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Evolution and Impact of Subclonal Mutations in Chronic Lymphocytic Leukemia

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SUMMARY

Clonal evolution is a key feature of cancer progression and relapse. We studied intratumoral heterogeneity in 149 chronic lymphocytic leukemia (CLL) cases by integrating whole-exome sequence and copy number to measure the fraction of cancer cells harboring each somatic mutation. We identified driver mutations as predominantly clonal (e.g., *MYD88*, trisomy 12, and *del(13q)*) or subclonal (e.g., *SF3B1* and *TP53*), corresponding to earlier and later events in CLL evolution. We sampled leukemia cells from 18 patients at two time points. Ten of twelve CLL cases treated with chemotherapy (but only one of six without treatment) underwent clonal evolution, predominantly involving subclones with driver mutations (e.g., *SF3B1* and *TP53*) that expanded over time. Furthermore, presence of a subclonal driver mutation was an independent risk factor for rapid disease progression. Our study thus uncovers patterns of clonal evolution in CLL, providing insights into its stepwise transformation, and links the presence of subclones with adverse clinical outcomes.

INTRODUCTION

Recent genomic studies have revealed that individual cancer samples are genetically heterogeneous and contain subclonal

populations (Carter et al., 2012; Ding et al., 2012; Gerlinger et al., 2012; Mullighan et al., 2008; Navin et al., 2011; Nik-Zainal et al., 2012; Shah et al., 2012). Indeed, tumors likely evolve through competition and interactions between genetically diverse clones (Snuderl et al., 2011). While the existence of intratumoral subclones has long been appreciated, little is known about the frequency, identity, and evolution of subclonal genetic alterations or their impact on clinical course.

To examine the evolution and impact of subclonal mutations, we focused on chronic lymphocytic leukemia (CLL), a slow-growing B cell malignancy with disease onset in older individuals. CLL shows a highly variable disease course, partly explained by the diverse combinations of somatic mutations uncovered by sequencing studies (Quesada et al., 2012; Wang et al., 2011). We hypothesized that the presence, diversity, and evolutionary dynamics of subclonal mutations in CLL also contribute to the variations observed in disease tempo and response to therapy (Schuh et al., 2012; Stilgenbauer et al., 2007). Importantly, the slow growth of CLL-B cells (relative to other malignancies) provides an extended window for observing the process of clonal evolution, as it may take months to years for a new clone to fully replace previous clones (Schuh et al., 2012; Wu, 2012).

Subclonal mutations in CLL have been detected by fluorescence in situ hybridization (FISH) (Shanafelt et al., 2008) and microarrays (Grubor et al., 2009), showing that they harbor driver lesions and evolve over time. Because these methods can only be used to detect a limited number of genetic alterations, more recent studies have used whole-genome sequencing to quantify thousands of somatic mutations per sample and track subclones

by clustering alterations of similar allelic frequency (Ding et al., 2012; Egan et al., 2012; Nik-Zainal et al., 2012; Schuh et al., 2012; Shah et al., 2012; Walter et al., 2012). However, because genome-wide sequencing is currently not feasibly applied to large sample collections, the patterns of clonal evolution and their effects on disease course have not been fully elucidated.

Whole-exome sequencing (WES) (Gnirke et al., 2009) of tumors is an affordable, rapid, and comprehensive technology for detecting somatic coding mutations. We sought to refine and apply a method for analysis of subclonal mutations using WES because: (1) the high sequencing depth obtained by WES (typically $\sim 100\times$ – $150\times$) enables reliable detection of subclonal mutations required for defining subclones and tracking them over time (Cibulskis et al., 2013); (2) coding mutations likely encompass many of the important driver events that provide fitness advantage for specific clones, and finally; and (3) the relatively low cost of WES permits studies of large cohorts, which is key for understanding the relative fitness and temporal order of driver mutations and for assessing the impact of clonal heterogeneity on disease outcome.

To this end, we performed large-scale WES of 160 CLL tumor/normal pairs that represented the broad clinical spectrum of CLL. In particular, we examined the roles of CLL subclones and the mutations that they harbor by integrative analysis of coding mutations and somatic copy number alterations, which enabled estimation of the cancer cell fraction. This was performed in samples from 149 CLL patients, including 18 patients sampled at two time points, for which both exome sequencing data and copy number data were available. This analysis allowed us to study mutation frequencies, observe clonal evolution, and link subclonal mutations to clinical outcome.

RESULTS

Large-Scale WES Analysis of CLL Expands the Compendium of CLL Drivers and Pathways

We performed WES of 160 matched CLL and germline DNA samples (including 82 of the 91 samples previously reported [Wang et al., 2011]). This cohort included patients with both low- and high-risk features based on established prognostic risk factors (Table S1 available online). We applied MuTect (a highly sensitive and specific mutation-calling algorithm; Cibulskis et al., 2013) to the WES data to detect somatic single nucleotide variations (sSNVs) present in as few as 10% of cancer cells. Average sequencing depth of WES across samples was $\sim 112\times$ (see Extended Experimental Procedures). In total, we detected 2,444 nonsynonymous and 837 synonymous mutations in protein-coding sequences, corresponding to a mean (\pm SD) somatic mutation rate of 0.6 ± 0.28 per megabase (range, 0.03–2.3) and an average of 15.3 nonsynonymous mutations per patient (range, 2–53) (Table S2A).

Expansion of our sample cohort provided us with the sensitivity to detect 20 putative CLL cancer genes ($q < 0.1$), which was accomplished through recurrence analysis to detect genes enriched with mutations beyond the background mutation rate (Figures 1A, top, and Figure S1) or genes with mutations that overlap with previously reported mutated sites (from COSMIC [Forbes et al., 2010]; Figure 1A, middle; Experimental Proce-

dures). These included eight of the nine genes identified in our initial report (*TP53*, *ATM*, *MYD88*, *SF3B1*, *NOTCH1*, *DDX3X*, *ZMYM3*, and *FBXW7*) (Wang et al., 2011). The missing gene, *MAPK1*, did not harbor additional mutations in the increased sample set, and therefore its overall mutation frequency now fell below our significance threshold. The 12 genes were mutated at lower frequencies and, hence, were not detected in the previously reported subset of samples. Three of the twelve additional candidate driver genes were identified in recent CLL sequencing efforts (*XPO1*, *CHD2*, and *POT1*) (Fabbri et al., 2011; Puente et al., 2011). The nine remaining genes represent candidate CLL drivers, with mutations occurring at highly conserved sites (Figure S2). These included six genes with known roles in cancer biology (*NRAS*, *KRAS* [Bos, 1989], *BCOR* [Grossmann et al., 2011], *EGR2* [Unoki and Nakamura, 2003], *MED12* [Mäkinen et al., 2011], and *RIPK1* [Hosgood et al., 2009]), two genes that affect immune pathways (*SAMHD1* [Rice et al., 2009] and *ITPKB* [Maréchal et al., 2011]), and a histone gene (*HIST1H1E* [Alami et al., 2003]).

Together, the 20 candidate CLL driver genes appeared to fall into seven core signaling pathways, in which the genes play well-established roles. These include all five pathways that we previously reported to play a role in CLL (DNA repair and cell-cycle control, Notch signaling, inflammatory pathways, Wnt signaling, RNA splicing, and processing). Two pathways were implicated by our analysis: B cell receptor signaling and chromatin modification (Figure 1B). We also noted that the CLL samples contained additional mutations in the genes that form these pathways, some of which are known drivers in other malignancies.

Because recurrent chromosomal abnormalities have defined roles in CLL biology (Döhner et al., 2000; Klein et al., 2010), we further searched for loci that were significantly amplified or deleted by analyzing somatic copy-number alterations (sCNAs). We applied GISTIC2.0 (Mermel et al., 2011) to 111 matched tumor and normal samples, which were analyzed by SNP6.0 arrays (Brown et al., 2012). Through this analysis, we identified deletions in chromosomes 8p, 13q, 11q, and 17p and trisomy of chromosome 12 as significantly recurrent events (Figure 1A, bottom). Thus, based on WES and copy number analysis, we altogether identified 20 mutated genes and five cytogenetic alterations as putative CLL driver events.

Inference of Genetic Evolution with Whole-Exome Sequencing Data

In order to study clonal evolution in CLL, we performed integrative analysis of sCNAs and sSNVs using a recently reported algorithm ABSOLUTE (Carter et al., 2012), which jointly estimated the purity of the sample (fraction of cancer nuclei) and the average ploidy of the cancer cells. All samples were estimated to have near-diploid DNA content; these estimates were confirmed by fluorescence-activated cell sorting (FACS) analysis of seven CLL samples (Figure S3A). Our data were sufficient for resolution of these quantities in 149 of the 160 samples (Table S2B), allowing for discrimination of subclonal from clonal alterations, including sCNAs, sSNVs, and selected indels (see Extended Experimental Procedures). Our analysis approach is outlined in Figure 2A. For each sSNV, we estimated its *allelic fraction* by

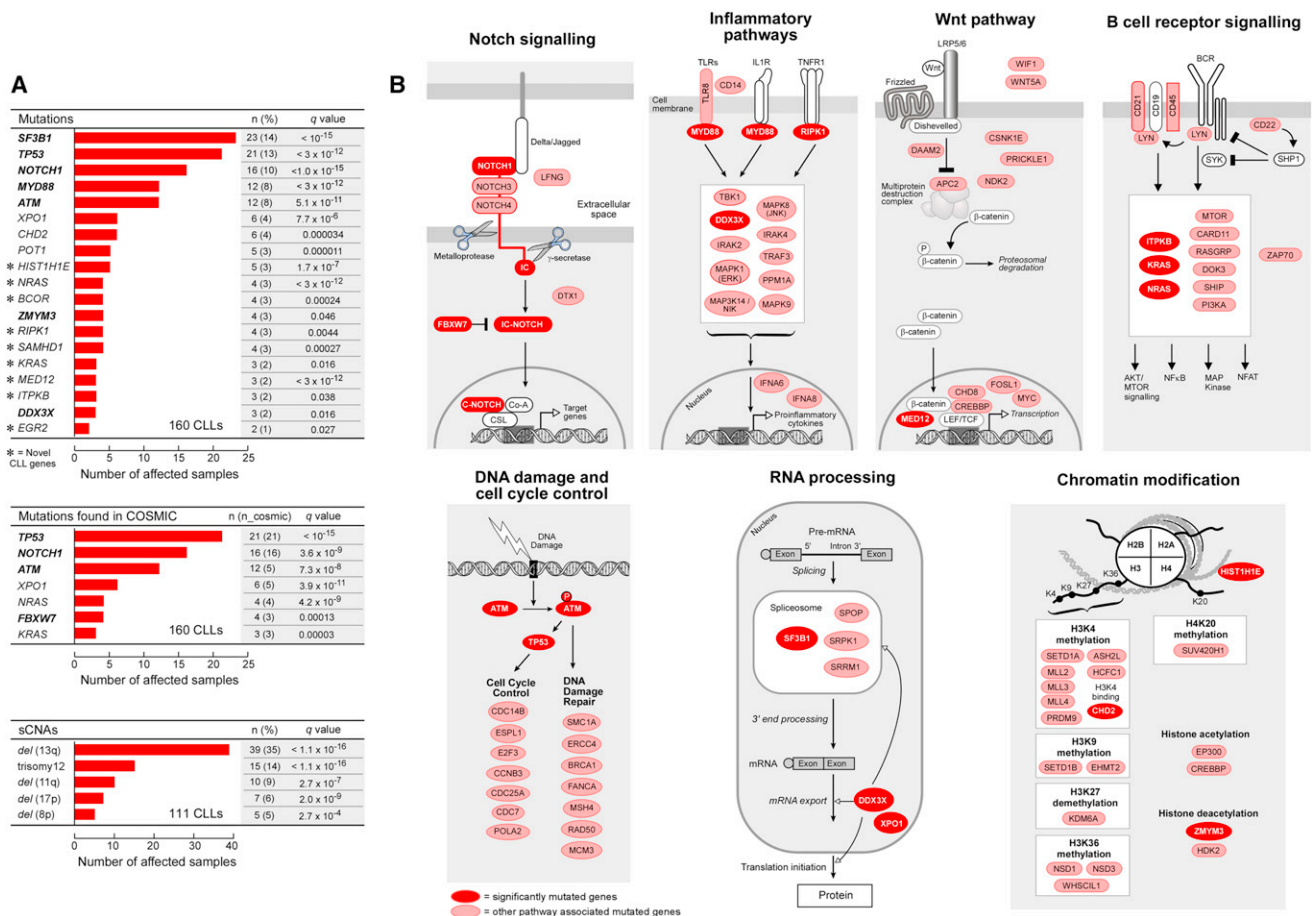


Figure 1. Significantly Mutated Genes and Associated Gene Pathways in 160 CLL Samples

(A) Mutation significance analysis using the MutSig2.0 and GISTIC2.0 algorithms identifies recurrently mutated genes and recurrent sCNAs in CLL, respectively. Bold: significantly mutated genes identified in a previous CLL sequencing effort (Wang et al., 2011); *, novel CLL genes identified in the present analysis (Figures S1 and S2); n, number of samples out of 160 CLLs harboring a mutation in a specific gene; n_cosmic, number of samples harboring a mutation in a specific gene at a site previously observed in the COSMIC database.

(B) The significantly mutated genes fall into seven core signaling pathways, in which the genes play well-established roles. Red: genes with significant mutation frequencies; pink: additional pathway genes with mutations. See also Figures S1, S2, and Table S2A.

calculating the ratio of alternate to total number of reads covering the mutation site in the WES data. These estimates were consistent with independent deeper sequencing and RNA sequencing (Figures S3B and S3C; Tables S3 and S4). Next, we used ABSOLUTE to estimate the cancer cell fraction (CCF) harboring the mutation by correcting for sample purity and local copy-number at the sSNV sites (Experimental Procedures; Table S2C; Figure 2B). We classified a mutation as clonal if the CCF harboring it was >0.95 with probability >0.5 and subclonal otherwise (Figure 2A, inset). The results remained unchanged when more stringent cutoffs were used (Extended Experimental Procedures). For sSNVs designated as subclonal, median CCF was 0.49 with a range of 0.11–0.89.

Overall, we identified 1,543 clonal mutations (54% of all detected mutations, average of 10.3 ± 5.5 mutations per sample; Table S1). These mutations were likely acquired either before or during the most recent complete selective sweep. This set there-

fore includes both neutral somatic mutations that preceded transformation and the driver and passenger event(s) present in each complete clonal sweep. A total of 1,266 subclonal sSNVs were detected in 146 of 149 samples called by ABSOLUTE (46%; average of 8.5 ± 5.8 subclonal mutations per sample). These subclonal sSNVs exist in only a fraction of leukemic cells and, hence, occurred after the emergence of the “most recent common ancestor” and, by definition, also after disease initiation. The mutational spectra were similar in clonal and subclonal sSNVs (Figure S3D), consistent with a common set of mutational processes, giving rise to both groups.

Age and Mutated IGHV Status Are Associated with an Increased Number of Clonal Somatic Mutations

The identification of subclones enabled us to analyze several aspects of leukemia progression. We first addressed how clonal and subclonal mutations relate to the salient clinical

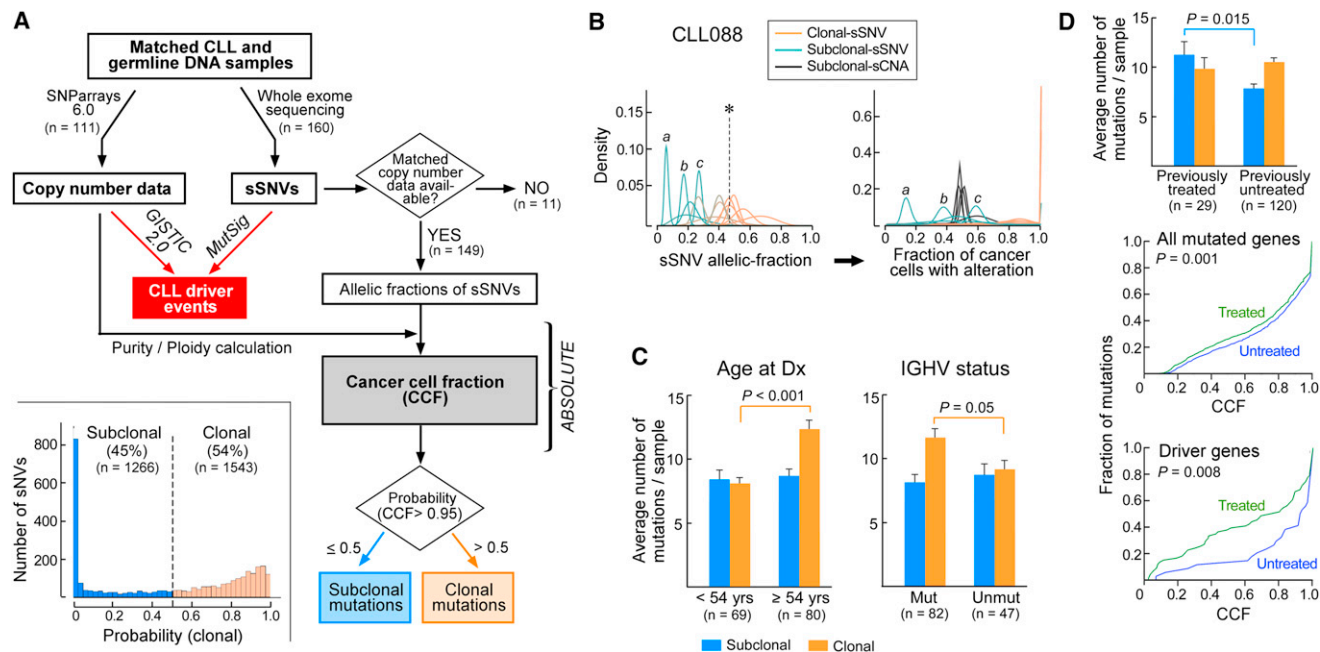


Figure 2. Subclonal and Clonal sSNVs Are Detected in CLL in Varying Quantities Based on Age at Diagnosis, *IGHV* Mutation Status, and Treatment Status

(A) The analysis workflow: “CLL driver events” (red box) were identified by mutation significance analysis using WES and SNP array data collected from matched germline and tumor DNA. For the 149 samples that had matched WES and copy number data, ABSOLUTE was applied to estimate the cancer cell fraction (CCF). Mutations were classified as subclonal (blue) or clonal (orange), based on the probability that their CCF is greater than 0.95 (clonal). Inset: histogram of the probability of being clonal for all sSNVs across 149 CLL samples.

(B) A representative example of the transformations generated by ABSOLUTE (for sample CLL088). First, probability density distributions of allelic fractions for each mutation are plotted (representative peaks for sSNVs a, b, and c shown). Second, these data are converted to CCF (right), incorporating purity and local copy number information. The probability of the event being clonal (i.e., affecting >0.95 of cells) is represented by a color spectrum: orange is high probability and blue is low probability. *, allelic fraction of a clonal mutation at multiplicity of one (for example, a heterozygous mutation in a diploid region).

(C) Comparison of the number of subclonal and clonal sSNVs/sample based on patient age at diagnosis and *IGHV* mutation status (error bars represent standard error of mean).

(D) Comparison of the number of subclonal and clonal sSNVs/sample based on treatment status at time of sample collection (top, error bars represent standard error of mean). Cumulative distribution of the sSNVs by CCF is shown for samples from treated and untreated patients for all (middle) and only driver sSNVs (bottom).

See also Figure S3 and Tables S1, S2B, and S2C.

characteristics of CLL. CLL is generally a disease of the elderly with established prognostic factors, such as the *IGHV* mutation (Döhner, 2005) and *ZAP70* expression. Patients with a high number of *IGHV* mutations (mutated *IGHV*) tend to have better prognosis than those with a low number (unmutated *IGHV*) (Döhner, 2005). This marker distinguishes between leukemias originating from B cells that have or have not yet, respectively, undergone the process of somatic hypermutation that occurs as part of normal B cell development. We examined the association of these factors, as well as patient age at diagnosis, with the prevalence of clonal and subclonal mutations. Age and mutated *IGHV* status (but not *ZAP70* expression) were found to associate with greater numbers of clonal (but not subclonal) mutations (age, $p < 0.001$; mutated versus unmutated *IGHV*, $p = 0.05$; Figure 2C; Table S1). Because CLL samples with mutated *IGHV* derive from B cells that have experienced a burst of mutagenesis as part of normal B cell somatic hypermutation, the increased number of clonal somatic mutations is likely related to aberrant mutagenesis that preceded clonal transfor-

mation (Deutsch et al., 2007; McCarthy et al., 2003). Furthermore, the higher number of clonal sSNVs in older individuals is consistent with the expectation that more neutral somatic mutations accumulate over the patient’s lifetime prior to the onset of cancer later in life (Stephens et al., 2012; Welch et al., 2012).

Subclonal Mutations Are Increased with Treatment

The effect of treatment on subclonal heterogeneity in CLL is unknown. In samples from 29 patients treated with chemotherapy prior to sample collection, we observed a significantly higher number of subclonal (but not clonal) sSNVs per sample than in the 120 patients who were chemotherapy-naïve at the time of sample (Figure 2D, top and middle). Using an analysis of covariance model, we observed that receipt of treatment prior to sample among the 149 patients was statistically significant ($p = 0.048$) but time from diagnosis to sample was not ($p = 0.31$). Because patients that do not require treatment in the long-term may have a distinct subtype of CLL, we also restricted the comparison of the 29 pretreated CLLs to only the 42 that

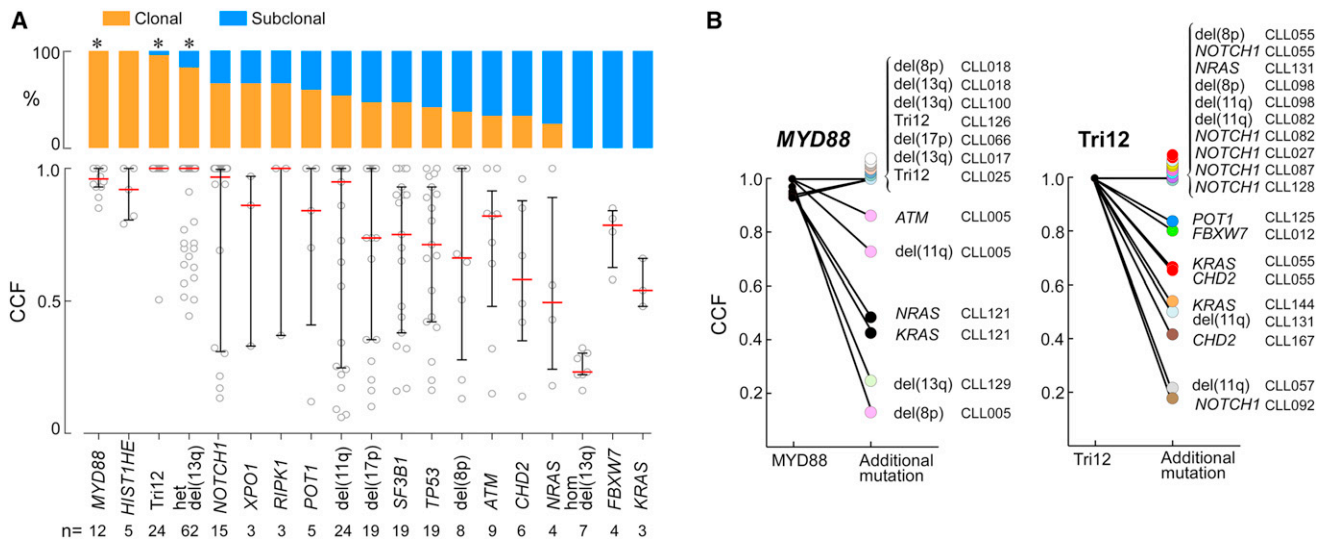


Figure 3. Identification of Earlier and Later CLL Driver Mutations

(A) Distribution of estimated CCF with median and interquartile range shown in black (bottom) and percent of the mutations classified as clonal (orange) or subclonal (blue) for CLL drivers (top). *, drivers with q -values < 0.1 for a higher proportion of clonal mutations compared with the entire CLL drivers set. Het, heterozygous deletion; Hom, homozygous deletion. The analysis includes all recurrently mutated genes (Figure 1A) with three or more events in the 149 samples, excluding sSNVs affecting the X chromosome currently not analyzable by ABSOLUTE and also excluding indels in genes other than *NOTCH1*.

(B) All CLL samples with *MYD88* (left) or trisomy 12 (right) and at least one additional defined CLL driver (i.e., 9 of 12 samples with mutated *MYD88* and 14 of 16 tumors with trisomy 12) are depicted. Each dot color denotes separate individual CLL samples.

See also Figure S4 and Table S2C.

were eventually treated after sample collection and again confirmed this finding ($p = 0.02$). In these 42 patients, a higher number of subclonal mutations was not correlated with a shorter time to treatment (correlation coefficient = 0.03; $p = 0.87$). Thus, therapy prior to sample was associated with a higher number of subclonal mutations, and furthermore, the number of subclonal sSNVs detected increased with the number of prior therapies ($p = 0.011$, Table S1).

Cancer therapy has been theorized to be an evolutionary bottleneck, in which a massive reduction in malignant cell numbers results in reduced genetic variation in the cell population (Gerlinger and Swanton, 2010). It is likely that the overall diversity in CLL is diminished after therapeutic bottlenecks as well. Because most of the genetic heterogeneity within a cancer is present at very low frequencies (Gerstung et al., 2012)—below the level of detection afforded by the $\sim 112\times$ sequence coverage we generated—we were unable to directly assess reduction in overall genetic variation.

However, in the range of larger subclones that were observable by our methods ($>10\%$ of malignant cells), we witnessed increased diversity after therapy (Figure 2D). Although the available data cannot definitively rule out extensive diversification following therapy, this increase likely results, at least in part, from outgrowth of pre-existing minor subclones (Schuh et al., 2012; Wu, 2012). This may result from the removal of dominant clones by cytotoxic treatment, eliminating competition for growth and allowing the expansion of one or more fit subclones to frequencies above our detection threshold. Further supporting our interpretation that fitter clones grow more effectively and become detectable after treatment, we observed an increased

frequency of subclonal driver events (which are presumably fitter) in treated relative to untreated patients (Figure 2D, bottom) (note that driver events include CLL driver mutations [Figure 1A] and sSNVs in highly conserved sites of genes in the Cancer Gene Census [Futreal et al., 2004]).

Inferring the Order of Genetic Changes Underlying CLL

While general aspects of temporal evolution could not be completely resolved in single time point WES samples, the order of driver mutation acquisition could be partially inferred from the aggregate frequencies at which they are found to be clonal or subclonal. We considered the 149 samples as a series of “snapshots” taken along a temporal axis. Clonal status in all or most mutations affecting a specific gene or chromosomal lesion would suggest that this alteration was acquired at or prior to the most recent selective sweep before sampling and hence could be defined as a stereotypically early event. Conversely, predominantly subclonal status in a specific genetic alteration implies a likely later event that is tolerated and selected for only in the presence of an additional mutation.

This strategy was used to infer temporal ordering of the recurrent sSNVs and sCNAs (Figures 3A and S4). We focused on alterations found in at least three samples within the cohort of 149 CLL samples. We found that three driver mutations—*MYD88* ($n = 12$), trisomy 12 ($n = 24$), and hemizygous *del(13q)* ($n = 70$)—were clonal in 80%–100% of samples harboring these alterations, a significantly higher level than for other driver events ($q < 0.1$, Fisher exact test with Benjamini-Hochberg FDR [Benjamini and Hochberg, 1995]), implying that they arise earlier in typical CLL development. Mutations in *HIST1H1E*, although

clonal in five of five affected samples, did not reach statistical significance. Other recurrent CLL drivers—for example, *ATM*, *TP53*, and *SF3B1* (9, 19, and 19 mutations in 6, 17, and 19 samples, respectively)—were more often subclonal, indicating that they tend to arise later in leukemic development and contribute to disease progression. We note that the above approach assumed that different CLL samples evolve along a common temporal progression axis. We therefore examined specifically CLL samples that harbored one “early” driver mutation and any additional driver alteration(s). As expected, the early events had either similar or a higher CCF compared to “later” events (examples for trisomy 12 and *MYD88* given in Figure 3B).

Direct Observation of Clonal Evolution by Longitudinal Data Analysis of Chemotherapy-Treated CLL

To directly assess the evolution of somatic mutations in a subset of patients, we compared CCF for each alteration across two clinical time points in 18 of the 149 samples (median years between time points was 3.5; range 3.1–4.5). Six patients (“untreated”) did not receive treatment throughout the time of study. The remaining 12 patients (“treated”) received intervening chemotherapy (primarily fludarabine and/or rituxan-based) (Table S3). The two patient groups were not significantly different in terms of elapsed time between first and second sample (median 3.7 years for the six untreated patients compared to 3.5 years for the 12 treated patients, $p = 0.62$; exact Wilcoxon rank-sum test), nor did it differ between time of diagnosis to first sample ($p = 0.29$).

Analysis of the 18 sets of data revealed that 11% of mutations increased (34 sSNVs, 15 sCNAs), 2% decreased (six sSNVs, two sCNAs), and 87% did not change their CCF over time ($q < 0.1$ for significant change in CCF, Table S5C). As suggested by our single time point analysis, we observed a shift of subclonal driver mutations (e.g., *del(11q)*, *SF3B1*, and *TP53*) toward clonality over time. Changes in the genetic composition of CLL cells with clonal evolution were associated with network level changes in gene expression related to emergence of specific subclonal populations (e.g., changes in signatures associated with *SF3B1* or *NRAS* mutation [Figures S5D and S5E; Table S6]). Finally, expanding sSNVs were enriched in genes included in the Cancer Gene Census (Futreal et al., 2004) ($p = 0.021$) and in CLL drivers ($p = 0.028$), consistent with the expected positive selection for the subclones harboring them.

Clustering analysis of CCF distributions of individual genetic events over the two time points (Extended Experimental Procedures) revealed clear clonal evolution in 11 of 18 CLL sample pairs. We observed clonal evolution in 10 of 12 sample pairs that had undergone intervening treatment between time points 1 and 2 (Figures 4B and S5A–S5C). This was contrasted with the six untreated CLLs, five of which demonstrated equilibrium between subpopulations that was maintained over several years (Figure 4A; $p = 0.012$, Fisher exact test). Of the 11 patients with subclonal evolution across the sampling interval, five followed a branched evolution pattern, as indicated by the disappearance of mutations with high CCF co-occurring with the expansion of other subclones (Figure 4B). This finding demonstrates that co-existing sibling subclones are at least as common in CLL as are linear nested subclones, as demonstrated in other hemato-

logical malignancies (Ding et al., 2012; Egan et al., 2012). We conclude that chemotherapy-treated CLLs often undergo clonal evolution, resulting in the expansion of previously minor subclones. Thus, these longitudinal data validate the insights obtained in the cross-sectional analysis, namely that (1) later driver events expand over time (Figure 3A), and (2) treatment results in the expansion of subclones enriched with drivers (and thus presumably have higher fitness) (Figure 2D).

Presence of Subclonal Drivers Adversely Impacts Clinical Outcome

We observed treatment-associated clonal evolution to lead to the replacement of the incumbent clone by a fitter pre-existing subclone (Figure 4B). Therefore, we would expect a shorter time to relapse in individuals with evidence of clonal evolution following treatment. As a measure of relapse, we assessed failure-free survival from time of sample (“FFS_Sample”) and failure-free survival from time of next therapy (“FFS_Rx”) (Figure 5A), where failure is defined as retreatment (a recognized endpoint in slow growing lymphomas [Cheson et al., 2007]) or death. For the study of clonal evolution in CLL, retreatment as an endpoint is preferable to other measures, such as progression alone, as this is a well-defined event that reflects CLL disease aggressiveness. For example, disease progression alone in CLL may be asymptomatic without necessitating treatment; conversely, treatment is administered only in the setting of symptomatic disease or active disease relapse (Hallek et al., 2008).

Within the 12 of 18 longitudinally analyzed samples that received intervening treatment, we observed that the ten samples with clonal evolution exhibited shortened FFS_Rx (log-rank test; $p = 0.015$, Figure 5B). Importantly, the somatic driver mutations that expanded to take over the entire population upon relapse (“time point-2”) were often already detectable in the pretreatment (“time point-1”) sample (Figures 4B and S5B). Our results thus suggested that presence of detectable subclonal drivers in pretreatment samples can anticipate clonal evolution in association with treatment. Indeed, the 8 of 12 samples with presence of subclonal drivers in pretreatment samples exhibited shorter FFS_Rx than the four samples with subclonal drivers absent ($p = 0.041$, Figure 5C). Together, the results of our longitudinally studied patient samples suggested that the presence of driver events within subclones may impact prognosis and clinical outcome.

We tested this hypothesis in the set of 149 patient samples, of which subclonal driver mutations were detected in 46% (Figure 6A; Extended Experimental Procedures; Table S4). Indeed, we found that CLL samples with subclonal driver mutations were associated with a shorter time from sample collection to treatment or death (FFS_Sample, $p < 0.001$, Figure 6B; Tables S7A and S7C), which seemed to be independent of established markers of poor prognosis (i.e., unmutated *IGHV* or presence of *del(11q)* or *del(17p)*, Figure S6). Moreover, we tested specifically whether the presence of pretreatment subclonal drivers was associated with a shorter FFS_Rx, as we observed in the longitudinal data. Therefore, we focused on the 67 patients who were treated after sample collection (median time to first therapy from time of sample was 11 months [range 1–45]). These patients

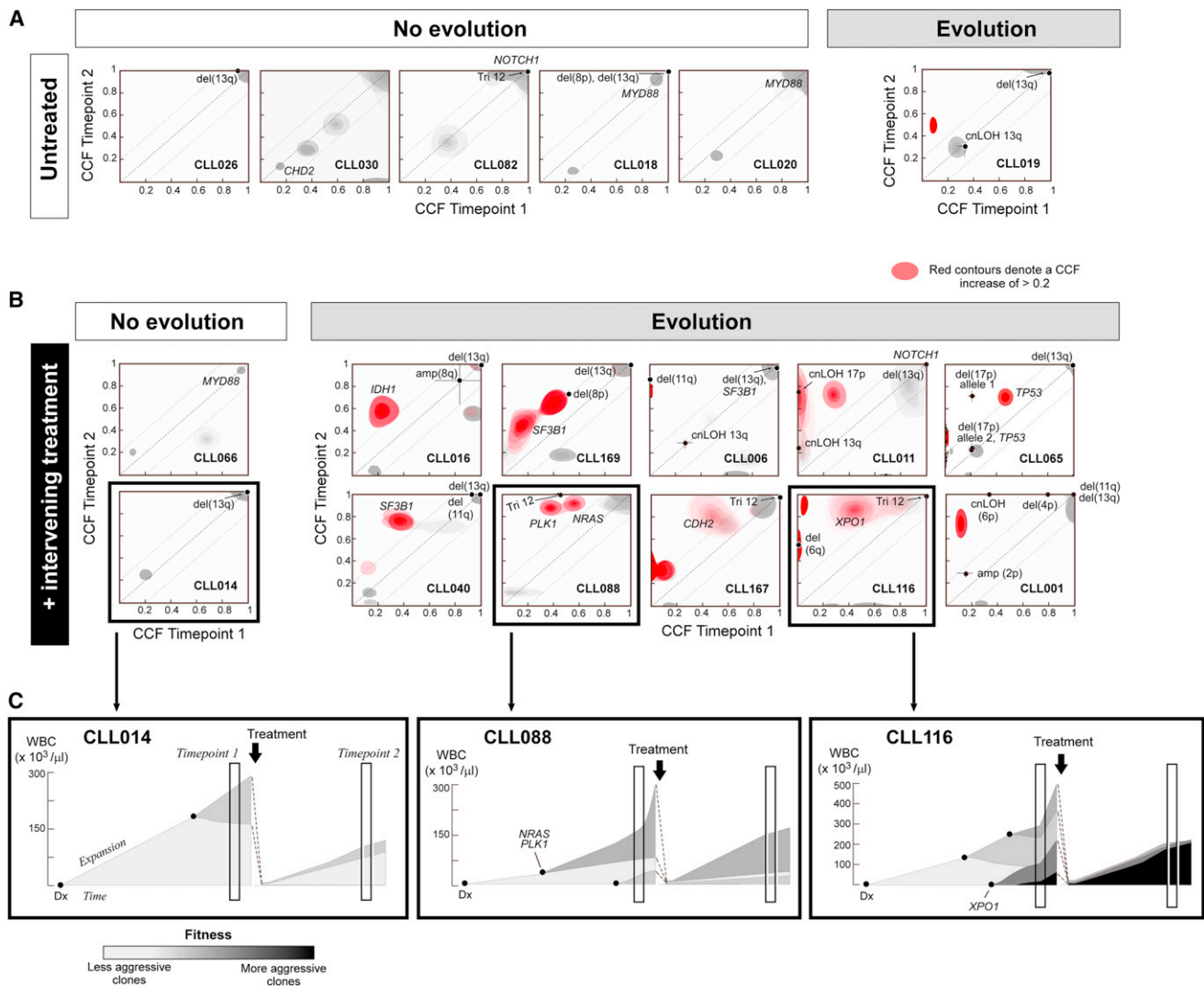


Figure 4. Longitudinal Analysis of Subclonal Evolution in CLL and Its Relation to Therapy

(A and B) Joint distributions of cancer cell fraction (CCF) values across two time points were estimated using clustering analysis (see [Extended Experimental Procedures](#)). Red: a mutation with an increase in CCF of greater than 0.2 (with probability >0.5). The dotted diagonal line represents $y = x$ or where identical CCF values across the two time points fall; the dotted parallel lines denote the 0.2 CCF interval on either side. Likely driver mutations were labeled. Six CLLs with no intervening treatment (A) and 12 CLLs with intervening treatment (B) were classified according to clonal evolution status, based on the presence of mutations with an increase of CCF > 0.2.

(C) Hypothesized sequence of evolution, inferred from the patients' WBC counts, treatment dates, and changes in CCF for three representative examples. See also [Figure S5](#) and [Table S5C](#).

could be divided into two groups based on the presence ($n = 39$) or absence ($n = 29$) of a subclonal driver (62% and 64%, respectively, were treated with fludarabine-based immunochemotherapy, $p = 0.4$). The 39 of these patients in which subclonal CLL drivers were detected required earlier retreatment or died (shorter FFS_{Rx}; log-rank test, $p = 0.006$, [Figure 6C](#); [Table S7A](#)), indicative of a more rapid disease course.

Regression models adjusting for multiple CLL prognostic factors (*IGHV* status, prior therapy, and high-risk cytogenetics) supported the presence of a subclonal driver as an independent risk factor for earlier retreatment (adjusted hazard ratio [HR] of 3.61 [CI 1.42–9.18], Cox $p = 0.007$; unadjusted HR, 3.20 [CI

1.35–7.60], [Figure 6D](#)), comparable to the strongest known CLL risk factors. In similar modeling within a subset of 62 patients who had at least one driver (clonal or subclonal), the association of the presence of a subclonal driver with a shorter time to retreatment or death was also significant ($p = 0.012$, [Table S7B](#)), reflecting that this difference is not merely attributable to the presence of a driver. Additionally, an increased number of subclonal driver mutations per sample (but not clonal drivers) was also associated with a stronger HR for shorter FFS_{Rx} ([Table S7D](#)). Finally, this association retained significance (Cox $p = 0.033$, [Table S7E](#)) after adjusting for the presence of mutations previously associated with poor prognosis (*ATM*,

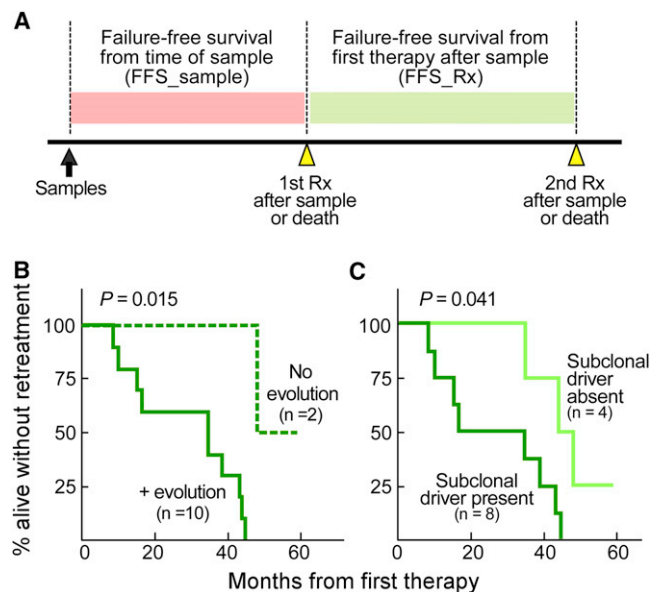


Figure 5. Genetic Evolution and Clonal Heterogeneity Result in Altered Clinical Outcome

(A) Schema of the main clinical outcome measures that were analyzed: failure-free survival from time of sample (FFS_Sample) and from initiation of first treatment after sampling (FFS_Rx). Within the longitudinally followed CLLs that received intervening treatment (12 of 18), shorter FFS_Rx was observed in CLL samples that (B) had evidence of genetic evolution ($n = 10$) compared to samples with absent or minimal evolution ($n = 2$; Fisher exact test) and that (C) harbored a detectable subclonal driver in the pretreatment sample ($n = 8$) compared to samples with absent subclonal driver ($n = 4$). See also Table S3.

TP53, and *SF3B1*), suggesting that, in addition to the driver's identity, its subclonal status also affects clinical outcome.

DISCUSSION

While intertumoral (Quesada et al., 2012; Wang et al., 2011) and intratumoral (Schuh et al., 2012; Stilgenbauer et al., 2007) genetic heterogeneity had been previously demonstrated in CLL, our use of WES-based algorithms enabled a more comprehensive study of clonal evolution and its clinical impact. We propose the existence of distinct periods in CLL progression. In the first period prior to transformation, passenger events accumulate in the cell that will eventually be the founder of the leukemia (in proportion to the age of the patient, Figure 2C), and are thus clonal mutations (Figure 7A). In the second period, the founding CLL mutation appears in a single cell and leads to transformation (Figure 7B); these are also clonal mutations, but unlike passenger mutations, these are recurrent across patients. We identified driver mutations that were consistently clonal (del(13q), *MYD88*, and trisomy 12 (Figure 3A), which appear to be relatively specific drivers of CLL or B cell malignancies (Beroukhi et al., 2010; Döhner et al., 2000; Ngo et al., 2010). In the third period of disease progression, subclonal mutations expand over time as a function of their fitness-integrating intrinsic factors (e.g., proliferation and apoptosis) and extrinsic

pressures (e.g., interclonal competition and therapy) (Figures 7C and 7D). The subclonal drivers include ubiquitous cancer genes, such as *ATM*, *TP53*, or *RAS* mutations (Figure 3A). These data suggest that mutations that selectively affect B cells may contribute more to the initiation of disease and precede selection of more generic cancer drivers that underlie disease progression—providing predictions that can be tested in human B cells or animal models of CLL.

An important question addressed here is how treatment affects clonal evolution in CLL. In the 18 patients monitored at two time points, we observed two general patterns—clonal equilibrium, in which the relative sizes of each subclone were maintained, and clonal evolution, in which some subclones emerge as dominant (Figure 4). We propose that, in untreated samples, more time is needed for a new fit clone to take over the population in the presence of existing dominant clones (Figure 7D, top). In contrast, in treated samples, cytotoxic therapy typically removes the incumbent clones (Jablonski, 2001)—acting like a “mass extinction” event (Jablonski, 2001)—and shifts the evolutionary landscape (Nowak and Sigmund, 2004; Vincent and Gatenby, 2008) in favor of one or more aggressive subclones (Maley et al., 2006; Figure 7D, bottom). Thus, highly fit subclones likely benefit from treatment and exhibit rapid outgrowth (Greaves and Maley, 2012).

CLL is an incurable disease with a prolonged course of remissions and relapses. It has been long recognized that relapsed disease responds increasingly less well to therapy over time. We now show an association between increased clinical aggressiveness and genetic evolution, which has therapeutic implications. We found that the presence of pretreatment subclonal driver mutations anticipated the dominant genetic composition of the relapsing tumor. Such information may eventually guide the selection of therapies to prevent the expansion of highly fit subclones. In addition, the potential hastening of the evolutionary process with treatment provides a mechanistic justification for the empirical practice of “watch and wait” as the CLL treatment paradigm (CLL Trialists Collaborative Group, 1999). The detection of driver mutations in subclones (a testimony to an active evolutionary process) may thus provide a prognostic approach in CLL, which can now be rigorously tested in larger clinical trials.

In conclusion, we demonstrate the ability to study tumor heterogeneity and clonal evolution with standard WES. These innovations will allow characterization of the subclonal mutation spectrum in large, publicly available data sets (Masica and Karchin, 2011). The implementation described here may also be readily adopted for clinical applications. Even more importantly, our studies underscore the importance of evolutionary development as the engine driving cancer relapse. This knowledge challenges us to develop therapeutic paradigms that not only target specific drivers (i.e., “targeted therapy”) but also the evolutionary landscape (Nowak and Sigmund, 2004) of these drivers.

EXPERIMENTAL PROCEDURES

One hundred forty-nine patients with CLL provided tumor and normal DNA for exome-sequencing and copy number assessment in this study. Sample

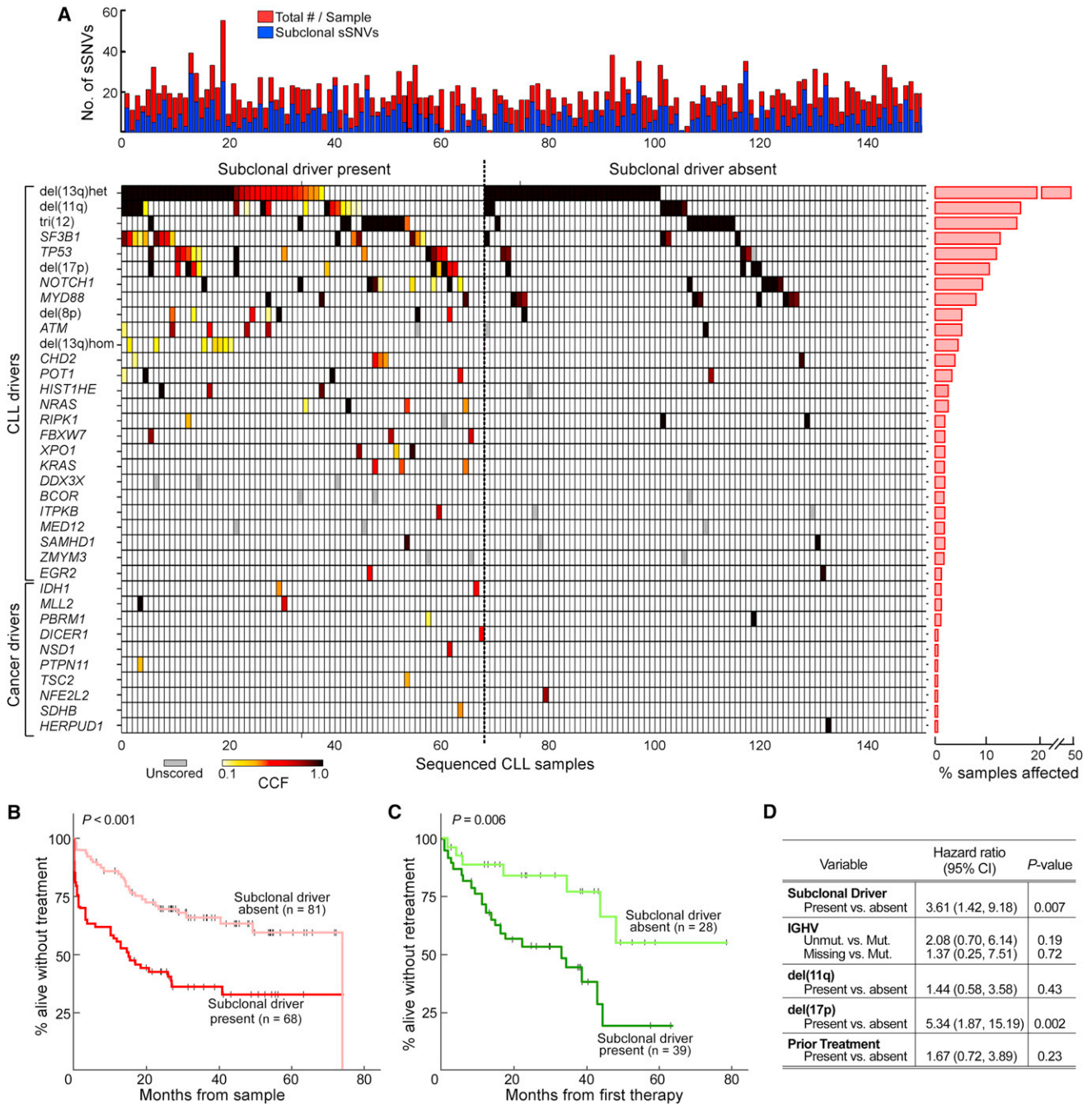


Figure 6. Presence of Subclonal Drivers Mutations Adversely Impacts Clinical Outcome

(A) Analysis of genetic evolution and clonal heterogeneity in 149 CLL samples. Top: total number (red) and the number of subclonal (blue) mutations per sample. Bottom: co-occurring CLL or cancer drivers (sSNVs in highly conserved sites in Cancer Gene Census genes) detected in the 149 samples. Color spectrum (light yellow to black) corresponds to estimated CCF; white boxes: not detected; gray: CCF not estimated (genes on the X chromosome and indels other than in *NOTCH1*).

(B and C) Subclonal drivers are associated with adverse clinical outcome. (B) CLL samples containing a detectable subclonal driver (n = 68) exhibited shorter FFS_Sample compared to samples with absent subclonal drivers (n = 81) (also see Figure S6). (C) Subclonal drivers were associated with shorter FFS_Rx in 67 samples, which were treated after sampling.

(D) A Cox multivariable regression model designed to test for prognostic factors contributing to shorter FFS_Rx showed that presence of a subclonal driver was an independent predictor of outcome.

See also Figure S6 and Tables S4 and S7.

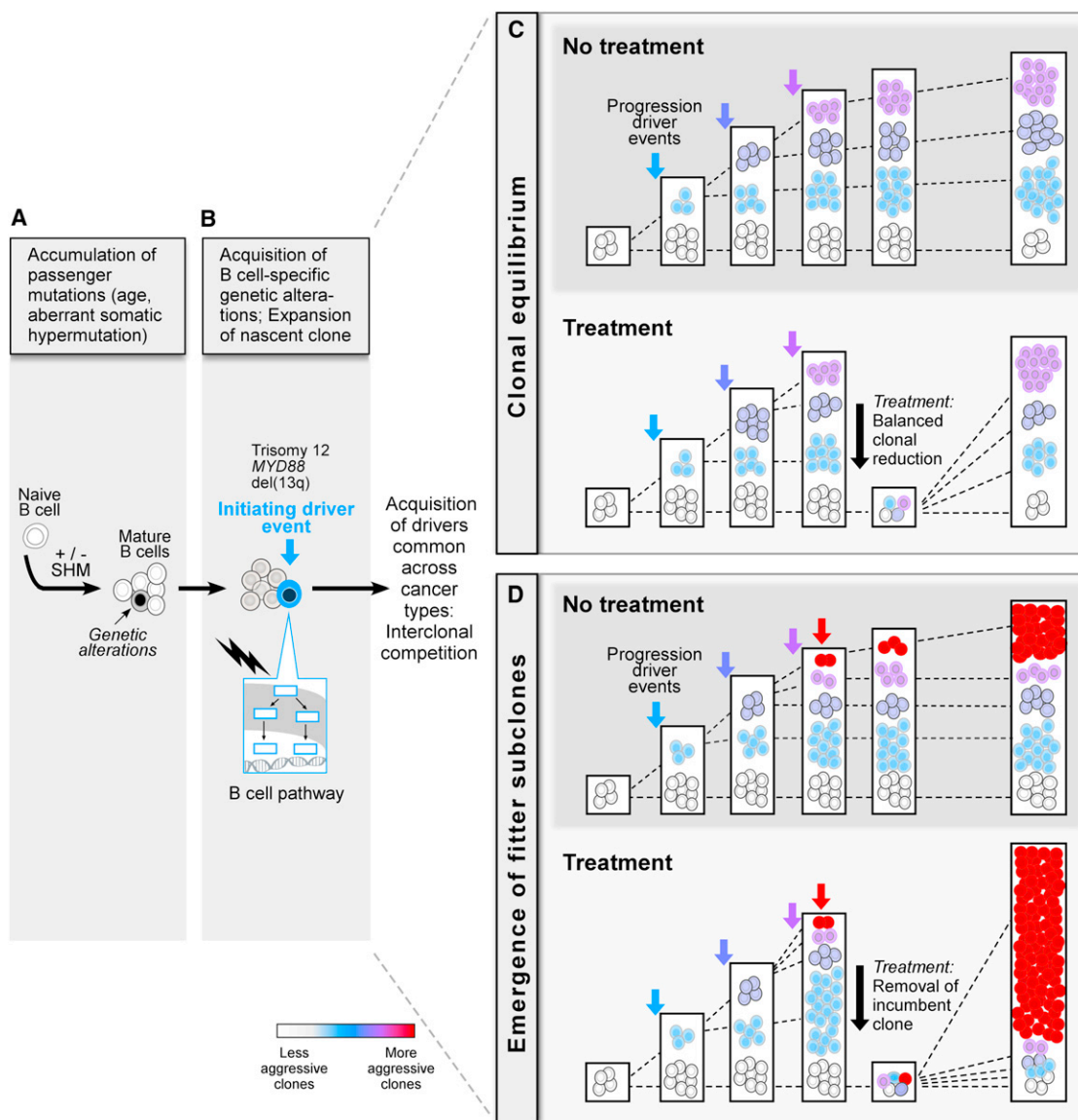


Figure 7. A Model for the Stepwise Transformation of CLL

(A–D) Our data suggest distinct periods in the history of CLL. We observed an increase in clonal mutations in older patients and in the *IGHV* mutated subtype, likely corresponding to pretransformation mutagenesis (A). We identified earlier and later mutations in CLL, consistent with B cell-specific (B) and ubiquitous cancer events (C and D), respectively. Finally, clonal evolution and treatment show a complex relationship. Most untreated CLLs and a minority of treated CLLs maintain stable clonal equilibrium over years (C). However, in the presence of a subclone containing a strong driver, treatment may disrupt interclonal equilibrium and hasten clonal evolution (D).

material was obtained from patients enrolled in clinical research protocols at the Dana-Farber Harvard Cancer Center (DFHCC), approved by the DFHCC Human Subjects Protection Committee. Tumor and normal DNA from 11 additional patients were also analyzed by DNA sequencing alone (a total of 160 CLL samples). Eighty-two CLL samples were previously reported (Wang et al., 2011), and the raw BAM files for these samples were reprocessed and reanalyzed together with the new data to ensure the consistency of the results and to enable the detection of smaller subclones made possible with a newer version of the mutation caller. Written informed consent was obtained prior to sample collection according to the Declaration of Helsinki. DNA was extracted from blood- or marrow-derived lymphocytes (tumor) and autologous epithelial cells (saliva), fibroblasts, or granulocytes (normal).

Libraries for WES were constructed and sequenced on either an Illumina HiSeq 2000 or GA-IIX using 76 bp paired-end reads (Berger et al., 2011; Chapman et al., 2011). Output from Illumina software was processed by the Picard data processing pipeline to yield BAM files containing well-calibrated, aligned reads (Chapman et al., 2011; DePristo et al., 2011). sSNVs and indels were identified using MuTect (V119, [Cibulskis et al., 2013]) and indelocator (V61, [Wang et al., 2011]), respectively. Recurrent sSNV and indels in 160 CLLs were identified using MutSig2.0 (Lohr et al., 2012). For 111 of 149 matched CLL-normal DNA samples, copy number profiles were obtained using the Affymetrix Genome-wide Human SNP Array 6.0, with allele-specific analysis (HAPSEG [Carter et al., 2011]). Recurrent sCNAs were identified using the GISTIC2.0 algorithm (Mermel et al., 2011), after excluding germline copy

number variants. For CLL samples with no available SNP arrays (38 of 149 CLLs), sCNAs were estimated directly from the WES data based on the ratio of CLL sample read-depth to the average read-depth observed in normal samples for that region. We applied ABSOLUTE to estimate sample purity, ploidy, and absolute somatic copy numbers. These were used to infer the CCFs of point mutations from the WES data. Following the framework previously described (Carter et al., 2012), we computed the posterior probability distribution over CCF c as follows. Consider a somatic mutation observed in a of N sequencing reads on a locus of absolute somatic copy number q in a sample of purity α . The expected allele-fraction f of a mutation present in one copy in a fraction c of cancer cells is calculated by $f(c) = \alpha c / (2(1 - \alpha) + \alpha q)$, with $c \in [0.01, 1]$. Then, $P(c) \propto \text{Binom}(a|N, f(c))$, assuming a uniform prior on c . The distribution over CCF was then obtained by calculating these values over a regular grid of 100 c values and normalizing by dividing them by their sum, which is the constant of proportionality in the above equation. Mutations were thereafter classified as clonal based on the posterior probability that the CCF exceeded 0.95 and subclonal otherwise. Validation of allelic fraction was performed by using deep sequencing with indexed libraries recovered on a Fluidigm chip. Resulting normalized libraries were loaded on a MiSeq instrument (Illumina) and sequenced using paired-end 150 bp sequencing reads to an average coverage depth of 4,200 \times .

Associations between mutation rates and clinical features were assessed by the Wilcoxon rank-sum test, Fisher exact test, or the Kruskal–Wallis test, as appropriate. Time to event data were estimated by the method of Kaplan and Meier, and differences between groups were assessed using the log-rank test. Unadjusted and adjusted Cox modeling was performed to assess the impact of the presence of a subclonal driver on clinical outcome measures alone and in the presence of clinical features known to impact outcome. A chi-square test with 1 degree of freedom and the -2 Log-likelihood statistic were used to test the prognostic independence of subclonal status in Cox modeling.

A complete description of the materials and methods is provided in the [Extended Experimental Procedures](#).

ACCESSION NUMBERS

The dbGaP accession number for the WES data reported in this paper is phs000435.v1.p1. The National Center for Biotechnology Information Gene Expression Omnibus accession number for the array data reported in this paper is GSE37168.

SUPPLEMENTAL INFORMATION

Supplemental Information includes Extended Experimental Procedures, six figures, and seven tables and can be found with this article online at <http://dx.doi.org/10.1016/j.cell.2013.01.019>.

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