</i>	0.9579 <i>1.5374</i>	-0.0881 <i>0.1503</i>	1.0009 <i>1.5029</i>	2.6046 <i>18.1027</i>
	δ	0.0111** <i>0.0038</i>	0.1660 <i>2.0437</i>	-0.0357 <i>0.1054</i>	0.0253 <i>0.0208</i>	0.0643 <i>0.0329</i>	0.2120 <i>1.2092</i>
(6) MGDG, PRE	β	0.4059 <i>0.2170</i>	0.9063** <i>0.1916</i>	1.1353** <i>0.2419</i>	1.1681** <i>0.2716</i>	1.1832* <i>0.4921</i>	1.4515 <i>0.9977</i>
	δ	0.2140** <i>0.0615</i>	0.0848** <i>0.0197</i>	0.2163** <i>0.0418</i>	0.3608** <i>0.0593</i>	0.3795** <i>0.1101</i>	0.5833** <i>0.1910</i>
(7) MGDG, POST	β	0.0012 <i>0.2929</i>	0.3985** <i>0.0818</i>	0.3923** <i>0.0984</i>	0.1520* <i>0.0667</i>	0.9583** <i>0.1467</i>	1.8190** <i>0.5357</i>
	δ	0.2986 <i>0.1678</i>	0.0063 <i>0.0448</i>	-0.1860** <i>0.0706</i>	-0.1570* <i>0.0721</i>	0.0923 <i>0.0752</i>	0.0533 <i>0.1134</i>
(8) NO CROSS, PRE	β	0.3606 <i>0.2435</i>	0.8534* <i>0.4101</i>	1.2100* <i>0.5341</i>	1.2124 <i>0.8613</i>	1.1126 <i>0.5899</i>	1.3821 <i>0.9823</i>
	δ	0.1548** <i>0.0369</i>	0.1316** <i>0.0364</i>	0.2615** <i>0.0841</i>	0.3970** <i>0.1220</i>	0.3857* <i>0.1509</i>	0.5746** <i>0.2012</i>
(9) NO CROSS, POST	β	0.1425** <i>0.0542</i>	0.3656* <i>0.1455</i>	-1.1842 <i>0.6257</i>	0.5738** <i>0.1802</i>	0.8037** <i>0.2048</i>	2.0393 <i>1.0932</i>
	δ	0.0368** <i>0.0126</i>	0.0037 <i>0.0091</i>	0.1361* <i>0.0621</i>	-0.0559 <i>0.0337</i>	0.0409 <i>0.0306</i>	-0.0691 <i>0.0793</i>

Notes: The policy rule coefficient on inflation is β and on the output gap is δ . HAC standard errors in *italics*. The markers * and ** denote significance at 5% and 1% levels, respectively. See the notes for Table 3.6 or the text of Section 3.6 for descriptions of the alternate specifications. Point estimates and standard errors from two-step nonlinear GMM. Data run over 1994:M1-2007:M7

looks to be modest. However, the longer horizon estimates are accompanied by large standard errors, rendering them statistical insignificant. Still, the overidentifying tests in Table 3.6 fail to reject at the 5% level.

Specifications (6) and (7) of Table 3.7 give evidence that our baseline results are robust to other measures of output. The pre-2000 output response coefficients are very similar to the baseline, with a slightly larger 0.21 response at the one-month

horizon and virtually unchanged 0.58 response at the six-month horizon. The profile for the post-2000 response is similar to the baseline results, again with the three- and four-month horizon responses wrongly signed. Tests of the overidentifying restrictions in Table 3.6 are quite supportive of the assumptions.

3.6.2 Tests of Cross-Equation Restrictions

In addition to the average change in the risk premium on fed funds futures contracts, the constant term $\eta_{r,k}$ in equation (3.12) would incorporate any non-zero mean for the specification error that represented day-to-day changes in the market forecasts of potential output, the inflation target, and the policy rule residual (see expression (3.9)). If this constant terms turned out to be different for different indicators k , that could be evidence of general mis-specification. For example, if the indicators were in part providing signals about changes in potential output, and if the value of this signal differed across indicators, that might show up as differences in $\eta_{r,k}$ across different k .

It is easy to conduct tests of the restriction (3.16) that the policy rule constant is identical across indicators based again on Hansen's J -statistic

$$TQ\left(\hat{\theta}_R^{(h)}, \mathcal{Y}_T^{(h)}\right) - TQ\left(\hat{\theta}_U^{(h)}, \mathcal{Y}_T^{(h)}\right) \approx \chi^2(2)$$

where $\hat{\theta}_R$ is the GMM parameter estimate subject to the cross-equation restriction $\eta_{r,1} = \eta_{r,2} = \eta_{r,3}$ and $\hat{\theta}_U$ is the unrestricted estimate. The p -values for this test are reported in rows 8 and 9 of Table 3.6. The restrictions are quite consistent with the data.

The unrestricted policy parameter estimates from $\hat{\theta}_U$ are reported in rows 8 and 9 of Table 3.7. Nothing substantive is lost, and statistical precision is noticeably gained, by imposing the cross-equation restriction that the policy rule constant is identical across economic indicators. Comparing rows 8 and 9 of Table 3.7 to Table 3.3, one sees that estimating separate policy rule constants reduces the statistical precision with which we estimate the policy rule response coefficients, in particular the inflation response coefficients at longer horizons.

3.6.3 Potential Output and the Inflation Target

A challenge for standard methods of estimating monetary policy rules is the difficulty in measuring potential output y_t^* and the inflation target π_t^* . We have argued that our approach can avoid these problems to the extent that the daily news items of which we make use have negligible consequences for y^* or π^* . Here we provide additional evidence on why we believe that is a reasonable assumption.

To explore this issue empirically, we will be looking at the properties of the Congressional Budget Office's series for quarterly potential real GDP growth, denoted y_q^* where q indexes quarters. As currently reported, y_q^* is an extremely smooth and highly predictable series. However, over time the CBO will make many revisions to its estimate of the value of y_q^* for a given historical quarter q . For example, on April 17, 1996, CBO estimated the growth rate of potential GDP for $q = 1995:Q4$ to be 1.98% (at an annual rate), whereas by January 8, 2009, they had revised the estimate for $y_{1995:Q4}^*$ up to 2.76%. Orphanides (2001) and Orphanides and van Norden (2002) demonstrated that such revisions can pose a big problem for traditional Taylor

Rule estimates. Is it reasonable to assert that the daily news events exploited in our analysis had negligible implications for these subsequent revisions of potential GDP?

Let $\Omega(q)$ denote the information set available to the public as of the 20th calendar day of the first month of quarter $q + 1$. For example, for $q = 1995:Q4$, $\Omega(q)$ would represent information publicly reported as of January 20, 1996. By this date, values for the percentage growth in nonfarm payrolls for each month of quarter q would have been reported, denoted $x_{1q|\Omega(q)}$, $x_{2q|\Omega(q)}$, and $x_{3q|\Omega(q)}$, though the actual GDP growth rate for quarter q would not yet be known. Thus for example for $q = 1995:Q4$, $x_{1q|\Omega(q)}$ would be the growth rate of seasonally adjusted nonfarm payroll employment during the month of October 1995 as reported by the Bureau of Labor Statistics on January 6, 1996, while $x_{2q|\Omega(q)}$ would be the November 1995 growth rate as reported on January 6. Let $\{y_{q-1|\Omega(q)}^*, \dots, y_{q-4|\Omega(q)}^*\}$ denote the four most recent quarterly growth rates for potential GDP as they would have been reported by CBO prior to date $\Omega(q)$; for example, for $q = 1995:Q4$, $y_{q-1|\Omega(q)}^*$ is the potential growth rate for 1995:Q3 as estimated by CBO on February 1, 1996 (the most recent CBO estimate released prior to January 20, 1996). Finally, let $y_{q|T}^*$ denote the potential GDP growth rate for quarter q as reported on January 8, 2009. Vintage values for $x_{iq|\Omega(q)}$ and $y_{q-j|\Omega(q)}^*$ were obtained from ALFRED, the real-time archived data set maintained by the Federal Reserve Bank of St. Louis.

We then estimated the following regression by OLS for $q = 1994:Q1$ to $2007:Q3$:

$$y_{q|T}^* = \alpha_0 + \sum_{j=1}^3 \alpha_j x_{jq|\Omega(q)} + \sum_{j=1}^4 \gamma_j y_{q-j|\Omega(q)}^* + \epsilon_q.$$

The coefficients α_j can tell us the extent to which the values of nonfarm payroll

growth that arrive during quarter q could help predict the potential GDP growth rate for quarter q as it would ultimately be reported, relative to information about potential GDP that had arrived prior to the quarter's actual GDP report. We fail to reject the null hypothesis that $\alpha_1 = \alpha_2 = \alpha_3 = 0$ ($F(3, 46) = 0.27, p = 0.85$). On the other hand, a parallel regression for predicting the actual real GDP growth rates as eventually reported,

$$y_{q|T} = \tilde{\alpha}_0 + \sum_{j=1}^3 \tilde{\alpha}_j x_{jq|\Omega(q)} + \sum_{j=1}^4 \tilde{\gamma}_j y_{q-j|\Omega(q)} + \tilde{\epsilon}_q,$$

leads to rejection of $H_0 : \tilde{\alpha}_1 = \tilde{\alpha}_2 = \tilde{\alpha}_3 = 0$ ($F(3, 46) = 3.37, p = 0.03$). Nonfarm payrolls contain useful information about the current quarter's actual GDP growth but little information about the current quarter's potential GDP growth.

We repeated the same calculations using monthly industrial production growth rates in place of nonfarm payroll employment growth.^{3.12} We again found that industrial production is of no use in predicting potential GDP ($F(3, 46) = 0.98, p = 0.41$), but is helpful for predicting actual GDP ($F(3, 46) = 4.06, p = 0.01$). Our maintained assumption that markets are responding to news about near-term economic conditions y_{t+h} and not potential output y_{t+h}^* is thus fully consistent with these hypothesis tests.

As far as the inflation target is concerned, the validity of our identifying assumption seems even more compelling. Although there may be changes in the Fed's inflation objectives over time, the suggestion that the FOMC is changing its long-run inflation target on a daily basis in response to the latest economic news would

^{3.12}Release of the December 1995 value for industrial production was delayed until January 24, 1996. We used this January 24, 1996 release for $q = 1995:Q4$.

seem quite strange to those who actually implement monetary policy. Apart from the discrete effects of personnel changes, the Fed's long-run inflation target should by definition be an even smoother series than potential GDP.

3.7 Conclusion

It is important to be able to measure market participants' beliefs, manifest through their behavior, about how monetary policy is conducted. Previous work has identified futures contract prices as powerful predictors of their underlying; in particular, fed funds futures contracts are good predictors of future Federal Reserve policy. This paper proposed that market participants forecast future policy along with future economic conditions, and linked the two by the Taylor Rule. This enabled us to measure the market's beliefs about how the Federal Reserve responds to inflation and the output gap. Additionally, by focusing on daily forecast updates, we are able to nearly eliminate the impact of potential output and the inflation target on our main focus: the market-perceived monetary policy response to inflation and output.

Our baseline results for the 1994–2007 sample suggest the market perceives that the Federal Reserve gradually responds to inflation and real activity. Similar to previous literature working on post-Volcker data, we find the Federal Reserve follows the Taylor Principle, a greater than one-for-one response to inflation. We also find evidence that the market-perceived monetary policy rule changed over our sample. During the 1990s market-perceived policy responded robustly to output and quickly to inflation; during the 2000s market-perceived policy doesn't respond to output and responds at a more measured pace to inflation, though its long-run

inflation response is greater than before. We quantify the importance of the inflation response path and long-run magnitude in a standard model, and find that raising the long-run magnitude is effective at lowering inflation volatility while making the path more gradual is counterproductive. Our baseline results were found to be robust to alternative possible specifications.

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A Appendix

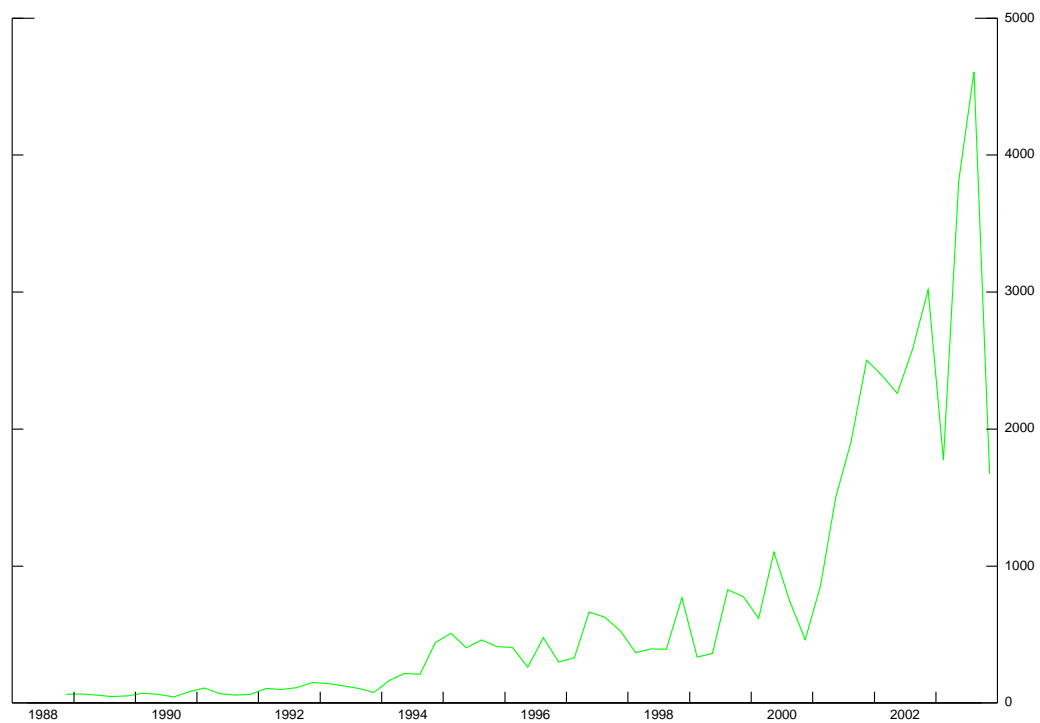
A.1 Tables and Figures

Table A1: POLICY RULE CONSTANT ESTIMATES

	h					
	1	2	3	4	5	6
BASILINE η_r	-0.4024** <i>0.0787</i>	-0.4750** <i>0.1031</i>	-0.6223** <i>0.1351</i>	-0.5060** <i>0.1223</i>	-0.6844** <i>0.1041</i>	-0.6056** <i>0.1046</i>
BASILINE, PRE η_r	-0.4085** <i>0.0897</i>	-0.4744** <i>0.0693</i>	-0.6187** <i>0.1050</i>	-0.5288** <i>0.1459</i>	-0.7056** <i>0.2027</i>	-0.6310* <i>0.2691</i>
BASILINE, POST η_r	-0.4228** <i>0.1174</i>	-0.5163** <i>0.1545</i>	-0.6179** <i>0.0924</i>	-0.5194** <i>0.1440</i>	-0.6075** <i>0.1945</i>	-0.6850** <i>0.1587</i>

Notes: η_r is the average risk premium change. HAC standard errors in *italics*. The markers * and ** denote significance at 5% and 1% levels, respectively. Point estimates and standard errors from two-step nonlinear GMM. Data run over 1994:M1-2007:M7

Figure A1: TRADING VOLUME ON FED FUNDS FUTURES CONTRACTS



Notes: Data from Chicago Board of Trade. As quarterly average.

Chapter 3, in full, is joint work with James Hamilton and Seth Pruitt. The dissertation author was a primary author of this paper.